UNIVERSITY FOR DEVELOPMENT STUDIES

MODERN AGRICULTURAL PRACTICES AND TECHNOLOGIES ON MAIZE PRODUCTION: ASSESSING CLIMATE CHANGE IN THE LAWRA MUNICIPALITY OF THE UPPER WEST REGION OF GHANA

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BY

IBRAHIM HASHIM

(HND STATISTICS, BSc. STATISTICS, PGD APPLIED STATISTICS)

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THESIS SUBMITTED TO THE DEPARTMENT OF STATISTICS, FACULTY OF MATHEMATICAL SCIENCES, UNIVERSITY FOR DEVELOPMENT STUDIES, IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF MASTER OF PHILOSOPHY DEGREE IN BIOMETRY

SEPTEMBER, 2021

DECLARATION

I hereby declare that this thesis is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Signature:…………………. Date: ………………………

Ibrahim Hashim

Candidate

Supervisors

We hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of the thesis laid down by the University for Development Studies.

Signature: …………………… Date: …………………....

Dr. Abukari Alhassan

Principal Supervisor

Signature:………………………. Date:………………………..

Dr. Richard Puurbalanta

Co-Supervisor

ABSTRACT

The main aim of the study was to examine the influence of modern agricultural practices and technologies on maize production. Data on yields for five different farming seasons and other attributes of Climate Smart Agriculture Technologies were obtained from three communities in the Lawra Municipality. The study identified a six factor solution which explained the correlation in the observed data without substantial loss of information. Multinomial Logistic Regression and Mixed Effect Linear Regression were used to model the impact of the independent variables on the Climate Smart Agriculture Practices and Technologies and the yields of maize. The results from the Multinomial Logistic Regression revealed the determinants (farming experience and status of household head) do not impact significantly in predicting Climate Smart Agriculture Technology Practices. The results shows that farmers who have practiced Climate Smart Agriculture Technology ranging from 6 to 10 years were found to be accompanied by a low probability of 15.47% of using improved variety/treated seeds as compared to those farmers having practiced Climate Smart Agriculture Technology for a period of 1-5 years but such a decrease in probability was however significant at the 5% level. Also tied ridges as a modern technology practice by farmers resulted in high probability of 11.44% for high yields relative to low yields. Results from the Mixed Effect Linear Regression showed that number of years of practising Climate Smart Agriculture (6-10 years and above 11 years) tends to decrease average maize yield by 1.8339 and 0.7937 units respectively as compared to those of Climate Smart Agriculture experience of 1-5 years which was statistically significant.

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DEDICATION

I dedicate this work to my lovely wife and children, Safura Kanyir Hashim, Abdul Raqeeb Ajaangsuma Hashim, Afaayat Junoo Hashim and Faa-iq Sungsuma Hashim.

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LIST OF ABBREVIATIONS

CCAFS	Climate Change Agriculture and Food Security
CSA	Climate Smart Agriculture
CSIR	Council for Scientific and Industrial Research
ICRISAT	International Crops Research Institute for Semi-Ari Tropical
IPCC	Intergovernmental Panel on Climate Change
NGO	Non-Governmental Organization
NPK	Nitrogen Phosphorus Potassium
SA	Sulphate of Ammonia
SARI	Savanna Agricultural Research Institute

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The agricultural sector is critical in the fight against extreme poverty and hunger, supporting the lives of nearly 1.5 billion people living in smallholder rural households around the world (World Bank, 2008). The sector is also found to be the overarching drivers of the economic growth of many economies (Gebremariam and Tesfaye, 2018; Manda et al., 2017).

Despite its critical importance, the agricultural sector is highly vulnerable to climate change and variability (Van de Steeg et al., 2009; Schlenker and Lobell, 2010), with small-scale farmers suffering disproportionately due to poverty, high reliance on natural resources and insufficient ability to adopt new livelihood strategies (Osbahr and Viner, 2006). Also, a study by Mendelsohn et al. (2000b) posited that the sector suffers from a lack of high-yielding technology, droughts as a result of the dominance of climate, floods and the effects of climate change.

Climate change and extreme weather occurrences lends credence to food insecurity crises and offer new obstacles to the continent’s long-term development (Aggarwal et al., 2018; Ubilava, 2018). Furthermore, SSA is especially vulnerable to climate change and major weather shocks due to its heavy reliance on rain-fed agriculture and preponderance of large agriculture (Asfaw et al., 2016; Binswanger-Mkhize and Savastano, 2017). For instance the recent El Niño droughts wreaked havoc on maize yields in the 2015/16 crop seasons, resulting in significant food security issues in the region (Ubilava, 2018; World Food Programme, 2017).

From the foregoing, climate change and extreme weather events can result in famine and hence retard socioeconomic development of nations. A classical case is attributed to a third of Africa's populations living in famine-prone areas, with 220 million people experiencing famine each year (IPCC, 2014). Due to this, climate change is expected to increase and worsen weather and extreme events, resulting in estimated yield reductions of up to 50% in some African nations in 2020, and net crop returns of up to 90% by 2100 (Boko et al., 2007). This will jeopardise food security and the achievement of major developmental goals resulting to the need for SSA countries to critically examine these negative impacts of climate change and extreme weather events on agriculture.

Several techniques including Climate Smart Agriculture (CSA) have been proposed in reaction to these unforeseen changes in the agriculture sector particularly among peasant farmers. According to FAO (2010) and FAO (2013), CSA increases production in a long-term, improves resilience, reduces greenhouse gas emissions, and aids in the achievement of national food security and development goals.

This technique can be used to implement policies such as the adoption of climate-tolerant varieties, weather information, crop insurance, and the use of climate data in farming, among others. These methods are largely focused on long-term sustainability and agricultural intensification, both of which are necessary for greater output and food security.

1.2 Problem Statement

Climate change continues to be an unpredictable event and a threat to food security in developing countries. This has resulted to a decrease and an unstable production exacerbating food insecurity and poverty in emerging countries. The consequences of these climatic shifts will even have a greater impact on peasant farmers whose activities of farming are weather dependent and vulnerable to climate change (Schlenker et al., 2010; Rao et al., 2011). In other to ensure resilience, adoption of climate smart practices among peasant farmers is necessary.

Despite the critical significance of climate smart practices in strengthening resilience, increasing production, lowering greenhouse gas emissions, and mitigating environmental degradation, peasant farmers have been slow to embrace them globally (FAO, 2013; Fanen et al., 2014). This is due to a number of flaws and issues that have yet to be addressed (Dzanku and Sarpong, 2011). Most research have focused on the influence of climate change on agriculture and adaption measures, but few have examined the factors that necessitates the adoption of adaptation approaches (Schlenker et al., 2010; Mburu, 2013).

According to the Ghana Statistical Service, the Upper West region is one of the lowest among the ten regions of Ghana, placed 10th on the poverty ranking, exposing the region to susceptibilities including climate change and variability (GSS, 2014). However, over the years improved technologies including climate smart practices in the Lawra municipality remain unclear among peasant farmers towards the adaptation of these unfavourable climatic conditions. Also, in response to the climate smart practices adopted by farmers that gives highest maize production remains not investigated and hence to fill this knowledge gap, this study is instituted in the Lawra municipality using peasant farmers.

1.3 General Objective of the Study

The main objective of the study is to examine the influence of climate change in light of modern agricultural practices and technologies on maize production in the Lawra municipality of the Upper West region.

1.3.1 Specific Objectives of the Study

The study seeks;

1. To model the determinants of CSA technologies on maize production.
2. To examine the determinants of maize yields of farmers using on CSA technologies.
3. To determine the underlying constructs of CSA practices on maize production.

1.4 Research Questions

This study seeks to address the following research questions:

1. What are the determinants of CSA technologies on maize production?
2. What determinants promote maize yields of farmers using CSA technologies?
3. What are the underlying constructs of CSA practices on maize production?

1.5 Significance of the Study

By modelling the determinants of the modern agricultural technologies on maize production, the study is of significance in several ways. The results of the study will ease the design of necessary interventions which will boost the knowledge and practices of climate smart among peasant farmers in areas with comparable ecological and socioeconomic conditions within the study area of Ghana. This will consequently lead to improved resilience to climate change, increase food security, poverty alleviation among peasant farmers, economic growth and mitigation of climate change.

The result of this study will equally contribute to the body of literature on the efforts to mitigate the adverse effects of climate change and variability associated with maize production through the adoption of policies and interventions in the area climate smart practices in the Lawra Municipality and the country at large. Finally, this study will help peasant farmers to make informed decisions on the adoption climate smart practices that will require substantial resources, skills and time to implement and manage.

1.6 Scope of the Study

This study was carried out in the Upper West Region which targeted peasant farmers of three communities (Bompari, Dazuuri and Toto) under the Lawra municipality. The study captured information regarding five farming season yields (2016-2020) of peasant farmers into the production of maize. Also, CSA practices adopted by these peasant farmers were also captured. Furthermore, demographic and farming characteristics were sought to establish how they influence the adoption of these CSA practices and maize yields respectively. Also, the CSA practices were further explored to determine the underlying constructs of maize production in the Lawra municipality.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter will delve into the works of other researchers to address the research objectives. It also constitutes sections and sub-sections in the area of climate change and variability, CSA practices, maize production and the impacts on yield in developing countries.

2.1. Definition of Key Concept

This section outlines essential ideas related to climate change and practices measures. According to the IPCC (2014), climate change is defined as a change in the state of the climate that can be recognised by changes in the mean and/or variability of its attributes and that lasts for a long period of time. Climate change impacts are the direct or indirect repercussions of extreme weather events that threaten not just agricultural output but also infrastructure and human livelihoods. Climate variability is defined by FAO (2012a) as fluctuations in the mean state of the climate on all time-based and geographic scales beyond that of individual weather occurrences. Unpredictability can be caused by natural internal processes within the climate system (internal variability) or by changes in natural or artificial external forcing (external variability). Perceptions of farmers on long-term variations in temperature and precipitation have been characterized by some researchers as farmers' capacity to interpret climate change occurrences based on their expertise.

Several studies have identified various characteristics that impact farmers' views, such as farmers' age, education, agricultural experience, and, in certain cases, access to climatic information (Gbetibouo, 2009; Ndambiri et al., 2013). According to the IPCC (2014), technological practices are the process of mitigating the damages or harm caused by extreme weather occurrences such as floods, droughts, landslides, storms among others. All actions designed to adapt to actual or predicted climatic stimuli and their repercussions are included in technology practices. Technology practices are heavily reliant on an affected system's, regions, or community's adaptive capability or flexibility to cope with the consequences and hazards of climate change. The socioeconomic qualities of communities determine their capability. Adaptive capacity, as defined by Burton et al. (2001), is the potential or ability of a system, area, or community to adjust to the effects of climate change. Other academics described adaptation and practices as acts or tactics undertaken by families and communities to improve the resilience of vulnerable systems and mitigate climate change-related damages in order to satisfy their livelihood demands (Rennie and Singh, 1996; Scheraga and Grambsch, 1998).

2.2 Climate Change and Variability

Climate variability according to Bizikova *et al.* (2009), refers to variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate on all spatial and temporal scales beyond that of individual weather events. Variability may be due to natural internal processes within the climate system (internal variability), or to variations in natural or anthropogenic external forcing (external variability).

2.2.1 Climate Change Impacts on Agriculture

Agriculture, as a key source of food, is very vulnerable to extreme weather events, which reduce agricultural productivity globally. Climate change may have an influence on agriculture by either increasing water demand or decreasing water supply in regions suitable for irrigation (IPCC, 2007; Kang et al., 2009). Despite the fact that climate change is reducing agricultural productivity in various dimensions and that developing countries are experiencing a series of extreme weather events that necessitate high practice costs, agriculture is receiving increased attention around the world in terms of adjusting to the negative impacts in order to meet the needs of disadvantaged people who rely heavily on agriculture for food (World Bank, 2010a; SIDA, 2010; FAO, 2012b). Globally, arable land utilized for agricultural production is around 1.4 billion hectares, with about 200 million hectares of arable land irrigated (FAO, 2012a). In certain cases, the effects of climate change are connected to population expansion, particularly in developing nations, because population expansion is the primary source of rising Green House Gas (GHG) emissions.

Some shreds of evidence indicated that the population of the East Africa region has increased to an unexpected extent between 1961 and 2011. Likewise, the population projection in this region is somehow problematic as the impacts of climate change associated with population growth are unpredictably affecting the region (Cooper *et al*., 2013; FAO, 2012a).

2.2.2 Climate Change and Maize Production

Maize is produced on nearly 100 million hectares in developing countries, with almost 70% of the total maize production in the developing world coming from low and lower middle income countries (FAOSTAT, 2010). It is the third most cultivated field crop after wheat and rice in the world. Jaliya *et al*. (2008) reported that maize is the most popular due to its high yield, ease of processing and low cost of production. Maize is the most important cereal crop in most parts of West Africa (Fosu *et al*., 2004). It is one of the most relevant food crops and very common in all parts of SSA. In 2010, 53 million tons of maize was produced in SSA on about a third of the total harvested crop land area (~33 million ha) (Waha *et al.*, 2013). The crop has been increasing in production since 1965 (Morris *et al.*, 1999; FAO, 2008). Maize production plays a vital role in food security for many poor households in Ghana (SRID, 2010) with a per capita consumption of over 100 kg while also serving as a cash crop (FAO, 2008).

Maize is produced mostly by smallholder farmers who are also resourced poorly especially under rain-fed conditions (Altieri and Koohafkan, 2008). Based on the most recent domestic production data, it is estimated that the shortfall between domestic production and domestic consumption would reach 267,000 Mt by 2015 in case there is no productivity improvement (SRID, 2010).

According to MIDA (2012), maize represents the second largest commodity crop in the country after cocoa. Maize production forms 45% of agricultural production which remains the main source of livelihood for most Ghanaians, providing employment to more than 60 percent of the population and contributing about 30% of gross domestic product (ISSER, 2011) and its production contributes over 20% of incomes earned by smallholder farmers in Ghana (Acquah *et al.*, 2012).

Maize yields remain low and highly variable between years across SSA at 1.6 t/ha, only just enough to reach self-sufficiency in many areas (Bänziger and

Diallo, 2001; FAOSTAT, 2010) the average yield registered by the Ministry of Agriculture in 2010 was 1.9 Mt/ha against an estimated achievable estimated yield of 2.5 to 4 Mt/ha (Ministry of Food and Agriculture, 2010). Previous research strongly suggests maize growing regions of SSA will encounter increased growing season temperatures and frequency of droughts (IPCC, 2007). An estimated 40-90% yield loss may occur at flowering and grain filling stages as a result of drought (Nesmith and Ritchie, 1992; Menkir and Akintunde, 2001).

2.3 The Concept of Climate Smart Agriculture

Climate smart agriculture is an agriculture practice that sustainably increases food production, builds resilience to climate change (adaptation), reduces/removes greenhouse gases (mitigation) and enhance the achievement of national food security and development goals (FAO, 2010). According to the FAO during the 2010 Hague conference on Food Security and climate change, Climate-smart Agriculture (CSA), contributes to the achievement of sustainable development goals. It integrates the three dimensions of sustainable development (economic, social and environmental) by jointly addressing food security and climate challenges (FAO, 2013). Strategies aimed at agricultural development have migrated from the promotion of one-size-fits-all technologies intending to improve productivity to the recent push for improved agricultural practices which takes into account livelihood and environmental outco0mes (Defries *et al*., 2010). The term "Climate Smart" has however commonly been used in the context of agriculture (Roe et al., 2016). The CSA concept was developed by the FAO and "identifies interactions and trade-offs among food security, adaptation and mitigation as grounds for informing and reorienting policy in response to climate change" (Lipper *et al*., 2014). "CSA calls for a set of actions by decision-makers from the farm to the global level" in transforming agriculture toward "climate-smart pathways" (Lipper *et al*., 2014). CSA practices are not or must not be necessarily new, in fact, according to Schaller *et al*. (2017), any agricultural practice or technique contributing to achieving the three pillars can be considered climate smart. The different techniques employed in CSA often perform differently over the pillars and as a result have to be combined as an integrated approach to complement each other to maximize the benefits (World Bank, 2015; FAO, 2015).

