KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY,

KUMASI, GHANA

ASSESSING THE PATTERNS OF CLIMATE VARIABILITY, LAND USE LAND COVER CHANGE AND NORTH-SOUTH MIGRATION IN GHANA

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A Thesis submitted to the Department of Civil Engineering, College of Engineering, in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

In

Climate Change and Land Use

August 2023

CERTIFICATION

I hereby declare that this submission is my own work towards the award of PhD in Climate Change and Land Use and that, to the best of my knowledge, it contains no material previously published by another person nor material that has been accepted for the award of any other degree or diploma at Kwame Nkrumah University of Science and Technology, Kumasi or any educational institution, except where due acknowledgement has been made in the thesis.

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DEDICATION

I dedicate this work to my late father, Mr. Alexander Pius Dordah; my mother, Mrs. Rose Dordah; my wife; my children; and my siblings, for their unwavering support.

ABSTRACT

Climate Variability and Land Use Land Cover Change (LULCC) profoundly impact ecosystems and livelihoods globally, particularly affecting those with limited adaptation strategies. Such changes frequently drive migration from vulnerable regions, exemplified by northern Ghana, where reliance on rain-fed agriculture and natural resources makes communities susceptible. This research explores the intricate interplay between climate variability, LULCC, and the patterns of North-South Migration in Ghana. It offers a comprehensive understanding of these interconnected phenomena and their implications. Northern Ghana, heavily reliant on agriculture, grapples with adverse weather conditions marked by erratic Rainfall, rising temperatures, prolonged droughts, and relentless harmattan winds. These environmental challenges not only imperil the region's agrarian economy but also the livelihoods of its inhabitants. A significant consequence of this climatic turmoil has been the escalating trend of North-South Migration, with a noticeable surge in participation among young people and females, traditionally underrepresented in this movement. The study rigorously analyses climate data from 1990 to 2020 to explore these trends, employing the Mann-Kendall trend analysis and standardized precipitation evapotranspiration index. These methods assess climate variability and drought severity trends in northern Ghana. In addition, Landsat images from the United States Geological Survey (USGS) for four distinct epochs (1990, 2000, 2010, and 2020) are classified using Google Earth Engine (GEE) and post-processed in QGIS to generate LULC(C) maps for the region. The research utilises a mixed-method approach, combining interviews and perception surveys conducted among migrants in southern Ghana and potential migrants in northern Ghana, employing digitized questionnaires via the Open Data Kit (ODK). These surveys investigate perceptions regarding climate variability, land use, land cover change, and North-South Migration patterns. The climate variability analysis consistently reveals a troubling decrease in Rainfall during critical farming months, exacerbated by rising temperatures and intensified drought severity, particularly in the last decade. These scientific findings corroborate the perceptions of local farmers, emphasizing the urgent need for adaptive measures. The analysis of LULCC patterns in the region underscores cropland as the dominant land use, accompanied by a noticeable expansion of shrub/grassland and woodlands, alongside a concerning reduction in water bodies. Also, the LULCC maps indicate the conversion of croplands to shrub/grassland and woodland, signalling potential abandonment. These visible transformations are directly attributed to human activities identified by farming communities, further accentuating the need for sustainable land management practices. The results illuminate the complex interplay of push and pull factors driving North-South Migration. Climate variability and LULCC emerge as prominent push factors, while socio-economic considerations, particularly for female and less-educated migrants, act as attractive forces. In conclusion, this research unravels the intricate interplay between Climate Variability, LULCC, and North-South Migration patterns in Ghana.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS AND ACRONYMS

CHIRPS - Climate Hazards Group InfraRed Precipitation with Station data
ERA5 - Fifth generation of the European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis
EPA-Environmental Protection Agency
FC-Forestry Commission
GEE - Google Earth Engine
GIS - Geographic Information System
GMA - Ghana Meteorological Agency
GSS - Ghana Statistical Service
GTB - Gradient Tree Boosting
IPCC - Intergovernmental Panel on Climate Change
LULCC - Land Use and Land Cover Change
LULC - Land Use and Land Cover
MOFA-Ministry of Food and Agriculture
NADMO - National Disaster Management Organization
NASA - National Aeronautics and Space Administration
NDVI - Normalized Difference Vegetation Index
NDBI - Normalized Difference Built-Up Index
PET - Potential Evapotranspiration
PHC - Population and Housing Census
PM - Penman-Monteith (a method for modelling potential evapotranspiration)
QGIS - Quantum Geographic Information System
RF - Random Forest
RWAFF - Royal West African Frontier Force
SPEI - Standardized Precipitation Evapotranspiration Index
SPI - Standardized Precipitation Index
SSA - Sub-Saharan Africa
SVM - Support Vector Machine
TFPW - Trend-free pre-whitening
UNFCCC - United Nations Framework Convention on Climate Change
USGS - United States Geological Survey
WMO - World Meteorological Organization

ACKNOWLEDGMENTS

I thank the Almighty God for His grace bestowed upon me throughout my life and educational journey. I appreciate the scholarship opportunity and financial support from the WASCAL program and the German Federal Ministry for Education and Research (BMBF).

I am grateful to the Climate Change and Land Use (CCLU) program and the Kwame Nkrumah University of Science and Technology, Kumasi, Ghana, for the opportunity to conduct this research and to gain valuable experiences and collaborations with international scientists. I extend my gratitude to Prof. W. A. Agyare, the Director of the CCLU-KNUST program in Kumasi, and Prof. E. Forkuo, the same program Coordinator, for their support and guidance.

My appreciation goes to my supervisors: Prof. Edward M. Osei Jnr from the Department of Geomatic Engineering, KNUST; Prof. Divine O. Appiah, of the Department of Social Sciences, KNUST; Dr. Kwame O. Hackman, Data Management Department, WASCAL Competence Center, Burkina Faso, Dr. Michael Thiel, Julius-Maximilians-University of Würzburg. Their guidance, constructive criticism, encouragement, and motivation have been instrumental in shaping this thesis and my academic path. I am also grateful to Prof. Samuel Akorful-Andam and Dr. Asare Mensah, both in the Geomatic Engineering Department, KNUST, for their significant contributions to this work's success. To Mr. Paul Tawiah Stephens, Regional Meteorological Officer, Tamale, the Regional Meteorological Officers of Bole and WA, GSS, Accra District heads of MOFA, NADMO, for their assistance with Data for this work. To my colleagues, I appreciate all your support throughout this endeavour.

CHAPTER ONE

INTRODUCTION

1.1 Background

Human migration is a relocation or a displacement leading to a change of the abode (in general terms), the crossing of a spatial boundary of an individual or a group of people permanently, or, in the case of seasonal workers temporarily, for an appreciable duration (Kaczan and Orgill-Meyer, 2020; King, 2020). It is used symbolically in the transition involving abandoning one surrounding to another and a different one in human life (Jackson, 2022; King, 2020; Muir et al., 2020; Vincent, 2022). Migration, therefore, means not merely a shift of a certain number of undifferentiated persons from one place to another but also a change in the occupational and population structure of both sending and receiving regions (Mangalam, 2014). The distance of movement and the amount of spatial separation are essential elements of migration; thus, every study of migration should adopt an explicit definition of a suitable "spatial boundary" (Mangalam, 2014; Clark, 2020).

Migration can be classified into stateside, intra-regional, continental, inter-regional and global (Tolkach and Tung, 2019) and can be temporary, involving return journeys or permanent resettlement. Internal migration consists of moving within a state, country, or continent. In contrast, international migration consists of moving to a different state, country, or continent and typically follows established international migration routes, whether legally recognised or not (McLeman and Hunter, 2010). In many cases, migration exhibits common spatial patterns, such as the movement from rural areas to urban centres, known as rural-urban migration. Conversely, although less common, urban-rural migration, which involves movement from urban centres back to rural areas, also occurs (Tong and Lo, 2021). Additionally, migration patterns can take place within rural areas (rural-rural or intra-rural migration) or between cities (urban-urban or inter-urban migration) (McLeman, 2016; Tong and Lo, 2021). People who move from their home country are considered emigrants and are received as immigrants in the destination country (Zaiceva and Zimmermann, 2016).

In Ghana, various forms of migration take place, but one of the most significant is the continuous movement of people from the northern sector to the southern part of the country. This migration pattern dates back to the colonial era when labour was drawn from the north to work in farming and mining, particularly in the cocoa-growing areas and mining industries of the South (Sow et al., 2014; Tanle, 2015; Schraven and Rademacher-Schulz, 2016). In post-colonial Ghana, outmigration from the north to the South occurs for diverse reasons (Tanle, 2015; Sow et al., 2014), requiring thorough investigation and understanding.

Human migration is influenced by many factors, including political, social, economic, and environmental motivations. Notably, the climate and LULCC play significant roles in driving migration patterns on a global scale, resulting in far-reaching consequences such as climate-related migrations and population displacements (McLeman and Hunter, 2010), and Ghana is not exempt from these trends.

The IPCC (2007) published a report highlighting climate change's impacts, including the destabilisation of food and water supplies, increased flood occurrences in certain regions, and decreased yields in rain-fed agriculture. Consequently, lands may lose their capacity to sustain livelihoods, leading people to migrate to areas offering better opportunities for survival. In Sub-Saharan Africa (SSA), climate variability poses a significant challenge to food security due to high temperatures, low precipitation, and limited adoption of modern agricultural technologies (Amankwah, 2023; Ogisi and Begho, 2023).

Most SSA countries find it difficult to cope with existing climate stress and LULCC of the environment, and this is austere in areas where livelihood depends on rain-fed subsistence agriculture and natural resources, hence resulting in human movement (Brown, 2008; Kubik and Maurel, 2016; Nawrotzki and Bakhtsiyarava, 2017). Migration is the primary response to adverse climate threats for farmers in most African countries with limited adaptation strategies, such as improved techniques and irrigation facilities for crop production (Fielmua et al., 2017).

Studies on the causes of human migration, e.g., the impact of climate variability, most often distinguish between slow versus fast onset events and direct and indirect links (Bohra-Mishra et al., 2014). However, in practice, there is usually a continuum between fast and slow onsets and between direct and indirect impacts and voluntary and involuntary movement (Cattaneo et al., 2019). Addaney et al. (2022) state that rapid population growth has culminated in pressure on land, over-exploitation of scarce natural resources, and land degradation. These, coupled with climate variability (possible changes in

Rainfall, temperature, droughts, and perennial flooding), have affected agricultural productivity, resulting in migration increases in northern Ghana (Sows et al., 2014). Due to the diversity of the factors resulting in North-South Migration in Ghana, it is imperative to assess the implications of the different pull and push factors and ascertain which ones constitute the main drivers. It is gain saying to investigate the desired goals of migrants to verify if they are met.

1.2 Problem Statement

The weather conditions in northern Ghana are expected to worsen over the years in line with global climate trends (Asante et al., 2012). Rainfall distributions will likely become erratic with poor volumes, and mean annual temperature will continue to rise, resulting in extreme cases of the severe long dry season with extreme drought and sporadic floods (Asante et al., 2012; Nkegbe and Kuunibe, 2014). In addition, the harmattan will continue to exacerbate, bringing extreme cold winds with sweltering temperatures between November and March (Lyngsie et al., 2011). These environmental conditions in northern Ghana have adverse consequences on LULCC as well as making the area inauspicious for habitation, setting the tone of migration flow in motion and forcing an increase in outmigration (usually north to South of Ghana) for better conditions (Van der Geest, 2011).

Agricultural growth, a significant driver of poverty reduction in northern Ghana, is the largest source of employment for the people, with about ninety-seven percent (97.9%) of households (usually smallholder farmers practising seasonal and subsistence farming) engaged in crop and animal farming for their livelihood (Nkegbe and Kuunibe, 2014; Bawa, 2019). Shifts in rainfall distribution and temperature changes have an adverse significance on agriculture, food security, and the poverty level of farmer households because agriculture in northern Ghana is rain-fed with minimal irrigation coverage (Wossen et al., 2014; Nkegbe and Kuunibe, 2014; Antwi-Agyei et al., 2018). Climate variability and LULCC impacts on the environment are directly transmitted to the people through agricultural production since it remains the primary source of income, which is their source of livelihood. It causes production uncertainties, particularly related to agrarian income risks, and most people are likely to seek greener pastures at palaces that they perceive to present better opportunities (usually the South of Ghana).

In this regard, North-South Migration in Ghana, which hitherto largely involved male adults who moved to work, has since the 1970s attracted increasing numbers of independent females and young people (under 18 years of age) (Kwankye et al., 2009; Teye et al., 2019). If curbed, this canker will retain the northern part of Ghana of youthful human resources that constitute the area's workforce. Developing the appropriate adaptation and mitigation strategies to address this growing phenomenon is essential. Therefore, the correct information and knowledge regarding the causative factors in the sector need to be harnessed.

A considerable amount of work has been done on the effect of climate variability and LULCC on rural-urban migration in the northern part of Ghana. Many of these studies have been subjective rather than objective. Moreover, comprehensive studies have yet to establish the main driving factors behind North-South Migration in Ghana, specifically examining the interplay of climate variability, LULCC, and socio-economic factors encompassing both push and pull factors. For example, Fielmua et al. (2017), Jarawura and Smith (2015), Sow et al. (2014), and Van der Geest (2011) have conducted separate studies on the influence of climate and LULCC on migration in the northern part of Ghana but not with an integrated approach. None of these studies considered climate's impact on LULCC and its overarching influence on migration in the study area. In addition, most of the studies on climate variability and LULCC in the study area are either objective or subjective and need careful integration for comprehensive analysis.

Meanwhile, a scientific assessment (objective) and local perception (subjective) may be different but could complement ways of better understanding the local-scale impacts of this phenomenon. This study examines the trends in climate variability and LULCC in northern Ghana, utilizing scientific assessments and local perceptions to comprehensively understand the effects on farmers. Furthermore, this study will assess how climate variability and LULCC, as environmental factors, together with other socio-economic factors, influence the phenomenon of North-South Migration within the study area. The study will determine the key drivers (push and pull factors) among climate variability, land use and land cover change, and socio-economic factors contributing to North-South Migration in the study area.

1.3 Aim and Specific Objectives

1.3.1 Aim

The research aim is to assess climate variability, LULC changes, and North-South Migration patterns in Ghana through an integrated analysis approach.

1.3.2 Specific Objectives

1. To examine the climate variability patterns in northern Ghana.
2. To evaluate the changes in northern Ghana's LULC patterns.
3. To assess the influence of land use land cover change and climate variability on North-South Migration, in conjunction with other push and pull factors in Ghana.

1.4 Conceptual Framework

This section outlines a structured approach for conducting a comprehensive analysis of the complex patterns of climate variability, LULCC, and North-South Migration patterns in Ghana. It is important to note that this study will not involve any modelling. The independent variables to be investigated in this study will be gathered through open-ended questions.

1.4.1 Dependent Variable

North-South Migration Patterns

The central dependent variable in this study is the phenomenon of North-South Migration, which encompasses the movement of people from northern to southern Ghana.

1.4.2 Independent Variables

Climate Variability

- *Objective assessment:* This aspect involves examining northern Ghana's climate data from 1990 to 2020. Key indicators under scrutiny include rainfall, temperature, and the severity of droughts.
- *Subjective assessment:* Data will be gathered through interviews and perception surveys to gain insights into how local communities perceive,

experience changes in climate within the northern regions and how it influences migration in the study area.

LULCC

- *Objective assessment:* The analysis of remote sensing data and Geographic Information System (GIS) techniques will be employed to create land use and land cover change maps for the northern region.
- *Subjective assessment:* How local communities perceive changes in land use and land cover in their respective areas and its influence on migration will be collected through interviews and surveys.

Socio-Economic Factors

This facet of the study will assess the socio-economic factors motivating individuals to migrate to the south of Ghana using qualitative and quantitative approaches.

1.4.3 Mediating Variables

LULCC and Climate Variability Interaction

- *Objective Data Integration:* This component examines how climate variability impacts land use, land cover changes, and vice versa. Scientific assessments will be employed for this purpose.
- *Subjective Perceptions:* The study aims to understand how local communities perceive the interactions between climate and land use changes and how these perceptions influence migration decisions.

1.4.4 Control Variables

Demographic factors, including gender, age, occupation and educational background, will be considered control variables influencing migration patterns.

1.4.5 Research Questions

- What is the climate variability trend in northern Ghana from 1990 to 2020?
- What is the LULCC pattern in northern Ghana?
- To what extent do climate variability and LULCC drive North-South Migration in Ghana?

1.4.6 Hypotheses

- Hypothesis 1: Increasing climate variability in northern Ghana positively correlates with North-South Migration, as harsher climate conditions push people to seek better opportunities in the south.
- Hypothesis 2: Changes in land use and land cover in northern Ghana are positively correlated with North-South Migration, as shifts in land use affect livelihoods and economic prospects.
- Hypothesis 3: The interaction between climate variability and land use change mediates the relationship between these factors and North-South Migration.

1.4.7 Data Sources

- Climate data sources encompass meteorological records from the Ghana Metrological Agency (GMet) and satellite data (CHIRPS/ERA5).
- Land Use and Land Cover data will be derived from GIS and remote sensing data.
- Demographic and Socio-economic data will be obtained through surveys, interviews/perception surveys, and existing reports (e.g., census data)

1.4.8 Analysis Techniques

- Mann-Kendall trend analysis will be utilised to assess climate variability and climate trends analysis.
- The Standardised Precipitation (Evapotranspiration) Index [SP(E)I] will be employed for drought severity analysis.
- Remote sensing and GIS techniques will be applied to analyse LULC changes.
- Interviews/perception surveys will be analysed using statistical methods.

1.4.9 Conclusion and Policy Implications

- This conceptual framework will guide the analysis of data, interpretation of findings, and formulation of conclusions.
- The study's outcomes will inform policy recommendations and address the patterns of climate variability, LULCC and North-South Migration in Ghana.

1.5 Comprehensive Overview of Study Areas

With an approximate population of 4.2 million, northern Ghana covers a land area of approximately 97,700 km^2, lying between latitudes 9° and 10° 30'N and longitudes 0° to 2° 30' (see Figure 1.1) (Ghana Statistical Service [GSS], 2012; Anim et al., 2013). It comprises five administrative regions: The Upper West, Upper East, Northern, North East, and Savannah Regions.

The vegetation in northern Ghana is characterized by the western Sudan savannah and a small part of the Guinean forest-savanna mosaic, with a land cover consisting of savannah grassland and interior wooded savannah, respectively (Hackman et al., 2017; Adonadaga et al., 2022). The area lies in the tropical continental climate zone, experiencing two main seasons, rainy and dry, with a unimodal rainfall distribution from May to October, yielding a mean rainfall variation of between 1000 mm and 1150 mm. The duration of the dry season spans from November to March/April (Tanle and Awusabo-Asare, 2012; Amikuzuno and Donkoh, 2012; Hackman et al., 2017; Asante and Amuakwa-Mensah, 2014; Adonadaga et al., 2022) resulting in seasonal variations causing changes in land-cover characteristics and atmospheric conditions. For example, anthropogenic and natural fires during the dry season result in seasonal land-cover changes, while cloud coverage increases during the rainy season (Hackman et al., 2017). Maximum temperatures range between 30°C and 36°C and occur towards the end of the dry season (March/April), while minimum temperatures of 24°C-27°C occur in December and January (Tanle and Awusabo-Asare, 2012).

The northern part of Ghana is predominantly rural, with most of the population engaged in crop farming and livestock rearing (Bawa, 2019). The agriculture sector, dominated by smallholder farmers and practised on seasonal and subsistence levels, is the largest source of employment for the people in this area (Nkegbe and Kuunibe, 2014; Bawa, 2019). Agricultural growth depends on rainfall patterns and land expansion (Limantol et al., 2016; Bawa, 2019). Therefore, changes in climate variables and the physiological changes of the land due to land use and land cover changes can directly impact the populace's livelihood, which may push them to seek better conditions elsewhere, usually in southern Ghana.

In this research, three districts situated across three regions in northern Ghana were chosen for conducting social surveys involving household heads (potential migrants), the analysis of climate variability trends, and the evaluation of LULCC patterns. These districts, Wa in the Upper West Region, Tamale in the Northern Region, and Bole in the Savannah Region were selected following preliminary surveys conducted among migrants in southern Ghana. In addition, the districts share common attributes within the northern region of Ghana.

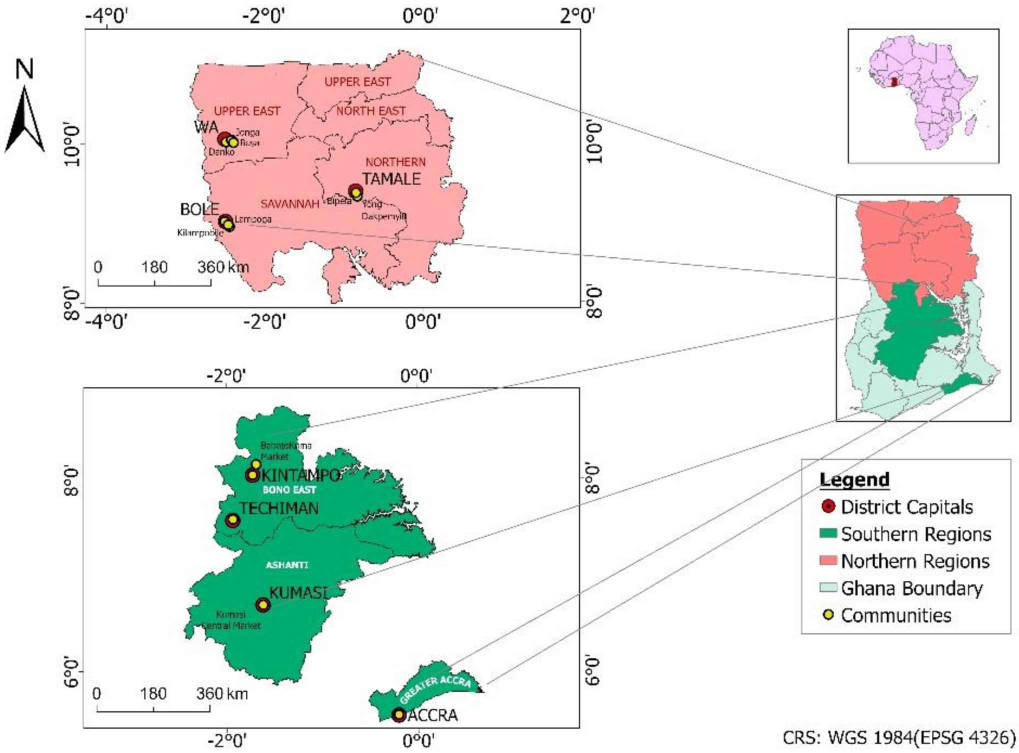

Figure 1.1 Study Areas

In contrast, the southern part of Ghana generally experiences relatively good weather conditions and is more economically endowed than the north (Fielmua et al., 2017). It experiences a bimodal rainfall distribution and has arable lands, making it suitable for habitation and agricultural activities, which is a pull factor for most northern migrants. For this research, social surveys were conducted on migrants in some southern districts of Ghana, including Kumasi in the Ashanti Region, Accra in the Greater Accra Region, and Techiman and Kintampo in the Bono East Region. The vegetation in these districts mainly comprises semi-deciduous forest (Ayensu et al., 2020; Agyare et al., 2020; Asori et al., 2022) found around Ashanti and Bono areas, and coastal savanna for Greater Accra (AMA, 2006; Mattah et al., 2018). Annual Rainfall is relatively high in these areas, and temperatures are low. For instance, Accra has an average temperature of 26.8°C, with the hottest month being March at 28°C and the coldest month being August at 24.7°C (Mattah et al., 2018). These conditions present better living conditions, attracting people from northern Ghana.

1.6 Organization of Thesis Chapters

There are six chapters in this thesis, with Chapter One presenting the background of the study, the problem statement, specific objectives, conceptual framework, a general description of the study area and the organization of chapters. Chapter two reviews the literature on the different concepts and theories regarding this research. Chapter three presents an analysis of climate variability and the impact of the same on the livelihood of northern Ghana. Chapter Four delivers the patterns of LULCC in the north of Ghana, and Chapter Five analyses the main drivers (push and pull factors) of North-South Migration in Ghana. Chapter Six summarizes the essential findings and provides the conclusions, recommendations, policy interventions, limitations and suggestions for future research.

CHAPTER TWO

LITERATURE REVIEW AND THEORITICAL APPROACH

2.1 Introduction

Modern migration studies traced its origin to Ernst Georg Ravenstein in the 19th century. He used Britain's census data to identify internal and international migration patterns and propounded theories about the same in his work, the 'Laws of Migration' (1889). Many of Ravenstein's observations are still held today. For instance, he observed that migration flows from rural areas to urban centres, that migration patterns for People are different, and that the availability of employment opportunities leads to migration. The distance between the destination and place of origin is a relevant factor.

Ghana has a high migration rate, with no less than a migrant in more than 43 percent of all households (Ackah and Medvedev, 2012). There has been persistent migration in Ghana within (internal migration) and to or from other countries (international migration). In the late 1960s, skilled and unskilled Ghanaians emigrated to North America, Europe, and some West African countries, such as the Republic of Côte d'Ivoire and Nigeria (Yaro et al., 2011). From the pre-colonial era, the country enjoyed some form of economic boom and hence became an attraction for many migrants from other African countries. In recent years, Ghana has also grown in popularity as a location for young migrants from West Africa due to the large numbers of Nigerians and other West African nationalities who currently reside in some of Accra's peri-urban suburbs (Spencer et al., 2022).

In Ghana, inter-regional migration holds greater significance than intra-regional migration, mainly from North to South (Fielmua et al., 2017), the primary attention of this study. The Ghana Statistical Service (GSS) surveyed the origin of the country's street children. Among the estimated 6.4 million children aged 5 to 17 in Ghana, over 50% were found to come from Northern Ghana (Kwankye et al., 2009).

The movement of people from the North to the South has long marked Ghana's internal migration. The primary purpose of the movement of people to the South in the colonial era was to serve as a labour force in mining and farming on cocoa plantation areas aside from their conscription into the Royal West African Frontier Force (RWAFF) of the British colony (Sow et al., 2014; Fielmua et al., 2017). However, the post-colonial era has seen people embarking on voluntary persistent outmigration from the North to the South of Ghana (Hashim, 2005; Sow et al., 2014) for various reasons.

The reasons for voluntary North-South Migration, especially by the non-skilled, are varied. While some authors attribute this to agroecological, the inability of parents to cater for wards, an independent strategy by the youth, and preparation by some young females for marriage (push factors), many writers have attributed North-South Migration in Ghana to the spatial distribution of natural resources. The southern part of Ghana is comparatively considered more naturally endowed than the northern part, hence an attraction (pull factors) to migrants. In addition, the return of migrants with some so-called better lifestyle motivates other young ones to embark on the same feat (Fielmua et al., 2017). On a broader scale, the International Organization for Migration [(IOM)] (2022) noted that migration can powerfully drive sustainable development for migrants and their communities. They further stated that there are significant benefits, including the acquisition of skills, strengthening the labour force, investment and cultural diversity, and improving the lives of communities in their countries by transferring skills and financial resources. Furthermore, due to this more optimistic perspective on the developmental impacts of migration, it was incorporated into the 2030 Global Development Agenda and the Sustainable Development Goals (SDGs) in 2015 (Teye et al., 2019).

Amidst various concepts regarding Migration, Fielmua et al. (2017) noted that voluntarism concerning migration is contentious, and there are always implicit interwoven drivers confined to the migrant. Hence, even when migration is attributed to voluntarism, embedded factors (push or pull) initiate the movement, without which it will not occur. This argument is supported by the fact that migration is an expensive venture, and people who usually undertake it are the rural poor who will only engage in it with compelling force (Fielmua et al., 2017). Most of Ghana's population reported as living in poverty are in the North. The prevalent underdevelopment apparent in its poor healthcare and transport infrastructure as well as in low rates of access to water, sanitation, electricity, and suitable housing (Rademacher-Schulz et al., 2014), the populace will not have the luxury of voluntary but some form of forced migration.

2.2 North-South Migration in Ghana

The spatial distribution of natural resources in Ghana could be linked to North-South Migration because southern Ghana is naturally endowed more than the north (Fielmua et al., 2017). The structural factors that cause people's movement can be resource endowment, income levels, or access to facilities and services (Kwankye et al., 2009). One strategy for diversification is migration, and rural mobility is often explained as a result of push and pull factors. Push factors induce desperation and involuntary migration (for example, land scarcity), while pull factors induce proactive, voluntary migration (e.g., high urban wages) (Wouterse, 2010).

Environmental push is essential in explaining the migration system in the north-south, and the primary pull factors could be linked to low population density and good crop cultivation conditions. Natural resource scarcity in the north is a significant reason for Migration to the South. Natural resource scarcity is indicated by Rainfall, vegetation, crop yields, and population pressure (Van der Geest, 2011). According to estimates, one out of every five people born in northern Ghana lives or has lived in southern Ghana. Ghana's internal Migration from North to South has resulted in movement from poorer rural communities to urban areas, with young people frequently migrating to cities for work, education, and a higher living standard (Spencer et al., 2022).

Fielmua (2017) looked at the factors influencing individuals' and households' decisions to use migration as a climate change adaptation strategy in North-western Ghana. The study's significant findings indicate that the debate over climate change and migration should shift from whether climate change causes human migration to how climate change influences migration choices and what households consider before embarking on migration as an adaptation strategy. A relationship could be drawn between economic and environmental factors:

shifting rainfalls, deteriorating soils, drought, and floods all contribute to a decline in crop and animal production, resulting in lower household incomes.

Also, Laube (2012) investigated how farmers in Northern Ghana adapt to the dynamics and limits of climate change. The findings of this study confirm that farmer-driven small-scale irrigation can play a crucial role in climate change adaptation. Furthermore, Van der Geest (2011) determined the environment as a significant driver of North-South Migration in Ghana. The findings of this paper suggest that the environment plays a vital role in explaining migration from northern Ghana to southern Ghana and that structural scarcity, rather than degradation, is the environmental driver of migration. The structural agroecological differences between north and south Ghana significantly motivate people to relocate. North-South Migration proclivities have steadily increased over the twentieth century; environmentally poor districts have higher outmigration rates; and, surprisingly, North-South Migration declined during severe environmental stress.

2.3 Influence of Climate Variability on LULCC and North-South Migration in Ghana

Human Migration is commonly mentioned as a possible social impact of climate change and variability, and these effects are often thought to have been more pronounced when economies were less established and markets more regionalised (Jennings and Gray, 2015). Climate change's effect on migration has been a topic of an expanding amount of research in recent times. Gray and Wise (2016) state that theoretical advancements in migration studies and human-environment research support a revised understanding of climate-induced migration.