The CSA concept combines multiple conventional agricultural practices and approaches such as conservation agriculture, agro ecology and agroforestry, soil management, sustainable agriculture and sustainable intensification as well as climate-smart landscapes (Chandra *et al*., 2016). CSA and Conservation Agriculture (CA) are related in the sense that, CA supports adaptation by reducing risks of soil erosions as a result of rainfall-runoff and mitigation through carbon sequestration despite the benefits not being massive on a global scale (Richards *et al*., 2014). According to Sudjen (2015), governmental and non-governmental stakeholder views on CSA are divided raising questions on how the approach meets food security issues of smallholder farmers. McCarthy *et al*. (2011) also argue that institutional barriers limit the adoption and upscaling of CSA practices and technologies. For policymakers, a key challenge in operationalizing CSA is the identification and prioritization of CSA portfolios and options and its valuation in terms of cost-benefit and trade-off analysis (Sogoba *et al*., 2016).

2.4 Defining Smallholder Farmer

Definition of peasant farming by different authors has always brought about ambiguities that pose challenges in addressing the specific needs of smallholder farmers. Despite the controversies surrounding the acceptable definition, the commonest definition has always been associated with size, since it varies across several geographical regions (Nagayets, 2005). For instance, studies have shown that peasant farmers in sub-Saharan Africa occupy operational landholdings of 2 ha or less, while in South Asia and Latin America, they occupy average landholdings of 1.6 ha and 10 ha respectively (Narayanan and Gulati, 2002). Risks conditions and resources may also vary across smallholder farmers in different geographical regions, undermining the use of values or size to define peasant farming systems. It is argued that sometimes "a small piece of irrigated peri-urban land, suitable for vegetable farming or herb gardening, has a higher profit potential than 500 hectares of low quality land in the Karoo in South Africa" (Kirsten and Van Zyl, 1998). In the same light, defining smallholder farming systems in Ghana have demonstrated varied opinions by different authors. Ghana's Food and Agriculture Sector Development Policy, FASDEP II, states that agriculture in Ghana is dominated by smallholder farming systems and it is characterized by landholdings of 2 ha coupled with the use of crude technologies to produce a greater percentage (80%) of the country's agriculture output. Chamberlin (2007) however posits that indeed, smallholders form a chunk of Ghana's rural economy and operates less than 3 ha with regional disparities across the country. Further analysis by Chamberlin indicates that Southern Ghana has an average landholding size of less than a hectare, while Northern Ghana is dominated by larger landholdings with the Upper West region being one of the regions with a greater concentration of smallholders. Paradoxically, the prevalence of larger holding size in Northern Ghana has not translated into higher outputs due to factors not limited to poor soils, type of crops grown, labour constraints, rudimentary technologies or climatic factors. In cases where farmers can increase productivity, they are challenged by storage facilities and market access. More smallholders in the South have taken advantage of the bimodal rainfall pattern, extension services and market access to grow both high value crops and staple crops for consumption and sale, improving livelihoods than their counterparts in the North., Al-hassan and Diao (2007) assert that the growth of high value crops backed by improved policies have contributed to the developmental gap between the North and the South, where Northern Ghana lags. Generally, it is estimated that there are about 570 million farms in the world of which 72% have farm sizes that are less than a hectare, with only a percentage covering farm sizes of 10-20 ha, (FAO, 2014). Farm sizes are however gradually decreasing due to rapid population growth with other competing needs for land use (Lowder *et al.*, 2014). Thus, for this study, smallholder farmers cover resource poor farmers operating on a holding less than 2 ha and depend on household members for most of the labour.

Some of the practices that are consistent with CSA and practice in smallholder systems in West Africa as well as in line with the AU-NEPAD Agriculture Climate Change Adaptation-Mitigation Framework are presented in Table 2.1.

In general, all the practices in Table 2.1 address food security and lead to higher productivity, but their ability to address adaptation and mitigation varies.

Table 2.1: Uesfulness of Climate-Smart Agriculture Practices in Smallholder Agricultural Production

Crop management	**Livestock management**	**Soil and water management**	**Agroforestry**	**Integrated food energy systems**
• Crop rotations • New crop varieties(e.g. drought tolerant) • Intercropping with legumes • Greater crop diversity • Improved storage and processing techniques	• Grassland restoration and conservation • Improved livestock health • Improved feeding strategies (e.g. cut and carry) • Rotational grazing • Fodder crops • Manure treatment • Animal husbandry Improvements	• Contour planting • Terraces and bunds • Alternate wetting and drying (rice) • Dams, pits, ridges • Improved irrigation (e.g. drip) • Conservation agriculture (e.g. minimum tillage)	• Improved fallow with fertilizer shrubs • Nitrogen-fixing trees farms • Multipurpose trees • Boundary trees and hedgerows • Woodlots • Fruit orchards	• Improved stoves • production of energy plants • Biogas

Source:AU-NEPAD(2010)

2.5 Effects of Climate Variables on Maize Crop Production Yield

The review examined the effects of some climatic variables in respect of the increase in temperature and changes in rainfall patterns.

2.5.1 Effects of Increase in Temperature

The world average temperature is gradually rising, and agriculture remains the primary source of GHG emissions into the sky (Ludwig et al., 2007; FAO 2012a). According to the IPCC's most recent study, average global temperature climbed between 1.8 and 4.0 ^{0}C from 1980 to 1999 and is anticipated to rise between 1.1 and 6.4 ^{0}C over the twenty-first century (IPCC, 2007).

Other researchers confirmed that the minimum temperature climbed almost twice as rapidly (0.204^{0}C each decade) as the maximum temperature (141^{0}C per decade). To some extent, global warming may affect crop yield in equatorial and tropical nations while increasing agricultural output in temperate nations where the ambient temperature is lower than in equatorial and tropical climatic zones (Vose et al., 2005; Zhang et al., 2013).

2.5.2 Effects of Changes in Rainfall Pattern

Depending on the intensity of the rainfall, crop output might either grow or decrease. Almost 20% of the world's population lives in river basins that are expected to be impacted by the increased precipitation. Increased rainfall intensity may raise the danger of flooding in moist areas dominated by agriculture (IPCC, 2007). It has been determined that significant and unpredictable rainfall, which can result in floods, is a limiting factor for agricultural productivity in poor countries. Farmers were forced to adjust by moving crops, diversifying their crops, and planting trees (Gina et al., 2006;

Ludwig et al., 2007). Due to a lengthy dry period, the regions encompassed by the tropics and hemispheres, where SSA nations are situated, face a 20% drop in rainfall. This might result in the loss of agricultural land due to decreasing soil moisture, increased sterility, increased salinity, and groundwater depletion (Vose et al., 2005; IPCC, 2007; Oyiga et al., 2011).

2.6 Mitigation and Adaptation of Climate Change

To combat climate change, two techniques that address both the source and the consequence of climate change have been identified. Mitigation focuses on reducing greenhouse gas emissions, whereas adaptation focuses on mitigating the effects of global warming. The Kyoto Protocol, signed in 1997, established worldwide mitigation objectives. The agreement required Annex I nations (developed nations and economies in transition) to commit to decreasing greenhouse gas emissions by around 5% relative to 1990 levels between 2008 and 2012. At the European level, the European Union established a 20 objective, with the goal of keeping the world average temperature increase to less than 20 degrees Celsius over pre-industrial levels (CEC, 2007). The 2009 UNFCCC Conference of the Parties in Copenhagen adopted a non-binding Copenhagen Accord that endorses the scientific position that global temperature increases should be limited to less than 2^0C (UNFCCC, 2010a). However, it is currently unclear whether international climate negotiations concerning the Kyoto Protocol's follow-up will reach a consensus on reducing greenhouse gas emissions, and whether the 20^0C target of reducing emissions is sufficient to counteract the most severe effects of climate change caused by temperature rise. The IPCC defines adaptation to climate change as "modification of natural or human systems in response to present or anticipated climatic incentives or their consequences, which mitigates damage or capitalizes on favourable possibilities" (Parry et al., 2007). Technology approaches entail making investment decisions to mitigate the possible effects of climate change and seizing new possibilities. Through practice measures, the system's adaptive capacity and sensitivity are increased, minimizing society's susceptibility to the effects of climate change (Mastrandrea et al., 2010). There are several types of practices distinguished, including reactive, anticipatory (proactive), autonomous, and planned adaptation, with anticipatory adaptation seen as an essential component of the optimal response to climate change because it is likely to be much less expensive than relying solely on reactive adaptation (Fankhauser et al., 1999). Practices are carried out at many geographic scales and necessitate a coordinated response. Policymakers have a critical role in making well-considered policy decisions to reduce susceptibility to climate change (Klein et al., 2003). According to the IPCC, "the challenge for decision-makers is to determine which actions are currently appropriate and likely to be robust in the face of the many long-term uncertainties" (Klein et al., 2007). Through systematic assessment of adaptation measures, policymakers can make well-informed choices about which measures to implement.

2.7 Empirical Study of Climate Smart Agriculture (CSA)

A study was conducted to assess farmers' preference for CSA and willingness to pay (WTP) for various climate-smart interventions in the Indo-Gangetic Plains (IGP). The Indo-Gangetic plains were selected because of their vulnerability to climate change against the rice-wheat production system and food security in the region. The study used scoring and bidding protocols implemented through focus group meetings in two distinct regions (Eastern and Western IGP). The study discovered that laser land levelling (LLL), crop insurance, and weather advisory services were the preferred interventions in the Eastern IGP. From the Western IGP, farmers preferred LLL, direct seeding, zero tillage, irrigation scheduling and crop insurance. The study added that farmers were willing to pay for new technologies that could transform current agricultural practices into relatively low-carbon and more productive farming methods through bidding. The study concluded that adoption of preferred climate-smart technologies and other interventions require access to funding and capacity building among promoters and users (Garima *et al*., 2014).

Another study was conducted to investigate the barriers to the adoption and diffusion of technological innovations for CSA in Europe: Evidence from the Netherlands, France, Switzerland and Italy. Data for the study was collected using semi-structured interviews with CSA technology providers and members of the agriculture supply chain. The data were thematically coded and categorized to identify key barrier typologies. The study reported that barriers exist in both demand (user) and supply (technology provider) sides. The study recommended that adoption and diffusion of CSA technological innovations be increased as well as the implications for CSA and innovation literature (Thomas *et al*., 2015).

Victor *et al*. (2019) also conducted a study on the dynamics of climate change adaptation in Sub-Saharan Africa: a review of CSA among small-scale farmers. The study revealed from the literature that age, farm size, nature of farming, and access to extension services influence CSA practices. The study also reported that many investments in climate adaptation projects have found little success because of a sole focus on technology-oriented approach and allowing unskilled farmers to deal with the innovative approach alone. The study concluded that the prospects of CSA in small-scale agriculture lie in holistic socio-economic outcomes that appreciate the heterogeneity of small farmers' environment and the identification and analysis of capacities of farming households for adoption and implementation.

A study was also conducted by David *et al*. (2013), to review the current practice of agroforestry and conservation agriculture in Malawi and Zambia. The study focused on improving agricultural productivity to meet Africa's growing population and climate change, through increasing yields, reducing vulnerability to climate change, and reducing GHG emissions. The study added that Malawi and Zambia are two African countries that are prioritizing the use of agroforestry and conservation agriculture to improve smallholder agricultural systems under climate change. This study reported based on evidence of the use, socio-economic impacts, and the yield of farming techniques. The study concluded that agroforestry is a promising venture for smallholder farmers with well-documented yields and profitability improvements. Also, conservation agriculture is positive but weak in Africa.

The impact of CSA practices on cotton production and livelihood of farmers in Punjab, Pakistan, was equally a study on CSA conducted by Muhammad *et al*. (2018). The study investigated the financial performance and impact of CSA through sustainable water use management on cotton production in the Lower Bari Doab Canal (LBDC) irrigation system of Punjab, using cobb-Douglas production functions. The study used six focus group discussions to select adopters of CSA in cotton production. A well-structured questionnaire was used to collect from 133 adopters of CSA and 65 conventional cotton growers for the

2016-2017 cropping season. The farmers adopted the water-smart (raising crops on beds, laser land levelling, conjunctive use of water and drainage management), the energy-smart (minimum tillage), the carbon-smart (less use of chemicals), and the knowledge-smart (crop rotation and improved varieties; resistance to drought, flood, and heat/cold stresses) practices and technologies of CSA. The study revealed that most farmers opted for CSA practices and technologies due to lack of canal water system, climate change, drought prone, massive groundwater extraction, rapidly declining groundwater table and increasing soil salinity over time. The study found that the CSA practices and technologies brought improvement in uniform germination, higher yield, increased resources use efficiency and financial returns. Also, the CSA encouraged judicious use of water and fertilizer, groundwater quality, access to extension services and appropriate method and time of picking. The study recommended the adoption of CSA practices and technologies on large scales throughout Punjab and beyond.

A similar study was conducted by Munyaradzi *et al*. (2019) on a cost-benefit analysis (CBA) of CSA options in Southern Africa: Balancing gender and technology. The study employed CBA and a mixed-method approach to assess the likelihood of investment in various CSA technology combinations. The study collected data from 1440, 696, and 1448 sample households in Malawi, Mozambique and Zambia, respectively, covering 3622, 2106, and 5212 maize-legume plots, respectively from the countries, over two years. The CBA and stochastic dominance results showed that CSA options that combined soil and water conservation management practices, improved varieties, and associations of cereal-legume crop species were economically viable and recommended for smallholder farmers. The dynamic mixed multinomial logit demonstrated that women's bargaining power, drought shock, and access to CSA technology information positively influenced the probability of investing in CSA technology combinations.

Another study was conducted into the adoption of small-scale irrigation farming as a CSA practice and its influence on household income in the Chinyanja Triangle, Southern Africa. The study employed binary logistic and ordinary least square regressions to determine factors that influence the adoption of small-scale irrigation farming as a CSA practice and its influence on income among smallholder farmers. According to the study, off-farm employment, access to irrigation equipment, access to reliable water sources and awareness of water conservation practices, such as rainwater harvesting, have a significant influence on the adoption of small-scale irrigation farming. However, the age of farmer, market distance, and nature of employment negatively influence the adoption of small-scale irrigation farming. Using the ordinary least square regression, the study found that the adoption of small-scale irrigation farming as a CSA practice has a significant positive influence on agricultural income. The study recommended that the countries formulate policies that will enhance the adoption of small-scale irrigation farming in the Chinyanja Triangle (Nelson *et al*., 2018).

A study was conducted to examine a set of potentially CSA practices, such as reduced tillage, crop rotation and legume intercropping, combined with inorganic fertilizer and improved seeds, for their effects on maize yields in Zambia. The study used geo-referenced rainfall and temperature data, with data from rural incomes and livelihood surveys. The study estimated the impact of maize yield on soil disturbance, crop rotation, legume intercropping, and a set of climate variables. The study revealed that minimum soil disturbance and crop rotation have no significant impact on yield outcomes. However, legume intercropping significantly increases yields and reduces the probability of low yields even under critical weather stress. Also, improved seeds and fertilizer are significantly conditioned by climate variables. The study reported that timely access to fertilizer is a critical determinant of yields and their resilience (Aslihan *et al*., 2015).

Thanh and Koji (2019) conducted an empirical study in the Mekong Delta of Vietnam to assess the effects of CSA and climate change adaptation on the technical efficiency of rice farming. The study employed the propensity score matching approach to assess the effects. In-depth interviews were used to collect data from 352 rice farm households in the Mekong Delta. The study found that 71% of local farmers adapted their rice farms to climate change concerning soil salinity and drought, while 29% of farmers did not. Also, only 22 rice farmers were included in the CSA pilot program by the local Government and institutions. The adoption of CSA was significantly influenced by agricultural extension services, belief in climate change, the area of farmland, and geographical locations. The study revealed that CSA improved the technical efficiency of rice production by 13% -14% compared to rice production without adaption. The participants of the CSA pilot program achieved 5%-8% higher technical efficiency than the non-participants.

Synthesis of empirical evidence of food security and mitigation benefits from improved cropland management was conducted under CSA in 2011. The study reported that improving cropland management is a key to increase crop productivity without further degrading soil and water resources. The study added that sustainable agriculture can reduce GHG emissions and increase carbon sequestration, thereby, mitigating climate change. The study synthesized the results of literature on different sustainable land management practices aimed at increasing and stabilizing crop productivity in developing countries. The study revealed that soil and climate characteristics are key in the interpretation of the impact of crop yields and mitigation of different agricultural practices (Giacomo *et al*., 2011).

CHAPTER THREE

METHODOLOGY

3.0 Introduction

This chapter centres on the study area, sampling techniques involved in the data collection, data type, sources of data collection and the techniques used in the statistical analysis as well as the theoretical and practical models of the study.