To conduct the study more accurately and impartially, various studies that directly or indirectly influence the current work are analysed while considering the significance of the associated literature. Jennings and Gray (2015) assessed climate variability on Migration in the Netherlands, combining historical climate data with a unique dataset capturing 24,835 migrants in the Netherlands. The findings revealed that age groups and place of residence also affect the relationship between climate variables and migration. For instance, the study by Jennings and Gray (2015) showed that climate has a more substantial influence on the migration of individuals over 25 years. The study also established that climate variability significantly influences migration, with models that include temperature, Rainfall, and coastal flooding as the best climatic parameters. High temperatures reduce short-distance Migration in the later period, while precipitation negatively predicts long and international moves in the early period.

Similarly, Mastrorillo et al. (2016) conducted a study in South Africa on the influence of climate variability on Internal Migration. The study, which employed a gravity approach combined with climatic data as a panel database in South Africa, also establishes similar findings as the work of (Jennings and Gray, 2015). Based on the results of Mastrorillo et al. (2016), increases in positive temperature extremes and positive and negative excess Rainfall at the origin act as a push factor influencing outmigration. However, per migrant characteristics, the significance of the effect of climate on migration varies. Although there is much interest in the connections between historical climate data and migration, only some studies have employed statistical techniques to connect migration responses to historical climatic changes. However, some have looked at long-term, overall patterns. A notable exception is a study by Gutmann et al. (2005) on migration and environment in the US Great Plains. The study indicated how, through time, the connections between climate and migration at the county level might evolve and become "less Malthusian" but closely tied to recreational and lifestyle factors.

Jha et al. (2018) evaluated the linkage between climate/weather change and farmer migration in Bihar, India. The study's main finding was that climate-related livelihood risk issues are one of the main drivers of farmer migration. Farmers' perceptions of climate change influence migration, as do socio-economic factors. The study offers micro-evidence of migration's influence on farmer adaptive capacity and access to climate and agricultural extension services, which will aid analyses of climate-induced migration in other developing countries with a greater agricultural reliance.

Stojanov et al. (2016) investigated the perceptions of local experts on migration as a change in climate adaptation strategy for Bangladeshis. According to the findings, local experts believe that the use of migration to adapt to climate change in Bangladesh will continue. However, migration is not solely for climate change adaptation but is intertwined with all other factors influencing migration-related decisions. Bangladesh is one example where environmental changes have long been cited as one of the many reasons for migration, with current climate change cited as a significant impetus for increased migration.

Ndamani and Watanabe (2015) analyzed the perceived importance of climate change adaptation practices among farmers and the barriers to adaptation. Over the last ten years, 87% of respondents, according to the findings, perceived a decrease in rainfall amount, and yet 82% perceived an increase in temperature. According to the study, (93.2%) perceived adaptation as primarily in response to dry spells and droughts rather than floods. In response to climate change, approximately 67% of respondents have adjusted their farming activities. According to the empirical findings of the weighted average index analysis, farmers ranked improved crop varieties and irrigation as the most essential adaptation measures. It also revealed that farmers could not practice highly rated adaptation practices.

Fosu-Mensah (2012) investigated farmers' perceptions of climate change in the Sekyedumase district of Ghana's Ashanti region and analysed farmers' adaptation to climate change. According to the findings, approximately 92% of respondents perceived temperature increases, while 87% perceived precipitation decreases over time. Crop diversification, planting of short-season varieties, crop species change, and planting date shift were among the significant adaptation strategies identified. The four most crucial factors influencing farmers' perception and adaptation are access to extension services, credit, soil fertility, and land tenure. The main barriers were needing more information on adaptation strategies, poverty, and a lack of weather information. Even though communities are aware of climate issues, only 44.4% of farmers have changed their farming practices to mitigate the effects of rising temperatures and 40.6% to mitigate the impact of falling precipitation, citing a lack of funds as the main barrier to implementing adaptation measures.

Also, studies by Thiede et al. (2016) on the effect of climate variability on migration in eight South American countries, emphasising the effects of prolonged shocks and anomalous conditions, show several notable patterns consistent with the literature. Contextually, findings from Thiede et al. (2016) revealed that temperature changes tend to have more robust effects on migration than rainfall changes, a conclusion consistent with recent research. Additionally, the study establishes that climatic variability increases the likelihood of inter-province migration across the region. Further, the study demonstrates that climatic variability increases the likelihood of regional inter-province migration.

Related theoretical stances integrate climate and Migration literature to offer a broader framework for migratory responses to climatic circumstances. For instance, a study by McLeman and Hunter (2010) confirmed migration as an adaptation to climate variability interwoven with societal processes. Employing a conceptual model developed to investigate the relationship between climate and human migration established that the migration patterns observed in the case study are consistent with the central elements of the climate change-migration model developed.

There are other concerns related to climate-induced migration that have significant policy ramifications. Evidence on the makeup of climate-induced migration is also required to evaluate a migratory stream's anticipated social and economic ramifications (Thiede et al., 2016). Literature from Cattaneo et al. (2019) and McLeman and Hunter (2010) examined the relationship between climate change and migration. The findings of Cattaneo et al. (2019) indicate that slow-onset climate phenomena, such as temperature and drought increase, tend to cause migration (Kaczan and Orgill-Meyer, 2020), typically seen as voluntary and frequently driven primarily by economic factors or immobility. On the other hand, rapid-onset catastrophes like storms, hurricanes and floods tend to cause abrupt, unconscious, short-term, and close-range actions.

According to McLeman and Hunter (2010), within a more extensive range of potential adaptive reactions that people and families might take when sensitive systems are subjected to changing environmental conditions or stress, migration is only one type of adaptation that is potential.

Developing Countries are generally predicted to be more severely impacted by climate change than developed countries (Lilleør and Van den Broeck, 2011). Climate change seriously challenges Africa's sustainable growth and development (Asante and Amuakwa-Mensah, 2014). Asante and Amuakwa-Mensah (2014) established that since agriculture provides a larger share of the national revenue in most African countries, any adverse impact of climate change affects agricultural productivity negatively and slows the growth of African nations. Understanding Africa's current non-climate vulnerabilities is necessary to grasp the impact of changes in climate on the continent. From the average society to the global world, awareness of climate effects has increased (Fielmua et al., 2017).

Ghana is among the most susceptible nations in Sub-Saharan Africa to changes in climate and variability (Fielmua et al., 2017). Given this, in June 1992, Ghana became a member of the United Nations Framework Convention on Climate Change (UNFCCC), organised at the Rio de Janeiro Earth Summit to combat climate change (Asante and Amuakwa-Mensah, 2014). According to a study by the World Bank (2010), Ghana's rainfall patterns show extraordinarily high levels of variation both within and between years. Based on World Bank projections, Ghana's temperature is expected to rise from 2010 to 2050 across the country, with areas in Northern Ghana seeing the most incredible temperatures. Ghana's agriculture industry is susceptible to climate change and fluctuation since it depends so heavily on Rainfall; low productivity levels have become a sector feature (Asante and Amuakwa-Mensah, 2014).

2.4 Influence of LULCC on North-South Migration in Ghana

In Northern Ghana, yields are declining, and crops are failing, which has led to more poverty in Ghana's poorest area because of climate change and soil degradation (Laube et al., 2012). Contextually, Fielmua et al. (2017) sought to find the rationale behind migrants in the North-western part of Ghana migration as an adaption strategy to changes in climate rather than other strategies. The study's findings suggested that, with limited adaptation options that would encourage rural northern people to stay due to the impact of climate change on rain-fed rural livelihoods, migration becomes the primary option in these locations. Fielmua et al. (2017) stated that the period people migrate from the north to the south to participate in farming, often between May and June, coincides with food scarcity at their places of origin (North). On that basis, they set up how Climate change-related migration decisions are affected by perceived or actual better socioeconomic opportunities and conditions at the destinations, the degree of deprivation at the source, individual challenges, and the presence of human values, the already-existing informal institution's social networks at the destination.

According to Laube et al. (2012), since colonial rule (1904–1957), the Upper East Region of Northern Ghana has been the country's poorest region. The region experiences challenging climate conditions, a disproportionately large population density, and trends of underdevelopment. Similar findings in most parts of the Northern Region, the livelihoods of farming communities, which strongly rely on the weather and environment, are subject to severe uncertainties because of the changing climate (Asante et al., 2021).

GIS and Remote Sensing have been used to assess LULCC and other social factors. For example, a study by Mahbubur et al. (2018) used GIS and Remote sensing to explore Migration and LULCC in Dhaka City. The study also employed spatiotemporal growth of the city's irregular and informal settlements occupied by rural–urban migrants. Available data from the study indicated that migration into Dhaka city will continue to grow, which may worsen the situation. The result of the study showed that high rates of rural–urban migration influence the land cover, land use pattern and urban infrastructure, resulting in rapid growth and distribution of informal urban settlements occupied by a dense population.

Also, Bhawana et al. (2017) employed a Remote Sensing Technique combined with Nine focus group discussions with local community members to assess Internal Migration and LULCC in the middle mountains of Nepal. The findings indicated r that there is an increasing trend toward migration from upland areas to valley floors and that these population movements play a pivotal role in LULC change in the middle mountains of Nepal. According to the findings, motivation for migration was higher among young men, which increased the proportion of older people, women, and children in the villages. The findings of Bhawana et al. (2017) established that a vital role of migration is shaping LULCC in the middle mountains of Nepal. The Findings of Bhawana et al. (2017) also showed a consistent pattern with other literature to establish that migration plays a significant role in Land use and cover change.

A similar study by Kleemann et al. (2017) that assessed the drivers of LULCC in Upper East (Northern Ghana), utilizing GIS and Remote Sensing methods, established that the loss of natural vegetation had been the most visible evidence of land use and land cover change in the Upper East Region for the last ten years. Further Literature from Kleemann et al. (2017) describes LULCC as a growing threat to the adaptability of socio-ecological systems. Additionally, the results suggest that house development in the Upper East Region has led to cropland fragmentation. Culturally inherited agreements about customary land tenure due to inheritance rights make the task more difficult. Also, the study further termed migration as a cause and effect of LULCC and population pressure, which is connected to the cause of "labour shortage." Notwithstanding, it is a fact that northern Ghana is still growing despite significant outmigration. On that basis, Kleemann et al. (2017) concluded by asserting how, indirectly, population growth leads to changes in agricultural land use practices due to land pressure and, in the long round, causes people to migrate to uncultivated areas constantly.

2.5 Theoretical Frameworks for Analysing Climate Variability, LULCC and Migration

To adequately underpin this research, a range of pertinent theories from climate variability, LULCC, and migration fields are drawn upon. This section elucidates these relevant theories, with the selected theoretical framework poised to guide the research methodology and analysis (Varpio et al., 2020).

2.5.1 Climate Variability, LULCC and other Relevant Theories

Vulnerability Theory: Vulnerability Theory accentuates the interplay of economic, social, and environmental factors contributing to vulnerability in climate variability (Stojanov et al., 2016; Biswas, 2023). The theory underscores populations' exposure, sensitivity, and adaptive capacity to environmental changes and provides a framework for dissecting the interconnectedness of environmental, social, and economic factors in shaping vulnerability and migration patterns (Ford et al., 2018; Biswas, 2023). However, its intricacy and challenges in quantification may constrain its primary utilization (Comte et al., 2019). Additionally, it may not proffer prescriptive guidance on policy or adaptation strategies, as its emphasis lies in understanding vulnerabilities rather than prescribing specific interventions, necessitating the incorporation of other theories (Ford et al., 2018; Biswas, 2023).

Adaptation Theory: The Paris Agreement on global adaptation requires countries to report progress through periodic global stocktakes and aims to ensure adequate adaptation (Singhet al., 2022). Adaptation Theory directs its focus towards the responses of individuals and communities to shifting environmental conditions, including migration as an adaptive strategy (Jha et al., 2018). It can aid in assessing the efficacy of various adaptation measures in mitigating the impacts of climate change and land use changes, ultimately influencing migration patterns strategy (Jha et al., 2018). It can elucidate how communities in Northern Ghana adapt to climate variability and its repercussions on LULCC and migration. Nevertheless, Climate variability and change are complex dynamic processes with many interacting factors and should often be considered in the long term (Guilyardi et al., 2018). Adaptation strategies often rely on prediction modelling and mostly for the short-term. Still, uncertainties in climate projections can make it difficult to plan for specific impacts and responses and could be in the long-term (Guilyardi et al., 2018). It may not holistically address the root causes of North-South Migration and the broader socio-economic and political determinants shaping decision-making, thus warranting supplementation with other theories for a comprehensive analysis.

Land Change Science: Land Change Science is an interdisciplinary approach amalgamating geography, ecology, and social sciences to scrutinize land use changes (Messerli et al., 2013; Brown et al., 2013; Munroe et al., 2014). It furnishes valuable insights into the drivers and consequences of LULCC and facilitates the examination of the spatial and temporal dynamics of LULCC using remote sensing and GIS techniques (Messerli et al., 2013; Munroe et al., 2014). This framework aids in mapping and quantifying land cover changes, rendering valuable insights into their associations with climate variability and migration patterns (Messerli et al., 2013; Munroe et al., 2014). Given its applicability in evaluating LULCC patterns in Northern Ghana, it is highly relevant to the research. Nonetheless, it is imperative to acknowledge its limitations, including reliance on neoclassical economic models instead of a more flexible conceptualization of economic process (Munroe et al., 2014), data availability and the necessity for technical expertise in remote sensing and GIS. It may not sufficiently delve into land change's social and human dimensions, which is pivotal when scrutinizing migration decisions. It necessitates integration with other theories that elucidate human behaviour and adaptation.

Behavioural Decision Theory: Behavioral Decision Theory delves into the psychological factors that mould migration decisions, including risk perception and decision-making processes, concentrating on the psychological and cognitive processes underpinning decision-making (Kording, 2007). It can be invaluable in comprehending individual and household-level decision-making processes concerning migration in response to climate variability and LULCC. However, this theory should be complemented with broader socio-political and economic theories to account for the wider determinants influencing migration.

2.5.2 Migration Theories

Neoclassical Economic Theory: Neoclassical economics and labour migration theory were the earliest theoretical frameworks developed to elucidate labour migration (Porumbescu, 2018). According to this theory, migration results from geographical disparities between labour supply and demand. Although primarily focused on international migration, Neoclassical Economic Theory underscores the relevance of economic factors to internal migration. It aids in comprehending the economic drivers of global migration, which can provide insights into rural-urban and North-South Migration patterns within Ghana (Teye et al., 2019).

However, it may oversimplify human behaviour and overlook the environmental and non-economic factors driving migration in the context of climate change and LULCC.

Network Theory: Network theory examines the role of social networks in migration decisions, suggesting that migrants often follow paths established by family or community members who have previously migrated (Teye et al., 2019). While valuable, network theories, on their own, may not comprehensively address the complex interplay between climate variability, LULCC, and migration.

Lee's Push-Pull Theory: Everett Lee (1966) redefined Ravenstein's theories, shifting his focus towards the push factors within the internal. This theory posits that people migrate due to a combination of factors pushing them away from their current location (e.g., lack of job opportunities, environmental issues) and pulling them towards a new destination (e.g., better job prospects, improved quality of life) environment (Lee, 1966; OZCAN, 2022). He also emphasized the impact of obstacles like spatial distances and physical and political borders on migration. According to Lee, people respond differently to push-pull factors, depending on variations in age, gender, and social class, which influence them and their ability to overcome encountered obstacles (Porumbescu, 2018; OZCAN, 2022). In addition to these fundamental distinctions, specific factors, such as education, family ties, and other connections, can complicate an individual's decision to migrate (Porumbescu, 2018; OZCAN, 2022). Furthermore, certain elements related to the destination, such as familiarity with the host country's population, can shape migratory processes.

2.5.3 Justification for Push-Pull Theory

No single theory appears to be a perfect fit for a study which involves climate variability, LULCC, and migration; thus, for a comprehensive analysis of this complex interplay, it is prudent to consider adopting a theory that integrates elements from environmental degradation theory, economic theories, and sociocultural factors (Teye et al., 2019). Creating a comprehensive framework that considers the multifaceted aspects of migration within the context of climate change and LULCC is essential for this study.

The Push-Pull Theory acknowledges that many factors influence migration, both pushing individuals away from their current location and pulling them toward new destinations. The Push-Pull Theory takes a comprehensive view by considering both push factors (reasons people leave their current location) and pull factors (reasons people are attracted to a new destination). In the case of northern Ghana, climate variability and land use changes (push factors) can be intertwined with economic opportunities in the south (pull factors).

Zanabazar et al. (2021) used the push and pull theory to establish that the factors influencing the migration of Mongolians to the republic of South Korea were economically related, consisting of low or instable income, economic downturn and poverty. Kudeyarova (2023), as part of his work on Social and Demographic Prerequisites for Mass Migration in Italy and Spain in the XIX Century, adopted the push-pull theory for application. In addition, it was the anchor of Jiboku and Jiboku's (2022) study of Youth and Desperate Migration: Is there Social Protection in Nigeria? Igwedibia and Ezeonu (2023) noted that the push-pull migration theory captures the motives for which people move appropriately.

Adapted to environmental migration dynamics, the Push-Pull Theory is a robust framework for analysing climate variability, LULCC, and migration. It provides an understanding of the factors driving migration decisions and can inform policy interventions to enhance resilience and sustainable development in the face of environmental challenges. Consequently, an empirical approach centred on the Push-Pull theory is adopted to enable a blend of quantitative and qualitative methods to achieve this research's objectives effectively.

2.5.4 Application of Push-Pull Theory

To effectively apply the Push-Pull Theory in this research, a comprehensive analysis of climate variability in northern Ghana will be conducted to explore how these environmental stressors affect livelihoods and well-being, acting as push factors for migration. Also, factors such as economic opportunities in southern Ghana will be investigated to examine how these factors attract individuals and families from the north, acting as pull factors. Quantitative and qualitative data on climate variability, LULCC, Socio-economic conditions, and migration patterns in northern and southern Ghana will be collected and a comparative analysis, assessing the relative influence of push and pull factors on migration decisions assessed.

CHAPTER THREE

CLIMATE VARIABILITY IN NORTHERN GHANA

3.1 Introduction

Climate variability refers to the changes in average weather patterns in the short term, encompassing both slow-onset and fast-onset events (Abel et al., 2019; Cattaneo et al., 2019). Slow-onset events involve long-run climatic factors, such as levels, deviations, anomalies, or variability of precipitation and temperature. Meanwhile, fast-onset events are characterized by natural disasters, including temperature and precipitation extremes, floods, storms, and droughts. Climate variability has adverse effects on crop productivity, which has been empirically evident, posing a severe threat to food security and commodity prices (Amikuzuno and Donkor, 2012). Developing countries in Sub-Saharan Africa, particularly Ghana, are among the most susceptible to current and future climate variability threats. Despite agriculture being the central employment hub for most of the population, it is mainly rain-fed, making it highly dependent on rain for activities such as land preparation, crop planting, and harvesting (Amekudzi et al., 2015; Asante et al., 2021).

The annual mean temperature in Ghana increases, and monthly rainfall decreases per decade (De Pinto et al., 2012; Issahaku et al., 2016). The future projection over Africa shows an increasing mean annual temperature with variability in rainfall distributions (Almazroui et al., 2020). The IPCC (2014) model ensemble projects an 80mm monthly rainfall reduction during the June–August farming season, which will be exacerbated by high inter-annual rainfall variability characterized by a decrease in the number of rainy days. These changes have dire consequences on agrarian livelihoods and food security due to the pressure of population increases on scarce natural resources, multi-decadal rainfall variability, and desiccation (Wossen et al., 2014; Antwi-Agyei et al., 2014).

Most smallholder farmers in northern Ghana depend on livestock rearing and crop farming. Since agriculture in this region is mainly rain-fed, adverse climate variability changes could harm the people, especially their primary source of livelihood (Amikuzuno and Donkor, 2012). Therefore, analyzing rainfall, temperature patterns, and other climate variables is crucial for understanding the effects of climate variability on crop yields in this area (Hertel et al.,2010; Amikuzuno and Donkor, 2012).

One key challenge in addressing the impacts of climate variability on farmers in northern Ghana is bridging the gap between scientific assessments and local perceptions (IPCC, 2021; Oguntunde et al., 2013). While scientific reviews can provide valuable insights into long-term trends, local perceptions may be more immediate and relevant to farmers' needs. This challenge can be addressed by engaging the local communities and incorporating their perspectives and knowledge into decision-making processes related to climate adaptation and mitigation (Sulemana and James, 2014).

Dickinson et al. (2017) noted that understanding the pressing climate-related challenges in specific communities requires a local perspective. Therefore, combining scientific analysis of some climate variables with farmers' perceptions in the study area is essential for validation or otherwise. This study aimed to compare the trends of climate variability in northern Ghana as assessed scientifically (Objective) and perceived locally (subjective). The study conducts an annual time series analysis on precipitation, maximum temperature, and minimum temperature, as well as decadal periodic trends of the same, within selected year periods (1990-2000, 2000-2010, and 2010-2020) (Owusu et al., 2021) in three districts and compares results with the perception of farmers. Additionally, the study computes three monthly and six-monthly Standardised Precipitation Index (SPI) as well as the Standardised Precipitation Evapotranspiration Index (SPEI) for drought severity analysis in the study area (Acheampong et al., 2020).

3.2 Materials and Methods

This section presents an overview of the data sources used in the study and the methods employed to analyse the trends of climate variability. Additionally, it outlines the approach taken to investigate farmers' perceptions regarding these trends and their implications for the lives and livelihoods of the local population.

The study involved an analysis of climate variability across the entire northern region of Ghana, focusing on spatio-temporal trends. Further investigation was conducted at three specific stations: Tamale, Wa, and Bole (see section 1.5). Their selection was based on the significant number of north-south migrants from these districts observed in this study, as explained in Chapter 5, section 5.3.1. Moreover, these districts were chosen because they are farming communities where the local population heavily depends on agriculture, particularly subsistence farming (Adaween, 2017). Investigating changes in climate variables in these areas is vital because they can significantly impact the lives and livelihoods of the local population, potentially leading to adaptation strategies such as migration (Warner and Afifi, 2014; Fielmua et al., 2017). An outline of the processes used in this section is summarized in Figure 3.1.

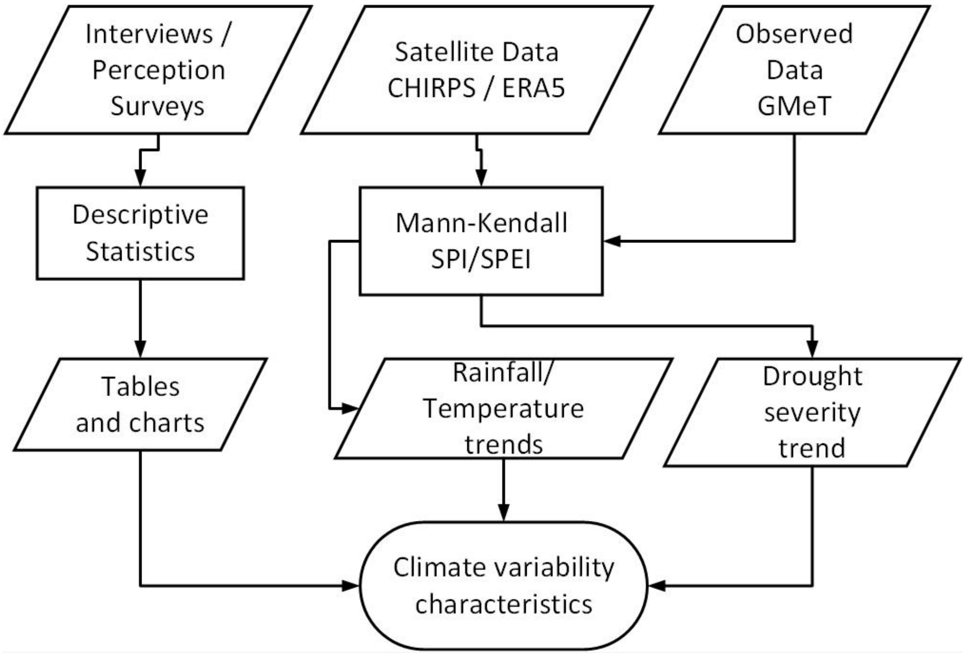

Figure 3.1 Process Diagram
Source: Authors' construction

Climate variability characteristics in northern Ghana were assessed using data (derived from satellite and GMet sources) gathered and scrutinized for trends utilizing suitable trend analysis methods (Mann-Kendall). Additionally, drought severity was evaluated using SPI and SPEI and Perception surveys were carried out and examined employing descriptive statistics (see Figure 3.1).

Table 3.1 Description of Climate Data Used for the Study

Data type	Spatial resolution	Temporal resolution	Source of data download
Maximum air temperature	0.1°(9km)	Daily converted to monthly and Annual	ERA5
Minimum air temperature	0.1°(9km)	Daily converted to monthly and Annual	ERA5
Precipitation data	0.05°(5.3km)	Daily converted to monthly and Annual	CHIRPS

Source: Authors' construction

The data used to analyse the impact of climate variability on changes in LULC and spatio-temporal trend analysis, satellite surface gridded precipitation data from CHIRPS and maximum and minimum temperatures from ERA5 were obtained. Daily precipitation data was obtained from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) and converted to monthly or annual values by summing them. Daily minimum and maximum temperature data were retrieved from the European Centre for Medium-Range Weather Forecasts Reanalysis version 5 (ECMWF/ERA5) and converted to monthly or annual values depending on the use. Table 3.1 presents the details of the climate data used.

Monthly synoptic ground observations of precipitation and maximum and minimum temperatures from three Ghana Meteorological Agency (GMet) stations in selected districts (Tamale, Bole, and Wa) were retrieved. The rationale for choosing these districts is explained in Section 5.3.1 of the study. In cases where the synoptic data sets had missing values, the missing data were estimated through linear interpolation. Specifically, the mean on the same day and month but at different years estimates the missing value on that particular date (World Meteorological Organization [WMO], 1983; Ismail et al., 2017).

3.2.1 Statistical Analysis of Data on Climate Variability

In this study, a comparison was made between the GMet and satellite datasets used for analysis. A paired t-test was used to assess their potential mean value differences (μ□□μ□) (Rahman et al., 2018). The test operates under a null hypothesis Ho :(μ□□μ□=0), which posits that no noteworthy difference exists between the mean values of the GMet and satellite datasets against an alternative hypothesis H1: (μ□□μ□≠0) asserting that a substantial distinction does indeed exist between the mean values of the GMet and satellite data (Rahman et al., 2018). A p-value of 0.05 or less will thus suggest a strong indication to reject the null hypothesis and vice versa (Andrade, 2019). The magnitude of the t-statistic is also important. Where μ□□μ□=0, the t-statistic is zero, and there is no difference between the paired groups. If the t-statistic is large (in absolute value), it suggests a substantial difference between the paired groups. Conversely, a small t-statistic suggests a smaller or less significant difference. A negative t-statistic indicates that, on average, the values in the first dataset are lower than those in the second and vice versa (Kim, 2015).

3.2.2 Analysing Temporal Trends and Determining Breakpoints

To identify trends in gridded (raster) data, both temporal and breakpoints in the trend (multi-temporal) were calculated using trend analysis. The trend values were computed for each grid cell while following the recommendations and guidelines of Forkel et al. (2013) for satellite time series, notably the NDVI time series.

Temporal Trend Analysis using Linear Regression

The temporal trends in each grid cell were calculated using linear regression.

The equation (1) used for the simple linear regression and slope estimation is by Salarijazi et al. (2012):

$$y=mx+b \tag{1}$$

Where:

- y represents the dependent variable (data values in the grid cell).
- x is the independent variable (time).
- m is the trend's slope, indicating the change rate.
- b is the intercept.

The slope m was determined using a non-parametric median-based slope estimator proposed by Sen (1968) and extended by Hirsch et al. (1982). The median of all possible pairwise slopes was computed, making it less sensitive to outliers using equation (2).

$$\beta = Median\left[\frac{(x_j - x_k)}{j-k}\right] \text{ for all } k < j \tag{2}$$

Where:

$1 < k < j < n$ and β is considered the median of all possible combinations of pairs for the whole data set.

Detection of Breakpoint (Change-Point Analysis)

The change-point analysis identified points where the trend significantly changed using the Pettitt test (Salarijazi et al., 2012). The idea is to split the time series into two segments at each time point and calculate the test statistic for detecting a change in distribution. The time point with the most significant test statistic indicates the likely location of a change point (Salarijazi et al., 2012). The Pettitt test statistic was calculated using the formula from Salarijazi et al. (2012).

$$U_t = \sum_{i=1}^{t} \sum_{j=t+1}^{n} \operatorname{sign}(y_i - y_j) \tag{3}$$

Where:

- U_t is the test statistic at time t.
- n is the total number of observations.
- y_i and y_j are the data values at times i and j, respectively.

The most significant U_t value time point indicates the most likely breakpoint.

In addition, the p-values of the trend in each segment were computed for significance analysis.

Mann-Kendall Normal Trend Test

The research employed the Mann-Kendall, a non-parametric trend test, to identify monotonic trends in the time series data of climate variability within the study area. The significance of long-term temporal trends in meteorological and hydrological data was assessed using the rank-based Mann-Kendall test, which is widely recommended by the World Meteorological Organization (Wang et al., 2013; Zarenistanak et al., 2014; Pirnia et al., 2019).

The results' reliability was ensured by evaluating serial correlation in the data series before conducting the Mann-Kendall test (Praveen et al., 2020). A trend-free pre-whitening (TFPW) technique, proposed by Hamed (2009), was applied to eliminate serial correlation. This technique involves simultaneously estimating the slope and lag-1 serial correlation coefficient. The lag-1 serial correlation coefficient was also corrected for bias before pre-whitening, following a modified Mann-Kendall approach that corrects the bias (Larbi et al., 2018). The trend analysis in this study was based on equations 4 to 11 proposed by Pirnia et al. (2019) and Praveen et al. (2020).

$$z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, \ if\ s > 0 \\ 0 \quad if\ s = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, if\ s < 0 \end{cases} \tag{4}$$

Where:

$$S = \sum_{i=1}^{n-1} \sum_{j=1+1}^{n} sgn(x_j - x_i) \tag{5}$$

$$\begin{cases} +1 & \theta > 0 \\ 0 & \theta = 0 \\ -1 & \theta < 0 \end{cases}$$

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_t t(t-1)(2t+5)}{18} \quad (5)$$

And x_j and x_i are the sequential values of the data

n the length of the data set,

m shows the amount of the series in which there is at least one repeated data value,

t is the extent of any given tie,

Var(s) = Variance of S

S = Mann-Kendall S statistic

Σ is the summation of overall ties.

A positive Z value shows an increasing trend in the time series, while a negative Z value shows a decreasing trend.