3.1 The Lawra Municipality

The data for the study was collected from three communities in the Lawra municipality, in the Upper West region of Ghana. This includes; Bompari, Dazuuri and Toto communities. Lawra Municipality has a total estimated population of 100.929 of which 48,641 are males and 52,288 are females. The population distributions of the three communities considered in this study stood at 800, 900 and 600 respectively for Bompari, Dazuuri and Toto (GSS, 2010). Lawra Municipality is one of the eleven districts that comprise the Upper West Region, and its formal existence dates back to Legislative Instrument (L.I) 1434 of 1988. (PNDCL 207, Act 462). It is located in Ghana's Upper West Region, in the northwestern region of the country. Nandom Municipal limits it to the north, Lambussie-Karni District to the east, and the Republic of Burkina Faso to the southwest and west.

It is located between the latitudes of 10^0 20 and 11^0 00 North and the longitudes of 2^0 50 and 2^0 45 West. The municipality's total land area is 527.37 square kilometers. This represents around 2.8 percent of the Region's total landmark area, which is estimated to be 18,476 square kilometers. Nearly 80% of the people of the Lawra Municipality live in rural regions. The Municipal population density is 104.1 people per square kilometer (GSS, 2010). A map of Lawra Municipality with the study areas is shown below. These three communities were selected purposively because there is an ongoing project implemented by Climate Change, Agriculture and Food Security (CCAFS) to promote climate smart agricultural practices and natural resource conservation in Bompari,Dazuuri and Toto.

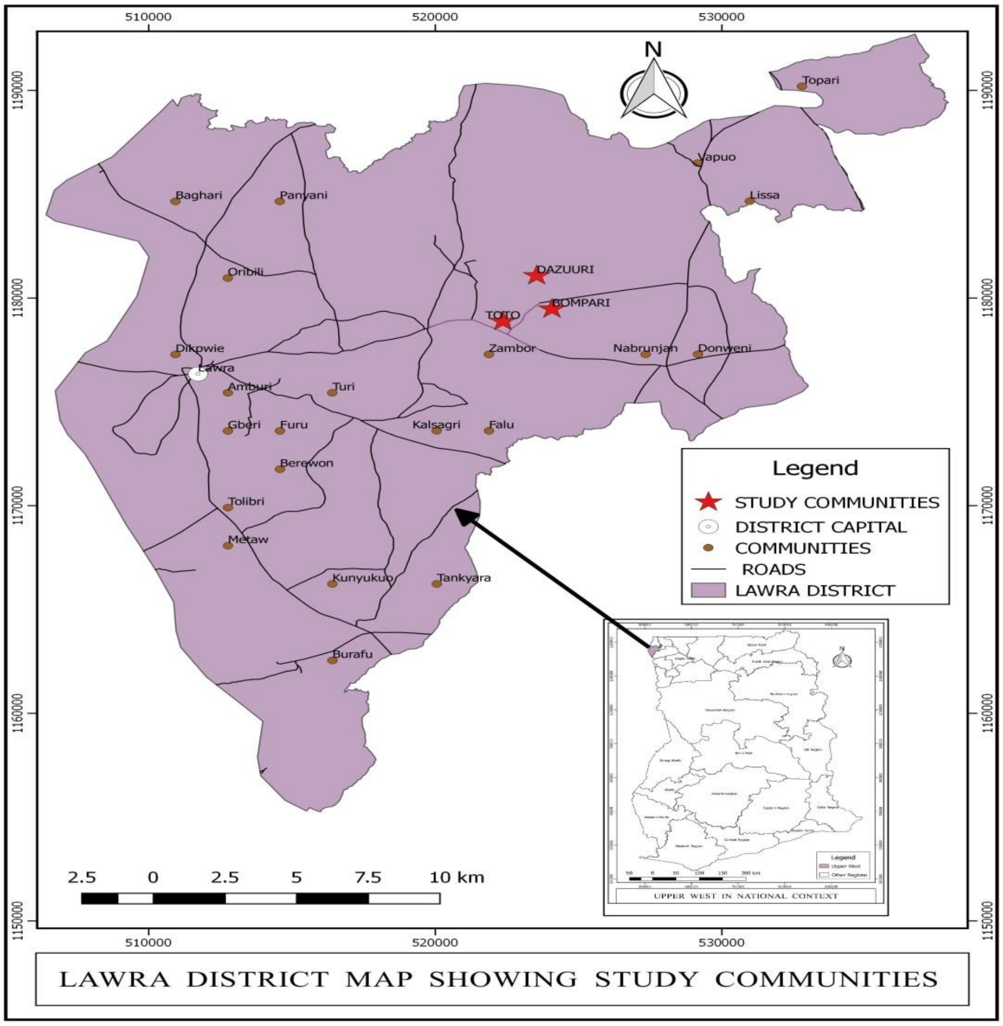

Fig 3.1 Sketch map of Lawra Municipal showing study Area

Source: Authors Construct (2021)

3.1.1 Soil and Drainage

Laterite soils make up the Lawra Municipality's soils. These are derived from the Birimian and granite rocks that lay under the region. There are also alluvial soil strips in the Black Volta's flood plains, as well as sandy loamy soils along some of its tributaries.

The vast geography of soils, along with outdated land use methods and rainfall patterns, have a negative impact on crop yield, resulting in a significant gap in food supply. This pushes the youth to seek better pastures elsewhere, a condition that jeopardizes the growth of Northern Ghana as a whole. The Lawra Municipal is making moderate development, with a few hills ranging from 180 to 300 meters above sea level. The Black Volta River shatters it to the west, forming a boundary between the municipality and the Republic of Burkina Faso. In the Municipal, the Black Volta River has various tributaries, the most notable of which are the Kamba/Dangbang, Nawer, and Duodaa. These sources of water, if used for irrigation, might provide agro-based employment for the youngsters who travel to the south during the dry season in quest of jobs that do not exist.

3.1.2 Climate and Vegetation

The Lawra Municipal fall within the Guinea Savannah Zone which is characterized by short grasses and few woody plants. Acacia, Shea trees, Dawadawa and Baobab which are drought and fire resistant interspaced in the municipality. The greenery is ideal for cattle rearing, which adds greatly to the Municipal's family income. The protracted dry season is a drawback of the vegetation. During the dry season, most grasses dry out and are eventually burned by bush fires. As a result, bush burning reduces vegetative cover and transpiration, which diverts average annual total rainfall, resulting in low agricultural yields because farmers rely heavily on rain-fed agriculture. The municipality has a tropical continental climate, with typical annual temperatures ranging between 27°C and 36°C. The warmest months are February and April. Despite the fact that climatic changes influence weather patterns, the Tropical Maritime air masses blow across the area between April and October, providing the sole cropping season of the year. The rainfall pattern is one of the main factors in the relocation of the youth for greener pasture to the southern part of Ghana, which as a result associated the municipality with underdevelopment in infrastructural and human resources.

3.1.3 Agriculture and Commerce

The main financial activity in the Lawra Municipality is agriculture; it employs about 78% of the working populace. The majority of the inhabitants are smallholder farmers which constitute about 80% of the population. The crops mainly produced in the Municipality include; groundnuts, soya bean, cowpea, maize and millet. Livestock and animal production is a supplement to a major source of income in the agricultural field. The main agricultural challenges include poor soils, erratic rainfall pattern, lack of capital, inadequate technical skill, pests and diseases infestation, inadequate and poor access to extension service and low/poor access to the market. These important barriers contribute to very low crops and livestock productivity in the municipality, which demoralizes farmers in commercializing it. Most indigenes within the active population migrate to southern parts of the country to search for job opportunities. The major Industrial established activities in the municipality are linked to the agricultural products which are mainly involved in processing, such as extraction of shea butter. The majority of industries in the Lawra Municipality are agrarian and small-scale. The people' main local economic activity include pito brewing, smock manufacturing, basket weaving, shea butter extraction, and so on. Increased access to financial capital and markets may improve the operations of some local industries. These small-scale companies rely on agricultural products for raw materials. Furthermore, they absorb excess labor in the municipality, assist farm-based households in spreading risks, provide more remunerative activities to supplement or replace agricultural income, provide income potential during the agricultural off-season, and provide a means to cope or survive when farming fails. Because of the industry's importance, the Lawra Municipality has certain institutions that provide assistance and training to assure increased production from the industrial sector. The municipal educational training institutes include the Eremon Technical Senior High School, the Boo Vocational School, and the Tanchara Vocational Institute. These institutions have provided talented human resources through the years. The Baare Xylophone Training Center and the Binne Basket Making Center, both of which are located in Lawra Township, are also making strides.

3.2 Research Design

The cross-sectional design was used to establish the determinants of practices of climate smart agriculture in the study area. Semi-structured questionnaires were administered via personal interviews to gather primary data from the respondents. For this research, descriptive analysis was used to expound the different types of crop production systems employed by farmers as well as knowledge of respondents concerning climate change and yields of maize. Quantitative analysis was used in examining the decision to adopt any of the climate-smart agricultural practices and their relationship to certain exogenous variables which relate to their socio-economic and demographic factors as well as farmers knowledge about climate change. Quantitative analysis was also used to estimate the effect of practices of climate-smart agriculture and its impact on maize production.

3.3 Data Sources and Types

The study used primary data and this was obtained from a cross-sectional survey of peasant farmers, especially maize producers in the Lawra municipality. Data on the socio-demographic and economic knowledge on climate smart agriculture were also collected for this research. The variables were measured in both continuous and discrete scales.

3.4 Sample Size Determination

According to Saunders *et al*. (2009), to conclude the study which reflects the general population under consideration it is important to determine the appropriate sample size for the study. Considering this, the study would have a sampling error or margin of error of ±5%, and 95% confidence level. The sample size for this study is calculated using the minimum sample size formula in equation (3.1), at a confidence level of 95% and a 5% margin of error. This formula is used since the study is a cross-sectional survey and the response variable is qualitative (Cochran, 1977). This required sample size formula is stated as:

$$n = \frac{N}{1 + N\ell^2}, \qquad (3.1)$$

where

n = is the required sample size,

N = the population size and

ℓ = Tolerable error (which in this study was pegged at 0.05).

The total population for the three communities is 2,300, hence the required sample size is:

$$n = \frac{2300}{1 + 2300(0.05)^2},$$

$$n = 340.704 \approx 341$$

Proportional allocation of sample size was then used to determine the samples to be taken from each stratum/community. The formula that was used in calculating the sample from each stratum/community is presented below:

$$n_k = \frac{N_h}{N} \times n, \qquad (3.2)$$

where

n_h = sample size of stratum h (that is the sample size for each community),

N = Total size of population,

n = Total sample size and

N_h = Population size of stratum h (population size of each community).

The table below show the sample distributions of the various communities

Table 3.1: Sample Distribution of the Communities

Community	Total Population	Sample Size
Bompari	800	118.61≈ 119
Dazuuri	900	133.43 ≈ 133
Toto	600	88.95 ≈ 89
Total	**2,300**	**341**

3.5 Variables for the Study

The study made use of dependent and independent variables. Twenty-one (21) attributes of CSA practices were used as independent variables in the Exploratory Factor Analysis to determine the underlying constructs in the observed data set. The dependent variable considered in the Multinomial Logistic Regression was CSA Technology Practices. Average maize yields (five different farming seasons) of peasant farmers engaged in CSA practices was used as dependent variable in the Mixed-Effect Linear Regression and its associated grouping variable (CSA Technology Practices (CSATP)) with five (5) groups specified as the level variable, while the independent variables comprised of gender, years of practising CSA, the status of yield (high or low) in bags (100kg), farming experience, the status of household head (migrant or indigene) and total land under cultivation.

3.6 Multinomial Logistic Regression

Unlike the Binary Logistic Regression which can model the dependent variable with only two categories, the Multinomial Logistic Regression is used when the dependent variable (CSA Technology Practices) has more than two categories where these categories of the dependent variable are of no natural ordering based on several several independent variables (gender, years of practising CSA, status of yield (high or low) in bags, farming experience and status of household head (migrant or indigene)). The model for the Multinomial Logistic Regression can be obtained by assuming that the outcomes that are $J = 1, 2, 3, \ldots, n$ being observed in the outcome variable (y) and predictor variables (X_i), then the estimated coefficients from the logit model can be given as:

$$\ln\left(\frac{\pi_i}{\pi_J}\right)=\psi_i+\phi^{(i)}X_i,\ \ i=1,2,3,\ldots,J-1. \tag{3.3}$$

The logit model from equation (3.3) through setting $\phi^{(1)}=0$, then a measure of changes relative to $\phi^{(1)}=1$ can be obtained from the coefficients $\left(\phi^{(2)},\phi^{(3)},\ldots,\phi^{(n)}\right)$. Also, the predicted probabilities can be ascertained from the following equations;

$$P(y=1)=\frac{1}{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)}. \tag{3.4}$$

$$P(y=2)=\frac{\exp\left(\phi^{(2)}X_2\right)}{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)}. \tag{3.5}$$

$$\vdots$$

$$P(y=n)=\frac{\exp\left(\phi^{(n)}X_n\right)}{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)}. \tag{3.6}$$

The relative probability of the categories of CSA Technology Practices (Mineral Chemical Fertilizer, Monoculture, Crop Rotation and Tied Ridges) that is in this case $y=2,3,\ldots,n$ to the reference category of CSA Technology Practice (Improved variety/treated seeds) that is, in this case, $y=1$ can be derived based on equations $(3.4),(3.5)$ and (3.6) as follows;

$$\frac{P(y=2)}{P(y=1)}=\frac{\exp\left(\phi^{(2)}X_2\right)\left\{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)\right\}}{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)}=\exp\left(\phi^{(2)}X_2\right) \tag{3.7}$$

$$\frac{P(y=3)}{P(y=1)}=\frac{\exp\left(\phi^{(3)}X_3\right)\left\{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)\right\}}{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)}=\exp\left(\phi^{(3)}X_3\right) \tag{3.8}$$

$$\vdots$$

$$\frac{P(y=n)}{P(y=1)}=\frac{\exp\left(\phi^{(n)}X_n\right)\left\{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)\right\}}{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)}=\exp\left(\phi^{(n)}X_n\right) \tag{3.9}$$

Considering that X_i and $\phi_k^{(n)}$ to be accompanied with the respective vectors $\left(x_1,x_2,\cdots,x_k\right)$ and $\left(\phi_1^{(n)},\phi_2^{(n)},\cdots,\phi_k^{(n)}\right)'$, a one-unit change in x_i, the ratio concerning the risk which is the risk of the outcome to the reference category (improved variety/treated seeds) can be obtained from;

$$\frac{\exp\left(\phi_1^{(n)}x_1\right)+\exp\left(\phi_2^{(n)}x_2\right)+\cdots+\exp\left(\phi_i^{(n)}x_{i+1}\right)+\exp\left(\phi_k^{(n)}x_k\right)}{\exp\left(\phi_1^{(n)}x_1\right)+\exp\left(\phi_2^{(n)}x_2\right)+\cdots+\exp\left(\phi_i^{(n)}x_i\right)+\exp\left(\phi_k^{(n)}x_k\right)}=\exp\left(\phi_i^{(n)}\right). \tag{3.10}$$

In Multinomial Logistic Regression, the estimates of the model tend to give the direction of the explanatory variables on the outcome variables which sometimes become difficult interpreting model coefficients. Based on this, the study made use of Average Marginal Effects purposely to obtain the actual magnitude of changes in probabilities.

The Average Marginal Effect can be achieved by considering that if there exist n factor levels of variable L;

$$h(x,\theta)=f\left(x,\theta\,|\,L=n\right)-f\left(x,\theta\,|\,L=improved\ \mathrm{var}iety/treated\ seeds\right). \tag{3.11}$$

3.6.1 Assumption of Multinomial Logistic Regression

The assumption underlying the model depends on the Independence of Irrelevant Alternatives (IIA). This assumption postulates that the inclusion or exclusion of categories of the dependent variable does not in any way affect the relative risks associated with the regressors in the remaining categories. However, this assumption does not hold in all instances (McFadden, 1974). Violating this assumption calls for a relaxation of the IIA through the application of the Hausman Test via the Seemingly Unrelated Estimation. This test allows for an assessment of equal common coefficients of the dependent variable across corresponding models for the null hypothesis. According to Hausman and McFadden (1984), the steps involved in testing the hypothesis of Independence of Irrelevant Alternatives for the Hausman type are:

1. Estimate the full model with the inclusion of all J outcomes for which these estimates are found in $\hat{\phi}_{Full}$.
2. Estimate the constrained (restricted) model of which one or more outcomes categories are eliminated and let these estimates be found in $\hat{\phi}_{\text{Re}duced}$.
3. Define $\hat{\phi}^{*}_{Full}$ as a subset of $\hat{\phi}_{Full}$ after the elimination of coefficients not found to be estimated in the constrained (restricted) model.

Following the above steps, then the Hausman test linking the Independence of Irrelevant Alternatives is provided as:

$$H_{IIA} = \left(\hat{\phi}_{\text{Re}duced} - \hat{\phi}^{*}_{Full}\right)' \left[\hat{V}\left(\hat{\phi}_{\text{Re}duced}\right) - \hat{V}\left(\hat{\phi}^{*}_{Full}\right)\right]^{-1} \left(\hat{\phi}_{\text{Re}duced} - \hat{\phi}^{*}_{Full}\right).$$

The test is asymptotically distributed as χ^2 with degrees of freedom found equals the rows in $\hat{\phi}_{\text{Re}duced}$ if the Independence of Irrelevant Alternatives is true. It is well established that failure to reject the null hypothesis $\left(H_{IIA}\right)$ at any significant level is a confirmation that the assumption of IIA holds (Abdul-Majeed et al., 2018) and that the Multinomial Logistic Regression can be employed in modelling the CSA Technology Practices.

3.7 Mixed-Effect Linear Regression

The Mixed-Effect Linear Regression is a form of linear regression that makes provision for both fixed effects (intercepts and slopes intended to describe the entire population just as it is in the case of standard linear regression) and random effects (intercepts and slopes that permit variations across subgroups of the sample). Suppose that the dependent variable Yields in bags (100kg) of five different farming seasons (2016-2020) found to be in wide format is transformed into the long format and defined as Yield in bags (100kg) to be continuous with fixed parameters (Gender defined as GE where 0=Female and 1=Male, years of practising CSA defined as CSAP where 0=1-5 years, 1=6-10 years and 2=11 and above years, status of yield defined as SY for which 0=Low yield and 1=High yield, Farming experience as continuous and defined as FME, status of household head defined as SHH where 0=Migrant and 1=Indigene, Total land under cultivation defined as TLC for which 0= $\leq$ 2 acres, 1=2.1-4 acres and 2=4.1+ acres, and its associated grouping variable (CSA Technology Practices (CSATP)) with five (5) groups specified as the level variable, then the standard linear regression model for equation (3.12) below revised to incorporate random effect (CSATP) for predicting Yield results to obtaining the Random Intercept model in equation (3.13) given respectively by:

$$Yield_{ij} = \alpha_0 + \alpha_1 GE_{ij} + \alpha_2 CSAP_{ij} + \alpha_3 SY_{ij} + \alpha_4 FME_{ij} + \alpha_5 SHH_{ij} + \alpha_6 TLC_{ij} + \varepsilon_{ij} \quad (3.12)$$

$$Yield_{ij} = \alpha_0 + \alpha_1 GE_{ij} + \alpha_2 CSAP_{ij} + \alpha_3 SY_{ij} + \alpha_4 FME_{ij} + \alpha_5 SHH_{ij} + \alpha_6 TLC_{ij} + \omega_{0j} + \varepsilon_{ij} \quad (3.13)$$

where from equation (3.13), $i = 1,2,\dots,n_i$ farmer and $j = 1,2,\dots,5$ CSATP. Also, extending equation (3.13) by denoting Gender, years of practising CSA, the status of yield, farming experience, the status of household head and total land under cultivation to indicate the side of the fixed effect (FE_{ij}) then the model for the random slope on Gender can be fitted for a random effect (CSA Technology Practices) specified as the level variable through incorporating the fixed effect (Gender) into equation (3.13) yielding:

$$Yield_{ij} = \alpha_0 + \alpha_i FE_{ij} + \omega_{0j} + h_{1j} GE_{ij} + \varepsilon_{ij} \tag{3.14}$$

where ω_{0j} in equation (3.13) and ω_{0j}, h_{1j} in equation (3.14) represents the random effects respectively for each CSA Technology Practices of which the total effect associated with the random effects can be positive (shifting the total effect up) or negative (shifting the total effect down). In this study, estimates of equation (3.13) and equation (3.14) were assessed using model fitting criteria's (such as Log Restricted-Likelihood (LRL), Likelihood Ratio Test (LRT) and Wald Chi-Square (χ^2) to determine the best model that well predicts the Yields. Also, the Likelihood Ratio test was devised as the random intercept model is nested within the random slope model for which the p-value of Likelihood Ratio χ^2 used to adjudge the best model in that regard. If the null hypothesis is supported then it is an attestation that the random intercept model is favoured and otherwise if the null hypothesis is rejected.

3.7.1 Parameter Estimations and Likelihood Functions in Mixed-Effect Linear Regression

The methods of Maximum Likelihoods (ML's) have become increasingly important during model parameter estimations. This method takes into account real/actual observations and chooses the parameters which make such observations most probable. In Linear Mixed Models (LMM's), assuming equations (3.13) and (3.14) can be respectively transformed to follow the matrix notations as found below:

$$y = X\beta + Zu + \varepsilon \tag{3.15}$$

where $y = (n \times 1)$ vector of observations, $X = (n \times p)$ known constant design matrix, $\beta = (p \times 1)$ unknown vectors, $Z = (n \times q)$ known constant design matrix, $u = (q \times 1)$ unknown vector of random individual-specific parameters and $\varepsilon = (n \times 1)$ vector of random within-subject or pure error term. Also, define $\in = Zu + \varepsilon$ to represent the total error term of the model and $N = \sum_{i=1}^{m} n_i$ as the total number of observations in the dataset. It is also evident from equation (3.15) that, the following assumptions hold for the model:

u is distributed normally with mean vector O and covariance matrix $D\left(u \sim N(\mathrm{O}, D)\right)$ where $D = \operatorname{var}(u)$ with associated dimension $(q \times q)$ and ε is normally distributed with mean vector O and covariance matrix $R\left(\varepsilon \sim N(\mathrm{O}, R)\right)$ which is independent of u where $R = \operatorname{var}(\varepsilon)$ having dimension $(n \times n)$. It is worth noting that the covariance matrices **D** and **R** are considered as unique parameters contained in the $(k \times 1)$ vector θ

The covariance matrix or the total variance that is Σ can be determined by taking the variance through equation (3.15) and this gives:

$$\operatorname{var}(y) = \operatorname{var}(X\beta + Zu + \varepsilon) \tag{3.16}$$

$$\Sigma = ZDZ' + R \tag{3.17}$$

Based on the above definitions, then the marginal log-likelihood function for equation (3.15) can be stated as:

$$l_{ML}(\theta) = -\frac{N}{2}\log(2\pi) - \frac{1}{2}\sum_{i=1}^{m}\log|\Sigma| - \frac{1}{2}\sum_{i=1}^{m}(y - X\beta)'\Sigma^{-1}(y - X\beta) \tag{3.18}$$

From the above likelihood function, standard software's such as STATA used in analysing the data find it more expedient to compute ML's with Negative Log-Likelihood (NLL) which by definition denote; $V = \Sigma$ and ψ =vector of parameters utilised for the two covariance matrices D and R. Also, by letting β =vector of fixed parameters then the NLL function for a linear mixed model is:

$$l_{NLL}(y,\beta,\psi) = \frac{1}{2}\left\{N\log(2\pi) + \log|V(\psi)| + (y - X\beta)'(V(\psi))^{-1}(y - X\beta)\right\} \tag{3.19}$$

$$\propto \frac{1}{2}\left\{\log|V(\psi)| + (y - X\beta)'(V(\psi))^{-1}(y - X\beta)\right\} \tag{3.20}$$

The parameter estimates can be determined as:

$$(\hat{\beta},\hat{\psi}) = \underset{(\beta,\psi)}{\arg\min}\, l_{NLL}(y,\beta,\psi) \tag{3.21}$$

On this note, the minimum can be gotten by estimating the fixed effects parameter β which is expressed as a function of the random effect parameters ψ that is:

$$\hat{\beta}(\psi) = \left\{X'(V(\psi))^{-1}X\right\}^{-1}X'\{V(\psi)\}^{-1}y \tag{3.22}$$

The estimate of the random effect parameters is determined by minimizing $l_{NLL}\left\{y,\hat{\beta}(\psi),\psi\right\}$ as a function of ψ and the fixed effect parameters are worked through utilizing $\hat{\beta} = \hat{\beta}(\hat{\psi})$.

Notwithstanding this, Mathew (2006) noted that the estimate of the random effect parameters based on ML are underestimated or more precisely the estimator of the variance is biased. Hence this study adopted the Restricted

Maximum Likelihood (REML) approach as justified by Mathew (2006) to address the unbiasedness associated with the variance component in LMM's. The REML maximises the joint likelihood of all error contrasts rather than of all contrasts as in ML (Arthur et al., 1995). This means that REML utilises the errors in its estimation, unlike actual observations which are utilised in ordinary ML. The REML in LMM's according to Verbeke and Molenberghs (2000) tend to produce accurate estimators of the variance components of which this study as among other objectives focuses on estimating the random effects of yields across the various CSA Technology Practices. Harville (1974) indicated that based on original observations, the Restricted Log-Likelihood (RLL) function can be stated as:

$$l_{REML}(\beta,\psi) = \frac{1}{2}\left\{\begin{matrix}(N-p)\log(2\pi)+\log|V(\psi)|+(y-X\beta)'(V(\psi))^{-1} \\ (y-X\beta)+\log\left(\left|X'(V(\psi))^{-1}X\right|\right)\end{matrix}\right\} \tag{3.23}$$

$$\propto \frac{1}{2}\left\{\log|V(\psi)|+(y-X\beta)'(V(\psi))^{-1}(y-X\beta)+\log\left(\left|X'(V(\psi))^{-1}X\right|\right)\right\} \tag{3.24}$$

where by defining the matrix $V(\psi)=V(\sigma_{\beta}^{2},\sigma_{\varepsilon}^{2})$, X are predictors with fixed effects β and $N-p$ is a residual degree of freedom.

To obtain the Restricted Negative Log-Likelihood (RENLL) function, begin by determining:

$$\begin{aligned}\log\left(\left|X'(V(\psi))^{-1}X\right|\right) &= \log\left|\frac{X'X}{\sigma^2}\right| \\ &= \log\left|\frac{N}{\sigma^2}\right| \\ &= \log(N)-\log(\sigma^2)\end{aligned} \tag{3.25}$$

Inserting equation (3.25) into equation (3.23) gives the RENLL function;

$$l_{RENLL}(y,\beta,\psi)=\frac{1}{2}\left[\begin{array}{l}(N-1)\log(2\pi)+N\log(\sigma^2)+\\ \frac{1}{\sigma^2}\sum_{i=1}^{m}(y_i-\mu)^2+\log(N)-\log(\sigma^2)\end{array}\right]$$

$$=\frac{1}{2}\left[\log(N)+(N-1)\log(2\pi)+(N-1)\log(\sigma^2)+\frac{1}{\sigma^2}\sum_{i=1}^{m}(y_i-\mu)^2\right] \quad (3.26)$$

$$\propto\frac{1}{2}\left[(N-1)\log(\sigma^2)+\frac{1}{\sigma^2}\sum_{i=1}^{m}(y_i-\mu)^2\right] \quad (3.27)$$

The estimate of the variance $\hat{\sigma}^2$ can be obtained by taking the partial derivatives of either equation (3.26) or (3.27) for σ^2 and setting the result to zero to obtain the same outcome as below:

$$\hat{\sigma}^2=\frac{1}{N-1}\sum_{i=1}^{m}(y_i-\bar{y})^2 \quad (3.28)$$

3.7.2 Model Diagnostic Tests of the Mixed Effect Linear Regression

The study employed various measures of fit tests such as Wald χ^2, RLL and LRT using model nesting to determine the suitable model to utilise in making predictions on the Yields.

LR Tests (LRT's) via any ML approach seek to ascertain whether a random intercept model provides the same fit as a random slope model. LRT with the REML was adopted in the study since the fixed effects specification in both models is the same. This is justified in a study by Verbeke and Molenberghs (2000) indicating that LRT grounded on REML log-likelihood function is invalid specifically in comparing models with a different set of fixed effects.

In this light, the model nesting approach involving LRT using REML of which the random intercept model is nested within the random slope model. Assume that the random intercept and random slope models are denoted as the RENLL of the reduced model, l_{RM} and the RENLL of the full model as l_{FM} respectively, and then the LRT which seeks to compare the ratio of the RENLL of the full model to the RENLL of the reduced model can be written as:

$$\begin{aligned} LR &= 2\ln\left(\frac{\ell_{FM}}{\ell_{RM}}\right) \\ &= 2(\ell_{FM}) - 2(\ell_{RM}) \\ &= -2[\ell_{RM} - \ell_{FM}]. \end{aligned} \tag{3.29}$$

Hence, under the null hypothesis that the random intercept model is adequate, we find the Likelihood Ratio (LR) to be distributed as χ^2 with degrees of freedom given as $df = d_{FM} - d_{RM}$ (Greene, 2008).

3.8 Factor Analysis Model

Factor Analysis (FA) can be seen to be a data reduction technique. According to Hair *et al*. (1992), factor analysis signifies an analytical process of altering statistical data (as measurements) into linear combinations of variables; it is an important statistical method used for reducing a large amount of data into a considerably smaller number of factors without a substantial loss of information. The factor analysis was used to reduce the number of CSA Technology Practices to a reasonable level before running the multiple linear regression.

The model for FA can be seen through defining the actual variables as $x_1, x_2, \cdots, x_p$ where $m < p$ for $m-$factors and p dimensions, then in matrix form;

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{pmatrix} = \begin{pmatrix} \psi_{11} & \psi_{12} & \cdots & \psi_{1m} \\ \psi_{21} & \psi_{22} & \cdots & \psi_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \psi_{p1} & \psi_{p2} & \cdots & \psi_{pm} \end{pmatrix} \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_m \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{pmatrix}. \tag{3.30}$$

From equation (3.30), the compressed form is given by:

$$\underset{(p\times 1)}{X} = \underset{(p\times m)}{\Lambda}\underset{(m\times 1)}{F} + \underset{(p\times 1)}{\varepsilon}, \tag{3.31}$$

with $X_{(p\times 1)}$ being the solution attributed to the factor, $\Lambda_{(p\times m)}$ is the loadings from the matrix, $F_{(m\times 1)}$ are factors from the vector and the error terms $\varepsilon_{(p\times 1)}$ are found to be a vector of unique factors. Also, consider that equations (3.30) and (3.31) to be restated as:

$$X_i = \sum_{j=1}^{m} \psi_{ij} f_j + \varepsilon_i, \tag{3.32}$$

where $i = 1, 2, \cdots, p;\ j = 1, 2, \cdots, m.$ Hence equation (3.32) is regarded as the $M - Factor\ Model$ in FA. The variance which also known as the Communality in FA analysis is given by:

$$Var(X_i) = \sum_{j=1}^{m} \psi_{ij}^2, \tag{3.33}$$

since $Var(f_j) = 1$ and $Var(\varepsilon_i) = 0.$ Also, the uniqueness (unexplained variations) of X_i is given by:

$$Var(\varepsilon_i) = 1 - \sum_{j=1}^{m} \psi_{ij}^2 \tag{3.34}$$

3.8.1 Assumptions of the Factor Analysis (FA)

To use the Factor Analysis approach, it is incumbent to assess that the various assumption underlying the model are satisfied before making inferences and drawing conclusions. These assumptions of the FA technique are:

$$E(x) = \underset{(p\times 1)}{0}, E(F) = \underset{(m\times 1)}{0}, \operatorname{var}(F) = \underset{(m\times m)}{I}, E(\varepsilon) = \underset{(p\times 1)}{0}, \operatorname{cov}(\varepsilon, F) = \underset{(p\times m)}{0}$$

$$\text{and } \operatorname{cov}(\varepsilon) = \underset{(p\times p)}{\xi} = \begin{pmatrix} \xi_1 & 0 & \cdots & 0 \\ 0 & \xi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \xi_p \end{pmatrix}.$$

3.8.2 Goodness of Fit Test of Factor Analysis

The goodness of fit test was used to check whether the data do conform to a real-world situation. Given this, the internal consistency, Bartlett's test of Sphericity and Kaiser-Meyer-Olkins (KMO) Measure of Sampling Adequacy was used to conduct this assessment.