For Z > 1.96 and Z> 2.575, there is a significant trend at the 0.05 and 0.01 confidence levels, respectively (Pirnia et al., 2019).

Mann-Kendall (Mk) trend was calculated from Equation 6

$$S = \sum_{i=1}^{n} \sum_{j=1+1}^{n} sgn(K_j - K_i) \quad (6)$$

Where:

$$\mathrm{sgn(kj - Ki)} = \begin{matrix} 1 & if(K_j - K_i) > 0 \\ 0 & if(K_j - K_i) = 0 \\ -1 & if(K_j - K_i) < 0 \end{matrix} \quad (7)$$

K_i is a time series, with i=1, 2, 3, ………. n, and S must be like the normal distribution with a mean of 0.

The discrepancy of statistics S is computed using Equation 8

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{y=1}^{x} \mathrm{ty}(\mathrm{ty}-1)(2\mathrm{ty}+5)}{18} \quad (8)$$

Source: Praveen et al., (2020)

Mann-Kendall Z statistic (Z_{MK}) value is computed using Equation 9 to determine whether the time series information demonstrates a significant trend.

$$Z_{MK} = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, & if\ s > 0 \\ 0 & if\ s = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, & if\ s < 0 \end{cases} \quad (9)$$

Source: Praveen et al., (2020)

Value or layers obtained from the trend analysis include:

1. Z_{MK} = Mann-Kendall Z statistic

2. Sen's slope = Sen's slope

3. S = Mann-Kendall S statistic

4. Var(s) = Variance of S

5. P-value = Mann-Kendall p-value

The modified Mann-Kendall model is represented by Equations 10 and 11.

$$y_t = \rho y_{t-1} + \alpha + \beta_t + \varepsilon_t \quad (10)$$

Source: Serinaldi and Kilsby (2016)

where y_t and y_{t-1} are observed records at time t and t - 1, ρ is the lag-1 autocorrelation coefficient, α is the intercept of the linear trend, β_t is the trend slope, and ε_t indicates uncorrelated residuals. The corresponding pre-whitened time series is written as follows:

$$y_t - \rho y_{t-1} = \alpha + \beta_t + \varepsilon_t \tag{11}$$

Source: Serinaldi and Kilsby (2016)

3.2.3 Analysing Drought and Wet Spells Using SPI and SPEI Indices

In this research, two, the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI), were employed to analyse drought and wet spells. The SPI, introduced by McKee et al. (1993), provides a simplified categorization of drought and wet periods. The SPI was calculated by accumulating monthly precipitation data over i-monthly periods, typically 1 to 12 months. The accumulated precipitation data were divided into 12 annual time series, with each month represented by a separate time series. Each of these time series was fitted with a univariate parametric distribution. Subsequently, the probabilities of the fitted data were converted into quantiles of a standard normal distribution (Laimighofer and Laaha, 2022).

On the other hand, the SPEI was computed by considering the monthly difference between precipitation and potential evapotranspiration (PET). This difference reflects a simple climatic water balance initially proposed by Thornthwaite in 1948. PET quantification plays a crucial role in SPEI calculation, with the Penman-Monteith (PM) method being suggested for modelling. The PM method requires various variables, such as humidity, water vapour pressure, surface temperature, soil incoming radiation, and ground atmosphere latent and sensible heat fluxes (Allen et al., 1998; Vicente-Serrano et al., 2010; Laimighofer and Laaha, 2022). However, the specific method used to calculate PET is not critical, as the objective is to obtain a relative temporal estimation for the drought index (Droogers and Allen, 2002; Vicente-Serrano et al., 2010). In this study, the data available consisted of precipitation and monthly mean temperatures; thus, the Thornthwaite method (1948), a more straightforward approach, was employed to calculate PET (Vicente-Serrano et al., 2010; Laimighofer and Laaha, 2022).

The SPEI, in particular, offers advantages over previous multiscalar drought indicators like the SPI, as it incorporates the influence of evaporative demand in its calculation. This feature makes the SPEI well-suited for examining the effects of global warming on drought occurrence (Vicente-Serrano et al., 2010). Furthermore, the SPEI is considered an improved drought index, specifically applicable for analysing drought severity in agricultural regimes. It quantifies the impact of reference evapotranspiration on the extent of drought and can be computed relatively easily. The utilization of the SPEI methodology was recommended by Begueria et al. (2014) and further validated as an effective approach by Sha and Manekar (2015).

3.2.4 Survey on Farmers Perception of Climate Variability

For information on local perceptions, the study conducted perception surveys on farmers to ascertain their perception of the magnitude and trends of various climate variables. The study aimed to gather information on the farmer's perception and knowledge of climate variability, including changes in onset and cessation, rainfall volumes, temperature fluctuations, and drought severity. The farmers were asked explicitly about the onset and cessation of rainfall, the amount of rain, the intensity of temperature fluctuations, and the drought frequency. In addition, information on the impact of climate variability on crop yield and adaptation strategies for mitigation was collected. Krejcie and Morgan's (1970) formula was used to compute the sample size from the total number of agricultural households (21,352) from the 2010 Population and Housing Census (PHC) in the three selected districts. A total of 410 farmers were interviewed, resulting in a diverse and comprehensive dataset.

3.3 Results and Discussions

This section compares GMet and Satellite data, scientifically determined trends in precipitation, maximum and minimum temperatures, and farmers' perceptions in northern Ghana.

3.3.1 Analysis of Correlation and Paired t-Test between GMet and Satellite Data

The computation of correlation and t-test statistics for GMet and satellite (gridded) data of the same year are displayed in Table 3.2. The remaining tables showing t-tests for all years are found in Appendix 1A.

Table 3.2 T-Test Comparison of Precipitation Data between 1990 GMET and CHIRPS Data for Wa

T-test: Paired Two Sample for Means		
	1990_Gmet	1990_Satellite
Mean	75.525	73.34104
Variance	7161.837	5422.85
Observations	12	12
Pearson Correlation	0.956746	
Hypothesized Mean Difference	0	
Df	11	
t Stat	0.294519	
P(T<=t) one-tail	0.386922	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.773845	
t Critical two-tail	2.200985	

Source: Authors' computation

Results of the Pearson correlation and p-values obtained from the paired t-test between the GMet and Satellite data are shown in Tables 3.3, 3.4 and 3.5, and their implication (on precipitation, maximum and minimum temperatures) for all three stations are explained in this section.

Precipitation

Table 3.3 Correlation Analysis and Paired t-Test Results for Precipitation in GMet and Satellite Datasets for Tamale, Wa, and Bole

Precipitation									
	Tamale			Wa			Bole		
Year	**COR**	**t Stat**	**P(T<=t)**	**COR**	**t Stat**	**P(T<=t)**	**COR**	**t Stat**	**P(T<=t)**
1990	0.845	0.913	0.381	0.957	0.295	0.774	0.495	1.068	0.309
2000	0.883	-1.063	0.311	0.932	1.181	0.262	0.842	1.400	0.189
2010	0.843	-0.273	0.790	0.852	-0.226	0.826	0.845	0.856	0.410
2020	0.913	-0.188	0.854	0.905	0.839	0.419	0.833	0.221	0.829

Source: Authors' computation

In Table 3.3, the correlation coefficients for precipitation in the three stations across all the years generally display a positive trend. However, it is important to note that all other values exhibit strong positive correlations except for Bole in 1990, which had a correlation coefficient lower than 0.5. For instance, the correlation for Wa was 0.957 in 1990, 0.932 in 2000, 0.852 in 2010, and 0.905 in 2020, all of which are closely approaching 1. These high positive correlations indicate a consistent variation between the GMet and Satellite datasets over the years.

The t-statistics, in general, were relatively low (less than 1), except for the year 1990 in Bole and the year 2000 across all stations. These low statistics indicate minimal disparities between GMet and satellite datasets across all stations except for the mentioned years. Additionally, some t-statistics were negative (Tamale

2000, 2010, and 2020), suggesting that the magnitude of the GMet data was lower than that of the satellite data. The p-values for all the stations are greater than the conventional significance level of 0.05. Thus, there is no statistical indication to reject the null hypothesis, which posits no significant difference between the datasets (Rahman et al., 2018; Andrade, 2019). Therefore, there is no noteworthy difference between the means of the GMet and Satellite datasets for precipitation at all the stations for all the years under consideration. The results also suggested that any observed difference between the GMet and satellite data is due to random variation or chance.

Maximum Temperature

Table 3.4 Statistical Analysis of Pearson Correlation (COR) and P-Values for Maximum Temperature in GMet and Satellite Datasets: Paired t-Test Results for Tamale, Wa, and Bole

Maximum Temperature									
	Tamale			Wa			Bole		
Year	COR	t Stat	P(T<=t)	COR	t Stat	P(T<=t)	COR	t Stat	P(T<=t)
1990	0.991	11.182	0.000	0.981	10.298	0.000	0.962	5.008	0.000
2000	0.957	3.285	0.007	0.979	5.678	0.000	0.973	3.487	0.005
2010	0.984	3.190	0.009	0.982	3.667	0.004	0.992	3.351	0.006
2020	0.942	2.790	0.018	0.988	2.790	0.018	0.950	-0.38	0.711

Source: Authors' computation

Table 3.4 presents notably high correlation coefficients for maximum temperature across all the examined stations. For instance, in Wa, these correlations ranged from 0.979 to 0.988 over the years under scrutiny, indicating a robust and positive relationship.

The t-statistics reveal substantial differences between the GMet and satellite datasets across all years and stations, with the only exception being the year 2020 in Bole, where such differences did not reach statistical significance.

Furthermore, all p-values were less than 0.05, except for the 2020 value in Bole. These p-values provide a strong statistical indication to reject the null hypothesis, suggesting no significant difference between the maximum temperatures in the two datasets. Thus, significant distinctions exist between the GMet and satellite datasets in representing maximum temperature, except for the year 2020 in Bole.

Minimum Temperature

Table 3.5 Statistical Analysis of Pearson Correlation (COR) and P-Values for Minimum Temperature in GMet and Satellite Datasets: Paired t-Test Results for Tamale, Wa, and Bole

Minimum Temperature									
	Tamale			**Wa**			**Bole**		
Year	**COR**	**t Stat**	**P(T<=t)**	**COR**	**t Stat**	**P(T<=t)**	**COR**	**t Stat**	**P(T<=t)**
1990	0.845	-3.339	0.007	0.995	-4.422	0.001	0.832	-5.560	0.000
2000	0.930	-2.779	0.018	0.923	0.434	0.673	0.914	-8.457	0.000
2010	0.980	-5.987	0.000	0.972	0.420	0.682	0.968	-2.913	0.014
2020	0.981	-3.231	0.008	0.962	-4.802	0.000	0.813	-2.172	0.053

Source: Authors' computation

Table 3.5 displays correlation coefficients demonstrating a strong positive relationship across all the stations under examination. However, the t-statistics yielded negative values, all exceeding 1, except for the values in Wa for 2000 and 2010, which were positive and less than 1. Moreover, the p-values highlight significant disparities between GMet and satellite datasets for all the years, indicating noticeable distinctions in their representations, except for the datasets of 2000 and 2010 in Wa.

The analysis reveals consistent positive correlations between GMet and Satellite datasets for precipitation and maximum and minimum temperatures across all years and locations. However, the p-values obtained for maximum and minimum temperatures indicate variations in their representations. In contrast, for precipitation, the p-values show consistent patterns for all stations and do not indicate significant differences in representation. It is essential to consider these discrepancies when utilizing climate datasets for research and decision-making in these regions.

Both datasets were considered for some selected paralleled climate variability analysis for comparison. A comparison of the monthly trends in decadal periods for precipitation and temperature using the GMet and satellite datasets revealed similar patterns in both datasets, albeit with varying magnitudes in temperature. Notably, the CHIRPS precipitation data exhibited recorded precipitation in January and December, while the GMet data displayed limited to no precipitation records for these months, except for a few outliers. This disparity in precipitation records between the two datasets suggests potential discrepancies in data collection or measurement methodologies. For the annual precipitation and temperature trends, both satellite and GMet data showed a slight increase in precipitation in Wa, while that for Tamale and Bole decreased. Both datasets had a rise in both minimum and maximum temperatures across the districts in the last decade (2010 to 2020) (Asante et al., 2021).

3.3.2 Assessing Climate Variability Trends in Northern Ghana Using Sen's Slope and P-Values

Sen's slope is a non-parametric method to estimate trends or rates of change within datasets, especially when dealing with data that may not exhibit a linear pattern (Khattak et al., 2011). The climate variability trends were evaluated by calculating the Sen's slope and p-values for precipitation, maximum, and minimum temperatures from the Spatio-temporal satellite and GMet data. This approach aimed to discern any trends in rainfall and temperature patterns and whether these trends were statistically significant. The estimated Sen's slop and P-values for the spatio-temporal trend of Precipitation, maximum and minimum temperatures are shown pictorially in Figures 3.2, 3.3, and 3.4. In addition, Sen's slope and corresponding p-values, calculated for the three selected synoptic stations in northern Ghana (Tamale, Wa, and Bole) using GMet data, are displayed in Table 3.6.

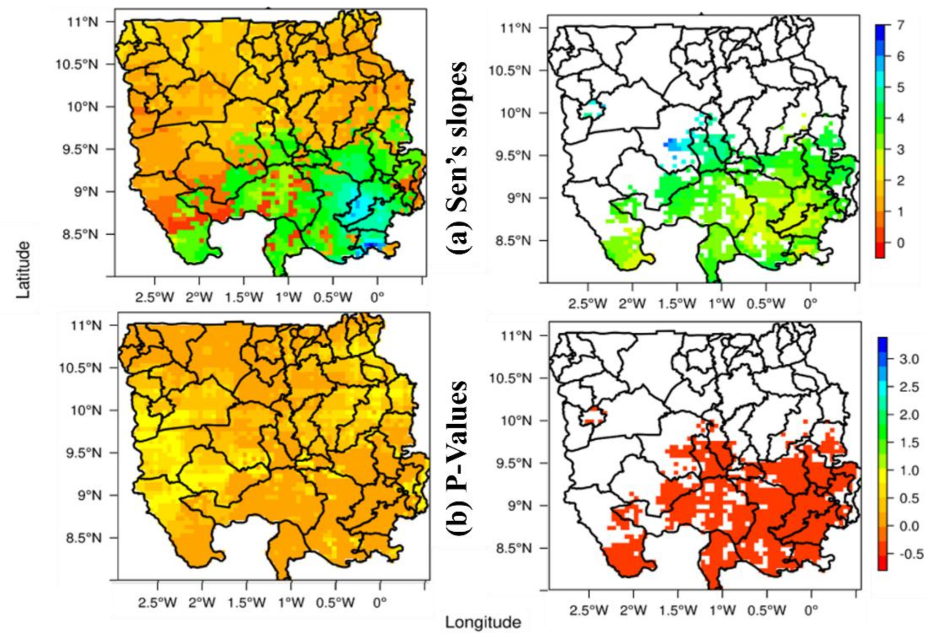

Figure 3.2 Sen's Slopes (a) and P-values (b) for Precipitation and Breakpoints derived from CHIRPS in Northern Ghana.
Source: Authors' computation

From figure 3.2, an analysis of precipitation trends revealed relatively low Sen's slope values, especially for the central and upper parts of northern Ghana, indicating a weak change in trend. The p-values were mostly higher than 0.05 in these parts of northern Ghana, indicating that precipitation trends are not statistically significant for these areas. Conversely, the southern part, particularly the south-eastern part, and some parts of the Savannah region showed high Sen's slopes indicative of strong changes in trend. The p-values in these parts were mostly higher than 0.05, indicating that the precipitation changes over time are not significant (see Figure 3.2). Notably, the breakpoints occurred in northern Ghana's southern and south-eastern parts. They showed a high Sen's slope and low p-values, indicating a significant difference in the data (see Figure 3.2).

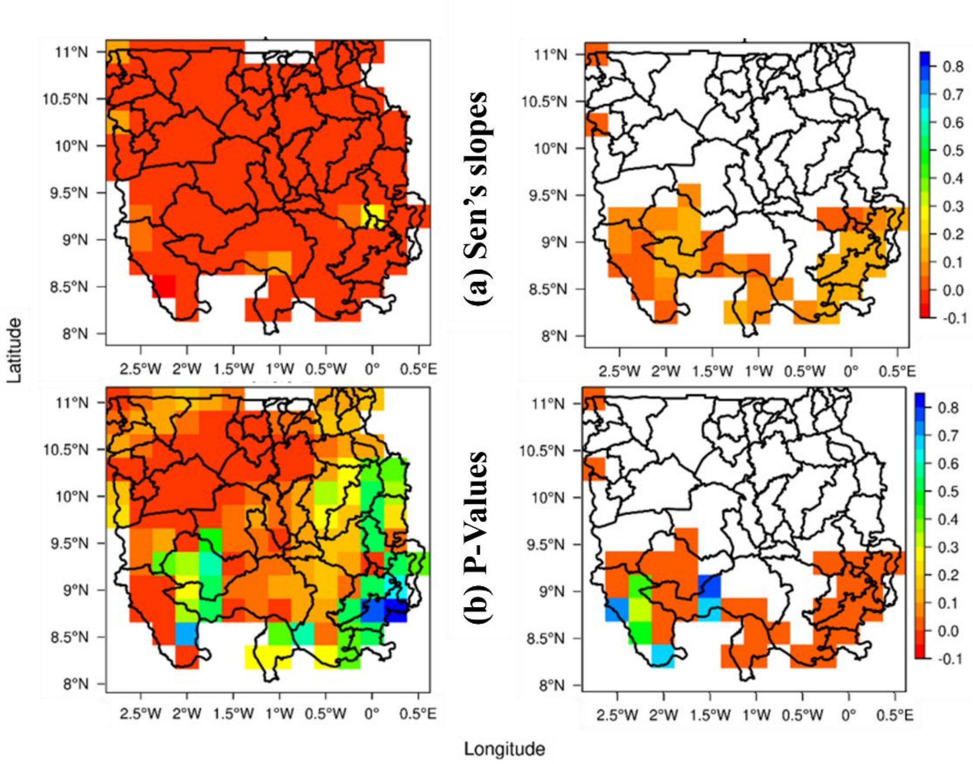

Figure 3.3 Sen's Slopes (a) and P-values (b) for Maximum temperature and Breakpoints Calculated from ERA5 in Northern Ghana
Source: Authors' computation

From Figure 3.3, a significant portion of northern Ghana exhibited a low Sen's Slope, with high p-values, particularly in the south-eastern parts and parts of the Savannah Region. It implies that the maximum temperature changes over time are low and not significant for these parts of northern Ghana. The breakpoints (Figure 3.3) displayed comparatively higher Sen's slopes and lower p-values, respectively.

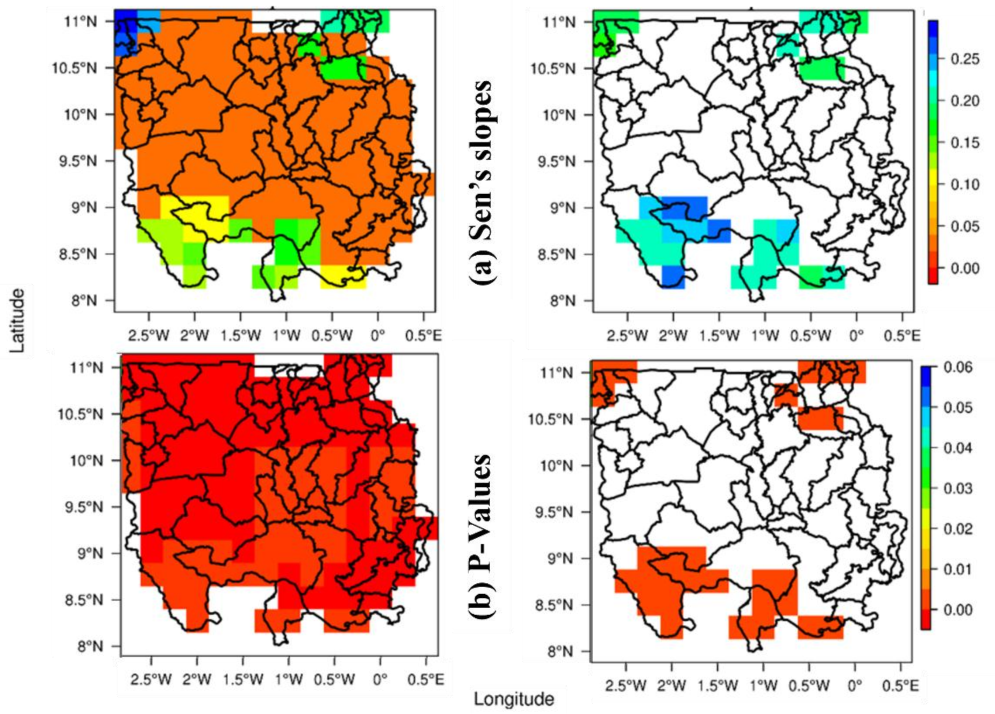

Figure 3.4 Sen's Slopes (a) and P-values (b) for Minimum temperature and Breakpoints calculated from ERA5 in Northern Ghana

Source: Authors' computation

The Sen's slopes computed for minimum temperature were lower except for the southern parts, some parts of the Savannah region and the extreme corners of the Upper Regions. At the same time, the p-values were low across the regions (See Figure 3.4). Showing that even though the trends in minimum temperature are small, they are significant. The change points exhibited comparatively higher Sen's Slopes and lower p-values. It means the breakpoint changes are more significant in northern Ghana.

Table 3.6 Computed Sen's Slopes and P-Values for Tamale, Wa, and Bole Using the Mann-Kendall Method

	Tamale		Wa		Bole	
Variable	**Sen's slope**	**P-value**	**Sen's slope**	**P-value**	**Sen's slope**	**P-value**
Precipitation	0.000	0.67	0.000	0.884	-0.015	0.456
Max. Temperature.	0.017	0.287	0.024	0.118	0.028	0.124
Min. Temperature.	0.036	0.001	0.022	0.026	0.062	0.000

Source: Authors' computation

From Table 3.6, the calculated Sen's slopes and p-values of precipitation in Tamale and Wa indicated a minimal trend that is not statistically significant, as observed in the central and upper part of the temporal map of northern Ghana (see Figure 3.2). Consistent with some portions of the Savannah region, Bole exhibited a negative Sen's slope and high p-values greater than 0.05, suggesting a decrease, albeit not significant, trend in precipitation.

For maximum temperature, despite their low values, the Sen's slopes were positive at all three stations, indicating an increasing trend in maximum temperature over the study period confirmed by the temporal map (see Figure 3.3). Nevertheless, the p-values showed that the trend is not significant.

However, the Sen's slopes for minimum temperature displayed were comparatively higher than those for maximum temperature. They were indicating a comparatively higher increase in temperature trend. Also, the p-values were lower, showing that the trend in minimum temperature is statistically significant, as observed in the temporal map (see Figure 3.4).

3.3.3 Analysing Climate Trends and Breakpoints in Northern Ghana (1990-2020)

The time series plots from Figures 3.5 to 3.22 and Appendix 1B were utilized to analyse the annual trend of climate variables (precipitation, maximum and minimum temperatures) between 1990 and 2020. These plots revealed fluctuations in the climate variables over the studied period, indicating both increases and decreases. Moreover, breakpoints played a crucial role in detecting abrupt changes or discontinuities in the data, which could signify shifts in the underlying climate processes. For instance, changes in temperature or precipitation patterns might be linked to alterations in land use.

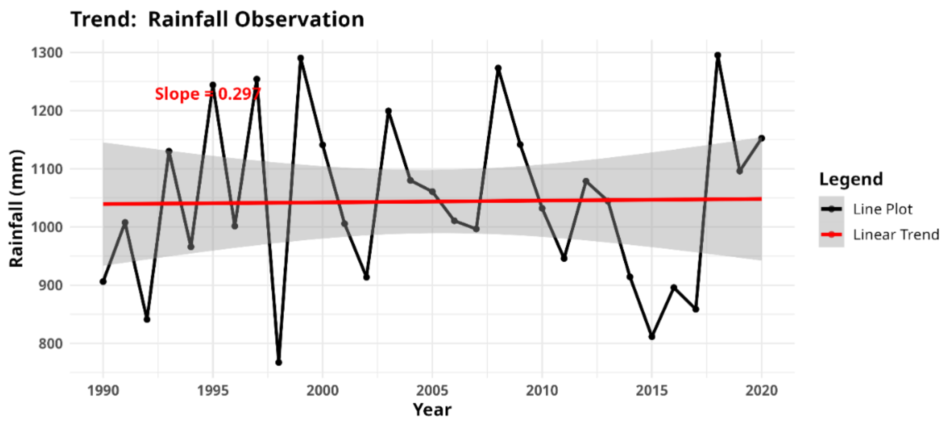

Figure 3.5 Time Series Plot showing the Trend line for Precipitation for Wa Municipal
Source: Authors' construction

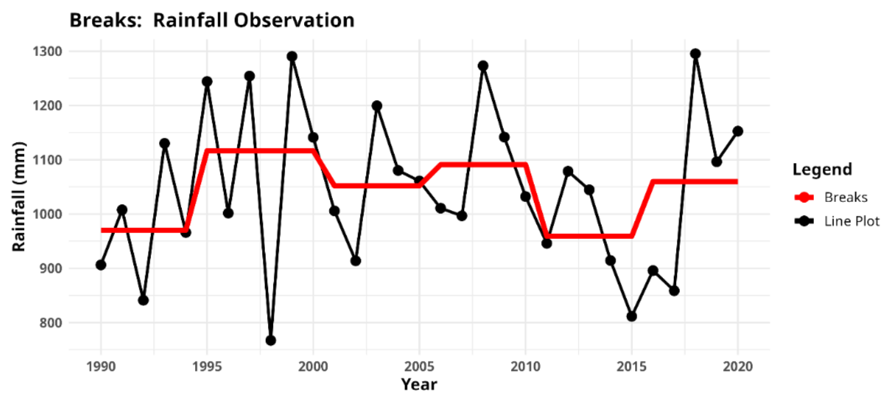

Figure 3.6 Time Series Plot showing Breakpoints for Precipitation for Wa Municipal
Source: Authors' construction

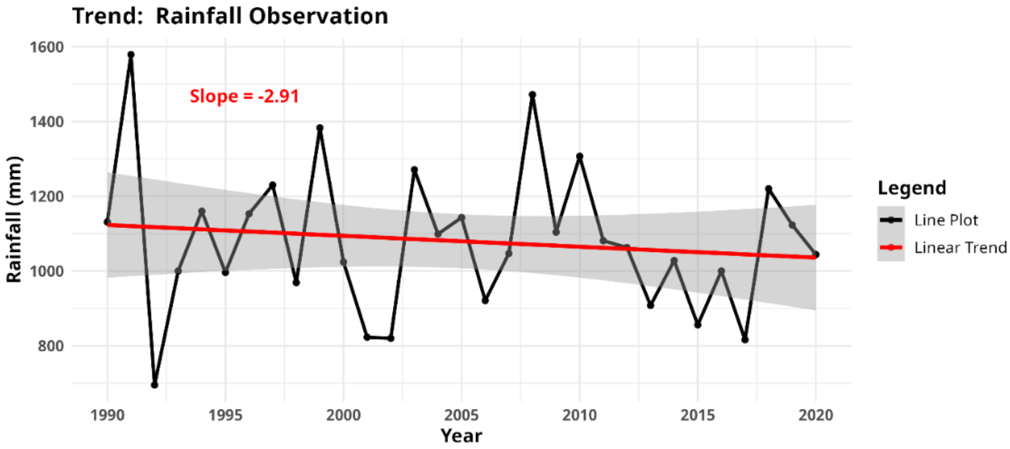

Figure 3.7 Time Series Plot showing the Trend line for Precipitation for Tamale Metropolis
Source: Authors' construction

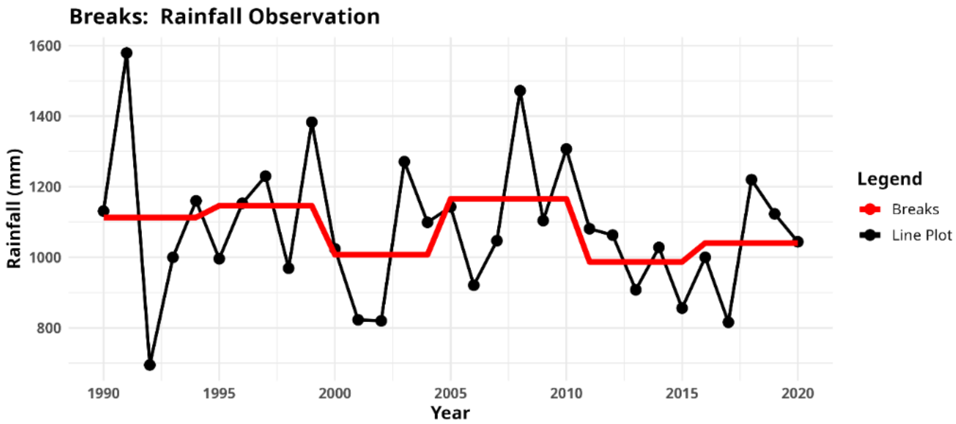

Figure 3.8 Time Series Plot showing Breakpoints for Precipitation for Tamale Metropolis
Source: Authors' construction

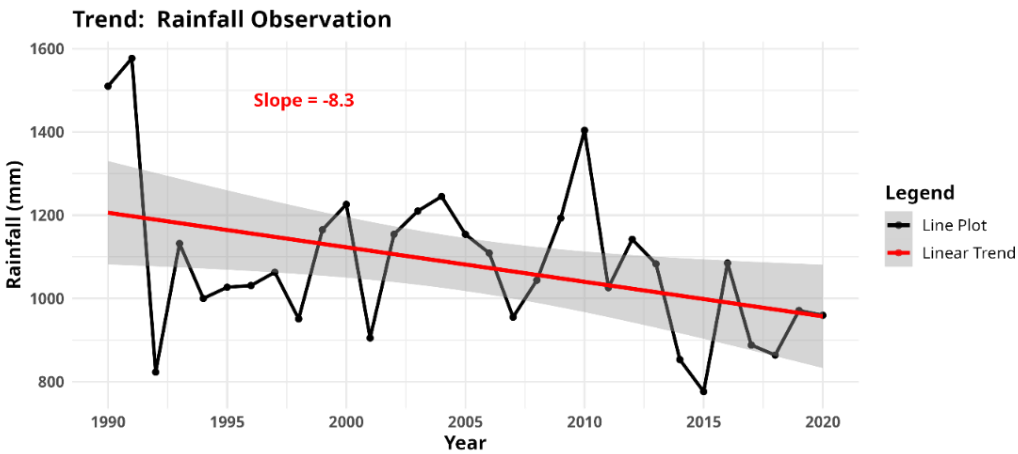

Figure 3.9 Time Series Plot showing the Trend line for Precipitation for Bole District
Source: Authors' construction

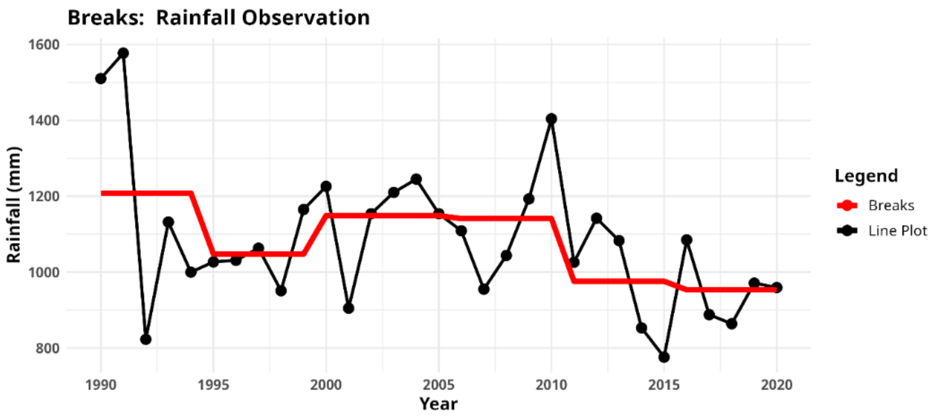

Figure 3.10 Time Series Plot showing Breakpoints for Precipitation for Bole District
Source: Authors' construction

The findings from the time series plots revealed interesting patterns in precipitation trends among the three districts: Wa, Tamale, and Bole district. Precipitation remained stable in Wa, slightly increasing over the years (see Figure 3.5). On the other hand, Tamale experienced a slight decrease in rainfall (see Figure 3.7). The most striking observation was Bole, where a steep decline of approximately 250mm (from 1200mm to 950mm) occurred from 1990 to 2020 (see Figure 3.9 and Appendix 1B). These decreases in precipitation align with studies by Amikuzuno and Donkor (2012), who related similar trends. The slight increase in precipitation in Wa confirms earlier studies showing slight increases in annual precipitation in some parts of the West African region (Anyamba et al., 2014). However, more than a slight increase in annual rainfall may be required to dispel the region's negative impacts of drought and water scarcity, as Baryeh (2019) found.

Further analysis of break points in precipitation revealed significant shifts between 1994 and 1995, resulting in an increase in rainfall for Wa, a slight increase for Tamale, and a decrease for Bole. Another break occurred between 1999 and 2000, leading to reduced precipitation for Wa and Tamale, while Bole experienced an increase. Additionally, a significant break was observed between 2010 and 2011, causing a decrease in rainfall across all three districts. These findings shed light on the complex nature of precipitation variability in the study area, with each district exhibiting unique trends and responses to climatic shifts. The observed changes in precipitation patterns could have profound implications for local communities, agriculture, and water resource management.

Time series plots for minimum and maximum temperatures

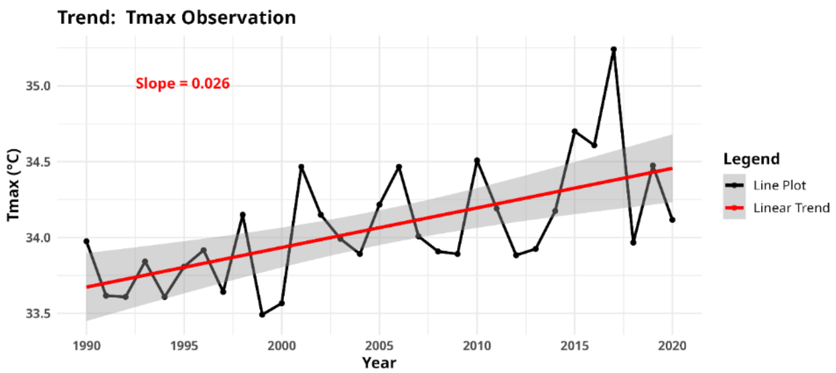

Figure 3.11 Time Series Plot showing the Trend line for Maximum temperature for Wa Municipal
Source: Authors' construction

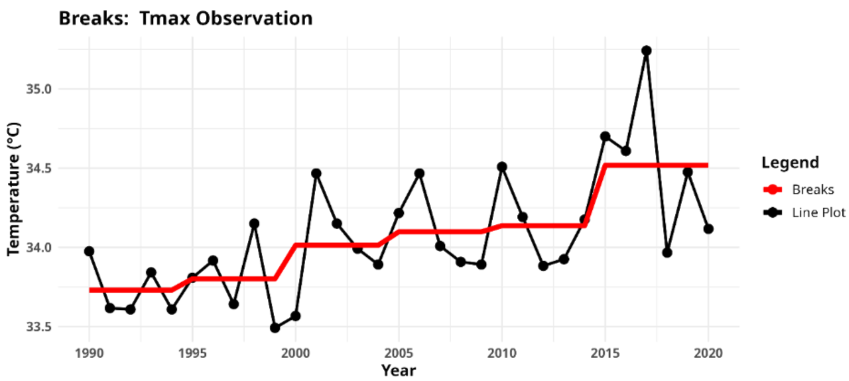

Figure 3.12 Time Series Plot showing breakpoints for Maximum temperature for Wa Municipal
Source: Authors' construction

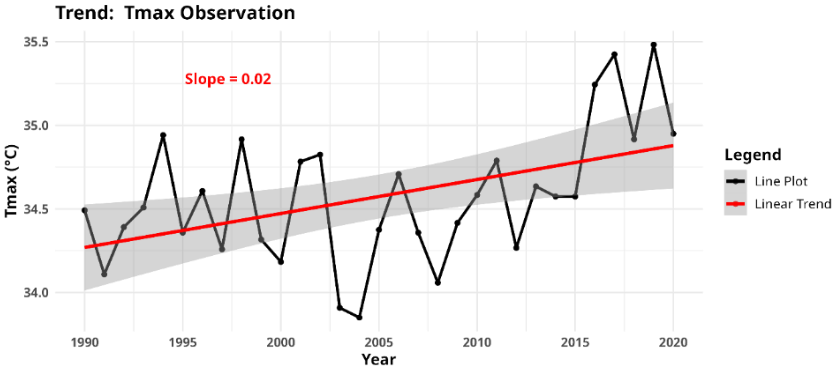

Figure 3.13 Time Series Plot showing the Trend line for Maximum temperature for Tamale Metropolis
Source: Authors' construction

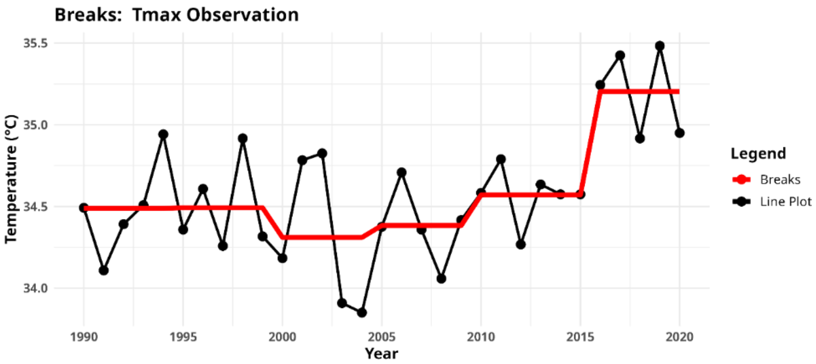

Figure 3.14 Time Series Plot showing Breakpoints for Maximum temperature for Tamale Metropolis
Source: Authors' construction

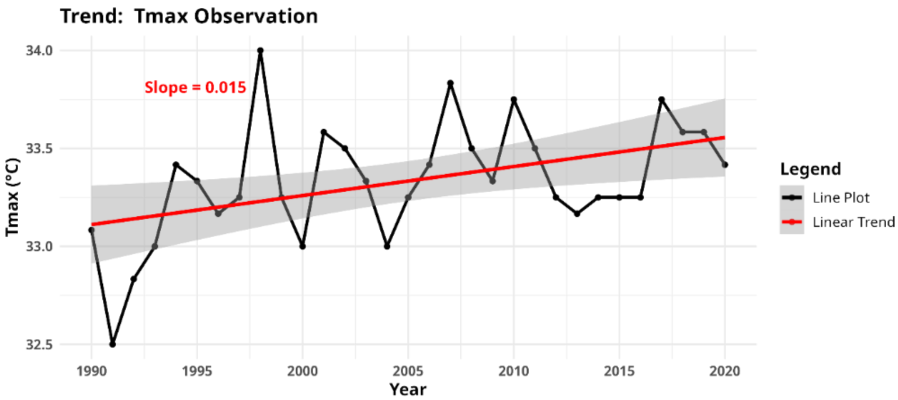

Figure 3.15 Time Series Plot showing the Trend line for Maximum temperature for Bole District
Source: Authors' construction

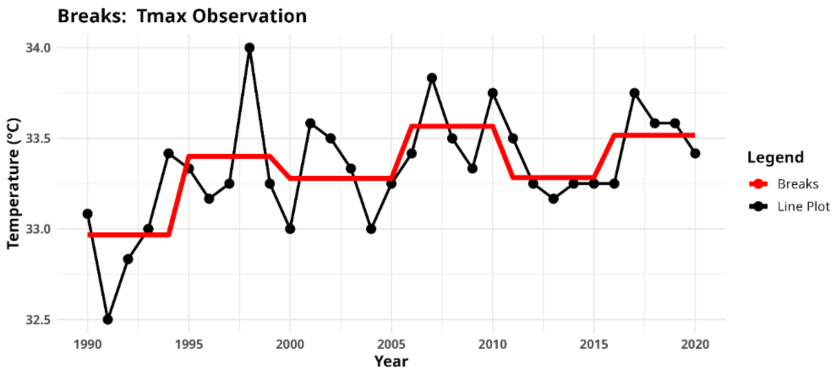

Figure 3.16 Time Series Plot showing Breakpoints for Maximum temperature for Bole District

Source: Authors' construction

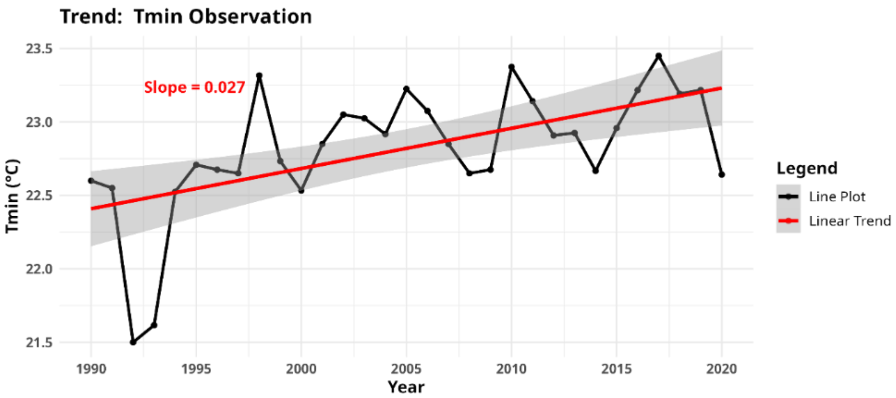

Figure 3.17 Time Series plot showing the Trend line for Minimum temperature for Wa Municipal

Source: Authors' construction

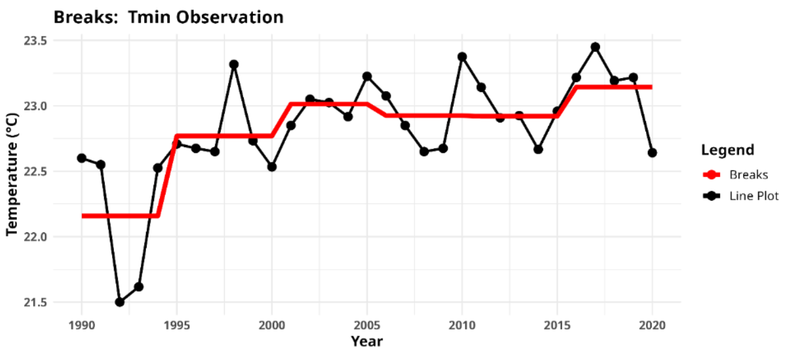

Figure 3.18 Time Series Plot showing Breakpoints for Minimum temperature for Wa Municipal

Source: Authors' construction

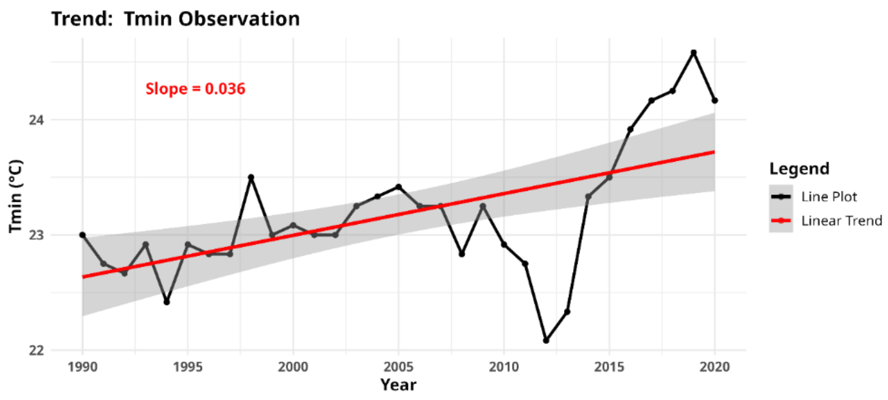

Figure 3.19 Time Series Plot showing the Trend line for Minimum temperature for Tamale Metropolis
Source: Authors' construction

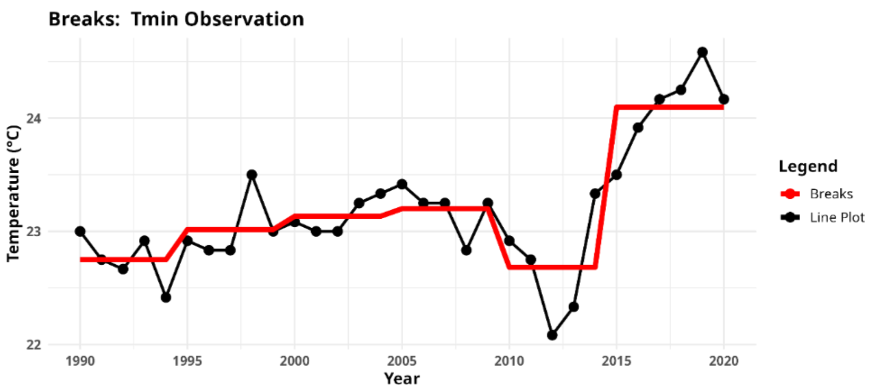

Figure 3.20 Time Series Plot showing Breakpoints for Minimum temperature for Tamale Metropolis
Source: Authors' construction

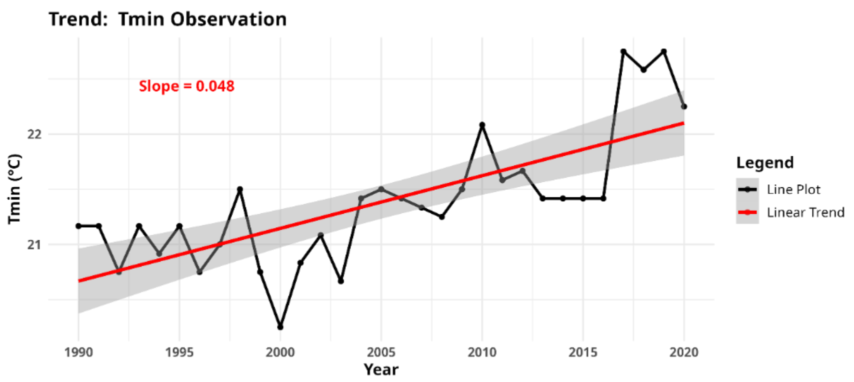

Figure 3.21 Time Series Plot showing the Trend line for Minimum temperature for Bole District
Source: Authors' construction

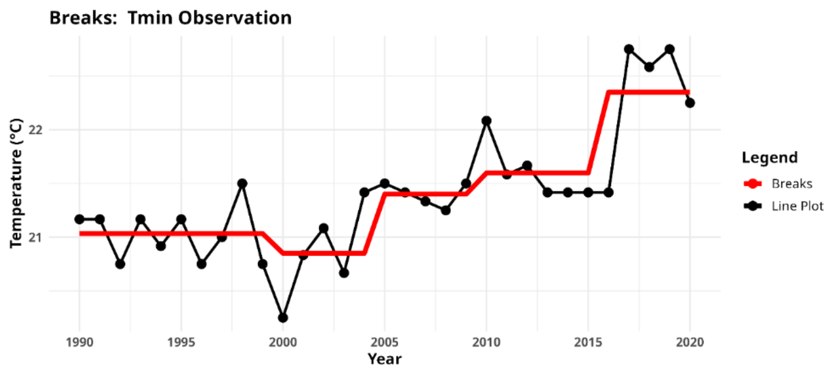

Figure 3.22. Time Series Plot showing Breakpoints for Minimum temperature for Bole District
Source: Authors' construction

Based on the findings, it is evident that both maximum and minimum temperatures demonstrated a consistent upward trend throughout the study period, aligning with the research conducted by Malhi et al. (2021) and Mohanty (2021). These temperature increases have a detrimental effect on plant growth, as pointed out by Amikuzuno and Donkoh (2012), and this impact on plant growth was also confirmed by Asante et al. (2021). This factor has the potential to contribute to migration within the study area.

Examining breakpoints in maximum temperatures (refer to Figures 3.12. 3.14, and 3.16) revealed minor variations in Wa and Tamale but significant variations in Bole. Of interest, the last breakpoint observed in 2015 led to a rise in maximum temperature across all three districts. These breakpoint analyses demonstrate distinct patterns in maximum temperature changes over time and highlight the significance of the 2015 event, which impacted all districts in the study area. In 2014, the minimum temperature breakpoints exhibited significant changes within the Tamale metropolis, followed by the Bole district and Wa municipal.

3.3.4 Decadal Trends in Precipitation and Temperature Variations in Northern Ghana

The analysis unveiled noteworthy fluctuations in the monthly precipitation and the maximum and minimum temperatures per decade (see figures 3.23 to 3.31 and Appendix 1C). The study investigated the monthly precipitation variations in maximum and minimum temperatures over decadal periods. The results revealed significant changes in monthly variations per decade, indicating a decrease in precipitation and an increase in temperatures during the 2010 to 2020 period. These decadal fluctuations in rainfall and temperature imply that climate change may impact weather patterns in northern Ghana.

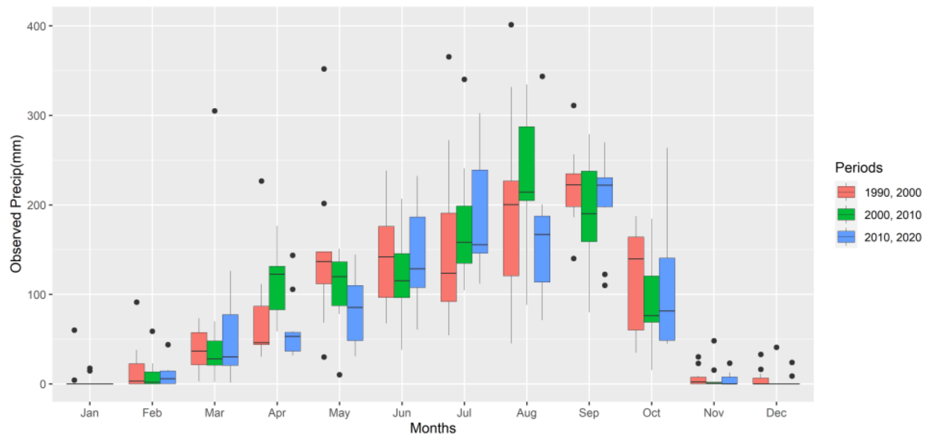

Figure 3.23 Periodic Precipitation Variation for Tamale Metropolis
Source: Authors' construction

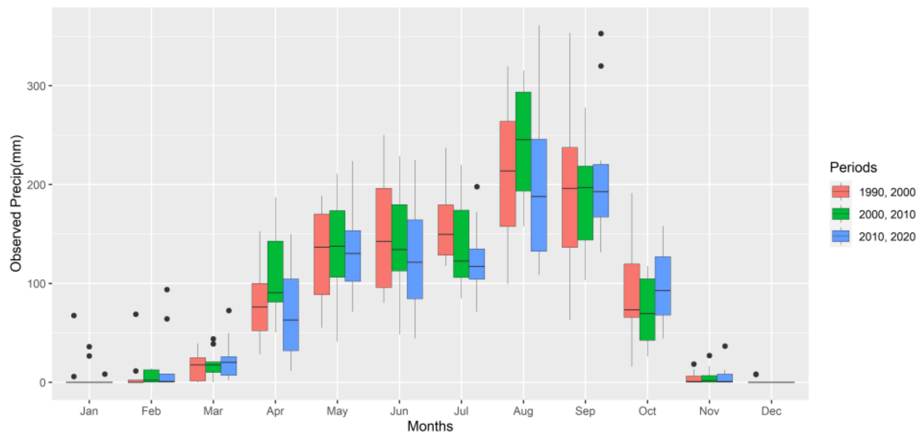

Figure 3.24 Periodic Precipitation Variation for Wa municipal
Source: Authors' construction

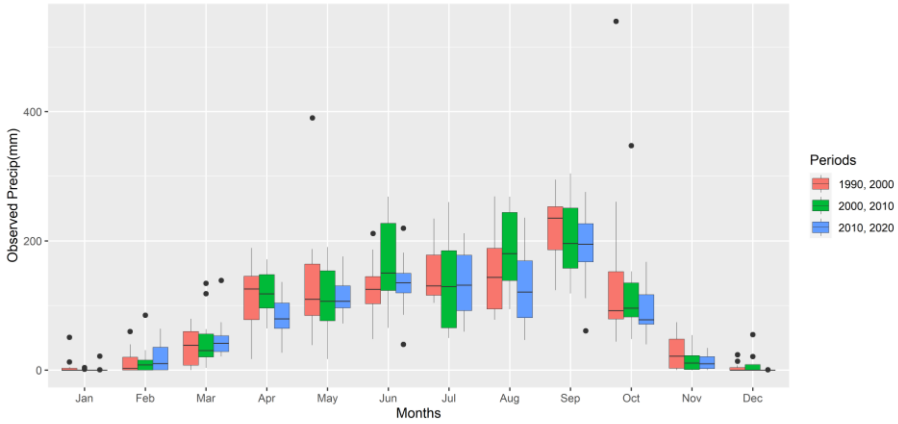

Figure 3.25 Periodic Precipitation Variation for Bole District
Source: Authors' construction

The analysis of monthly decadal precipitation patterns in Tamale, Wa, and Bole (refer to Figures 3.23 to 3.25 and Appendix 1C) reveals a constant monthly trend. Consistent with a similar study by Nyadzi (2016), the findings show low rainfall from January to March, followed by increased rainfall from April to September and a cessation of rain from October to November.

Overall, the results indicate monthly variations in rainfall during specific periods. The monthly precipitation pattern between 2010 and 2020 consistently declines, with a significant reduction observed in April and August (prime months of the farming season in northern Ghana) across all three districts. This phenomenon is problematic as these months' rains play a crucial role in the success of crop cultivation and water resource management in northern Ghana. April is the traditional month for land preparation and the initiation of crop cultivation (Amikuzuno and Donkor, 2012).

An analysis of the monthly variation in maximum and minimum temperatures over decadal periods is illustrated in Figures 3.26 to 3.31 and Appendix 1C.

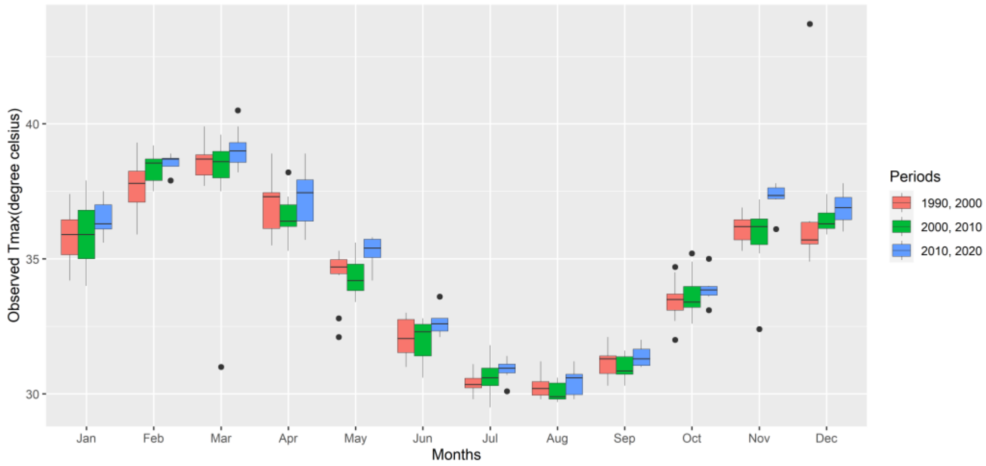

Figure 3.26 Periodic Maximum temperature Variation for Tamale Metropolis
Source: Authors' construction

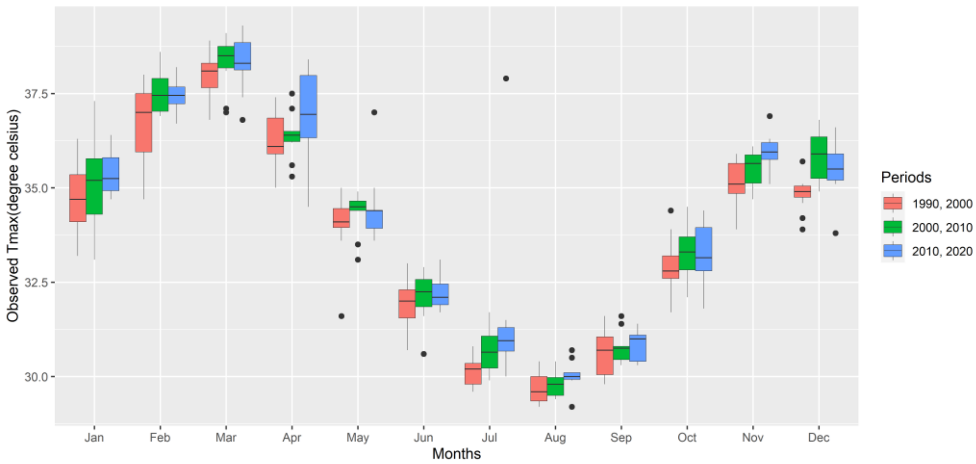

Figure 3.27 Periodic Maximum temperature Variation for Wa municipal
Source: Authors' construction

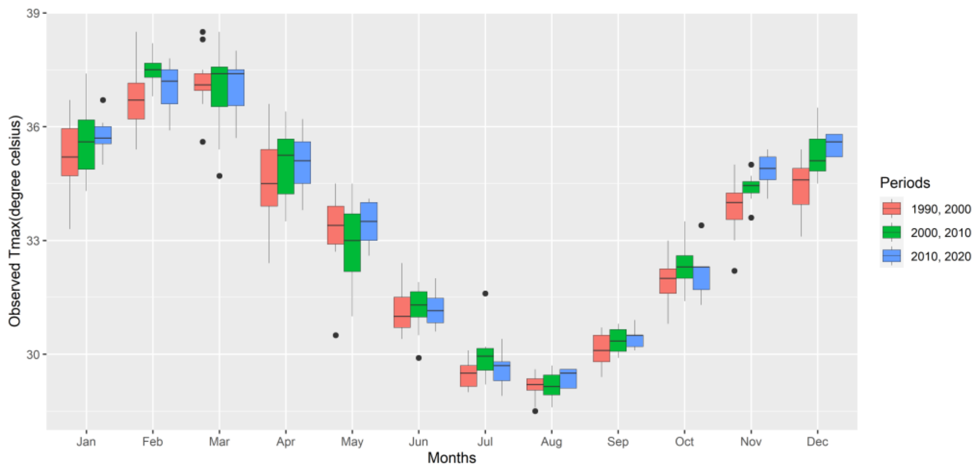

Figure 3.28 Periodic Maximum temperature Variation for Bole District
Source: Authors' construction

In general, temperatures increase from February to reaching their peak in March, then decline to their lowest point in August. Subsequently, temperatures rise again until November, decreasing from December to January. This pattern is consistent across all weather stations, as Nyadzi (2016) reported. Furthermore, research conducted by Oguntunde et al. (2020) confirms the existence of a seasonal temperature pattern in West Africa, characterized by a peak in March and a minimum in August. Notably, there is an overall increase in maximum temperature levels between 2010 and 2020, with high temperatures recorded in November across all stations.

Temperature variations are crucial for agriculture, as they can significantly impact crop growth and development (Hatfield and Prueger 2015).