3.8.2.1 Test of Internal Consistency

The study made use of the Cronbach alpha to determine the internal consistency of the instrument to be employed. According to Hair *et al*. (1998), the satisfactory common lower limit value of 0.60 to 0.70 for Cronbach alpha indicate acceptability for an estimate of reliability. Also, other studies such as Hair *et al*. (1995) resorted to a coefficient of less than 0.6 to indicate marginal to low internal consistency and a value of 0.6 or more indicates satisfactory internal consistency reliability (Churchill, 1979). The study adopted a reliability coefficient of 0.6 as indicated by Hair *et al*. (1995) to signify the existence of internal consistency of the instrument.

3.8.2.2 Bartlett's Test of Sphericity

The test was introduced by Bartlett (1951) to test the null hypothesis the variables are not correlated. In light of this, the p-value of less than 0.05 then is a confirmation that the variables have some patterned relationship. Assume that

that for k sample of size n_i and S_i^2 as the sample variance then the Bartlett test statistic is given as:

$$\chi^2 = \frac{(N-k)\ln\left(S_p^2\right) - \sum_{i=1}^{k}(n_i-1)\ln\left(S_i^2\right)}{1+\frac{1}{3(k-1)}\left(\sum_{i=1}^{k}\left(\frac{1}{n_i-1}\right)-\frac{1}{N-k}\right)}. \qquad (3.35)$$

From equation (3.35), let $N = \sum_{i=1}^{k} n_i$, $S_p^2 = \frac{1}{N-k}\sum_{i}(n_i-1)S_i^2$ is the variance of the pooled estimate, and $\chi^2 > \chi^2_{k-1,\alpha}$ as the rejection of the null hypothesis.

3.8.2.3 Kaiser-Meyer-Olkins Measure of Sampling Adequacy

Kaiser (1970) developed the KMO statistic to measure the sampling adequacy in FA. This has resulted in its usage in Exploratory FA. Kaiser (1974) has proposed a range of values and their corresponding assigned names for the KMO of which this study will stick to draw inferences. The details can be obtained from Table 3.2.

Table 3.2: Summary of KMO Values and Corresponding Assigned Terminology

Value of KMO	Terminology
$0.90-1.00$	Marvellous
$0.80-0.89$	Meritorious
$0.70-0.79$	Middling
$0.60-0.69$	Mediocre
$0.50-0.59$	Miserable
$0.00-0.49$	Unacceptable

The KMO statistic for the test can be seen as:

$$KMO_j = \frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j}\eta}. \qquad (3.36)$$

From equation (3.36), define $R = \left[r_{ij} \right]$ as the correlation matrix and η as the partial covariance matrix. High values of KMO is an indication that the independent variables used in the study have much in common to justify the basis for the application of FA to the observed data.

3.8.3 Determining the Number of Factors to Retain in Factor Analysis

Several techniques have been introduced to confirm the factor number to retain in FA. However, these approaches are noted to come along with their intrinsic issues. For instance, the scree test, the rule of eigenvalue greater than one principle and Parallel analysis are some of the approaches to detect the number of factors to retain (Kaiser, 1960; Cattell, 1966; Horn, 1965). In this study, two of the approaches (scree test and eigenvalue greater than one) was used to confirm the number of factor retention. The scree test adopted in the study facilitated the search for the "elbow" point to confirm the number of factors. Also, due to the problem of discontinuity in the "elbow" point in the scree plot, the eigenvalue greater than one as suggested by Henson and Roberts (2006), the threshold of between small and large values at an eigenvalue of one ought to be fixed of which an eigenvalue greater than one will constitute a factor.

3.8.4 Factor Rotation

There are situations that unrotated factor becomes very difficult to interpret. This happens when the independent variable(s) load high in more than one component. Hence factor rotation must be performed to address the shortfall as found with the unrotated factor. Kaiser Varimax rotation was used in this study. The Kaiser Varimax rotation maximizes the squared loadings of the sum of the variance. Kaiser (1958) provided the test statistic for the Varimax criterion as:

$$R_{Varimax} = \arg\max_{R} \left(\frac{1}{p} \sum_{j=1}^{k} \sum_{i=1}^{p} (\Lambda R)_{ij}^{4} - \sum_{j=1}^{k} \left(\frac{1}{p} \sum_{i=1}^{p} (\Lambda R)_{ij}^{2} \right)^{2} \right). \quad (3.37)$$

3.8.5 Factor Score

The study as part of the objective stated in this study was to determine the influential factors of CSA Technology Practices. This can be achieved by using factor scores in FA. The value of the factor score to be resorted to in this study is just a score for a household head on a factor and an estimate for each household head if essential will be used instead of the observed variables (factors of CSA Technology Practices). Charles (2015) defined factor score connecting to that of this study as a linear combination of j household head factor of CSA Technology Practices (independent variables). For instance in this study; factor score for household head i on a given factor k can be stated mathematically as:

$$\hat{F}_{ik} = \widehat{\psi}_1 X_{i1} + \widehat{\psi}_2 X_{i2} + \cdots + \widehat{\psi}_k X_{ik}. \quad (3.38)$$

From equation (3.38), let $\hat{F}_{ik}$ to be the estimated factor score of the factor k for household head i, $\widehat{\psi}_k$ to be the estimated coefficient of factor score for the independent variable and X_{ik} is the $k-th$ household head of factor of CSA Technology Practices (observed variables) for household head i.

Comrey and Lee (1992) opted for a more flexible approach towards the estimation of factor scores for each household head which is the summation of the raw scores corresponding to all household choice on the CSA Technology Practices attributes loading on a factor.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.0 Introduction

This chapter presents the results and discussions of the study based on the data captured from the field. The first part of this section looks at the socio-economic characteristics of the households as well as the CSA technology practices. The second part considers Factor Analysis to examine variables that come together to form the latent factor. Also, several measures of fit tests were considered to establish the suitability of the Factor Analysis Model. The third part present the Multinomial Logistic Regression with the assumption of Independence of Irrelevant Alternatives (IIA) assessed using the Hausman Specification Test via Seemingly Unrelated Estimation. The forth and last part presents the parameter estimates and model fitting criteria from Mixed-Effect Linear Regression.

4.1 Descriptive Statistics

This section presents the socio-economic characteristics of the households under study as well as the CSA technology practices revealed from the findings. These results form the basis of data analysis and offer data summaries across observations (Trochim, 2006).

4.1.1 Socio-Economic Characteristics of Households

Table 4.1 presents a description of the backgrounds of respondents in the study. Out of three hundred (300) household interviewed, 185(61.7%) were males while 115(33.3%) representing females. The majority of the respondent were indigenes numbering 231(77.6%) while 69(22.4%) migrated from other parts of the region purposely for farming or settlement.

Climate Smart Agriculture plays crucial roles in the current farming practices. Some of these practices revealed and used in the modelling include improved variety/treated seeds (30.39%) practised by farmers, mineral chemical fertilizer (25.44%), monoculture (18.02%), crop rotation (13.78%) and tied ridges (12.37%).

The result indicated that the majority of the household 151(53.95%) practised CSA technology and have gained working experience between 1 and 5 years while 106(37.86%) practised CSA technology with working experience between 6 and 10 years. Few farmers of about 23(8.21%) practised CSA technologies for eleven (11) years and more.

Table 4.1 revealed that the majority of the participated respondent (75.78%) on average had high yields ($\geq$ 18 bags) while the 24.22% on average had low yields (< 18 bags) for the five farming seasons (2016 to 2020) the farming season.

Table 4.1: Descriptive Statistics of Respondents

	Frequency	Percent
Gender		
Female	115	38.33
Male	185	61.67
Status of HH		
Migrant	69	22.74
Indigene	231	77.26
CSA Technology Practice		
Improved variety/treated seed	86	30.39
Mineral chemical fertilizer	72	25.44
Monoculture	51	18.02
Crop Rotation	39	13.78
Tied Ridges	35	12.37
Years of CSA Practice		
1-5 years	151	53.93
6-10 years	106	37.86
11 and above	23	8.21
Status of Yield (in 100kg bags)		
Low yield ($<$18 bags)	54	24.22
High yield ($\geq$ 18 bags)	169	75.78

Table 4.2 presents the Chi-square analysis of the status of yield and each independent variables. The null hypothesis for the test states that the status of yield is not associated with each of the explanatory variables as found in Table 4.2. The p-values of the status of yield versus Gender and that of the status of

yield versus total land under cultivation were all significant at the 5% level. This is an indication that the status of yield is associated with Gender and total land under cultivation respectively.

Table 4.2: Chi-Square Analysis of Status of Yield on each Independent Variables

Variables	χ^2 value	d.f	p-value
Status of Yield vs Gender	10.2522	1	**0.001**
Status of Yield vs Status of HH	0.0400	1	0.841
Status of Yield vs Years of CSA Practice	1.4834	2	0.476
Status of Yield vs Total Land under Cultivation	44.5033	2	**0.000**
Status of Yield vs CSA Technology Practice	7.4251	4	0.115

4.2 Model Diagnostic Test of Multinomial Logistic Regression

In other to decide on the model to use in making predictions on CSA Technology practices, the study adopted the model building strategies of which all the candidate models have one of the categories (improved variety/treated seeds) omitted in model one. This was followed by an omission of mineral chemical fertiliser, monoculture, crop rotation and tied ridges for models 2 to model 5 respectively. From the output in Table 4.3, except for model 1 and model 2, all the other models were not significant at the 5% level of significance. This means that models 1 and 2 have a strong explanatory power as compared to the other models (Hausman and McFadden, 1984). However, further evaluation of these two models (model 1 and model 2) finds a high Likelihood Ratio χ^2 (36.99) and least log-likelihood (-302.0844) to favour model 1 and hence to be utilised in assessing the assumption of Independence of Irrelevant Alternatives (IIA) (Hausman and McFadden, 1984).

Table 4.3: Hausman Specification Test with and without constraints on CSA Technology Practices

		Constrained Models			
	Model 1	Model 2	Model 3	Model 4	Model 5
N	209	153	171	185	183
df	24	18	18	18	18
p-value	**0.0438**	**0.0228**	0.0795	0.0951	0.1565
LR χ^2	**36.99**	31.87	26.97	26.21	23.96
LL	**-302.0844**	-183.1736	-207.9992	-232.9672	-230.1018

Footnote: Models 2-5 are the constraint models, N=Number of observations, df=degree of freedom, LR=Likelihood Ratio, LL=Log Likelihood

4.2.1 Test of Assumption of Independence of Irrelevant Alternatives

The tradition of any model is that it must satisfy the necessary basic assumptions. In this study, the Multinomial Logistic Regression as utilised in modelling the data made use of the assumption of Independence of Irrelevant Alternatives. This assumption posits that considering any two alternatives then the probabilities of its ratios should be independent of other alternatives available. Notwithstanding, this assumption does not always hold in all cases (McFadden, 1974). A classical illustration is present in a study by McFadden (1974) in the area of a transportation model with four possible alternatives (rides a train to work, takes a bus to work, drives the Ford to work and drives the Chevrollet). The study indicated that "drives Ford to work" is a closer replacement to "drives the Chevrolet" as compared to "ride the train" (at least for most people). The impulse from the view of McFadden can be conveyed to mean that not considering or excluding "drives the Ford" from the transportation model is expected to affect the relative risks of the remaining alternatives hence deviate the assumption of

Independence of Irrelevant Alternatives. Based on this, Seemingly Unrelated Estimation is devised in this study to relax the assumption of IIA (Abdul-Majeed et al., 2018). The test seeks to determine whether the coefficients associated with CSA Technology Practices are the same across the various models.

The results from Table 4.4 finds the coefficients associated with each of the dependent variable (Model 2 to Model 5) to be the same with p-values not exceeding the 5% level of significance. Also, the simultaneous tests of the coefficients of the dependent variables fail to reject the null hypothesis of equal coefficients across the various models. This means that the assumption of Independence of Irrelevant Alternatives holds (Abdul-Majeed et al., 2018).

Table 4.4: Test of IIA Assumption via Seemingly Unrelated Estimation

Model+Intercept	d.f	χ^2	p-value
Mineral Chemical Fertilizer	21	3.48	1.0000
Monoculture	21	3.29	1.0000
Crop Rotation	21	5.70	0.9996
Tied Ridges	21	9.20	0.9875
Accumulation	42	47.31	0.2647

4.2.2 Multinomial Logistic Regression on CSA Technology Practices

Table 4.5 present the Average Marginal Effects from Multinomial Logistic Regression on the CSA technology practised by farmers in the Lawra Municipal of the Upper West region. In all, gender, years of CSA practice, the status of yield, farming experience and household head status were used in predicting the choice of CSA technology practices by farmers of the Lawra municipal. STATA 16.1 was used to estimate the parameters for the direction of the explanatory variables on the dependent variables. Also, the estimates from Multinomial Logistic Regression were further subjected to post estimation in STATA 16.1 to obtain the Average Marginal Effects (that is the average changes associated with the choice of CSA Technology Practices for a unit change in a specific independent variable).

It is worth noting from Table 4.5 that, the Likelihood Ratio Chi-square statistic of 36.99 with a degree of freedom of 24 is significant (p-value <0.0438) at the 5% level which signifies that the model has strong explanatory power. Also, the Pseudo R-squares for McFadden, the Cragg & Uhler and the Maximum Likelihood stands at about 0.0580,0.170 and 0.162 respectively which indicates that the explanatory variables accounted for 5.8%, 17% and 16.2% of the variation of CSA Technologies practised by farmers (Abdul-Majeed et al., 2018). The standards of the Pseudo R-squares reveal that there is a weaker relationship between the outcome variable (CSA Technologies practised by farmers) and the explanatory variables (gender, years of CSA practice, status of yield, farming experience and household head status) in the model. For the interpretation of the estimates in connection with the Average Marginal Effects, a positive value means that the predictor contributes positively to the choice of CSA Technology practised by the farmer and a negative value shows that the predictor contributes negatively to the choice of CSA Technology practised by the farmer.

From Table 4.5, being a male has a high probability but a non-significant effect on the following CSA Technology practices (that is improved varieties/treated seeds, monoculture and tied ridges) as compared to female in the Lawra Municipality. This is because men stand the chance of attending meetings with institutions that know such aforementioned CSA technology practices. For instance, the study revealed that male farmers have a higher probability of using improved variety by 8.49%, monoculture by 2.12% and tied ridges by 4.98% respectively relative to female farmers. The outcome also confirms the positions of Bent et al. (2017) and Marie (2020) that males are more likely to adopt CSA technology practices than their female counterparts. Also, male farmers have a lower probability of 0.06% and 15.53% of using mineral chemical fertilizers and crop rotation respectively however such a decrease in marginal effect of gender under crop rotation was found to be significant (p-value=0.010).

The data shows that farmers who have practised CSA Technology ranging from 6 to 10 years was found to be accompanied by a low probability of 15.47% of using improved variety/treated seeds as compared to those farmers having practised CSA Technology for 1-5 years but such a decrease in probability was significant at the 5% level. This means that farmers with 1 to 5 years of experience stand the chance of using improved varieties/treated seeds than those with 6 to10 years of farming experience as well as eleven (11) or more years with a decrease in the probability of 5.28%. Also, the data found years of CSA practice by farmers of 6 to 10 years to have a low probability of 0.76% for using mineral chemical fertilizer relative to the base outcome (1 to 5 years of CSA practice). However, 6-10 years of practising CSA was found to have high probabilities of 0.71%, 6.92% and 8.60% of using monoculture, crop rotation and tie ridges respectively relative to the reference outcome (1-5 years of CSA practice). Meanwhile, these probabilities were not significant at the 5% level. The result further revealed that farmers who have CSA practice experience of eleven or more years in using CSA Technology were found to be connected with low probabilities of 5.58%, 6.85% and 5.54% for improved varieties/treated seeds, mineral chemical fertilizer and tied ridges respectively as compared to that of 1 to 5 years of CSA practice by farmers. Higher probabilities were recorded for CSA practice of eleven and more years towards the use of monoculture and crop rotation by 15.08% and about 2.89% respectively as compared to the reference level (1 to 5 years of CSA Practice). However, these observed probabilities were not significant at the 5% level of significance.