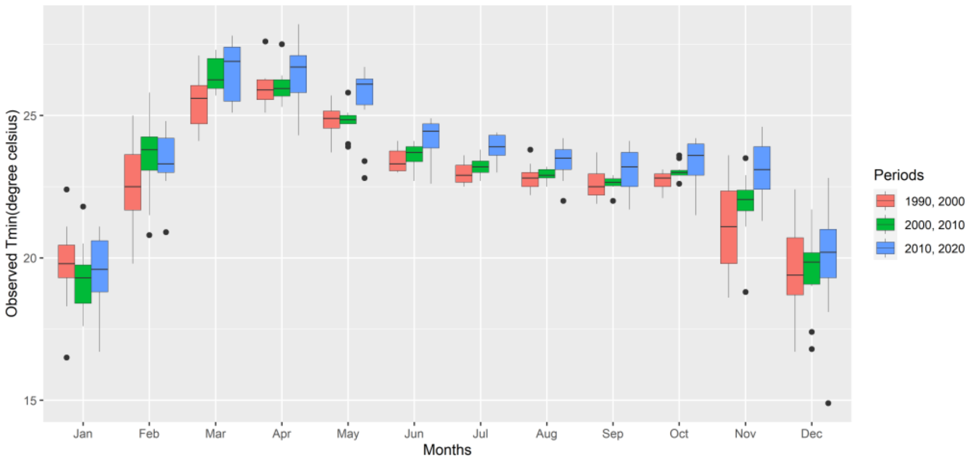

Figure 3.29 Periodic Minimum temperature Variation for Tamale Metropolis
Source: Authors' construction

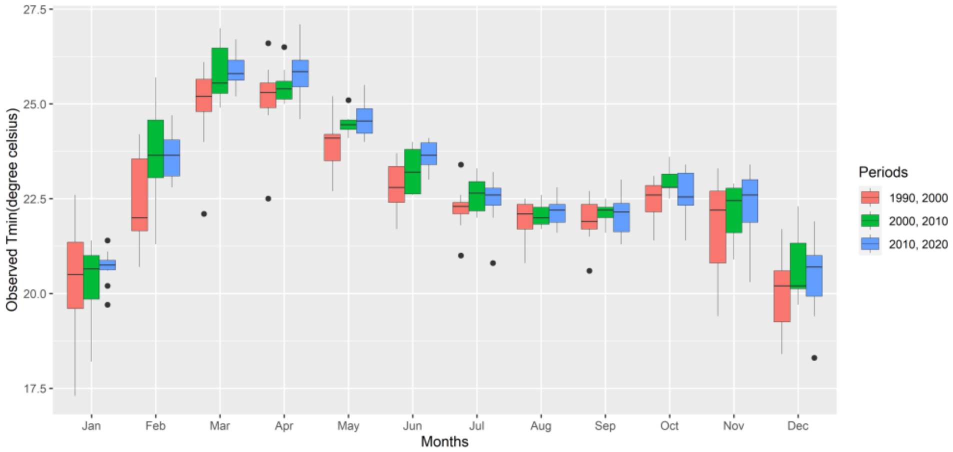

Figure 3.30 Periodic Minimum temperature Variation for Wa municipal
Source: Authors' construction

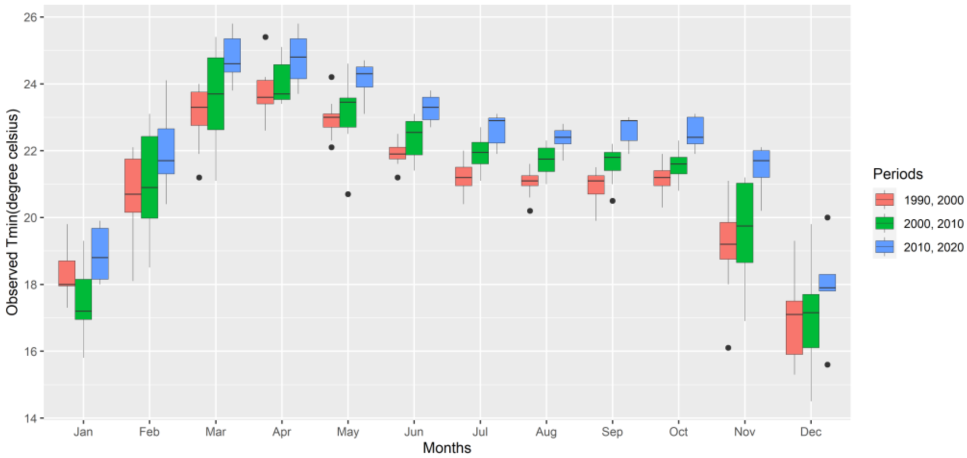

Figure 3.31 Periodic Minimum temperature Variation for Bole District
Source: Authors' construction

The analysis of minimum temperature findings, as depicted in Figures 3.29 to 3.31, reveals a monthly variation pattern that closely mirrors the observed pattern in the maximum temperature data. Specifically, minimum temperatures exhibit a similar trend across all months and stations, with the highest minimum temperatures occurring in March. These temperatures rise from February to April and decrease from May to August, reaching their lowest points in December and January. These findings align with previous studies showing similar monthly variations in minimum temperatures in various regions of Africa and northern Ghana (Nyadzi, 2016; Issahaku et al., 2016).

Furthermore, a comparative analysis of periodic trends indicates an increasing trend in minimum temperatures between 2010 and 2020. Minimum temperature trends can impact crop yield (Hatfield et al., 2011) and influence migration in the study area.

3.3.5 Assessing Drought Severity Trends in Northern Ghana (1990-2020)

This section presents the trends of drought severity over the period of 1990 to 2020. Each figure contains the results of SPI/SPEI calculated from synoptic GMet data.

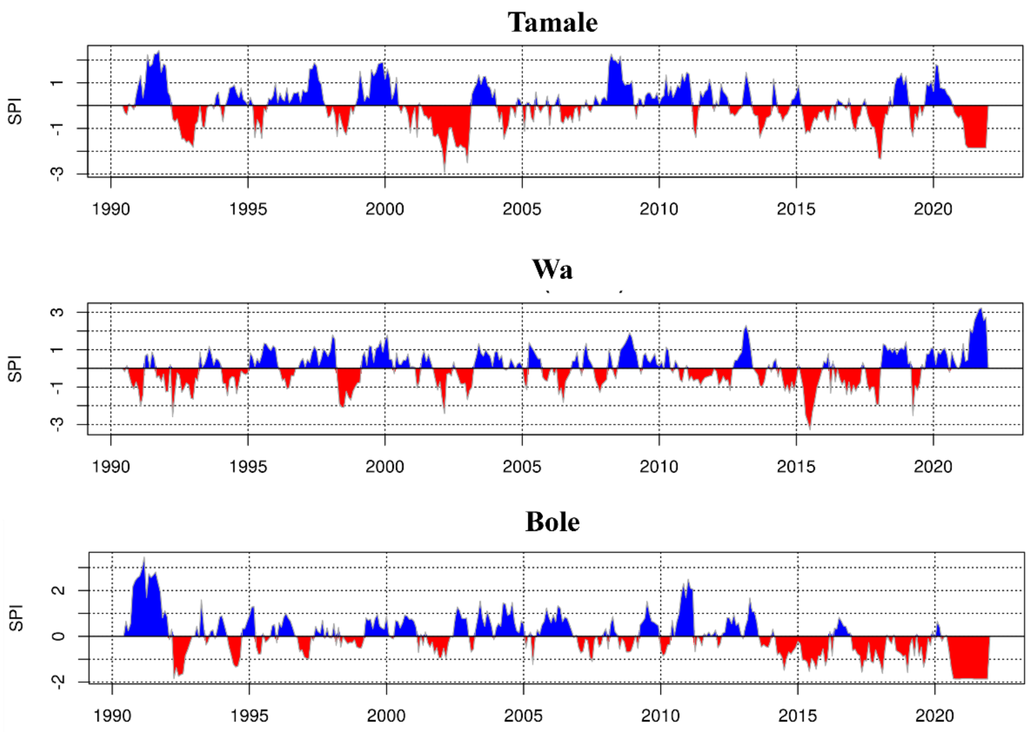

Figure 3.32 Six Months calculated SPI
Source: Authors' construction

The findings from the study (refer to Figures 3.32 and 3.33 and Appendix 1D) demonstrated a continuous trend of increasing drought severity, especially in the last decade. The drought severity from the SPI result in Bole is comparatively higher in the last decade.

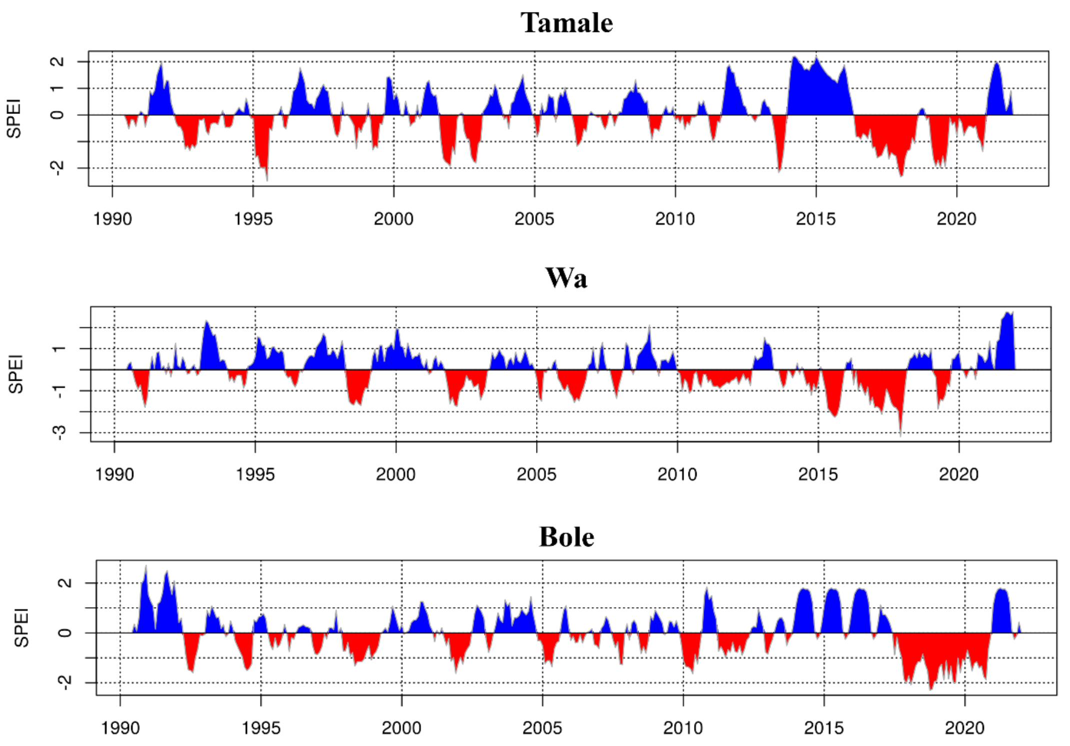

Figure 3.33 Six Months calculated SPEI
Source: Authors' construction

The computed SPI and SPEI values pointed to a rise in drought severity, consistent with the findings of Malhi et al. (2021). Furthermore, the six-month SPEI exhibited even more pronounced drought severity than the other timeframes. This phenomenon is a cause for concern as the six-month scale highlights agricultural droughts. The outcomes imply that agriculture in the study area could face substantial challenges if this trend persists. In addition, it is worth noting that the frequency of drought severity was higher in Tamale and Bole when compared to Wa.

3.3.6 Farmers' Perceptions of Climate Variability and Implications for Adaptation in Northern Ghana

This section looks at an analysis of the survey results of farmers and insights of critical informants and focus group discussions (see sections 5.2 and 5.3) on climate variability in the study area. Farmers demonstrated a varying understanding of the onset and cessation of rainfall, with diverse interpretations across the different districts. Additionally, perceptions regarding rainfall amounts differed, indicating a notable variability in farmers' observation and estimation skills. Similarly, farmers reported varying intensities of temperature fluctuations and frequencies of drought, reflecting the localized nature of climate experiences.

Perception of Changes in Onset and Cessation of Rainfall: The survey results indicated a strong consensus among the respondents, with 94% acknowledging a change in the onset and cessation of rainfall. Farmers in the study area perceived a shift in the timing of rains, specifically from April to May (sometimes June) for the onset and November to October (sometimes August) for the cessation, thus shortening the rainfall duration. The same assertion was held by most farmers during the focus group discussions and was collaborated by Key informants from MOFA and NADMO. These perceptions highlight farmers' awareness of changing weather patterns and suggest that they have observed significant shifts in the timing of rainfall events.

Perception of rainfall, temperature, and drought changes: The findings from the perception survey also revealed a strong consensus among the respondents regarding the rainfall pattern, temperature changes and drought severity (see

Figure 3.34). A significant majority, 94% of the participants, expressed the belief that there has been a decrease in the rainfall and an increase in the temperature patterns during the period considered. These patterns align with a similar farmer observation in a study by Nyadzi (2016) in the study area. Similarly, 93% of the respondents believed that drought severity increased within the same period. These results indicate a widespread recognition among the survey participants of the observed changes in rainfall and temperature and the subsequent intensification of drought conditions as is observed globally. These perceptions were confirmed by all GMA officials interviewed in the study area.

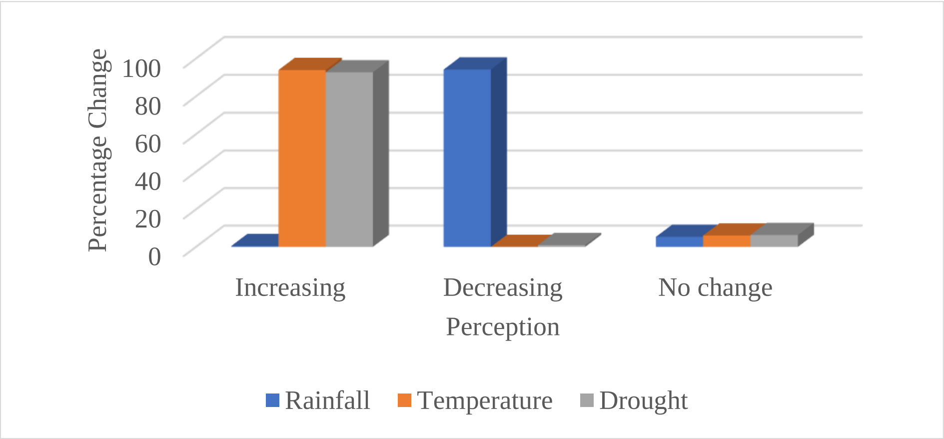

Figure 3.34 Perception of Farmers on the Magnitude of Rainfall, Temperature, and Drought
Source: Authors' construction

The findings highlighted diverse understandings and observations of climate variables, including the onset and cessation of rainfall, rainfall amounts, temperature fluctuations, and drought frequency. Farmers' words of these changes can significantly affect crop growth, water availability, and agricultural productivity.

Perception of the effect of climate variability on crop yield: From Figure 3.35, the findings revealed that many farmers attribute crop yield to the variability of rainfall, consistent with Amikuzuno (2012), who suggests that Variability in the level and distribution of rainfall is the most important determinant of crop yields in smallholder farmers who lack yield improving technology as is often reported.

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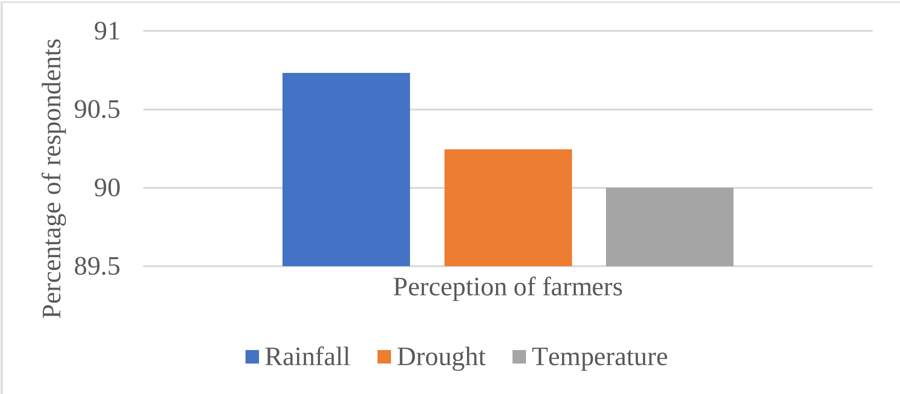


Figure 3.35 Perception of Farmers on the effect of Rainfall, Temperature, and Drought on Crop Yield
Source: Authors' construction

During the focus group discussions, some farmers lamented that the rain's uncertainty makes them unwilling to cultivate their farms. 2 of the 3 MOFA officials interviewed (specifically in Tamale and Bole) alluded to these claims and added that the unpredictability of the rains adversely impacts crop yield. They explained that the main challenge in the study area is the need for consistent rain.

Adaptation strategies used by farmers: Most farmers in the study area said they adapt to climate uncertainty by adopting and implementing improved farming systems. The second most common approach is relying on more enormous farmlands to compensate for low crop yields (See Figure 3.36).

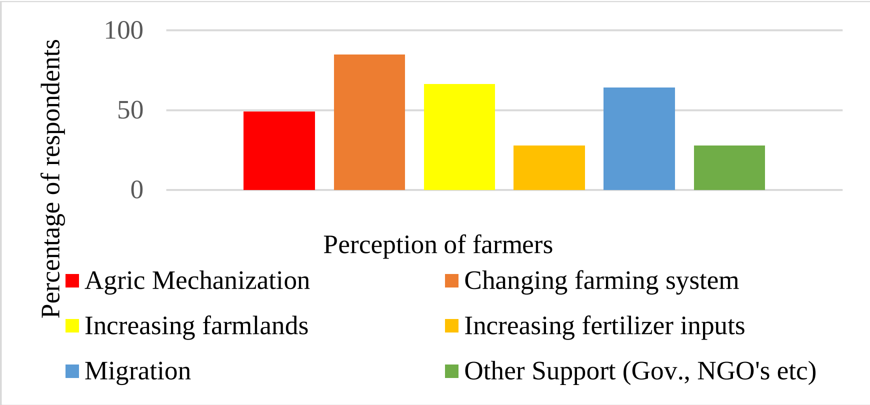


Figure 3.36 Perception of Farmers on their Adaptation strategies to Overcome the Effect of Climate Variability
Source: Authors' construction

According to Figure 3.36, most farmers proposed modifying their farming techniques in response to the adverse effects of changing climate variability. This finding is consistent with Fosu-Mensah's (2012) study. It is further supported by the study of Nyadzi (2016), both of which indicate that most adaptation strategies used by farmers in the study area revolved around altering their farming practices. Also, many farmers consider migrating from their communities as an adaptation strategy if climate variability worsens (Van der Geest, 2011; Adaawen and Owusu, 2013; Warner and Afifi, 2014). Despite receiving some support, some farmers expressed that this support was woefully in adequate. During the focus group discussions, a farmer said that "*the support we receive from government cannot take care of the initial preparation of the farmlands (a 57-year-old man from Bilpela in the Tamale Metropolis)*". "*We are unable to buy fertilizers for our farms since it has become very expensive (39-year-old lady farmer from Yonk Dapkemyili in Tamale Metropolis)",* another farmer added. Some key informants (mainly Agric extension officers) interviewed across the districts confirmed these challenges by farmers.

Inconsistencies with Scientific Analysis: It is important to note that based on scientific study, the changes in precipitation and temperature are not considered highly significant. These discrepancies raise questions about the factors influencing farmers' perceptions and the accuracy of their observations. The farmers' perceptions may be affected by the consistent decrease in the magnitude of rainfall as observed for April and August and the increase in temperature in November over the past decade (see section 3.3.4). The disparity between farmers' perceptions and scientific analysis may be attributed to the limitations of individual observations, localized weather patterns, or the influence of short-term weather fluctuations.

Implications for Adaptation Strategies: Understanding farmers' perceptions of climate variability is vital for developing effective adaptation strategies. Although there may be inconsistencies between farmers' perceptions and scientific analysis, their observations should not be disregarded. Farmers' knowledge, accumulated through years of experience and close interaction with the environment, can provide valuable insights into localized climate trends and adaptive practices.

Integrating Local Knowledge and Scientific Analysis: Integrating farmers' perceptions with scientific analysis can enhance the accuracy and relevance of adaptation strategies. Collaboration between farmers, scientists, and policymakers can help bridge local knowledge with scientific findings. By incorporating farmers' observations and experiences into climate models and projections, researchers can improve the accuracy of future climate predictions at the local level. Furthermore, effective communication and information exchange can enhance farmers' understanding of scientific analysis and empower them to make informed decisions regarding agricultural practices and adaptation measures.

The climate variability survey findings indicate a strong consensus among farmers regarding changes in the onset and cessation of rainfall, temperature patterns and drought severity. While these perceptions may not always align with scientific analysis, they reflect the farmers' observations and experiences. Recognizing and integrating farmers' knowledge into climate-related decision-making processes can contribute to developing context-specific adaptation strategies that are more effective in addressing the challenges posed by climate variability. By combining scientific expertise with local knowledge, policymakers and researchers can promote climate resilience and sustainability in agriculture.

3.4 Conclusions

Generally, the annual trends consistently demonstrate decreased rainfall, increased maximum and minimum temperatures, and increased drought severity frequency in the study area.

Periodic evaluations over decades reveal distinct patterns of decreasing rainfall in April and August, coupled with temperature increases, particularly in the last decade.

Several areas of agreement exist between perceptions of farmers in the study area and climate variability analysis. For instance, the farmers' perceptions in the study area corroborated the observed changes, including reduced rainfall, rising temperatures, and increased drought frequency.

3.5 Recommendations

Given the variability and irregular changes in precipitation and maximum and minimum temperatures observed across the different stations, it is recommended that efforts be made to improve data collection and monitoring across the region. It can be achieved by installing adequate weather stations and adopting advanced remote sensing technologies to improve data accuracy and reliability by the Ghana Meteorological Agency.

The irregular changes in precipitation and temperature observed in the study can increase the risk of climate-related disasters such as floods, droughts, and heat waves. It is, therefore, recommended that disaster preparedness and response mechanisms be strengthened to reduce the vulnerability of communities to such disasters by the National Disaster Management Organization (NADMO).

Given the observed changes in climate variables, increasing education and awareness about climate change and its impacts is essential. It can involve the development of climate change education programs in schools and providing training and awareness-raising activities for community members.

CHAPTER FOUR

LULCC IN NORTHERN GHANA

4.1 Introduction

LULCC arise from intricate interactions between the human and natural environments, potentially influencing climate change, ecosystem services, and human well-being (Pereira, 2020; Yang et al., 2022). Changes in the physiological environment can reduce agricultural lands, soil fertility, and crop production, forcing people to migrate to areas that offer better opportunities (Hsiang, 2010). Addae and Oppelt (2019) suggest that economic, political, demographic, and environmental factors significantly influence LULC changes in northern Ghana. For instance, the recent delineation of the north of Ghana into five regions and the rapid population growth present a dynamic tendency for rapid LULC changes.

Additionally, the creation of new regions has the potential to drive rapid development, requiring the provision of social amenities and infrastructure expansion. It could lead to the overexploitation of natural resources and agricultural lands. It may also result in a range of LULC change-related challenges, leading to the adaptation of environmental migration as a coping strategy.

Accurate characterization and monitoring of LULC change trends can provide essential information for understanding human activities' resulting social and environmental impacts. Moreover, it can facilitate further studies on climate change, public health, food security, carbon cycling, soil erosion, hydrology, atmospheric quality, plant functioning, biodiversity, and ecosystem management (Appiah et al., 2015; Liu et al., 2016; Hackman et al., 2017).

The availability of synoptic and continuous satellite data and techniques in remote sensing and Geographic Information Systems (GIS) enables the study, understanding, and analysis of LULC changes over time. GIS and remote sensing have become crucial tools in many parts of the world (Basommi et al., 2015; Addae and Oppelt, 2019). Remote sensing methods for characterizing LULC change include classifying land cover types and predicting attributes as continuous variables (Liu et al., 2016).

Satellite exploration, data acquisition, and algorithms have led to the availability of global and continental land-cover datasets at coarse and fine resolutions (Hackman et al., 2017). However, in developing countries like Ghana, geospatial technologies must be well-developed; satellite data, particularly Landsat images and sentinel, provide suitable options for LULC change analysis. Scholars have successfully used satellite data to quantify LULC changes (Addae and Oppelt, 2019).

Although substantial research has been done globally on using satellite data to model land use and cover dynamics (Appiah et al., 2015), only some studies have extensively focused on LULC change analysis in northern Ghana. Additionally, works conducted in the north of Ghana on LULC change are limited in scope, with many concentrated in small areas such as a community or region. For instance, Braimoh and Vlek (2005) identified the spatial determinants of land-cover change trajectories, while Braimoh (2006) considered dominant landscape changes in a 5400 km2 area in northern Ghana.

Forkuor et al. (2015) evaluated the sequential masking classification approach for improving crop discrimination in the Sudanian Savanna of West Africa. They concentrated on Vea in the Upper East, while Basommi et al. (2015) explored land use status and land cover change in the Wa East District using satellite imagery.

Furthermore, these works conducted in northern Ghana that focused on LULC change do not consider the perception of the populace in the study. Also, global LULC change maps, which provide total coverage, present some accuracy concerns due to the challenges associated with collecting accurate and representative training samples used as validation data on a global scale (Hackman et al., 2020). This study aims to produce LULC change maps for northern Ghana, compute changes for the selected land use classes, predict the future trends of these classes in selected districts and compare the results to the perception of farmers in the study area.

4.2 Materials and Methods

The study area (see section 1.5 and Figure 1.1) consists of northern Ghana and three districts: Tamale metropolis in the Northern Region, Wa municipal in the Upper West Region, and Bole district in the Savannah Region. Figure 4.1 presents a summary of the methodological flow chart for this study.

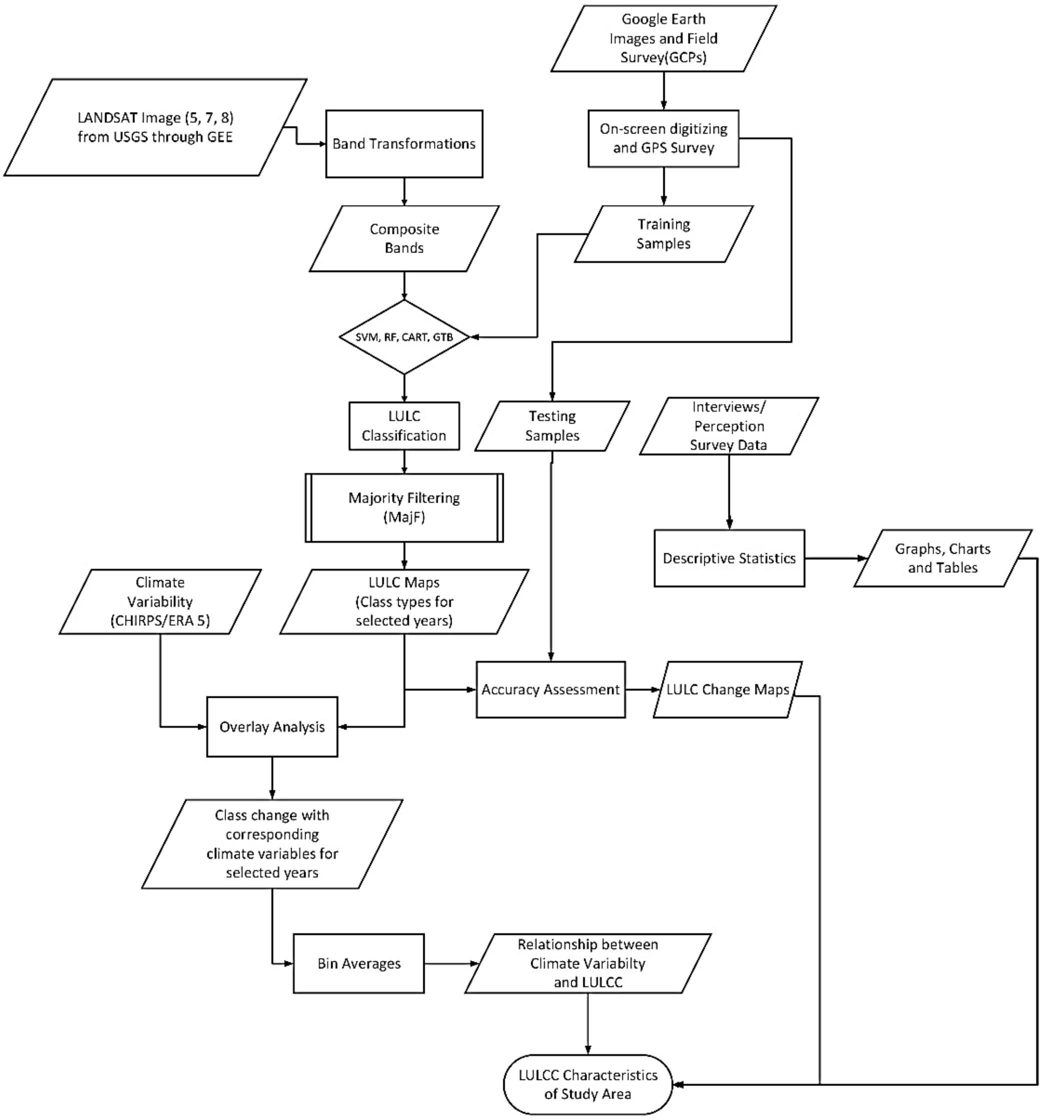


Figure 4.1 Workflow Diagram
Source: Authors' construction

All accessible Landsat images from Landsat 5, 7, and 8 for 1990, 2000, 2010, and 2020 were downloaded from the United States Geological Survey (USGS) through Google Earth Engine (GEE) (see Table 4.1 for the temporal Characteristics of the Landsat images used) (Srivastava et al., 2022). Multi-temporal cloud masking was implemented for each classification year, and the masked image collections from the three Landsat sensors were subsequently merged. A median filter was applied to the merged image collection to obtain a single, clear image for each classification year. Apart from the six raw bands, namely, Blue, Green, Red, Near Infrared, Shortwave Infrared 1, and Shortwave Infrared 2, two additional spectral indices, the Normalized Difference Built-up Index (NDBI) and the Normalized Difference Vegetation Index (NDVI) were computed to improve the accuracy of identification of vegetated and built areas. From these bands, an 8-band composite was produced for each classification year. The implementation steps and methods follow those described by Addae and Oppelt (2019) and Hackman et al. (2020). The decision to utilize Landsat images in this research was based on their greater availability over an extended period in northern Ghana than other satellite images.

For training and validation purposes, samples were collected from various sources, including onscreen samples from Google Earth high-resolution images and field samples manually collected between August and December 2021 using handheld GPS. Additionally, field samples gathered by Hackman et al. (2017) between September 2014 and April 2015 were incorporated. To ensure that the spectral variability within each land cover type was captured, the training samples were collected by carefully considering the different variations of each class.

The sample collection process involved generating random points within the study area, visually inspecting the land use within at least a 30m radius of homogeneous neighbourhoods and labelling them based on local knowledge. Specific assumptions were made for classifying densely built areas, present vegetated areas, and bare lands between settlements and the yet-to-be-built regions. These assumptions allowed the use of the same set of samples for training the classifiers and testing the resulting classified images for all the years considered. It was achieved by splitting the collected training samples into 70% for training and 30% for testing. Subsequently, the samples were divided into training and testing sets using the protocols of Basommi et al. (2015), Hackman et al. (2017), Hackman et al. (2020) and Srivastava et al. (2022). Interviews and perception surveys were conducted on farmers for comparison and validation purposes.

Table 4.1 Description of the Landsat Data Utilized in the Study

Data type	Spatial resolution	Temporal resolution	Radiometric resolution	Source of data
Landsat 5	Bands 1 to 5 and 7 are 30 meters, and Band 6 (thermal infrared) is 120 meters resampled to 30-meter pixels.	16 days	8 bits	United States Geological Survey
Landsat 7	Bands 1 to 5 and 7 are 30 meters, Band 6 (Thermal band) is 60 meters, and the panchromatic band 8 has a resolution of 15 meters.	16 days	12 bits	United States Geological Survey
Landsat 8	15 meters (panchromatic), 30 meters (visible, NIR, SWIR) and 100 meters (thermal).	16 days	12 bits	United States Geological Survey

Source: Authors' construction

4.2.1 Supervised Classification Method

Supervised classification methods are a type of machine-learning technique used to categorize or classify data into predefined classes or categories (Stephens and Diesing, 2014). Overall, supervised classification is a fundamental machine-learning technique that plays a crucial role in solving various real-world problems by automating the process of assigning labels or categories to data based on its features.

In supervised classification, a model is trained on a labelled dataset, where each data point is associated with a known class or category (Hu and Sadda, 2019). This dataset guides the model to learn the relationships between input features and their corresponding classes. Features are the characteristics or attributes of the data that the model uses to make predictions. These can be numerical, categorical, or even text-based, depending on the nature of the problem.

Various algorithms can be employed for supervised classification, including but not limited to Decision Trees, Random Forests, Support Vector Machines (SVM), Naive Bayes, k-Nearest Neighbors (k-NN), and Neural Networks (Stephens and Diesing, 2014; Hu and Sadda, 2019). The choice of algorithm depends on the problem and the nature of the data.

During training, the model learns to map input features to the correct class labels (Hu and Sadda, 2019). The goal is to find a decision boundary or a function that separates the different classes as accurately as possible. The trained model is tested on new, unseen data to evaluate its performance and the ability of the model to classify data correctly it has never encountered before is a measure of its generalization capability (Hu and Sadda, 2019).

Common evaluation metrics for supervised classification include accuracy, precision, recall, F1-score, and ROC curves. These metrics help assess the model's performance and ability to make correct predictions. Supervised classification has many applications, including spam email detection, image recognition, medical diagnosis, sentiment analysis, and more. It is used whenever data is needed to be categorised into predefined classes (Hu and Sadda, 2019).

4.2.2 Image Classification

In the classification process, four machine learning algorithms in GEE were employed, including Random Forest (RF), Classification and Regression Trees (CART), Gradient Tree Boosting (GTB), and Support Vector Machine (SVM).

Random Forest (RF) utilizes an ensemble approach to maintain decision trees. Each decision tree predicts a class result, and the class result with the most votes is selected as the tree's root (Srivastava et al., 2022). Due to the accuracy of the classifications of RF, it is commonly used within the remote sensing community (Belgiu and Drăguţ, 2016).

CART, a classification and regression tree algorithm, constructs decision trees through binary attribute splitting in a top-down, non-backtracking, and greedy manner. It employs Information Gain and the Gini index to select attributes that provide the most class-relevant information for tree construction (Zimmerman et al., 2016; Srivastava et al., 2022).

Gradient Tree Boost (GTB) also uses a decision tree for classification where each predictor corrects its predecessor's error with its base learner, CART. GTB eliminates bias errors (Srivastava et al., 2022). Support Vector Machines (SVM) address non-linearity through non-linear basis functions, employing a clever method to prevent overfitting and accommodating a relatively large number of features with efficient computation (Srivastava et al., 2022).

These algorithms were separately used to classify the images for each classification year (1990, 2000, 2010, and 2020). Moreover, to enhance the accuracy of the final LULC maps, they were converted to an image collection, after which a post-classification majority filtering (MajF) using the mode function was performed to obtain a single classified image. The classification scheme used for this study comprised five distinct classes: Settlement/Bare, Water, Cropland, Shrub/grassland, and Woodland (see Table 4.2 and Figure 4.2 for the description and pictorial representation of land cover classes), and was devised based on prior knowledge of the study area (Basommi et al., 2015; Hackman et al., 2017).

4.2.3 Accuracy Assessment of LULC Maps

The LULC maps created were assessed for all classifiers to determine the best classifier among the results (see Table 4.3). An unbiased estimate of the proportions for the entire study computed to include proportion correct, the various Kappa indices, omission error, commission error, producer's accuracy, user's accuracy, quantity disagreement and allocation disagreement is widely accepted as a measure of classification accuracy, both as an indicator of the model's precision and the user's classification accuracy (Pontius and Millones 2011; Appiah et al., 2015). Kappa values fall into different categories: <0 suggests no agreements, 0-0.2 indicates slight agreement, 0.2-0.41 is considered fair, 0.41-0.60 represents moderate, 0.60-0.80 is substantial, and 0.81-1.0 indicates almost perfect agreements (Appiah et al., 2015). In total, 1,367 GPS points were collected: Settlement/Bare-289, Water-320, Cropland-593, Shrub/grassland-513, and Woodland-211. Additionally, 559 testing samples were used, comprising Settlement/Bare-80, Water-95, Cropland-169, Shrub/grassland-154, and Woodland-61. The size of test samples was determined based on the rule of thumb outlined in Congalton (1991). A confusion matrix (Pontius and Millones, 2011) with the 559 independent test samples was generated in QGIS (see Appendix 2A) for each of the resulting LULC change maps for accuracy assessment. Furthermore, the actual change detection outcomes for various LULCC types and analyses of land use transitions among these categories were determined. However, only the most significant changes were considered to enhance the certainty of land cover dynamics. This approach was employed to distinguish genuine differences from potential misclassifications (Appiah et al., 2015).

Table 4.2 Description of LULC Classes

Classes	Description
Settlement/Bare	Buildings, built surfaces, and areas comprising bare lands in between settlements and yet-to-be-built lands with no vegetation cover
Water	Locations covered with water, e.g., rivers, damps
Cropland	Agriculturally cultivatable lands
Shrub/grassland	Dominated by grass and other small-to-medium-sized perennial woody plant
Woodland	Consisting of savannah woodland made up of short, dispersed trees

Source: Authors' construction

In Figure 4.2, pictorial representations depict the various land cover classes utilized as training samples in this study.

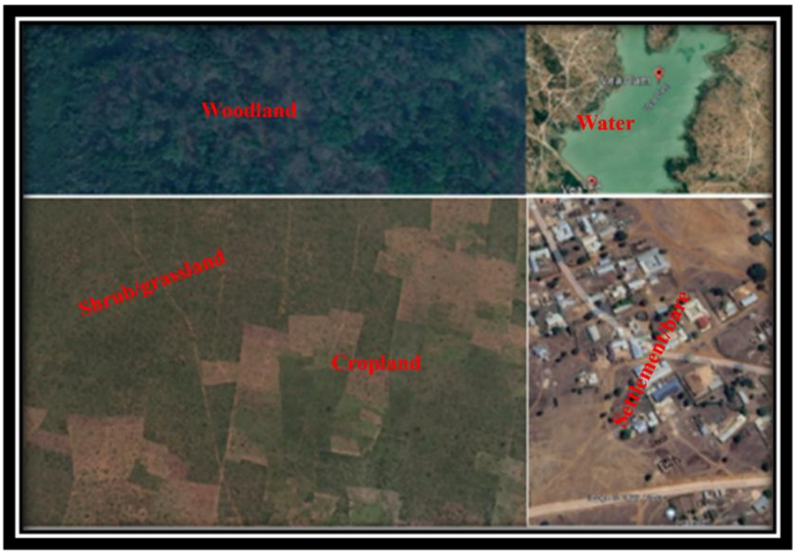


Figure 4.2 Sample Land Cover Classification Classes
Source: Authors' construction

4.2.4 Assessing Farmers' Perceptions on LULCC in the Study Area

The research incorporated field surveys to evaluate farmers' perceptions of the LULCC patterns within the study area. The farmers were interviewed to gather information about the initial land cover, any observed changes over time, and the factors that may have contributed to these changes, if relevant. Their perception of the tenure of land in their community was also assessed. In all, 410 farmers participated in the interviews and perception surveys (details of which are presented in Chapter 5, section 5.3.1).

4.2.5 The Interplay Between Climate Variability and LULCC in Northern Ghana

To establish a correlation between the climate variables and LULCC, five thousand (5000) regular random points were generated in the study using the "random points" tool in QGIS. The next step was to overlay the climate data (i.e., precipitation, maximum and minimum temperature data) on the results of class change for 2000, 2010, and 2020 from the LULC maps.

Next, the point sampling tool was employed to extract climate and LULC map variables as vectors at the 5000 points from the overlaid layers. Subsequently, these variables were grouped into bins, and their bin averages (McRoberts et al., 2016) were calculated to reveal patterns in the datasets.

4.3 Results and Discussions

4.3.1 Accuracy of LULC Maps

The results obtained, and discussions of the accuracy assessment, encompassing KP-Kappa, OA-Overall Accuracy, PA-Producer's Accuracy, UA-User's Accuracy, EO-Error of Omission and EC-Error of Commission (See Appendix 2A and Table 4.3) are presented in this section. These results are reported as found in studies conducted by Braimoh and Vlek (2005) and Addae and Oppelt (2019).

Table 4.3 Overall Accuracies and Kappa Values for Classifiers

Classifiers	1990		2000		2010		2020	
	OA%	KP (%)	OA%	KP (%)	OA%	KP (%)	OA%	KP (%)
RF	93.14	91.05	94.28	92.54	94.81	93.25	96.78	95.82
CART	91.16	88.48	93.56	91.63	91.59	89.07	96.24	95.14
GTB	93.86	92.01	94.81	93.26	95.35	93.95	96.60	95.59
SVM	80.32	74.34	84.43	79.63	87.84	84.15	90.88	88.15
MajF	94.04	92.23	94.99	93.49	95.35	93.95	96.78	95.82

Source: Authors' computation

From Table 4.3, the classifiers used in this study all achieved overall accuracies above 80%. However, when compared, the LULC maps produced using Majority filtering exhibited notably high overall accuracy and kappa values. Specifically, the overall classification accuracy of the images using majority filtering yielded 94.0%, 95.0%, 95.3%, and 96.8% for the 1990, 2000, 2010, and 2020 images, respectively. The corresponding kappa hat values were 92.0%, 93.0%, 94.0%, and 96.0%. These figures indicate moderately substantial to almost perfect agreement, as discussed earlier in this section. The overall accuracy was excellent, with both user and producer accuracy also high for all the land use classes (see Appendix 2A). The LULC maps were subjected to visual inspection to determine the one with the best image quality and most accurate representation of the land use classes in the study area. It involved comparing the LULCC maps of the same year (2020) for the different classifications performed (see Figure 4.3 and 4.4 and Appendix 2B). The accuracy obtained from each classifier (see Table 4.3) was also considered when selecting the LULCC maps for further analysis in this study.

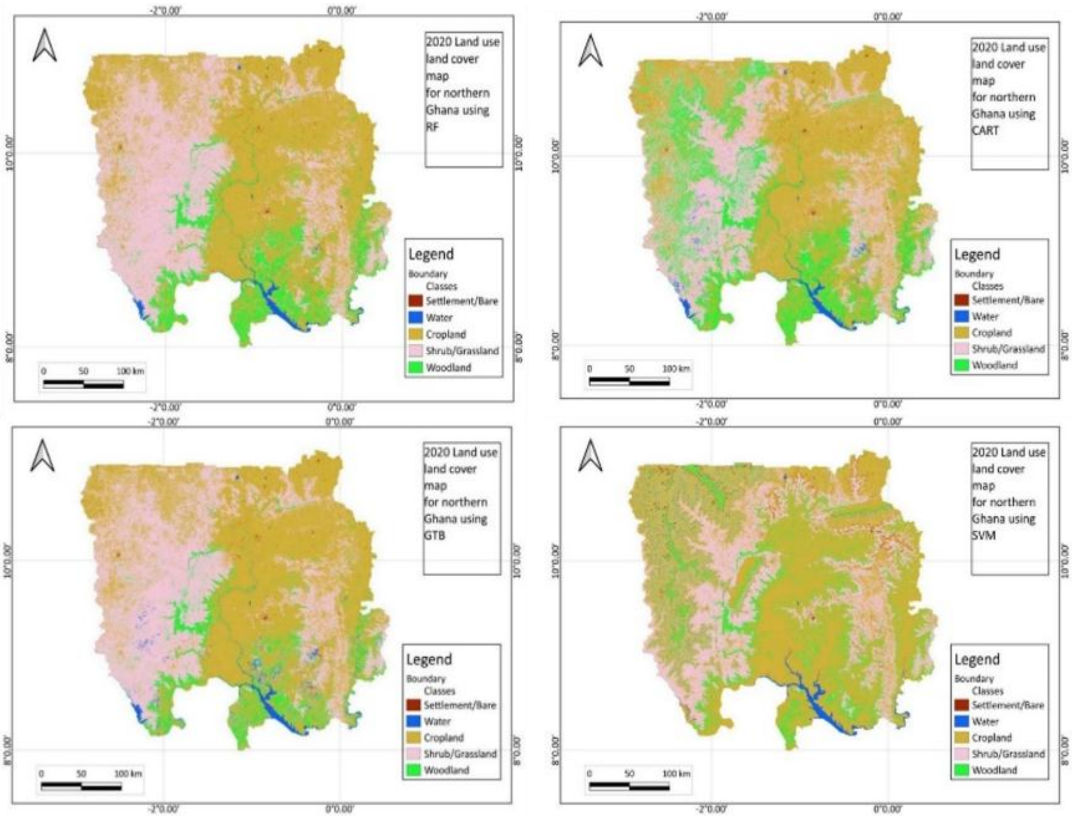


Figure 4.3 LULC map Generated for 2020 using RF top left, CART top right, GTB bottom left and SVM bottom right

Source: Authors' construction

The images from the CART and GTB classifiers (Figure 4.3), especially those from SVM, showed comparatively lower image quality. The diminished image quality might impede the ability to discern details, potentially affecting subsequent analysis and modelling efforts. LULC maps from RF demonstrated comparatively better accuracies, with the lowest class accuracy being 93.1% and the highest at 96.8%. There were some notable misclassifications of the settlement/bare and water classes, but all others were adequately represented.

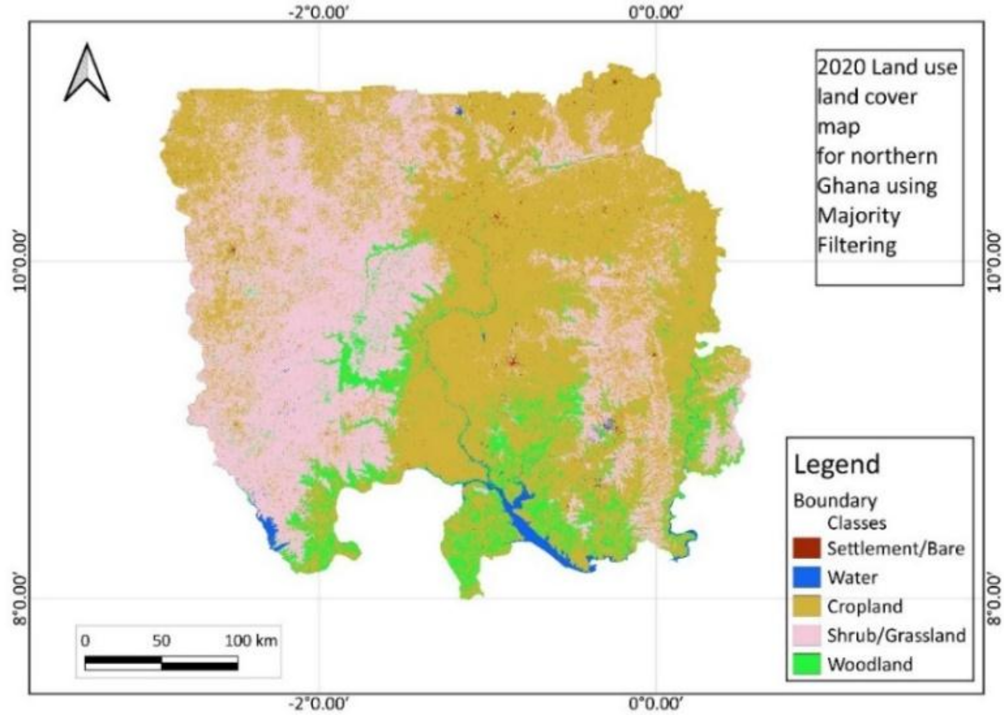


Figure 4.4 LULC Map for 2020 using Majority Filtering
Source: Authors' construction

The images classified using Majority filtering (refer to Figure 4.4) exhibited a diverse and well-balanced representation of different classes and highlighted good-quality image samples. Each class appeared visually clear and distinct, with sharp details and accurate colour representation. The combination of class representation and image quality in these images indicated a reliable dataset for further analysis.

Based on the visual impression of the LULC maps created and prior experience with the study area, the maps generated through majority filtering were deemed the better option for further analysis. As a result, the classified images from Majority Filtering were chosen for the change analysis of the study area. This decision was based not only on their superior accuracies but also on their comparatively better image quality.

4.3.2 Ground Truthing Validation of LULC Maps

The validation of LULC maps was done using the ground truthing approach. With a handheld GPS, the position of points representing some selected classes on the LULC maps was identified in the community for verification by the researcher. The classes (e.g., water, cropland, etc.) in the LULC maps collaborated with what existed on the ground. In addition, three communities, one each in each district (Bilpela in Tamale Metropolis, Busa in Wa Municipal and Kilampobile in Bole district), were selected for this process. Community members who have lived there for over 30 years (to span the period of the LULC maps created, i.e., 1990 to 2020) were purposively selected for this process. The selected members were then quizzed about the cover of land to confirm the LULC maps created.

4.3.3 Analysis of LULC Classes in Multi-Year LULC Maps

The analysis of LULC map classes was conducted using LULC maps created with majority filtering (see Appendix 2B). The areas of each class type for every year were calculated by summing the pixels representing each class in the LULC maps (refer to Table 4.4). The results from the classified images indicate that Croplands consistently dominated the landscape for all the years studied, followed by shrub/grassland, woodland, water, and settlement.

Table 4.4 Areas of Classes of LULC Maps

	Area (sq. Km)			
Class/Year	1990	2000	2010	2020
Settlement/Bare	2007.30	601.15	639.85	255.43
Water	2978.29	1573.36	1398.61	1265.52
Cropland	63914.73	70146.00	67801.07	53876.04
Shrub/grassland	23812.05	20397.85	22406.07	35540.57
Woodland	6089.98	6772.10	7240.06	8553.01

Source: Authors' computation

Figure 4.5 illustrates the study area's temporal dynamics and transformations of land use classes. This visual representation effectively captures land-use class changes over the specified period.

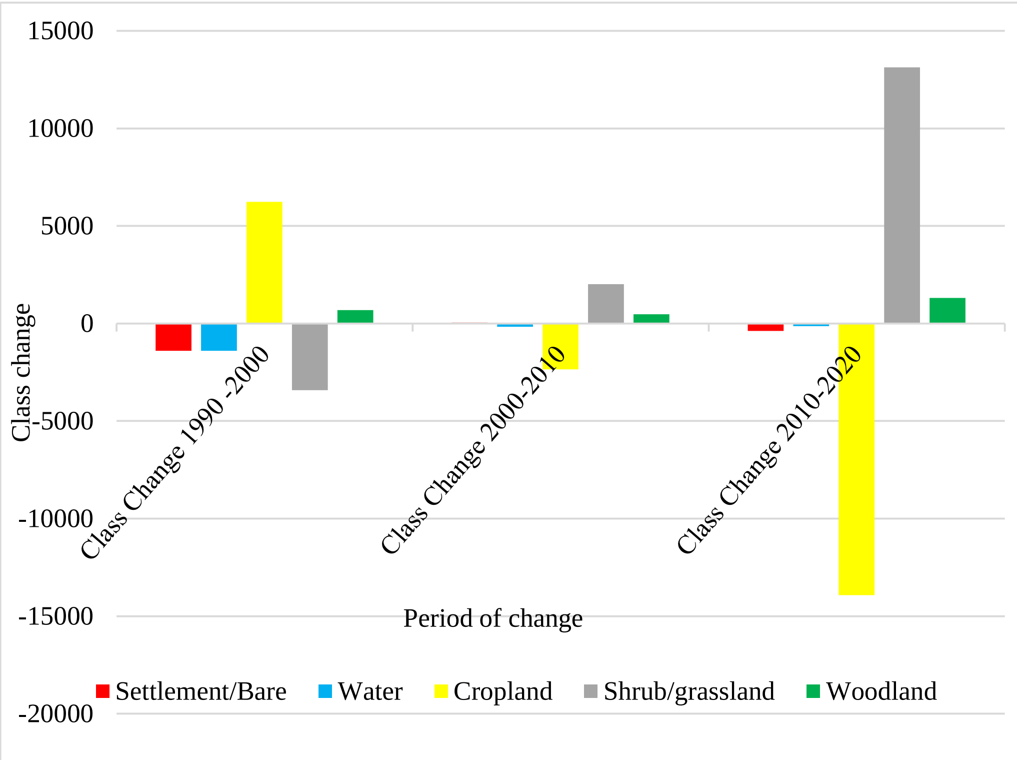


Figure 4.5 Changes in Land Use Classes Over Time
Source: Authors' construction

The analysis of the results reveals intriguing trends depicted in Figure 4.5. Firstly, there was a notable increase in cropland during the year 2000. However, in 2010, it experienced a slight decrease, followed by a considerable decline from 2020 onwards. On the other hand, woodland exhibited a consistent upward trend across all epochs. At the same time, the water class showed a declining pattern throughout the entire period, indicating a progressive increase in woodland and a decrease in water in the study area. In contrast to cropland, the shrub/grassland category displayed an opposite pattern, showing a reduction corresponding with the years of cropland expansion and vice versa. These dynamic changes in land cover provide valuable insights into the shifts observed within the different land use categories over the studied period.

Despite cropland dominating the landscape in the study area, a decreasing trend is observed concurrently with the increasing trends in shrub/grassland and woodland. The consistent forest rise, especially in the last decade, could be attributed to several tree-planting interventions ongoing in the study area, such as the Government's Green Ghana project.

4.3.4 Change Analysis of LULC Classes Over Three Decades

The land use maps were employed to generate change maps for three distinct time intervals: 1990 - 2000, 2000 - 2010, and 2010 - 2020. These change maps were created to assess and identify the specific changes within each land use class over these defined periods, providing valuable insights into the land use transformations, evolving patterns, and trends within each category. For further information on change statistics, please refer to Appendix 2C. The LULCC maps were validated using a similar approach as section 4.3.2.

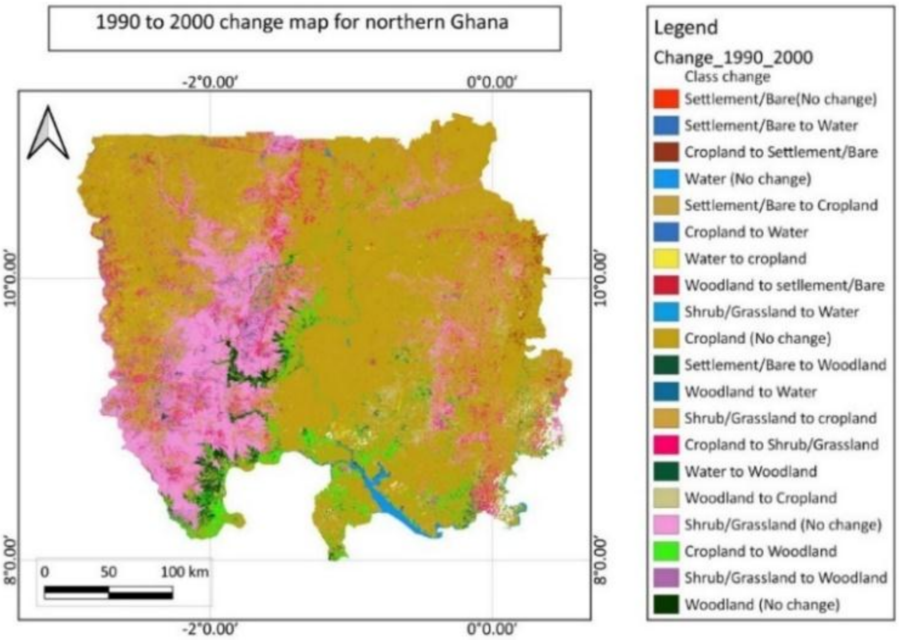


Figure 4.6 Change Map for 1990 to 2000 showing Class Change
Source: Authors' construction

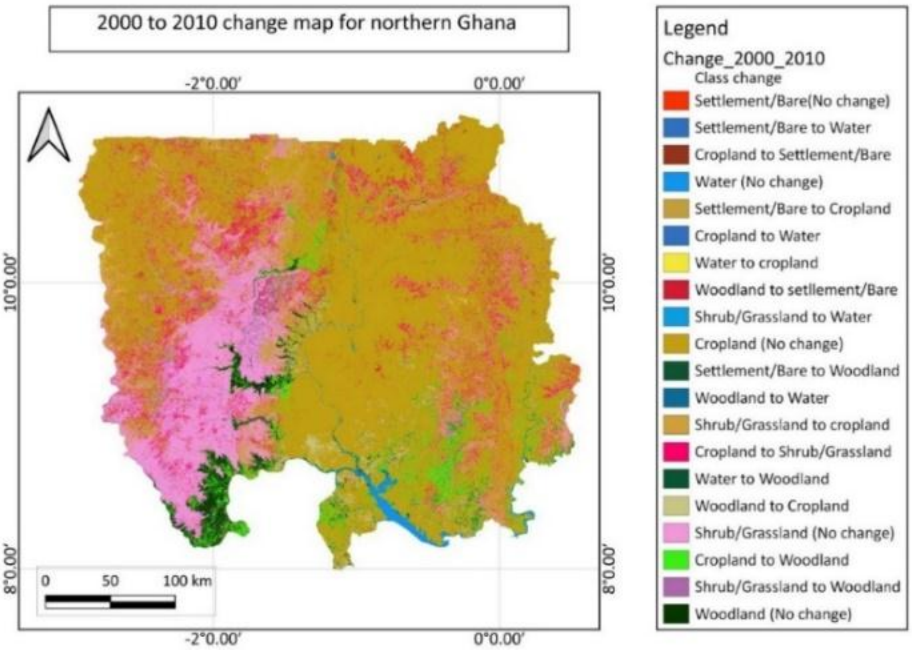


Figure 4.7 Change Map for 2000 to 2010 showing Class Change
Source: Authors' construction

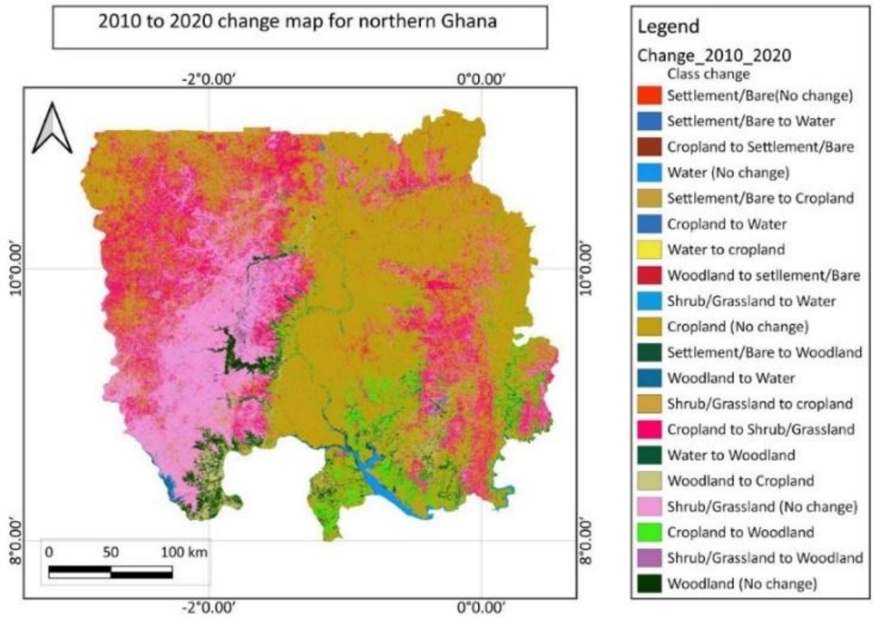


Figure 4.8 Change Map for 2010 to 2020 showing Class Change
Source: Authors' construction

The change detection results depicted in the change maps (refer to Figures 4.6 to 4.8) and the corresponding change statistics found in Appendix 2C revealed that three land use classes, namely cropland, shrub/grassland, and woodland, experienced higher conversion rates (see Figure 4.9). The conversion of cropland to shrub/grassland and woodland, and vice versa, emerged as a significant change in the study area. For example, from 1990-2000, 9264.553 sq. km of shrub/grassland was converted to cropland, while 4568.51 sq. km of cropland was converted to shrub/grassland. However, between 2010 and 2020, the conversion dynamics shifted, with 16268 sq. km of cropland converting to shrub/grassland and 3594.036 sq. km of shrub/grassland converting back to cropland (refer to Appendix 2C). The conversion dynamics of all the identified LULCC classes are illustrated in Figure 4.9.

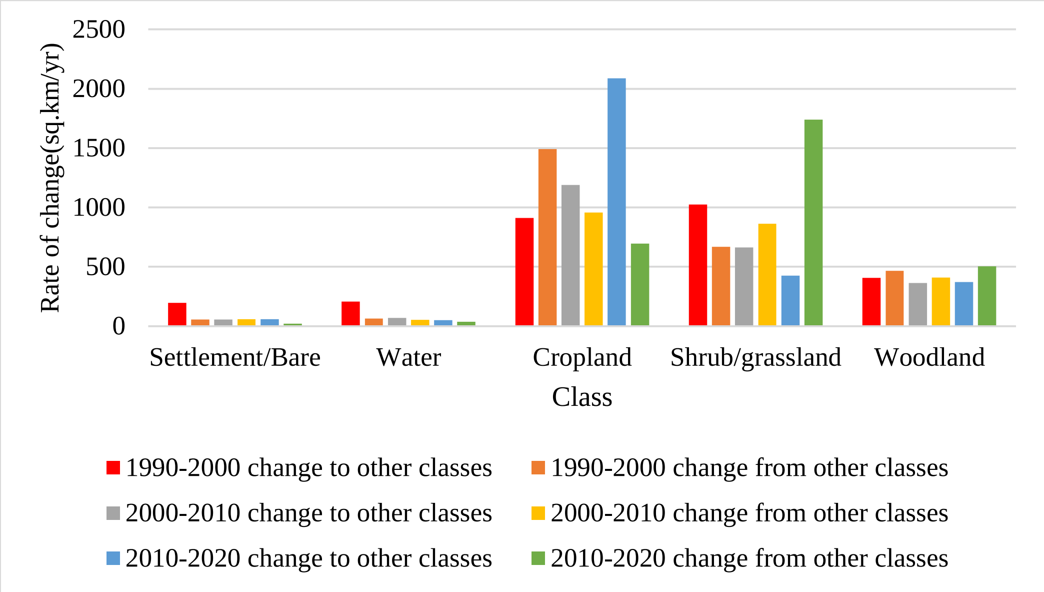


Figure 4.9 The Conversion Rate of LULC Classes
Source: Authors' construction from LULCC maps

Observations indicate that, from 1990 to 2000, the conversion rate of land from other classes to cropland exceeded the rate of cropland converting to different classes. However, in the subsequent years, a notable shift occurred, and the rate at which cropland converted to other types of classes surpassed the conversion of different types of classes to cropland. The most significant change in cropland occurred from 2010 to 2020, indicating a peak in the conversion process.