The study result indicated low probability found in connection with high yield towards the use of improved varieties/treated seeds (5.95%), mineral chemical fertilizer (4.94%), and monoculture (11.34%) as compared each to that of low yield. On the other hand, crop rotation and tied ridges recorded high probabilities of 0.91% and 11.44 respectively for high yield as compared to low yield meaning that crop rotation stands the chance of increasing yield by 0.91% and tied ridges by 11.44% as compared to a decrease in yield respectively. However, none of these probabilities was observed to be significant at the 5% level apart from tied ridges.

Farming experience refers to the number of years a household spends in crops cultivation. In this perspective, it can be anticipated that the more years a farmer is involved in the practice of farming the better the experience gathered in the activities of farming for all things being equal. The study revealed that an additional farming experience increases the use of improved varieties/treated seeds by 0.23%, monoculture by 0.34% and tied ridges by 0.07%. This outcome is in line with a study by Danso-Abbeam (2017) positing higher chances of adopting impoved maize variety for longer years of farming experience than less ones. Also, a study by Ojo and Ogunyemi (2014) was consistent with this study through establishing a significant positive relationship existing between length of farming experience and adopting of farming technologies. On the other hand, a unit increase in farming experience is found to decrease the use of mineral chemical fertilizer by 0.39% as well as crop rotation by 0.25%. These decreases recorded could be subjected to the cost associated with fertilizers and the issue of land litigation which barely makes it impossible for the aged who have stayed long in farming to practice such technologies. Meanwhile, none of these was significant at the 5% level.

From Table 4.5, households who are natives or indigenes of the study communities recorded low probabilities with regards to the use of improved varieties/treated seeds (5.91%), mineral chemical fertilizer (0.01%) and monoculture (2.09%) as compared to migrants respectively. This decrease associated with such CSA technology practices could be due to the lack of knowledge in the area of CSA within the communities. Also, an increase in probabilities was accompanied to indigenes on CSA technology practices for crop rotation (5.67%) and tied ridges (2.33%) as compared to migrants respectively.

Table 4.5: Average Marginal Effects from Multinomial Logistic Regression on CSA Technology Practices

	Improved Variety/Treated Seeds		Mineral Chemical Fertilizer		Monoculture		Crop Rotation		Tied Ridges	
	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value
Gender										
Female (*)										
Male	0.0849	0.215	-0.0006	0.993	0.0212	0.715	-0.1553	**0.010**	0.0498	0.294
Years of CSA Practice										
1-5 years (*)										
6-10 years	-0.1547	**0.024**	-0.0076	0.911	0.0071	0.899	0.0692	0.175	0.0860	0.098
11+	-0.0558	0.630	-0.0685	0.509	0.1508	0.166	0.0289	0.725	-0.0554	0.253
Status of Yield										
Low yield (*)										
High yield	-0.0595	0.451	-0.0494	0.483	-0.1134	0.108	0.0091	0.849	0.1144	**0.004**
Farming Experience	0.0023	0.350	-0.0039	0.131	0.0034	0.076	-0.0025	0.255	0.0007	0.665
Status of HH										
Migrant (*)										
Indigene	-0.0591	0.497	-0.0001	0.999	-0.0209	0.773	0.0567	0.221	0.0233	0.653

Number of Observations=209, LR χ^2 (24) =36.99, Prob> χ^2 =0.0438, McFadden's R^2 = 0.058, Log Likelihood=-302.0844, Cragg &Uhler R^2 =0.170, Maximum Likelihood R^2 =0.162

4.3 Mixed-Effect Linear Regression on CSA Technology

Table 4.6 presents the results of the estimates of competing models for both the random intercept model (Model A) and the random slope model (Model B) as well as the model fitting criteria used to evaluate the estimates associated with the respective models. The estimates associated with the Wald Chi-square (χ^2) for the two tentative models were highly significant at the 5% threshold level suggesting a model with fixed effects (predictors) fits the data better than a null or intercept model only. It was also revealed that the estimate of Log-Restricted-Likelihood (LRL) associated with Model A was lower than the Model B suggesting that Model A fits the data better as compared to Model B.

Assessing the two models through nesting revealed a LR Chi-square (χ^2) =0.8400 and Prob> (χ^2) =0.6564 suggesting that we fail to reject the null hypothesis at the 5% significance level. This means that a MELR model with random intercept (that is the model permitting only CSA Technology Practices specific shift) is much better than that of a random slope (that is the model permitting random CSA Technology Practices specific linear regression line) hence the equation for the selected model (Model A) can be stated as:

$$\begin{aligned} Yield_{ij} = {} & 0.3705 + 2.7502GE_{Male} - 1.8339CSAP_{6-10} - 0.7937CSAP_{11 and\ above} + \\ & 4.6691SY_{HYD} + 0.0760FME_{ij} - 0.2751SHH_{IG} + 1.1412TLC_{2.1-4acres} + \\ & 1.6473TLC_{4.1+acres} + \omega_{0j} + \varepsilon_{ij} \end{aligned} \quad (4.1)$$

From equation (4.1), the average yield is anticipated to increase by 0.3705 units considering that the fixed and random components are not included in the model. Based on gender, males increase average yield by 2.7502 units as compared to their female counterparts. The number of years of practising CSA (6-10 years and above 11 years) tends to decrease average yield by 1.8339 and 0.7937 units respectively as compared to those of CSA experience of 1-5 years. However, such a decrease in yield with 6-10 years of CSA experience was significant.

With regards to Climate Smart Agriculture, farmers who practice the technologies coupled with Good Agronomic Practice (GAP) have high yields (18+ bags). Based on this, farmers with a status of yield being high yields (18+ bags) increases the average yield by 4.6691 units as compared to those farmers possessing low yields (< 18 bags) however such an increase was significant considering the 5% threshold. On the other hand, an additional unit increase in farming experience is accompanied by a 0.0760 unit increase in the average yield. On the status of household head, indigenous farmers' decreases average yield by 0.2751 units relative to migrant farmers.

Moreover, farmers with total land under cultivation of 2.1-4 acres and 4.1+ acres were found to have increased the average yield by 1.1412 and 1.6473 units respectively as compared to farmers with less than or equal two (≤ 2) acres however the increase accompanying the total land under cultivation of 4.1+ acres were seen to be statistically significant at the 5% level.

Table 4.6: Parameter Estimates and Model Fitting Criteria from Mixed-Effect Linear Regression

	Tentative Models					
	Random-Intercept Model (Model A)			Random-Slope Model (Model B)		
Variables	**Coeff**	**Std Error**	**Sig.**	**Coeff**	**Std Error**	**Sig.**
	Fixed Effects Estimates					
Gender (GE)						
Female (*)						
Male (GE_{Male})	2.7502	0.5639	**0.000**	2.9424	0.6382	**0.000**
Years of CSA Practice (CSAP)						
1-5 years (*)						
6-10 years ($CSAP_{6-10}$)	-1.8339	0.5461	**0.001**	-1.8492	0.5461	**0.001**
11+ years ($CSAP_{11\ and\ above}$)	-0.7937	0.8974	0.376	-0.7789	0.8971	0.385
Status of Yield (SY)						
Low yield (*)						
High yield (HYD)	4.6691	0.6302	**0.000**	4.6194	0.6287	**0.000**
Farming Experience (FME)	0.0760	0.0195	**0.000**	0.0752	0.0196	**0.000**
Status of Household Head (SHH)						
Migrant (*)						
Indigene (IG)	-0.2751	0.6291	0.477	-0.3278	0.6314	0.604
Total Land under Cultivation (TLC)						
$\leq$ **2 acres** (*)						
2.1-4 acres	1.1412	0.6482	0.078	1.1906	0.6495	0.067
4.1+ acres	1.6473	0.6902	**0.017**	1.6568	0.6902	**0.016**
Constant	0.3705	0.9880	0.708	0.3533	0.9299	0.704
	Random Effects Estimates					
Variance (*Gender*)				0.4121	0.8390	
Variance (*Constant*)	0.7429	0.7651		0.0306	0.3638	
Variance (Residual)	58.9737	2.5962		58.8870	2.5924	
Covariance (*Gender*, *Constant*)				-0.1122	0.7732	
	Model Fitting Criteria					
Log Restricted-Likelihood	-3611.6934			-3611.1493		
Wald Chi-Square (χ^2)	176.5400		**0.000**	167.3200		**0.000**
Model A nested within Model B	LR Chi-square (χ^2)=0.8400, Prob>(χ^2)= 0.6564					

Table 4.7 and Figure 4.1 presents the estimated mean values for the random intercepts (ω_{0j}) by each CSA Technology Practice in equation (4.1) for the selected model (Model A). It was revealed that at any given level of the fixed effects (gender, CSA practice, status of yield, farming experience, status of household head and total land under cultivation), yields averages about 0.1249, 0.6611 and 0.6936 units higher for Monoculture, Crop Rotation and Tied Ridges respectively meaning that such intercepts for the corresponding CSA Technology Practices shift the total effect up.

Also on the average yield, the remaining CSA Technology Practices (Improved variety/treated seeds and Mineral chemical fertilizer) was associated with a shift of the total effect down but with the highest total effect downward shift of the intercept of 0.8244 units for Mineral chemical fertilizer and the least downward shift of the intercept of about 0.6552 units for improved variety/treated seeds.

Table 4.7: Predicted Random Intercepts from Model A

CSA Technology Practice	Mean
Improved variety/treated seeds	-0.6552
Mineral chemical fertilizer	-0.8244
Monoculture	0.1249
Crop Rotation	0.6611
Tied Ridges	0.6936

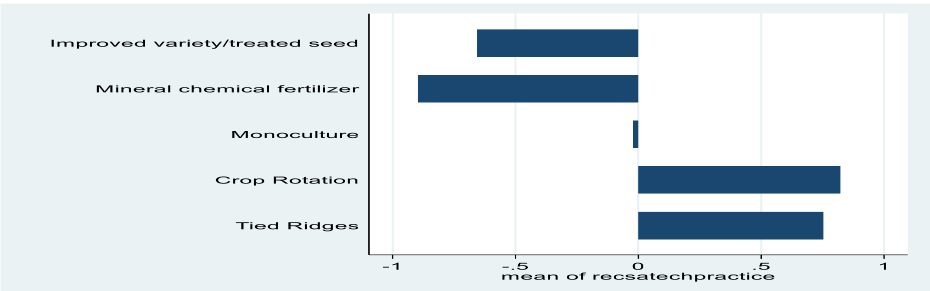

Fig 4. 1: Random Intercepts by CSA Technology Practices

4.4 Factor Analysis on Measured Variables of CSA Technology Practices

The factor analysis was used as a technique to examine the underlying correlation of the attributes of CSA Technology Practices. This technique was also used to measure the climate smartness of the CSA Technologies incorporated in the research instrument.

4.4.1 Spearman Rank Correlation Analysis of Observed Variables

Before the data was subjected to Factor Analysis in other to find the latent factors (dependent variables), it is imperative to conduct a spearman rank correlation analysis for the independent variables (as labels and corresponding variables names captured in section F of appendix). Correlations simply examine the relationships between variables. Because of this, this study found it expedient to find the possible pairings that exist between these original (observed) variables. Variables with high correlations were identified and paired together to give a hint as to the total number of labels or structures to expect before the data is subjected to Further Analysis.

Table 4.8 reveals that correlations among the pairs of independent variables range from 0.0025 to 0.7400. The lowest correlation of 0.0025 was observed between trees are planted in and around my farm which is Afforestation and legumes are planted among crops on the farm which is intercropping while the highest correlation of 0.7400 is between excessive use of water is reduced as a result of mulching and crop watering help control water usage (irrigation). Also, it can be observed that the significant correlations at the 5% level ranged from 0.1172 to 0.7400 and with the lowest correlation between information is shared with colleague farmers which is information sharing and access to information on market prices concerning produce and inputs whih is market information. Generally with the highly significant correlations among most of the observed variables is an indication of the fulfilment of the assumption of some moderate correlations among independent variables in Factor Analysis (Edward et al., 2018).

Table 4.8: Spearman Rank Correlation Matrix of Independent Variables

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21
X1	1																				
X2	0.3639*	1																			
X3	0.1625*	-0.1878*	1																		
X4	0.3027*	-0.1399*	0.4945*	1																	
X5	0.3577*	0.1377*	0.0202	0.2131*	1																
X6	0.1729*	-0.0339	0.1561*	-0.2352*	0.0273	1															
X7	0.5247*	0.1693*	0.2049*	0.4165*	0.5342*	0.0701	1														
X8	0.6320*	0.1628*	0.1654*	0.5892*	0.5145*	0.0195	0.7400*	1													
X9	0.2254*	0.1331*	0.2943*	0.4424*	0.2184*	-0.0150	0.2999*	0.3874*	1												
X10	0.4564*	0.0931	0.3026*	0.4698*	0.3999*	0.1669*	0.5361*	0.6306*	0.5333*	1											
X11	0.2872*	0.1240*	0.2684*	0.3020*	0.2256*	-0.0171	0.3211*	0.4195*	0.5388*	0.4890*	1										
X12	0.4003*	0.1189*	0.4289*	0.5327*	0.1349*	0.0402	0.4225*	0.5099*	0.3687*	0.6462*	0.4470*	1									
X13	0.2225*	0.1619*	0.2823*	0.2026*	0.1455*	0.0525	0.2547*	0.2493*	0.2523*	0.2471*	0.3751*	0.4902*	1								
X14	0.1755*	-0.1566*	0.0918	-0.0067	-0.1200*	0.3007*	0.0936	0.1222*	-0.1666*	0.0706	0.0307	0.3132*	0.3113*	1							
X15	0.1442*	0.0313	0.2352*	0.5355*	0.1787*	-0.1665*	0.3506*	0.4088*	0.6638*	0.5331*	0.4986*	0.3958*	0.1103	-0.1173*	1						
X16	0.2668*	0.1306*	0.0102	0.0791	0.0249	-0.0096	0.0082	0.1628*	0.2159*	0.1251*	0.1058	0.2110*	0.1515*	0.0984	0.2633*	1					
X17	0.3593*	0.0273	0.1302*	0.0914	0.1100	0.2431*	0.3178*	0.3278*	0.0830	0.3779*	0.2219*	0.4006*	0.2986*	0.4573*	-0.0025	0.1053	1				
X18	0.3215*	-0.0151	0.3829*	0.4239*	0.0848	0.0784	0.1191*	0.3745*	0.3779*	0.3839*	0.3160*	0.5041*	0.2252*	0.1800*	0.3703*	0.4327*	0.1840*	1			
X19	0.4072*	-0.0059	0.4104*	0.5932*	0.2223*	-0.0358	0.3873*	0.5367*	0.4693*	0.4034*	0.2792*	0.5277*	0.3329*	0.0329	0.3924*	0.2665*	0.2432*	0.5697*	1		
X20	0.5172*	0.2061*	0.3857*	0.6624*	0.3095*	-0.1153	0.5190*	0.6522*	0.4916*	0.5564*	0.3616*	0.6457*	0.3942*	-0.0598	0.4200*	0.2867*	0.2054*	0.4310*	0.6897*	1	
X21	0.1330*	0.0775	0.1575*	0.0288	0.1870*	0.2829*	0.1796*	0.1542*	-0.3005*	-0.0602	-0.1297*	0.1059	0.1948*	0.3110*	-0.3828*	-0.0832	0.2854*	0.0252	0.0574	0.1172*	1

***p-values<0.05**

4.4.2 Goodness of Fit Test of the Factor Analysis

The goodness of fit test in FA is used to check the factorability of the observed data. Because of this, the internal consistency, Bartlett's test of Sphericity and Kaiser-Meyer-Olkins (KMO) Measure of Sampling Adequacy was used to conduct this assessment.

From Table 4.9, the value of the Cronbach alpha reliability coefficient of 0.8784 was high. According to Hair et al. (1995), a reliability coefficient value of 0.6 or more indicates a satisfactory internal consistency among the observed variables. In other studies such as that of Nunnally (1978), a value of 0.7 which is less than the realised reliability coefficient value of 0.8784, tend to confirm that the items incorporated in the research instrument can be said to be reliable (consistent). Also, the reliability coefficient of 0.8784 can be interpreted to mean that in a related area of study, virtually 88% of the time the results that will be realized will always be consistent. That apart, the Bartlett test of sphericity with a χ^2 value of 3349.900 and corresponding highly significant p-value (0.000) implies that the variables exhibit patterned relationships. Besides, the p-value (0.000) for Bartlett' Test of Sphericity tend to reject the null hypothesis of an identity matrix for the correlation matrix. The KMO which is found to be a measure of sampling adequacy stands approximately at 0.80 hence can be regarded as "meritorious" (Kaiser, 1974) and a clear justification that the observed data warrants the application of Factor Analysis.