Remarkably, cropland conversion to shrub/grassland and woodland, notably shrub/grassland, exhibited a steady and continuous increase over time. Implying a noteworthy trend of cropland transforming into these specific land classes as the years progressed (see Figure 4.10).

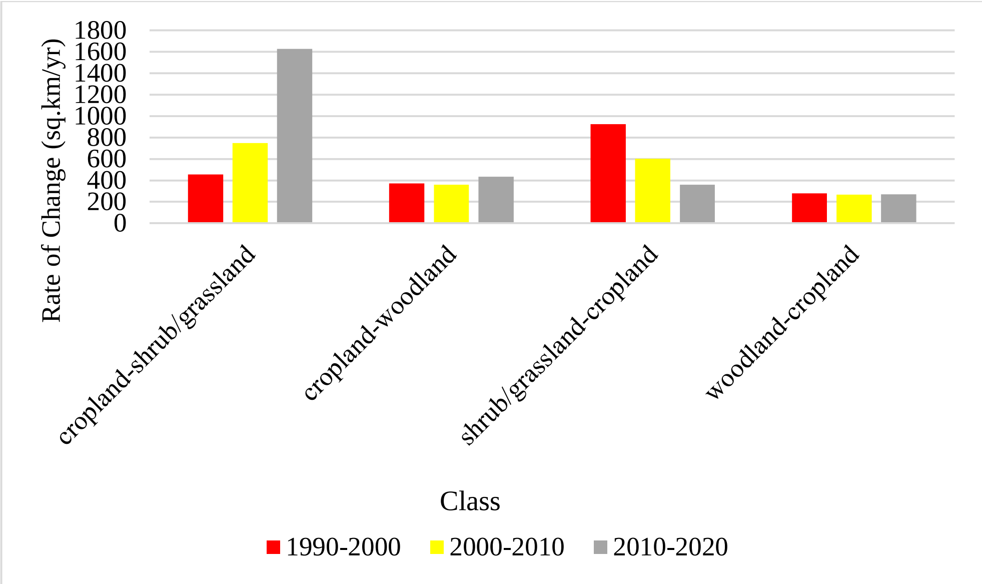


Figure 4.10 The Annual Conversion Rate of Cropland, Shrub/grassland, and Woodland
Source: Authors' construction from LULCC maps

The conversion of cropland to shrub/grassland suggests that portions of cropland are left unattended and turning into shrub/grassland (see Figure 4.14), as was also observed by Shrestha et al. (2022) in their study.

4.3.5 Farmers' Perceptions of LULCC and Their Impacts on Agriculture and Land Tenure Systems in Northern Ghana

The results of the perception survey of 410 farmers presented in Figure 4.11, in addition to focus group discussions and information gathered from key informants in northern Ghana, are analysed in this section.

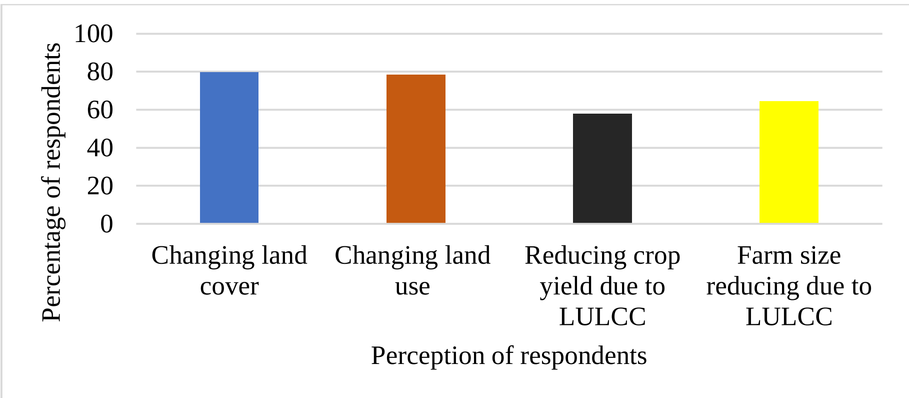


Figure 4.11 Farmers' Perceptions of LULCC and its impact on Crop Yield and Farmland Size
Source: Authors' construction

From the findings, over 70% of the respondents acknowledged changes in land use and land cover, indicating a high level of awareness among the farmers surveyed. Most farmers recognize the occurrence of LULCC in the study area. Furthermore, about half of the respondents, precisely 50%, believe that LULCC has a detrimental effect on their farmlands and crop yield. This perception highlights the concerns and potential challenges farmers face due to the observed land-use changes and covers a challenge confirmed by all 15 Key informants interviewed.

The survey results also show that 327 respondents, accounting for approximately 79.76% of the total respondents, perceive changes in land cover. It suggests a significant level of awareness among the surveyed farmers regarding alterations in land cover within their respective regions. Similarly, 321 respondents, representing about 78.29% of the total respondents, perceive changes in land use patterns. It indicates that a noteworthy proportion of the surveyed farmers are conscious of shifts in land use practices.

Regarding the impact of LULCC on crop yield, 237 respondents, comprising approximately 57.80% of the total respondents, perceive a reduction in crop productivity due to these changes. It underscores the substantial number of farmers who believe LULCC negatively affects crop yields. Moreover, 265 respondents, equivalent to about 64.63% of the total respondents, perceive a reduction in farm size resulting from LULCC. This finding highlights the considerable proportion of farmers who observe or believe that LULCC has led to a decrease in the size of their farms.

Overall, the findings reveal widespread recognition of LULCC among farmers and a substantial concern regarding its negative implications on farmlands, crop yield, and farm size assertions all 3 MOFA officials interviewed agreed to. These findings emphasize the importance of addressing and mitigating the impacts of LULCC on agricultural practices and livelihoods in the study area.

The data in Table 4.5 reflects the perceptions of 410 farmers regarding previous land cover, current land cover, current land use, and the perceived causes of land use and land cover change.

Table 4.5 Farmers' Perceptions of Land Use, Land Cover, and the Drivers of LULCC

Previous Landcover		**Current Landcover**		**Current land use**		**Causes of LULCC**	
Land Cover	**Respondent%**	**Land Cover**	**Respondent%**	**Land use**	**Respondents%**	**Causes**	**Respondents%**
Shrub/ grassland	28	Settlement/ Bare	29	Agricultural purposes	42	Bush fire	43
Woodland	21	Shrub/ grassland	32	Settlement	56	Logging	12
Cropland	49	Woodland	12	No response	1	Settlement purposes	29
Don't know	2	Cropland	24			Changing climate	10
		No response	3			Population growth	4
						Don't know	2

Source: Authors' computation

Out of the 410 respondents, 28% perceived shrub/grassland as the previous land cover, 21% perceived woodland as the previous land cover and 49% perceived cropland as the last cover of land. 2% of respondents said they did not know the previous land cover. About 29% of respondents perceived the current land cover as settlement/bare, 32% perceived shrub/grassland land as the current land cover and 24% perceived cropland as the current land cover. About 12% of the respondents perceived woodland as the current land cover, and 3% of respondents gave no response.

Furthermore, 42% of respondents perceived the current land use as agricultural purposes, while 56% perceived settlement as existing land use. 1% of respondents gave no response. On the causes of LULCC, 43% of the respondents perceived bushfires as the cause of LULCC in the study area, 12% perceived logging as the cause of the change in LULC, and 29% perceived construction leading to settlement as the primary cause (Haile et al., 2019). About 10% perceived changing climate as the cause, 4% of respondents perceived population growth as the cause, while 2% did not know the causes of land use and land cover change in the study area.

From the results, it is evident that cropland was the dominant previous land cover. However, farmers now perceive shrub/grassland and settlement/Bare as becoming the dominant land cover, and respondents reported that the primary use of the land is for settlement purposes, which was different from the scientific analysis of LULCC. This perceived shift in land cover and usage indicates significant changes in LULC in the study area. Most respondents acknowledged that the LULC of their immediate surroundings is changing. They perceive these changes to adversely impact their crop yield, suggesting that the alterations in land cover have practical implications for agricultural productivity in the region; hence, they have to travel long distances to cultivate farms. This position is consistent with the statement of Haile et al. (2019) that past land-cover type influences current agricultural performance through its effect on soil quality in Northern Ghana.

The findings also indicate that most farmers attribute the observed changes in LULC to anthropogenic activities, consistent with the study of Kleemann et al. (2017), a study in the Upper East of Ghana which points out that anthropogenic activities (e.g., use of wood for fuel) were considered very high drivers of LULCC compared to climate variability (e.g.., Temperature variability). They stated that land degradation was most often associated with intensive anthropogenic activities rather than climate variability. It suggests that human interventions and practices are significant drivers of the LULC changes experienced in the area, pointing to the dominant role of human activities (anthropogenic activities) as the primary drivers of LULCC in the study area (Chen et al., 2018).

Perception of Farmers on Land tenure system

The research findings shed light on the diverse land tenure arrangements among the surveyed farmers, encompassing community, family, self-owned, leased, and government-owned land. Table 4.6 presents the responses of farmers regarding their land ownership status.

According to the data, 134 farmers, comprising approximately 32.68% of the sample, reported having land tenure on community land. Indicating a prevailing pattern of communal land ownership or access within the surveyed population, reflecting the significance of collective ownership in the region. Aha and Ayitey (2017) indicated that more than half of the people in Ghana are involved in farming communal lands. Furthermore, most farmers, totalling 190 individuals and representing approximately 46.34% of the sample, reported having land tenure on family-owned land and making individual land ownership problematic, corroborating the assertion of Otsuka (1999), who stipulates that individual land rights on family-owned plots are weak in Ghana. Highlighting a substantial reliance on the ground passed down through generations or owned jointly by family members, signifying the importance of familial ties in land ownership.

Additionally, a subset of farmers, comprising 74 individuals and about 18.05% of the sample, reported having self-owned land tenure. It suggests a distinct group of farmers who have independently acquired and possess the land they cultivate, highlighting a level of individual ownership. Moreover, the data indicates that 10 farmers, representing approximately 2.44% of the sample, reported having land on lease. It implies that a small proportion of farmers have acquired land through lease agreements from private or institutional entities, which may indicate specific agricultural practices or economic circumstances. Finally, only 2 farmers, making up approximately 0.49% of the sample, reported having land tenure on government-owned land. It suggests a minimal presence of farmers cultivating land allocated by the government, indicating that government-allocated land is not a widespread source of agricultural production in the study area.

Table 4.6 Farmers' Perception of the Land Tenure System

Land Tenure	Number of farmers	Percentage
Community land	134	32.68
Family land	190	46.34
Self-owned	74	18.05
Lease	10	2.44
Government land	2	0.49

Source: Authors' computation

Table 4.6 shows that most farmers in the study area cultivate community and family-owned lands, while only a few own lands individually. Consequently, this situation leads to sharing the same farmland among community or family members. As a result, the size of each farmer's farmland is affected, which, in turn, impacts the quantity of crops they can cultivate. Since the farmland is shared among members, farmers cannot increase the size of their cultivated land when needed. This sharing of farmland limits their capacity to expand agricultural production and adapt to changing needs, which could affect their overall crop yields and economic outcomes (Kwapong et al., 2021; Otsuka, 1999). In addition, since the patrilinear family system is dominant, females are the most affected.

4.3.6 The Interplay Between Climate Variability and LULCC in Northern Ghana

Land systems provide essential products and ecosystem services vital to human sustainability (Viana et al., 2022). Population, income, and consumption rate projections have increased, thus increasing human demands on natural resources and ecosystem services (Krausmann et al., 2013). Likewise, there have been forecasts of alterations in global climate variability, including reductions in global precipitation and rising temperatures (Antwi-Agyei et al., 2018; Malhi et al., 2021). These increases and adopted methods and efforts of land-based mitigation, such as bio-energy production and afforestation, could exacerbate the pressure on land systems (Krausmann et al., 2013; Doelman et al., 2018).

The relationship between climate and LULCC is not unidirectional; changes in LULCC influence the climate, and vice versa. This section examines the relationship between climate variability and LULCC in the study area.

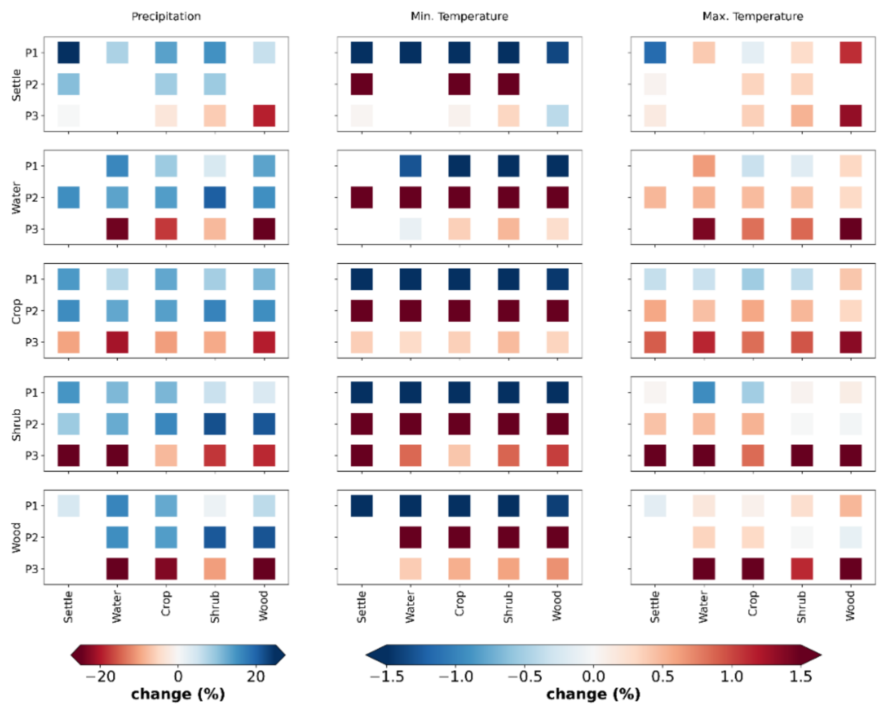


Figure 4.12 The Correlation between Climate Variability and LULCC in Northern Ghana

Source: Authors' construction

Based on the analysis presented in Figure 4.16, it is observed that the three periods, P1 (1990-2000), P2 (2000-2010), and P3 (2010-2020), coincide with changes in climate variability and corresponding LULC alterations. During these periods, there was a noticeable decline in precipitation (rainfall) from P1 to P3, with the most significant decrease occurring in the P3 period. Additionally, minimum and maximum temperatures consistently trended throughout these periods, with the most substantial increase observed during P3.

However, results indicate that while climate conditions have shifted towards decreased precipitation and increased temperatures, these changes do not directly correspond to the conversion of LULC classes in the periods under consideration (Kleemann et al., 2017). The result thus suggests that the two phenomena, LULCC and changes in climate variability, are not directly related, and this is consistent with the study of Kleemann et al. (2017), a study in the Upper East of Ghana an area close to the study area which points out that, anthropogenic activities (e.g., use of wood for fuel) were considered very high drivers of LULCC compared to climate variability (e.g.., Temperature variability). They stated that land degradation was most often associated with intensive anthropogenic activities rather than climate variability.

It points to the dominant role of human activities (anthropogenic activities) as the primary drivers of LULCC in the study area (Chen et al., 2018), supporting the perceptions of local farmers regarding land use changes and their environmental impact, as discussed in section 4.3.5.

4.4 Conclusions

Cropland dominated the landscape, followed by shrub/grassland, woodland, water, and settlement. Notably, there was a significant increase in woodland and a progressive decrease in water in the study area.

The analysis of change maps revealed that cropland, shrub/grassland, and woodland experienced higher conversion rates, with cropland transforming into shrub/grassland and woodland, and vice versa, being the significant changes observed.

Most farmers in the study area perceived land cover changes and expressed concerns about the negative impact of LULCC on crop yield and farm size. They attributed these changes to human activities, particularly bushfires.

The relationship between climate variability and LULCC in the study area indicates that while climate conditions have shown changes in precipitation and temperature, these changes do not directly correspond to the conversion of LULC classes. Human activities are the primary drivers of LULCC in the study.

4.5 Recommendations

Efforts should be made to promote sustainable land management to mitigate the adverse effects of LULCC on crop yield and livelihoods in the region. This could include initiatives to prevent bushfires and encourage responsible land use practices.

Implementing land-use planning strategies could help optimize agricultural production and manage the changing land cover dynamics, ensuring long-term sustainability and resilience of the farming systems in the study area.

Given the perception of farmers about the impact of LULCC on their crop yield, extension services and capacity-building programs could be organized to educate farmers on climate-smart agriculture and sustainable land use practices that can mitigate the adverse effects of LULCC on agricultural productivity.

CHAPTER FIVE

DRIVERS OF NORTH-SOUTH MIGRATION IN GHANA

5.1 Introduction

Migration is often the effect of a cause and a complex interplay of social, economic, political, and environmental factors (Hermans and Garbe, 2019) that drive individuals and communities to seek better opportunities, security, and well-being in different locations. In many cases, migration is not a voluntary choice but a response to circumstances beyond an individual's control, such as war, natural disasters, or discrimination, referred to as drivers (push and pull factors) (Mitchell and Pizzi, 2021).

Push and pull factors are reasons for migration that either drive people away from their original location or attract them to a new one (LEE, 1966). Push factors are usually negative, such as drought, conflict or lack of employment opportunities, whereas Pull aspects are generally positive, such as better opportunities, services, or living conditions (LEE, 1966; Mitchell and Pizzi, 2021). Migration often occurs due to a combination of push and pull factors, making it a complex and multifaceted phenomenon (Mitchell and Pizzi, 2021).

Although a complex concept, migration can be categorized based on the place, time, and purpose for which it is embarked. Migration, which indicates a change in place, could include rural-rural, rural-urban, urban-urban, and urban-rural (Sinha, 2005). Migration depicting time could be seasonal for a specific part of the year, usually between three and twelve months, determined by certain conditions. It can be referred to as temporary migration when it involves a change of residence for a brief period and becomes permanent when the change of residence of a person is for more than one year (Sinha, 2005). The purpose of migration includes political, social, economic, and environmental (Cattaneo et al., 2019; Schürmann et al., 2022). This chapter aims to ascertain the main drivers (push and pull factors) of North-South Migration in Ghana.

5.2 Materials and Methods

The study was conducted in six distinct regions, with an equal distribution of three regions in the south and the north of Ghana (see section 1.5 Figure 1.1).

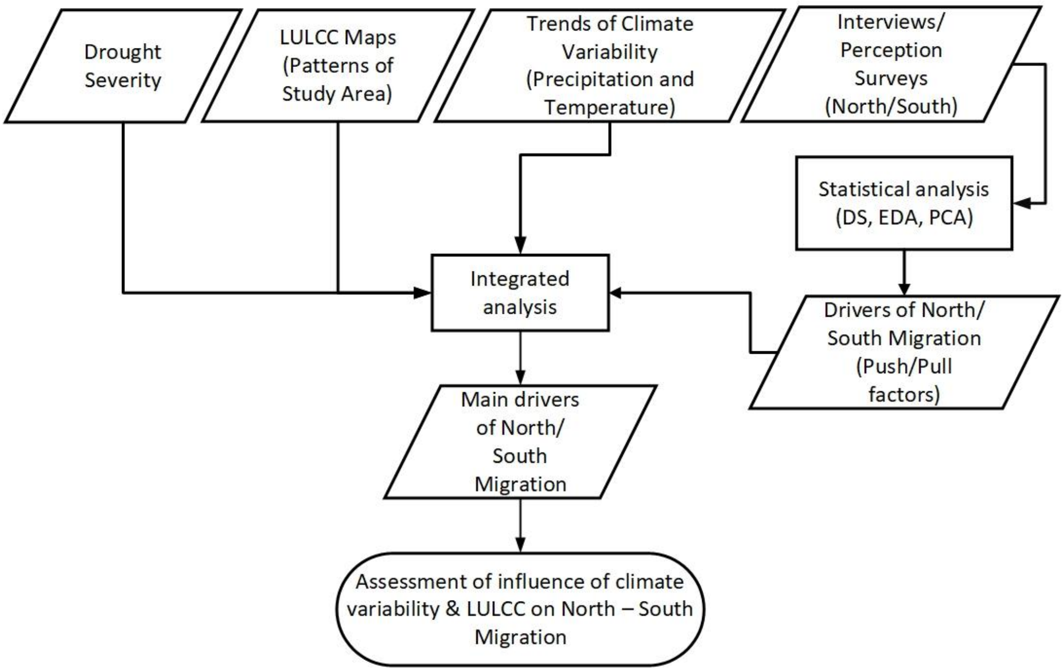


Figure 5.1 Flow Chart of Methodology
Source: Authors' construction

From Figure 5.1, data were collected from various sources, including social surveys conducted on migrants in the south of Ghana and potential migrants in the north. In addition, CHIRPS, ERA5 datasets and computed LULC class areas were used. Descriptive statistics (DS), Exploratory Data Analysis (EDA), and Principal Component Analysis (PCA) were used to identify and comprehend the factors (both push and pull factors) influencing North-South Migration in Ghana (Kainth, 2010). Results from climate variability analysis, drought severity and LULCC patterns were interpreted to collaborate with results from analysis of the perception survey of migrants for an integrated analysis of what constitutes the main drivers of North-South Migration in Ghana.

5.2.1 Factors Driving North-South Migration in Northern Ghana

While the specific factors causing migration may vary since it is not a linear process, each element varies in importance depending on the context and period (Abu et al., 2014; Adger et al., 2021). The objective of this section was to qualitatively ascertain the factors motivating North-South Migration by involving both migrants and potential migrants. An initial survey was conducted to distribute open-ended questionnaires and organise Focus Group Discussions (FGDs). These endeavours were designed to extract insights into the fundamental drivers of North-South Migration and to assist in crafting comprehensive questionnaires for forthcoming field surveys. The preliminary surveys and the subsequent validation of questionnaire items were carried out in May 2021.

Due to constraints in time and funding, 50 open-ended questionnaires were taken into the field to identify the primary factors that motivate and influence North-South Migration within the study area. These questionnaires were specifically designed to collect insights from individuals who are migrants from the northern regions and those who are contemplating migration from these northern areas of Ghana to the southern regions.

Two focus group discussions (FGD), each comprising 20 participants, were organized. One FGD occurred in the southern sector, while the other was conducted in the northern sector. Participants in these groups included head porters, truck pushers, chop bar attendants, fufu pounders, farm assistants, household heads (farmers), opinion leaders, and key informants, mainly agricultural extension officers, as indicated in Table 5.1.

Table 5.1 The Composition of Focus Group Discussions (FGDs)

Southern sector						
Category		**Gender**		**Age groups**		
	Number	**Male**	**Female**	**<18**	**18-35**	**>35**
Head potters/Truck pushers	12	2	10	4	6	2
Chop bar attendants/fufu pounders	6	2	4	2	3	1
Farm assistants	2	2	0	0	2	0
Northern Sector						
Household heads/farmers	15	10	5	0	4	11
Opinion leaders (Assemblymen)	3	3	0	0	0	3
Key informants (Agric extension officers)	2	1	1	0	1	1

Source: Authors' construction

The findings obtained from the initial survey guided the formulation of three comprehensive questionnaires. These questionnaires were tailored for three groups: individuals already migrating in the south, individuals considering migration, and key informants consisting of heads of the Environmental Protection Agency (EPA), the Ministry of Food and Agriculture (MOFA), the National Disaster Management Organization (NADMO), the Ghana Meteorological Agency (GMA) and the Forestry Commission (FC) in the north of Ghana.

The questionnaires underwent a pre-testing phase, during which they were purposively administered to a sample of 30 individuals. This sample was stratified as follows: 12 participants were migrants, 12 were potential migrants, and the remaining 6 were designated key informants. Within each of these groups, an equal distribution of gender was maintained, ensuring that out of the 30 respondents, 15 were males, and 15 were females. Furthermore, the age distribution within the sample was categorized as follows: 10 individuals were under 18 years old, 10 fell within the age range of 18 to 35 years old, and the remaining 10 were above 35 years old. For a balanced representation, participants with diverse educational backgrounds were deliberately selected.

The order of the questions, relevance, and comprehensiveness of the answers underwent evaluation after pretesting them on respondents (migrants, potential migrants and key informants). The insights gained from the pre-test were used to enhance the final questionnaires for use (refer to Appendix 3A). Subsequently, these questionnaires were transformed into a digital format for utilization through the Open Data Kit (ODK) platform.

5.2.2 Analysing North-South Migration in Ghana

Regarding the southern sector, information was obtained from the Population and Housing Census (PHC) 2010 analytical report, the most recent migration data available during the study (June 2021).

Table 5.2 Migrants from the Northern Ghana Residing in selected Southern Regions on the night of the 2010 Census

Migrants/Region	Greater Accra	Ashanti	Brong Ahafo	Total
Northern	93677	119585	88980	302242
Upper East	40809	133302	61469	235580
Upper West	16489	58291	105406	180186
Total	**150975**	**311178**	**255855**	**718008**

Source: (GSS, 2012)

From Table 5.2. on the census night, the three southern regions with the highest population of out-migrants from northern Ghana were Ashanti, Brong Ahafo (now divided into three regions: Bono, Bono East, and Ahafo), and Greater Accra (refer to Table 5.2). In addition, these regions have a substantial population of northern migrants, as indicated in previous studies by Kwankye et al. (2009) and Adaawen and Owusu (2013). Hence, due to budgetary and time constraints in this research, these regions were chosen for the field survey in the southern sector.

The study concentrated on communities located in the following areas: Kumasi Metropolis in the Ashanti Region, Accra Metropolis in the Greater Accra Region, and Techiman Municipal, as well as Kintampo North Municipal in the Bono East Region (formerly part of the Brong Ahafo Region). These chosen communities encompassed several locations, including Makola Market and Agbogloshie Market within the Accra Metropolis, Kejetia/Adum, and the Central Market Areas within Kumasi Metropolis, as well as the Techiman Market, Techiman Zongo, Kintampo lorry park, and Babatokuma yam market within the Techiman and Kintampo North Municipals, respectively.

The survey, which focused on the northern region of Ghana, was conducted in September 2021. For this study, specific locations were selected: Tamale Metropolis in the Northern Region, Wa Municipal in the Upper West Region, and Bole District in the Savannah Region. These selections were based on the results of field data analysis conducted on migrants in southern Ghana. It was found that most of the respondents from the survey conducted in the south had migrated from these three districts. Additionally, most migrants interviewed in the south had previously worked as farmers before moving from the north (please refer to section 5.3.1, Table 5.6). As a result, households in communities where agriculture was the primary occupation were targeted. Household heads in communities such as Bilpela and Yonk Dapkemyili in Tamale Metropolis, Jonga, Danko, and Busa in Wa Municipal, as well as Kilampobile, Jakala, and Lampoga in Bole district, were purposively selected for interviews. Furthermore, key informants in these three districts were also interviewed.

All respondents were contacted in person using smartphones, and their responses were sent to a central server for analysis. Trained indigenous field assistants, particularly in the north, conducted the surveys to ensure effective communication. An integrated approach was adopted by analysing the qualitative and quantitative results to assess Ghana's main drivers of North-South Migration.

5.2.3 Sampling Strategies for Data Collection

A mixed-method approach involving qualitative and quantitative methods was used for data collection (Antwi-Agyei et al., 2018; Salifu, 2022).

The study purposively focused on three distinct groups: migrants originally from northern regions who had already relocated to the southern part of Ghana, potential migrants who were household heads, as defined by Antwi-Agyie et al. (2018), and key informants residing in the study districts of northern Ghana.

The selection of communities for the survey of migrants in the southern region (see section 5.2.2) was purposive, focusing on their renown as preferred destinations for individuals from the northern regions (Adaawen and Owusu, 2013). In contrast, the choice of communities for the northern survey was guided by their significance as agricultural hubs.

The snowball sampling method was utilised, with the selection being dependent on the willingness and availability of individuals or household heads to participate in interviews (Awumbila and Ardayfio-Schandorf, 2008). This approach was adopted due to the constraints of time.

Sample size calculations

The equation by Krejcie and Morgan (1970) was used to determine the sample size, as shown in Equation 12.

$$n = \frac{N(\frac{Z^2P(1-P)}{E^2})}{\frac{Z^2P(1-P)}{E^2}+(N-1)} \tag{12}$$

where n= sample size, N=population, Z = z-score and E= margin of error and P=sample proportion.

The sample size for migrants in the south of Ghana

Based on a total population of 718,008 out-migrants (see Table 5.2) in the three selected regions, a sample size of 384 respondents was calculated using equation 12 with a sample proportion of 50%, confidence level of 95%, and margin of error of 5%. However, 402 respondents were considered for the analysis, utilizing the proportional stratified technique, with the three regions serving as strata. With the Regions as strata, the number of respondents for each Region was determined from the number of migrants in each area as follows: 174 for the Ashanti Region, 143 for the Brong Ahafo (Bono, Bono East, and Ahafo regions) Region, and 85 for the Greater Accra Region.

The sample size for households in northern Ghana

The total number of agricultural households in the three selected districts from the 2010 PHC was 21,352, distributed as follows: Tamale Metropolis - 9,251, Wa Municipal - 5,841, and Bole District - 6,260 (GSS, 2012).

Equation 12 was used to calculate a sample size of 378 from 21,352 households, with a confidence level of 95% and an interval of 5%. However, 410 household heads were included in the analysis. The distribution of respondents was achieved using the proportional stratified random sampling technique, resulting in 178 respondents from Tamale, 112 from Wa, and 120 from Bole.

5.3 Results and Discussion

5.3.1 Demographic Patterns and Motivations for North-South Migration in Ghana

In all, 812 respondents consisting of 402 migrants in the south and 410 potential migrants in the north were contacted across the six regions of this study and 15 key informants (1 each from the five departments in each of the three districts). Also, 309 people were reported by household heads to have migrated from the households to the south at the time of the interviews. Out of the 410 respondents in the north, 81, approximately 20%, were non-natives, indicating they migrated to their present communities. Additionally, 64, representing 16% of respondents, had prior migration experience, and 63, accounting for 15%, expressed an immediate desire to migrate to the south of Ghana. This desire can be motivated by non-environmental reasons, such as the desire to be free and independent, like lack of non-farm income opportunities and family conflicts (van der Geest, 2011), but also climate and land-related issues (Azumah and Ahmed, 2023; Sward, 2017).