Table 4.9: Goodness of Fit Test of the Factor Analysis

Cronbach alpha reliability coefficient		0.8784
	Bartlett test of sphericity	
	Chi-Square	3349.900
	Df	210
	p-value	0.000
	Kaiser-Meyer-Olkin	
	Measure of Sampling Adequacy	0.796

4.4.3 Factor Retention in Factor Analysis

Several techniques have been introduced to determine the number of factors to retain in Factor Analysis. However, these approaches are noted to come along with their intrinsic issues. For instance, the scree test, the rule of eigenvalue greater than one principle and Parallel analysis are some of the approaches to detect the number of factors to retain (Kaiser, 1960; Cattell, 1966; Horn, 1965).

4.4.3.1 Determining the Number of Factors to Retain in Factor Analysis

Table 4.10 revealed that six factors were considered significant and more important for the Factor Analysis due to the rule of eigenvalues greater than one. Using the retention criteria of Kaiser (1960), these six factors which were retained in the study represents 71.29% of the total variation being accounted for whereas the remaining fifteen factors partially accounted for the remaining 28.71% of the total variance unaccounted (unexplained).

The study further indicated that, the six factors with eigenvalues greater than one can be represented as the latent factors (dependent variables). On the other hand, the remaining fifteen factors can be said to have an insufficient variance to be regarded as factors and could be discarded without substantial loss of information.

Table 4.10: Total Explained Communalities

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	6.85834	4.27122	0.3266	0.3266
Factor 2	2.58712	0.70179	0.1232	0.4498
Factor 3	1.88533	0.47483	0.0898	0.5396
Factor 4	1.4105	0.20781	0.0672	0.6067
Factor 5	1.20269	0.17486	0.0573	0.6640
Factor 6	1.02782	0.06252	0.0489	0.7129
Factor 7	0.9653	0.15412	0.0460	0.7589
Factor 8	0.81118	0.25378	0.0386	0.7975
Factor 9	0.55741	0.0448	0.0265	0.8241
Factor 10	0.51261	0.01964	0.0244	0.8485
Factor 11	0.49297	0.04772	0.0235	0.8720
Factor 12	0.44525	0.01058	0.0212	0.8932
Factor 13	0.43467	0.04589	0.0207	0.9139
Factor 14	0.38878	0.07582	0.0185	0.9324
Factor 15	0.31296	0.05921	0.0149	0.9473
Factor 16	0.25375	0.02811	0.0121	0.9594
Factor 17	0.22563	0.04285	0.0107	0.9701
Factor 18	0.18278	0.00682	0.0087	0.9788
Factor 19	0.17596	0.02198	0.0084	0.9872
Factor 20	0.15398	0.03901	0.0073	0.9945
Factor 21	0.11497	.	0.0055	1

4.4.3.2: Graphical Approach for Detecting the Number of Factors to Retain

The scree test adopted in this study facilitated the search for the "elbow" point to confirm the number of factors. Besides, due to the problem of discontinuity in the "elbow" point in the scree plot, a threshold of between small and large values at an eigenvalue of one ought to be fixed of which an eigenvalue greater than one will constitute a factor.

The scree plot of Figure 4.2 confirms that the mean value (horizontal line) at one supports the six factors with eigenvalues greater than one principle as reported from Table 4.9. In this case, there is a consensus of the six factors to retain for Further Analysis for the two approaches (eigenvalue greater than one principle and the scree plot).

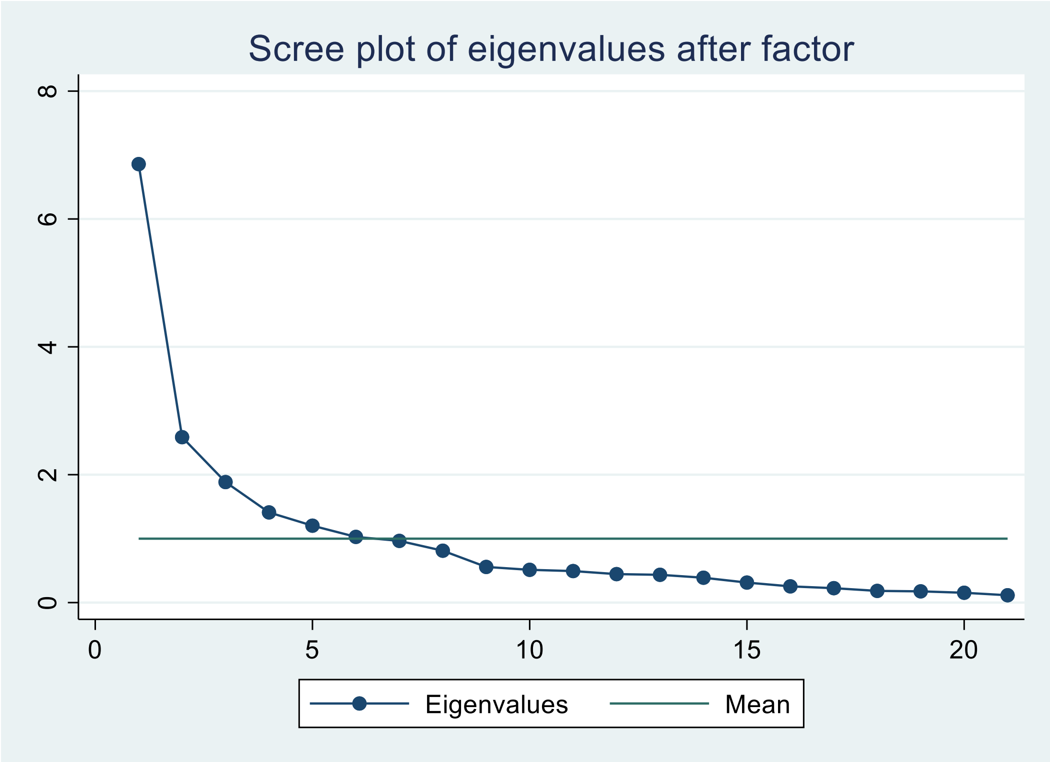

Figure 4.2: Scree Plot for Detecting the Number of Factors to Retain

4.4.4 Initial Variance, Communality and Uniqueness of Indicator Variables

Table 4.11 indicate the percentages of communalities (explained variances) and unique variances (unexplained variances) each of which were accounted for by the collective factor and the independent variables. It is obvious from Table 4.11 that except for the measured variable X6 (use the internet or mobile SMS to obtain weather information), all the measured variables recorded a percentage variability of 50% and above which shows that most of the observed variables have been explained by the common factors. Explained variability corresponding to a higher percentage of 81.19% was associated with the manifest (independent) variable X8 (Crop watering help control water usage) and a high unique variance of 52.59% was accompanied with the measured (independent) variable X6 (use the internet or mobile SMS to obtain weather information).

Table 4.11: Initial Variance, Communality and Uniqueness of Indicator Variables

Variables	Initial Variance	Communality	Uniqueness
X1	1	0.6407	0.3593
X2	1	0.7903	0.2097
X3	1	0.7140	0.2860
X4	1	0.8041	0.1959
X5	1	0.5659	0.4341
X6	1	0.4741	0.5259
X7	1	0.7572	0.2428
X8	1	0.8191	0.1809
X9	1	0.7722	0.2278
X10	1	0.7620	0.2380
X11	1	0.6526	0.3474
X12	1	0.7051	0.2949
X13	1	0.6855	0.3145
X14	1	0.7339	0.2661
X15	1	0.7626	0.2374
X16	1	0.7402	0.2598
X17	1	0.6351	0.3649
X18	1	0.6847	0.3153
X19	1	0.7058	0.2942
X20	1	0.8173	0.1827
X21	1	0.7494	0.2506

4.4.5 Rotated Factor Loadings of the Six Factor Model

For the interpretation of Factor Analysis, there is the need to consider the size of the factor loadings associated with the observed variables. Higher loadings portray that such observed variables constitute latent factors and low loadings are an indication of non-latent factors and hence could be discarded.

To assess the CSA Technology Practice smartness, a threshold or a cut-off point of 0.6 was adopted in this study. Using this threshold, Table 4.12 revealed that the first factor loaded low on X1 (farmers own experience to predict events of the weather for crop production). The other three factors loaded high on factor one from the Rotated Component Matrix that is X5 (use of crop insurance due to weather uncertainties), X7 (excessive use of water is reduced as a result of mulching) and X8 (crop watering help control water usage). A careful examination of these factors falls under "**weather and water smart technologies**". Factor two in Table 4.12 was seen to have variables like X3 (Access to weather information from an organisation through education/training), X4 (obtain information of the weather with a community information centre) and X19 (specific fertiliser/manure is used based on the soil type known as site specific nutrients application) loading high and a careful study of these observed variables relates with ''**weather and nitrogen smart technologies**''. The following observed variables are associated with ''**water, carbon and knowledge smart technologies**'' thus X9 (early planting help to make use of rain water), X11 (use of water conservation techniques thus tied ridging), X15 (trees are planted in and around my farm known as afforestation) and X21 (access to information on market prices concerning produce and inputs known as market information) loaded high on factor three as seen from Table 4.7. However with negative loading of 0.6278 associated with the independent variable X21 (access to information on market prices concerning produce and inputs known as market information) then factor three can be seen to be a "**shape factor**" that contrasts the **water and carbon smart technologies** with the **knowledge smart technology**. On the other hand, observed variables X6 (use the internet or mobile SMS to obtain weather information), X14 (plant different type of crops all together known as mix cropping) and X17 (legumes are planted among crops on the farm known as intercropping) loaded high on factor four. The nature of these loaded observed variables on factor four in Table 4.12 can best depict that of "**weather, carbon and nitrogen smart technologies**". On factor five, observed variables X16 (that is type of planted crops are changed on your land for some farming season known as crop rotation) and X18 (amount of fertilizer/manure required are estimated at a time known as precision fertilization) loaded high on factor five. A close examination of these loaded variables on factor five as witnessed in Table 4.12 can be described also as "**carbon and nitrogen smart technologies**". Lastly, the final observed variables X2 (that is utilise television/ radio to obtain weather information) loaded on factor six which by the nature of the observed variables in Table 4.12 can be termed as "**weather smart technology**". This outcome is in line with a study by Anuga et al. (2019) indicating that most farmers in the utilise the weather smart technology (reliance on radio/television to access weather information) in the Techiman municipality.

Table 4.12 presents the total factor score for each latent variables for the six factors. It is evident from Table 4.12 that, in order of importance, the "**weather and water smart technologies**" factor recorded the highest factor score of 6.3823, "**weather and nitrogen smart technologies**" factor recorded the next highest factor score of 6.1608, ‘‘**water, carbon and knowledge smart technologies**’’ factor recorded the third highest factor score of 4.0325, “**weather, carbon and nitrogen smart technologies**” factor with a fourth factor score of 3.5811. Also with the fifth and sixth total factor scores of 3.4228 and 2.6388 respectively for “**carbon and nitrogen smart technologies**” and “**weather smart technology**” factors.

Table 4.12: Rotated Factor Loadings (Pattern Matrix)

Variables	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
X1	**0.6244**	0.0572	0.0556	0.2777	0.3270	0.2456
X2	0.2157	-0.1757	0.0608	-0.1027	0.0965	**0.8302**
X3	-0.0240	**0.7982**	0.1610	0.1320	-0.1126	-0.1425
X4	0.4093	**0.6631**	0.1916	-0.1557	0.2001	0.3098
X5	**0.7248**	0.0007	0.0377	-0.0433	-0.1781	0.0742
X6	0.0174	0.0166	-0.0491	**0.6657**	-0.1671	0.0049
X7	**0.8188**	0.1694	0.1652	0.1513	-0.0749	0.0475
X8	**0.8179**	0.2254	0.2035	0.1075	0.2153	0.0087
X9	0.2202	0.3669	**0.7171**	-0.1689	0.1531	0.1509
X10	0.5265	0.2751	0.5711	0.2770	0.0774	0.0155
X11	0.1422	0.2475	**0.7072**	0.1485	-0.0274	0.2194
X12	0.2629	0.5761	0.3629	0.3084	0.2445	0.1326
X13	-0.0085	0.5648	0.1408	0.2933	0.0691	0.5058
X14	-0.0182	0.0961	-0.1193	**0.8105**	0.2171	-0.0783
X15	0.2578	0.2198	**0.7461**	-0.2043	0.1979	-0.1013
X16	-0.0335	0.0375	0.0860	0.0486	**0.8377**	0.1617
X17	0.2741	0.0134	0.0311	**0.7331**	0.1384	0.0479
X18	0.0667	0.4482	0.2715	0.1313	**0.6045**	-0.1515
X19	0.3450	**0.6315**	0.1313	-0.0602	0.4074	-0.0348
X20	0.5193	0.5982	0.1882	-0.1482	0.3080	0.1937
X21	0.2235	0.3308	**-0.6278**	0.3795	-0.1111	0.1988
TFS	**6.3823**	**6.1608**	**4.0325**	**3.5811**	**3.4228**	**2.6388**

Footnote: TFS=Total Factor Score for each latent factor

The residuals of the six factor model were assessed by finding the difference between the observed and fitted (reproduced) correlation matrix as found in Table 4.13. It can be seen in Table 4.13 that, all the coefficients associated with the pair of variables are almost zero. These results revealed from Table 4.13 confirms that the six factor model fit the actual data.

Table 4.13: Residual (Observed-Fitted) Correlation Matrix

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21
X1	0																				
X2	0.0161	0																			
X3	0.1400	0.0901	0																		
X4	0.0326	0.0566	-0.0544	0																	
X5	-0.0988	-0.1018	0.0179	-0.0913	0																
X6	0.0727	0.0498	0.0820	-0.0742	0.0229	0															
X7	-0.0628	-0.0144	0.0103	-0.0339	-0.0942	-0.0359	0														
X8	-0.0471	0.0074	-0.0474	0.0344	-0.0894	-0.0130	-0.0116	0													
X9	0.0006	-0.0112	0.0047	-0.0201	0.0360	0.1032	-0.0196	-0.0176	0												
X10	-0.0298	0.0141	0.0051	-0.0310	0.0050	0.0198	-0.0762	-0.0415	-0.0342	0											
X11	0.0151	-0.0853	-0.0546	0.0216	0.0233	-0.0995	-0.0155	0.0580	-0.0692	-0.1042	0										
X12	-0.0495	0.0358	-0.0711	0.0312	-0.0526	-0.1131	-0.0010	-0.0136	-0.0932	0.0526	-0.0573	0									
X13	-0.0662	-0.1584	-0.1295	0.0141	0.1074	-0.1154	0.0536	0.0382	-0.0342	-0.0319	-0.0281	-0.0525	0								
X14	-0.0508	0.0226	-0.0643	0.0646	0.0034	-0.1799	0.0426	0.0430	-0.0047	-0.0712	0.0135	0.0284	0.0671	0							
X15	-0.0695	0.0287	-0.0096	0.0097	0.0024	0.0300	0.0383	-0.0163	-0.0249	-0.0353	-0.0774	-0.0212	0.0321	0.0420	0						
X16	-0.0804	-0.1092	0.0697	-0.0507	0.1503	0.0868	0.0476	-0.0338	0.0223	0.0204	0.0296	-0.0590	0.0395	-0.0608	0.0441	0					
X17	-0.0509	0.0085	0.0006	0.0323	-0.0478	-0.2044	-0.0234	-0.0553	0.0138	-0.0163	-0.0329	0.0082	0.0011	-0.0747	-0.0092	-0.0578	0				
X18	-0.0044	0.0760	0.0236	-0.0613	0.1051	0.0931	-0.0319	0.0065	0.0004	0.0096	0.0401	-0.0507	0.0543	-0.0620	-0.0481	-0.0792	-0.0849	0			
X19	-0.0027	0.0076	-0.0376	-0.0915	-0.0008	0.0803	0.0014	-0.0339	0.0410	-0.0305	-0.0125	-0.0589	0.0076	-0.0355	-0.0194	-0.0741	0.0626	-0.0110	0		
X20	0.0024	-0.0333	-0.0246	-0.0228	-0.0768	0.0178	-0.0174	-0.0213	-0.0126	0.0411	-0.0143	0.0331	0.0434	-0.0090	-0.0267	-0.0106	0.0358	-0.0763	-0.0305	0	
X21	-0.1052	-0.0205	-0.0565	-0.0074	0.0370	0.0226	-0.0311	0.0088	0.0469	0.0228	0.1060	-0.0357	0.0750	-0.0327	0.0938	0.0843	-0.0355	0.0507	-0.0605	-0.0318	0

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This part of the study presents a summary and conclusions in section 5.1 and 5.2 respectively. It further presents recommendations and suggestions for future research.

5.1 Summary

As indicated in chapter one, the objective of the study is to examine the impact of modern agricultural technologies on maize production in the Lawra Municipality of the Upper West region of Ghana. To achieve this, a survey was carried in three communities which include; Bompari, Dazuuri and Toto where 300 households were interviewed.

The data collected on the attributes of CSA technologies were analysed to determine the underlying constructs of CSA Technologies Practices, examine the determinants of CSA technologies and finally to model the determinants of maize yields of farmers using CSA Technologies.

The majority of the respondent interviewed were indigenous 231(77.6%) while 69(22.4%) being migrants. As revealed by Table 4.1, 185(61.7%) of the household interviewed were male and 115(33.3%) were females. The CSA technologies primarily practised by farmers in the study area include improved variety/treated seed (39.9%), mineral chemical fertilizer (25.44%), monoculture

(18%), crop rotation (13.78%) and tied ridges (12.37%). Table 4.1 revealed that the majority of the participated respondents (75.78%) on average had high yields ($\geq$ 18 bags) while the 24.22% on average had low yields (< 18 bags) for the five (2016-2020) farming seasons. Also, Table 4.2 revealed that the status of yield is associated with gender and total land under cultivation respectively.

In modelling the determinants of CSA Technology Practices, model building strategies were devised of which it turned out that model 1 and 2 have strong explanatory power. However further evaluation through the LR and log-likelihood tend to support model 1 (that is model with improved variety omitted). Also, model 1 passed the assumption of the Hausman test of Independence of Irrelevant Alternatives (IIA) and hence found it appropriate to model the determinants of CSA Technology Practices.

The determinants of maize yields of farmers were modelled through a comparison of the random intercept (model A) and random slope (model B) models by considering CSA Technology Practices as the random effect in the models. The competing models through the model fitting criteria's (LRL) and model nesting with LR test with the Restricted Maximum Likelihood (REML) confirmed the random intercepts model (that is the model permitting only CSA Technology Practices specific shift) as appropriate for predicting the average maize yields.

To determine the number of factors associated with CSA practices on maize production, Factor Analysis was used. The study found the assumptions of this model to be adequately satisfied. For instance; the spearman rank correlation matrix suggests the presence of significant correlations among the twenty-one independent variables used to investigate the latent constructs that influences

CSA Technology Practices on maize production. Also, the KMO value of 0.796 was found to be meritorious and with the Bartlett test of Sphericity significant suggesting some kind of patterned relationship among the independent variables. The study found six factors to influence CSA Practices on maize production as observed from Table 4.10 and Figure 4.2. In achieving the appropriate labels for these six factors, a cut-off point of 0.6 for factor loadings was considered and it was established from Table 4.12 that these latent variables for factor 1 to factor 6 were "**weather and water smart technologies**", ''**weather and nitrogen smart technologies**'', "**water, carbon and knowledge smart technologies**'' found to be a shape factor contrasting the water and carbon smart technologies with the knowledge smart technology, "**weather, carbon and nitrogen smart technologies**", "**carbon and nitrogen smart technologies**" and "**weather smart technology**". However, in order of influence, the total factor scores from Table 4.12 revealed that the most influential factor can be subjected was "**weather and water smart technologies**" and the least influential factor is "**weather smart technology**" influencing CSA Technologies and Practices.

5.2 Conclusions

Based on the findings, the study concludes that males are less inclined to use crop rotation as compared to females. Also on the length of CSA practice by farmers, the duration of 6-10 years are less likely to use improve variety/treated seeds relative to those of 1-5 years. In addition, a conclusion can be drawn from the study that tied ridges as a CSA Technology Practice was more related to farmers of a high yield status as compared to that of low yield status.

Moreover, the determinants (farming experience and status of household head) in the Multinomial Logistic Regression model do not in any way impact significantly towards the prediction of the various CSA Technology Practices in light of maize production. Besides this, none of the determinants utilised under the Multinomial Logistic Regression model associate significantly with both Mineral Chemical Fertilizer and Monoculture relative to the base (reference) outcomes.

The study also conclude that the average yield of maize can best be predicted by gender, years of CSAP practice, the status of yield, farming experience and total land under cultivation. However, it can be concluded as well that the intercepts (CSA Technology Practices) in the random intercept model finds improved variety/treated seeds and mineral chemical fertilizer to be associated with a downward shift of the total effect respectively while monoculture, crop rotation and tied ridges are accompanied with an upward shift of the total effect respectively.

The study can be concluded that in order of importance, the factors that influence CSA Practices on maize production are "**weather and water smart technologies**", ''**weather and nitrogen smart technologies**'', "**water, carbon and knowledge smart technologies**'' found to be a shape factor contrasting the water and carbon smart technologies with the knowledge smart technology, "**weather, carbon and nitrogen smart technologies**", "**carbon and nitrogen smart technologies**" and "**weather smart technology**".

5.3 Recommendations

Following the summary and conclusions of the study, these recommendations are considerate in the area of CSA Technology and practices in respect of maize production:

i. Further investigation is carried out to ascertain the underlying reasons if any based on the non-significant relationship established at the 5% level between the determinants on Mineral Chemical Fertilizer and Monoculture respectively.

ii. A similar study should be instituted by relevant stakeholders and researchers in this area to better appreciate if any in respect of reasons for the downward shift in the total effect of maize yields for improved variety/treated seeds and mineral chemical fertilizer respectively.

iii. Stakeholders and all relevant bodies in the area of CSA should encourage peasant farmers to adopt "**weather and water smart technologies**" in the Lawra municipality. Also less attention should be given to "**weather smart technology**" by peasant farmers in terms of maize production.

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APPENDIX

Table A1: Cross Tabulation of Status of Yield and Gender

	Gender		
Status of Yield	Female	Male	Total
Low yield	30	24	54
	55.56	44.44	100
	36.14	17.14	24.22
High yield	53	116	169
	31.36	68.64	100
	63.86	82.86	75.78
Total	83	140	223
	37.22	62.78	100
	100	100	100

Table A2: Cross Tabulation of Status of Yield and Status of Household Head

	Status of Household Head		
Status of Yield	Migrant	Indigene	Total
Low yield	9	45	54
	16.67	83.33	100
	23.08	24.59	24.32
High yield	30	138	168
	17.86	82.14	100
	76.92	75.41	75.68
Total	39	183	222
	17.57	82.43	100
	100	100	100

Table A3: Cross Tabulation of Status of Yield and Total Land under Cultivation

	Total land under cultivation			
Status of Yield	≤ 2 acres	2.1-4 acres	4.1+ acres	Total
Low yield	41	7	6	54
	75.93	12.96	11.11	100
	48.81	10.45	8.33	24.22
High yield	43	60	66	169
	25.44	35.5	39.05	100
	51.19	89.55	91.67	75.78
Total	84	67	72	223
	37.67	30.04	32.29	100
	100	100	100	100

Table A4: Cross Tabulation of Status of Yield and Years of CSA Practice

	Years of CSA Practice			
Status of Yield	1-5 years	6-10 years	11 years and above	Total
Low yield	27	23	3	53
	50.94	43.4	5.66	100
	26.47	26.44	14.29	25.24
High yield	75	64	18	157
	47.77	40.76	11.46	100
	73.53	73.56	85.71	74.76
Total	102	87	21	210
	48.57	41.43	10	100
	100	100	100	100

Table A5: Cross Tabulation of Status of Yield and CSA Technology Practices

	CSA Technology Practices					
Status of Yield	Improved variety/ treated seeds	Mineral Chemical Fertilizer	Mono culture	Crop Rotation	Tied Ridges	Total
Low yield	18	12	14	7	2	53
	33.96	22.64	26.42	13.21	3.77	100
	27.69	21.43	35.9	29.17	7.69	25.24
High yield	47	44	25	17	24	157
	29.94	28.03	15.92	10.83	15.29	100
	72.31	78.57	64.1	70.83	92.31	74.76
Total	65	56	39	24	26	210
	30.95	26.67	18.57	11.43	12.38	100
	100	100	100	100	100	100

Table A6: Fitted (Reproduced) Correlation Matrix of Independent Variables

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21
X1	1																				
X2	0.335	1																			
X3	0.0045	-0.2784	1																		
X4	0.2503	-0.2384	0.5514	1																	
X5	0.4027	0.2074	-0.007	0.2525	1																
X6	0.1404	-0.0826	0.1109	-0.1299	0.012	1															
X7	0.5594	0.1736	0.1638	0.4258	0.6102	0.1224	1														
X8	0.6373	0.1662	0.1818	0.5468	0.5583	0.0435	0.7421	1													
X9	0.2386	0.184	0.342	0.4811	0.1781	-0.1626	0.331	0.4249	1												
X10	0.4823	0.0918	0.3245	0.4749	0.3787	0.1572	0.6089	0.6554	0.5938	1											
X11	0.2284	0.1944	0.2994	0.2612	0.1446	0.0763	0.3101	0.328	0.6331	0.5892	1										
X12	0.4155	0.0796	0.5062	0.5189	0.1575	0.1614	0.4074	0.5056	0.5349	0.6105	0.5048	1									
X13	0.2631	0.3039	0.4325	0.2095	0.012	0.1885	0.1752	0.1998	0.3437	0.3257	0.3907	0.5487	1								
X14	0.2643	-0.1554	0.1516	-0.0251	-0.0972	0.51	0.0843	0.1156	-0.1698	0.1888	0.0341	0.2999	0.2507	1							
X15	0.1982	0.0183	0.2546	0.497	0.1812	-0.1981	0.321	0.432	0.722	0.5795	0.5608	0.4371	0.1296	-0.1872	1						
X16	0.3132	0.2015	-0.0664	0.1376	-0.1603	-0.111	-0.0545	0.1856	0.2126	0.1227	0.0851	0.2853	0.1875	0.2026	0.2033	1					
X17	0.4342	0.0365	0.0835	0.0257	0.147	0.4685	0.3347	0.3425	-0.0078	0.3803	0.1799	0.3573	0.2584	0.613	-0.0304	0.1533	1				
X18	0.2794	-0.1288	0.3707	0.524	-0.0657	-0.0191	0.1428	0.3538	0.4214	0.3943	0.2821	0.5425	0.2945	0.259	0.4265	0.5262	0.2054	1			
X19	0.3668	-0.012	0.468	0.6867	0.1829	-0.0983	0.3698	0.5321	0.4691	0.4446	0.2704	0.5785	0.3651	0.0811	0.4221	0.3561	0.1176	0.5853	1		
X20	0.4761	0.2241	0.4135	0.67	0.3498	-0.1395	0.5213	0.65	0.5703	0.5313	0.3671	0.6047	0.4358	-0.0428	0.4774	0.3034	0.0995	0.4913	0.7093	1	
X21	0.2415	0.0673	0.1919	0.0476	0.1567	0.3124	0.2106	0.1482	-0.3307	-0.0502	-0.2273	0.1378	0.3007	0.3705	-0.4577	-0.0916	0.3185	-0.0547	0.1285	0.1439	1

QUESTIONNAIRE

UNIVERSITY FOR DEVELOPMENT STUDIES

DEPARTMENT OF STATISTICS

Please I am a final year student of the above-named institution, conducting research on the topic: Modeling the Impact of some Modern Agricultural Technologies on Climate Change in the Lawra Municipal of the Upper West Region of Ghana in partial fulfilment for the award of Master of Philosophy degree in Biometry. I will be most grateful if you could answer the questions to the best of your ability. Your responses will be treated confidentially and used only for academic purposes. Your participation is greatly appreciated.

SECTION A

ID No. /__/__/__/

Name of Enumerator	
District	
Community	
Date of interview	

SECTION B

1.0 Characteristics of the Household Head (HH)

1.1 Name of respondent (optional)		....
1.2 Gender of the respondent	…….	0=Female 1=Male
1.3 Status of the Household Head (HH)	….....	0=Migrant 1=Indigene

SECTION C

3.0. Details on the Crop Production Activities of the Farm

3.1 How long have you been farming?	/__/__/	
3.2 What is the total area of your land?	/__/__/__/.**ha**	(IN HECTARES**)**
3.3 In the 2016-2020 farming seasons, what was the average total area of land you cultivated?	/__/__/__/.**ha**	**(**IN HECTARES)
3.4 Do you cultivate maize?	/__/	0=Yes 1=No
3.5 What was the total area under cultivation for maize during the 2016-2020 farming seasons?	/__/__/__/.**ha**	

4.0 Do you apply fertilizer to your maize crop? /…../ (1=Yes 2=No)

4.1 What type of fertilizer do you apply? ……………….

4.2 What quantity of fertilizer did you apply per acre (kg)? (**Multiple questions)**

NPK…… ……SA…….. ….Urea……………Others specify……………….

5.0 Information on yield of CSA Technology (Maize)

Season of production (Year)	Area (Hectare)	Quantity produced (kg)
2016		
2017		
2018		
2019		
2020		

SECTION D

6.0 Climate Change Perception

6.1 Do you know what climate change is?....... (1=Yes 2=No)

6.2 Do you think the climate has changed over time? /......./ (1=Yes 2=No)

6.3 Do you get access to climate information? ……… (1=Yes 2=No)

6.4 Where is your main source of climate information?...…………………..

6.5 In your view what do you perceive to be some changes in the climate you have observed over the last 10 years?

Climatic Event	Increased	No change	Decreased	No Idea
Temperature				
Rainfall				
Drought				
Flooding				
Unpredictable rainfall				
Winds				
Harmattan				

7.0 Are you aware of climate smart agriculture technologies?/......../ 1=yes 2=No

7.1 Do you practise climate smart agriculture technologies? /……. / 1=Yes 2=No

7.2 How long have you been practising CSA technologies?.................................

7.3 Who taught you CSA technology in general?……………………………

8.0 Use of climate smart agricultural technologies

No.	**CSA Technology code**	**Have you already used this technology (1=yes, 2=No)**	**If yes, which year did you start to use it**	**Reason for the use of technology (code)**
1	Improve variety/treated seeds	/__/__/	/__/__//__/__/	/__/__/
2	Mineral chemical fertilizer	/__/__/	/__/__//__/__/	/__/__/
3	Monoculture	/__/__/	/__/__//__/__/	/__/__/
4	Crop rotation	/__/__/	/__/__//__/__/	/__/__/
5	Tied Ridges	/__/__/	/__/__//__/__/	/__/__/
Code: 0= Not applicable 1= Improves crops productivity, 2= Improve soil fertility, 3=reduce the risk of crop loss due to drought, 4=reduces the risk of crop loss by flooding, 5=improves household food security, 6= improves household income, 7= reduces the need for labour in the household 8= Others specify……………				

SECTION F

9.0 To what extent do you consider the following practices of CSA technologies on the improvement of your maize yield? Please pick from the alternatives 1, 2, 3, 4 and 5 where 1 - Not important, 2 – Fairly important, 3 – important, 4 – More important and 5 – Most important

Labels	CSA practices	Scale
X1	Own personal experience to predict events of the weather	
X2	Utilise TV, Radio to obtain weather information	
X3	Access weather information from an organization through education/training	
X4	Obtain information on the weather with the community information centre	
X5	Use of crop insurance due to weather uncertainties	
X6	Use the internet or mobile SMS to obtain weather information	
X7	Excessive use of water is reduced as a result of mulching	
X8	Crop watering help control water usage (irrigation)	
X9	Early planting help to make use of rain water	
X10	Soil moisture is maintained as a result of plant cover crops	
X11	Use of water conservation techniques (Tied ridging)	
X12	Less heavy equipment is used on my farm (Minimum tillage)	
X13	Use manure (animal and plant) for my farm (Organic manure)	
X14	Plant different type of crops all together (Mix cropping)	
X15	Trees are planted in and around my farm (Afforestation)	
X16	Type of planted crops are changed on your land for some farming season (Crop rotation)	
X17	Legumes are planted among crops on the farm (intercropping)	
X18	Amount of fertilizer/manure required is estimated at a time (Precision fertilization)	
X19	Specific fertilizer/manure is used based on the soil type (Site specific nutrients application)	
X20	Information is shared with colleague farmers (information sharing)	
X21	Access to information on market prices concerning produce and inputs(market information)	

THANK YOU FOR YOUR COOPERATION