Table 5.3 Suggested Migration towns of Potential Migrants in Ghana

Destination Towns of Potential Migrants	Number of respondents
Accra	28
Kumasi	12
Techiman	7
Sunyani	2
Kintampo	5
Tarkwa	1
Wenchi	3
Sefwi	3
Obuasi	2

Source: Authors' construction

From Table 5.3, the majority of potential migrants expressed a preference for migrating to the Greater Accra, Ashanti, and Brong Ahafo (Bono, Bono East, and Ahafo) regions as their preferred destinations (Van der Geest, 2011; Schraven and Rademacher-Schulz, 2016; Adaawen, 2017). Analysis of the results from the field survey on migrants in the south revealed that most migrants originated from the Northern Region, followed by the Upper West Region, Savannah Region, Upper East, and North East Regions, respectively (see Table 5.4). This finding contradicts Teye et al. (2019), who indicated that migrants moving across 5 regions, including the Northern Region, are consistently highest in the Upper West and Upper East regions.

Table 5.4 Distribution of migrants by region

Region	Number of Migrants	Percentage per Region
Northern	144	36
North East	47	12
Upper west	93	23
Upper East	49	12
Savannah	69	17

Source: Authors' computation

Districts from the three Regions (Northern, Upper West, and Savannah) with more migrants were selected for the survey in northern Ghana (see Table 5.4). Specifically, 32% of the migrants from the Northern Region had migrated from Tamale Metropolis, 31% of the migrants from the Upper West Region had migrated from Wa Municipal, and 35% of the migrants from the Savannah Region had migrated from Bole District. Consequently, these districts were chosen for the field survey on Potential Migrants and other related studies in this work. The demography and other characteristics of respondents are presented in Tables 5.5 and 5.6 from the field survey respondents. The number of respondents and their corresponding computed percentages (in brackets) are shown in each category.

Table 5.5 Characteristics of Migrants, Potential Migrants, and Household Migrants

Status of respondents		Number of migrants (n=402)	Number of Household heads (n=410)	Number of Potential migrants (n=63)	Number of Household migrants (n=309)
Age (years)	<18	47(11.69	0(0.0)	0(0.0)	15(4.85)
	18-35	199(49.50)	81(19.76)	19(30.16)	213(68.93)
	36-60	109(27.11)	246(60.00)	39(61.90)	80(25.89)
	>60	47(11.69)	83(20.24)	5(7.94)	1(0.32)
Gender	Male	213(52.99)	385(93.90)	62(98.0)	200(64.72)
	Female	189(47.01)	25(6.10)	1(2.0)	109(35.28)
Educational background	No Formal	90(22.39)	287(70.00)	42(67.0)	138(44.66)
	Below JHS	104(25.87)	35(8.54)	7(11.0)	52(16.83)
	JHS	127(31.59)	37(9.02)	6(10.0)	71(22.98)
	SHS	58(14.47)	37(9.02)	6(10.0)	42(13.59)
	Tertiary	23(5.72)	14(3.41)	2(3.0)	6(1.94)

Source: Authors' computation

From Table 5.5, most migrants (50% of 402) were 18 to 35 years old. In contrast, those below 18 and those above 60 accounted for a minority, making up 23.38% of the respondents, indicating that most migrants were youth. Among the 402 migrants in the south, 53% were male, and 47% were female. For household migrants, 65% were male, and 35% were female. These results indicate a shift in migration patterns, with more females now engaging in North-South Migration. These findings are consistent with studies by Hashim (2005) and Sow et al. (2014), indicating that migration from the north to the south, traditionally dominated by adult males, is now witnessing a growing number of women and children. Of the 410 potential migrants in the north, 94% were males, and 6% were females.

Additionally, 63 individuals (comprising 62 males and 1 female), which accounts for 15% of the respondents, indicated their intention to migrate to the south immediately and was subsequently utilized for further analysis. The higher proportion of male household heads can be attributed to the prevalent patrilineal system in northern Ghana (Fuseini and Kalule-Sabiti, 2015), where women seldom become household heads. Regarding education, most migrant respondents (80%) did not have secondary education, and 22% had no formal education. Similar trends were observed for potential and household migrants, indicating that most respondents had lower levels of formal education.

Table 5.6 Respondents' Employment Status

Employment type	Status of respondents	Migrants before migrating (n=402)	Migrants after migrating (n=402)	Household migrants before migrating (n=309)	Potential migrants (n=410)
Farmer	Female	115(28.61)	17(4.23)	35(11.33)	1(2.0)
	Male	151(37.56)	29(7.21)	138(44.66)	62(98.0)
Self-employment	Female	29(7.21)	65(16.17)	5(1.62)	0
	Male	25(6.22)	91(22.64)	15(4.85)	0
Menial Jobs	Female	12(2.99)	60(14.93)	22(7.12)	0
	Male	17(4.23)	60(14.93)	18(5.83)	0
White-Collar-Jobs	Female	4(1.00)	13(3.23)	0(0)	0
	Male	5(1.24)	16(3.98)	3(1.00)	0
Unemployed	Female	28(6.97)	24(5.97)	43(13.92)	0
	Male	15(3.73)	13(3.23	20(6.47)	0
Studying	Female	0(0.0)	9(2.24)	4(1.29)	0
	Male	1(0.25)	5(1.24)	6(1.94)	0

Source: Authors' computation

From Table 5.6, out of the 402 respondents surveyed in the south, a significant majority (266, which accounts for 66%) were engaged in farming before migrating, while the remaining 136 (34%) pursued other occupations. Of the 266 farmers, 57% were males, and 43% were females, indicating a noteworthy level of female participation in farming. 13% of the 402 migrants were self-employed, and 11% were unemployed. However, after migration, 46 individuals (11%) were found to be involved in farming, while the majority (89%) had taken up other jobs.

Among the household migrants, 56% were farmers before migrating, but their household heads could not provide their specific jobs in the migrated towns. Most migrants had resided at their migration destinations for a duration ranging from 10 to 30 years (see Figure 5.2), suggesting that most of them were not seasonal migrants.

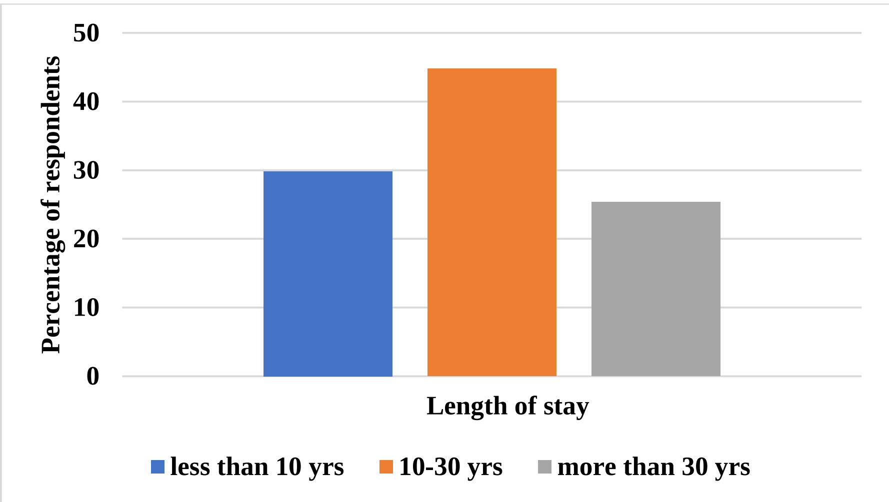


Figure 5.2 Migrants' Duration of Stay
Source: Authors' construction

5.3.2 Analysis of Drivers (Push and Pull factors) of North-South Migration in Ghana

The preliminary surveys of 50 respondents utilising open-ended questions unveiled that climate variability, land use and land cover change, and socio-economic factors significantly impact the migration of people from Northern Ghana to the south of the country. Out of the 50 respondents, 27 were males and 23 females. From the responses of migrants during this field survey and focus group discussions, drivers (push and pull factors) identified are categorised in Table 5.7. Also, their impact on respondents was analysed from the questionnaires.

Table 5.7 Identification of Push and Pull Factors among Migrants and Potential Migrants through Open-Ended Questions

Category	Push and pull factors mentioned	Number of respondents	Impact
Climate variability	reducing rainfall, increasing temperature, increasing drought, good climate	50	Very high
LULCC	scarce fertile farmland, good soil nutrients, good crop yield, available farmland, reducing crop yield, Soil degradation, reduced farmland	42	moderately high
Socio-economic	conflicts, distances to farm, land tenure system, displacement due to disasters, ancestral attachment, employment opportunities, family reasons, farm proximity, no conflicts	38	High

Source: Authors' construction

From Table 5.7, it is evident that all 50 respondents (100%) mentioned various climate-related factors, such as favourable climate conditions, droughts, unpredictable rainfall patterns, and extreme temperature events, as both pull and push factors motivating their migration. Moreover, over 80% of the respondents attributed their migration to LULCC factors, such as limited arable land, rich soil nutrients, available farmland, soil degradation, and reduced farmland, among other factors. Approximately 70% of respondents identified various socio-economic factors that influenced and drove their migration, including conflicts, distances to farms, the land tenure system, displacement caused by disasters, ancestral ties, employment opportunities, etc.

Insights from Open-Ended Questionnaires

According to the study, the dominant factor motivating the migration of most migrants was climate, with a very high level of significance, followed by moderately high importance for LULCC and high relevance for socio-economic-related factors.

5.3.3 Comparative Analysis of Perceptions of Push and Pull Factors of North-South Migration in Ghana

Descriptive analysis involved the computation of means and standard deviations based on the responses obtained from 402 migrants and 63 potential migrants (see Table 5.8).

Table 5.8 Descriptive Statistics for Push Factors among Migrants and Potential Migrants

Descriptive Statistics						
	Migrants			Potential Migrants		
Push factors	Std. Deviation	Mean	Analysis (N)	Std. Deviation	Mean	Analysis (N)
Reducing rainfall	1.06	3.12	402	1.26	2.84	63
Increasing temperature	0.97	3.18	402	1.28	2.71	63
Increasing drought	0.98	3.15	402	1.27	2.76	63
Land tenure system	0.91	1.83	402	1.05	2.32	63
Reducing farmland	0.87	1.77	402	1.08	2.51	63
Soil degradation	0.98	2.72	402	1.10	2.73	63
Reducing crop yield	1.04	2.77	402	1.07	2.78	63
Scarce fertile farmland	N/A	N/A	N/A	1.15	2.43	63
Farm proximity	N/A	N/A	N/A	1.03	2.21	63
Displacement due to disaster	0.84	1.98	402	0.76	1.51	63
Family reasons	0.87	1.85	402	1.14	1.89	63
Conflicts	0.95	2.05	402	1.05	2.08	63

Source: Authors' computation

From Table 5.8, migrants in the south generally had higher means for most factors, suggesting a stronger impact on their migration decision than potential migrants in the north. The standard deviations also indicate some variability in perceptions among both groups, especially for potential migrants.

Regarding land tenure, migrants in the south had a lower mean, indicating a less significant impact on their decision to migrate. However, both groups recognize soil degradation as an essential push factor, with similar mean scores showing a high level of agreement. Potential migrants perceive the scarcity of fertile farmland as a moderate push factor, whereas farm proximity has a lower influence on their migration decision. These findings align with previous research that suggests that dire environmental circumstances tend to encourage migration, even though it is not uniform. Gray (2011) demonstrated that soil quality moderately increases migration in Uganda but dramatically lowers migration in Kenya. Again, there is variability in perceptions regarding fertile farmland among potential migrants. Both groups consider displacement due to disasters and family reasons as push factors, just as Chumky et al. (2022) found in Bangladesh and Black et al. (2013) in Ghana, but the ratings are low compared to other factors.

The study reveals that climate variability-related factors (reducing rainfall, increasing temperature, and increasing drought) have higher means and are the most significant push factors influencing North-South Migration decisions in Ghana. This finding is consistent with the study of Teye and Nikoi (2022), which stipulates that households in some West African communities increasingly use seasonal and permanent migration to deal with climate change and variability. LULCC-related factors (reducing crop yield, soil degradation, scarce fertile farmland, and farm proximity) also have higher means than socio-economic factors (family reasons, displacement due to disasters, and conflicts), except for conflict.

Figure 5.3 provides a graphical representation of perceptions of migrants in the south and potential migrants in the north regarding the primary drivers of their migration to the south.

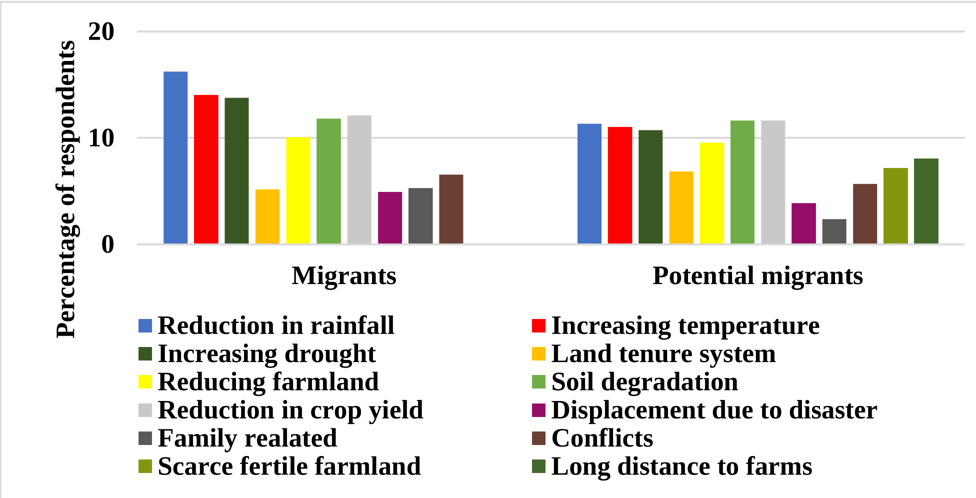


Figure 5.3 Comparing Push Factors between Migrants and Potential Migrants
Source: Authors' construction

The graph supports that climate variability-related factors influence North-South Migration more than other push and pull factors.

Table 5.9 displays the mean of means for the different push factors categorized under climate variability, LULCC, and socio-economic.

Table 5.9 Comparison of Mean of Means for Categorized Push Factors

	The mean of means statistics	
Category of factors	Migrants	Potential migrants
Climate variability	3.15	2.77
LULCC	2.27	2.49
Socio-economic	1.96	1.83

Source: Authors' computation

The findings in Table 5.9 indicate that climate variability is the sector's most significant driver of migration. Both migrants and potential migrants perceive climate variability, including reduced rainfall, increased temperatures, and heightened drought, as influential factors in migrating to the south, as noticed by Khavarian-Garmsir et al. (2019) in Khuzestan. They stipulated that climate and environmental changes, directly and indirectly, influence migrating patterns. Additionally, LULCC factors moderate migration, encompassing changes in land use and land cover, such as reduced farmland availability, scarcity of fertile farmland, soil degradation, and declining crop yield. While not as potent as climate variability, these changes in the physical landscape still contribute to migration decisions. However, socio-economic factors affect migration less than climate variability and LULCC.

Table 5.10 Analysing Descriptive Statistics for Pull Factors Among Migrants and Potential Migrants

Descriptive Statistics						
	Migrants			Potential Migrants		
Pull factors	Std. Deviation	Mean	Analysis (N)	Std. Deviation	Mean	Analysis (N)
Good climate	0.8235	3.42	402	0.856	3.57	63
Available farmland	0.8465	2.706	402	1.069	3.29	63
Employment opportunities	1.0698	3.072	402	0.521	3.62	63
Good soil nutrient	1.0895	3.01	402	1.043	2.9	63
Good crop yield	1.0701	3.067	402	1.164	3	63
Family reasons	0.8077	1.585	402	0.936	1.79	63
Ancestral attachments	0.5254	1.201	402	0.817	1.9	63
No conflicts	1.0379	2.868	402	1.157	2.98	63

Source: Authors' computation

From Table 5.10, collaborated by Figure 5.4, it is evident that both groups consider good climate a crucial pull factor, with potential migrants showing a slightly more positive perception than migrants. The low standard deviation indicates a consistent agreement among both groups regarding the importance of a favourable climate as a pull factor.

Available farmland is also perceived as a significant pull factor by both migrants and potential migrants, with potential migrants rating it even higher than migrants, as Bassie et al. (2022) noted in Northwest Ethiopia. However, the higher standard deviation for potential migrants suggests variations in their perceptions, indicating that not all potential migrants view available farmland equally positively.

Employment opportunities are regarded as an influential pull factor by both migrants and potential migrants, with potential migrants attributing even greater importance to it. Thorn et al. (2022) have also emphasized that employment opportunities serve as a primary driver of migration. The lower standard deviation for potential migrants suggests a higher level of agreement among them regarding the significance of employment opportunities compared to migrants.

Good soil nutrients and good crop yield are recognized as crucial pull factors by both migrants and potential migrants, although potential migrants rate them slightly lower than migrants (Gray, 2011). The standard deviations indicate some variation in the perceptions of both groups regarding the influence of these factors as pull factors.

Family reasons and ancestral attachments are perceived as relatively less influential pull factors by migrants and potential migrants, as Chumky et al. (2022) discussed. Potential migrants rate family reasons slightly higher than migrants but are considered less critical overall. The low standard deviations suggest a consistent perception regarding the limited influence of family reasons and ancestral attachments on migration decisions.

On the other hand, the absence of conflicts is viewed as a moderately influential pull factor by both migrants and potential migrants. When violence is considered in the context of migration motive and opportunity, migration numbers may vary, rising as people perceive or anticipate changes like the conflict (Crippa et al., 2022; Schon, 2019). The mean scores indicate that both groups perceive this factor as having a moderate impact on their migration decisions. The standard deviations suggest some variability in perceptions, with potential migrants exhibiting slightly higher variability than migrants.

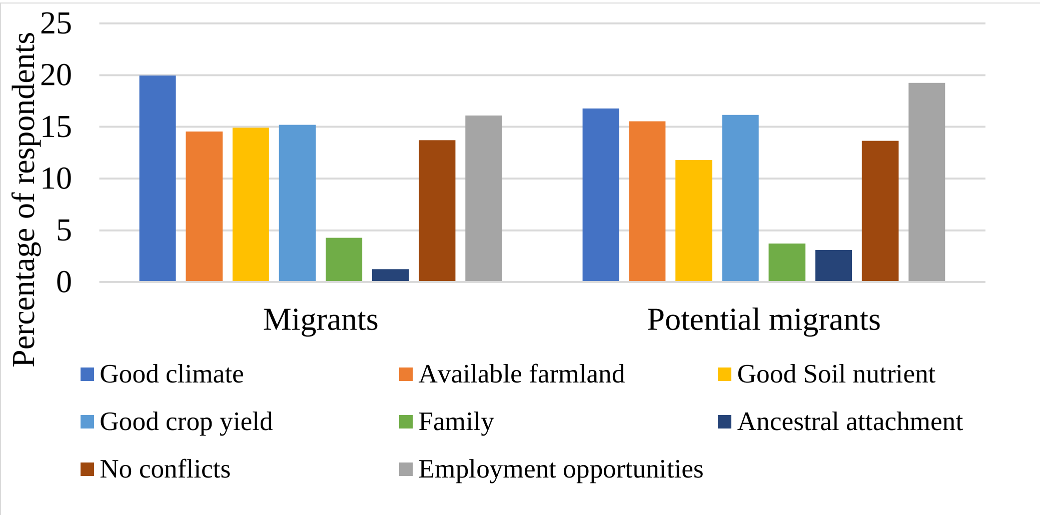


Figure 5.4 Comparing Pull Factors Between Migrants and Potential Migrants
Source: Authors' construction

Overall, the findings suggest that a good climate is the most influential pull factor for migrants. In contrast, potential migrants consider employment opportunities the most critical factor influencing their migration, as depicted in Figure 5.4.

5.3.4 Comprehensive Analysis of Influences of North-South Migration Drivers on Socio-Demographic Characteristics

This section considers the influence of the drivers of migration on the socio-demographic characteristics of migrants, such as gender, age and educational background. The findings show interesting revelations. The percentage influence of push and pull factors on migrants in the south is presented in tables and graphs for further analysis. The results based on gender and age groups are shown in Table 5.11.

Table 5.11 Assessing the Impact of Push Factors on Migrant Gender and Age

	Gender		Age(years)			
Push factors	**Male**	**Female**	**<18**	**18-35**	**36-60**	**> 60**
Reduction in rainfall	81	79	83	77	83	85
Increasing temperature	68	71	64	69	69	79
Increasing drought	71	65	55	67	72	77
Land tenure system	23	29	30	23	24	38
Reducing farmland	26	19	17	22	25	26
Soil degradation	62	57	57	60	58	66
Reduction in crop yield	61	56	51	54	66	68
Displacement due to disaster	23	26	15	27	23	28
Family realated	26	27	15	28	27	28
Conflicts	29	36	34	34	31	26

Source: Authors' computation

The findings from Table 5.11, collaborated by Figure 5.5, indicate that climate variability-related push factors as drivers of migration decisions were highest across gender and age groupings (Warner and Afifi, 2014). It was followed by some LULCC factors (i.e., Soil degradation and reducing crop yield). The socio-economic factors came last, with conflicts showing some significance within the groupings. Rainfall was consistently high within driver categories and socio-demographic groups, with more males citing it than females (Warner and Afifi, 2014). Also, more migrants above 60 cited reducing rainfall and the rest of the push factors, except for conflicts, as push factors responsible for their migration than other age groups.

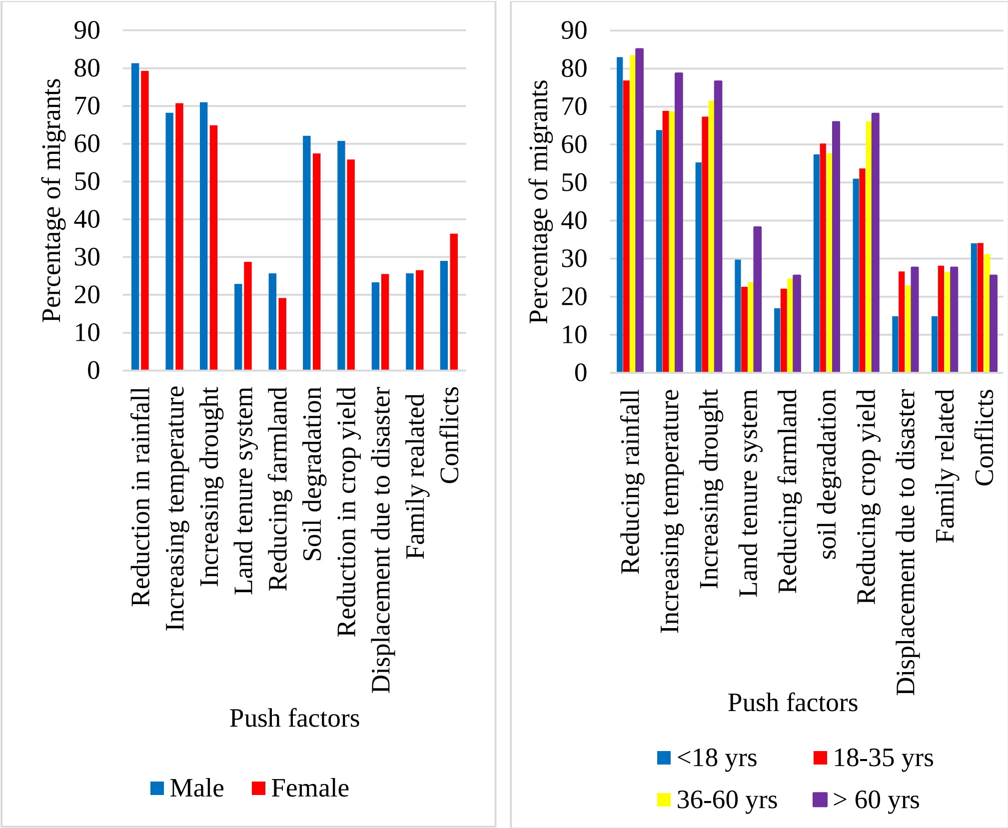


Figure 5.5 Analysis of Migrant Perceptions of Push Factors by Gender and Age Groups
Source: Authors' construction

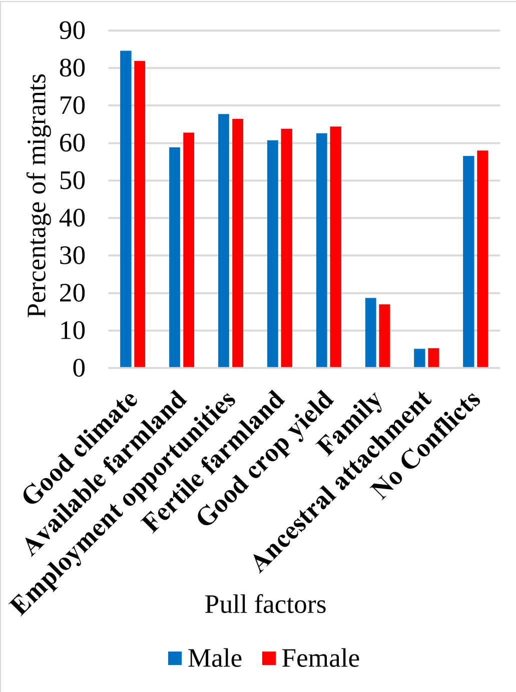
Interestingly, from Table 5.11 and Figure 5.5, more females than males cited increasing temperature, the land tenure system, displacement due to disaster, family reasons, and conflicts as push factors influencing their decision to migrate than males (see segment A of Figure 5.5). Females perceived these factors to impact their migration decisions more than their male counterparts significantly. Also, most migrants in the 36-60 age group attributed their migration to rainfall and LULCC-related drivers. In contrast, more migrants under 35 cited conflicts as the main driver for their migration. Table 5.12 and Figure 5.6 present the influence of pull factors on migrants based on gender and age.

Table 5.12 Impact of Gender and Age on Migrant Perceptions of Pull Factors

	Gender		Age(years)			
Pull factors	**Male**	**Female**	**<18**	**18-35**	**36-60**	**> 60**
Good climate	85	82	87	80	89	81
Available farmland	59	63	49	55	68	81
Employment opportunities	68	66	68	63	71	77
Fertile farmland	61	64	55	57	71	70
Good crop yield	63	64	49	63	67	72
Family	19	17	13	17	20	23
Ancestral attachment	5	5	2	4	10	4
No Conflicts	57	58	62	60	56	45

Source: Authors' computation

From Table 5.12, among migrants in the age category, the primary pull factor for migration was the good climate, while ancestral attachment was considered the least motivating factor for their migration.



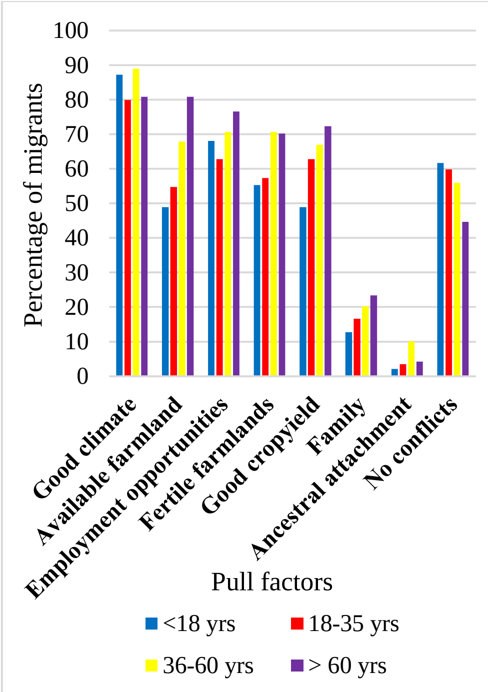


Figure 5.6 Impact of Gender and Age on Migrant Perceptions of Pull Factors
Source: Authors' construction

The influence of 'no conflict' as a motivation as a pull factor of North-South Migration diminished towards older age groups. Most respondents below 18 cited 'no conflict' as a pull factor, while those above 60 had the least consideration for this factor (refer to Table 5.12). The findings also indicate that more female migrants cited the availability of farmland, good crop yield, good soil nutrients, and the absence of conflicts that attracted them to the south of Ghana (see Figure 5.6).

Table 5.13 presents the varied perceptions of migrants regarding push factors of migration, grouped by their educational background and Occupation. As Ackah and Medvedev (2012) affirmed, although a direct correlation between lower education levels and migration likelihood has not been established, migrants may originate from areas with less access to educational resources. The groupings included No formal education (NFE), signifying migrants without formal education. Migrants who only had primary education were considered below JHS (BJHS). Those who progressed to junior and senior high schools are referred to as JHS and SHS, respectively, and those with education above SHS are grouped into Tertiary (T). For the Occupation of migrants before migrating, groupings are as follows: Farmers (F) refers to migrants whose livelihood depended on the cultivation of crops and raising of animals. The Self-employed (SE) are migrants who had their trades before migrating. Those involved in small jobs such as chop bar waters and fufu pounders are in the Menial jobs (MJ) group. White colour jobs (WCJ) refer to those with jobs that earned them regular structured salaries, while the Unemployed (UN) refers to those who had no occupation before migrating.

Table 5.13 Influence of Educational Background and Occupation on Migrant Perceptions of Push Factors

	Educational Background					Occupation before migration				
Push factors	NFE	BJHS	JHS	SHS	T	FM	SE	MJ	WCJ	UE
Reducing rainfall	86	69	95	86	43	91	70	48	67	53
Increasing temperature	72	59	85	72	39	79	48	62	33	53
Increasing drought	67	58	88	74	22	81	41	41	22	51
Land tenure system	28	21	33	28	4	32	13	10	22	14
Reducing farmland	30	18	31	16	0	29	11	10	11	7
soil degradation	76	48	70	55	30	64	50	72	44	42
Reducing crop yield	69	43	72	57	43	65	50	52	44	40
Displacement due to disaster	24	17	37	21	22	26	19	21	44	19
Family related	24	18	38	28	22	29	19	24	44	19
Conflicts	23	29	44	29	39	34	22	21	22	47

Source: Authors' computation

The data from Table 5.13 indicates that migrants with lower levels of education and those engaged in farming tend to have higher perceptions of various push factors. These factors include reductions in rainfall, increasing temperatures, growing drought, soil degradation, and diminishing crop yield. The findings suggest that individuals with lower educational attainment and specific occupations may be more vulnerable to these push factors, which could influence their decision to migrate.

Table 5.14 Influence of Educational Background and Occupation on Migrant Perceptions of Pull Factors

	Educational Background					Occupation before migration				
Pull factors	NFE	BJHS	JHS	SHS	T	FM	SE	MJ	WCJ	UE
Good climate	89	69	99	83	74	86	87	62	89	74
Available farmland	71	49	68	62	48	68	59	28	78	33
Employment opportunities	69	51	80	72	78	67	69	79	67	56
Fertile farmlands	67	50	71	64	70	61	72	69	78	47
Good cropyield	63	50	77	62	83	62	72	62	78	56
Family	19	13	24	22	4	20	19	7	22	9
Ancestral attachment	8	4	6	3	4	6	2	0	11	5
No conflicts	54	51	69	52	61	54	57	69	44	72

Source: Authors' computation

From Table 5.14, migrants with lower educational levels and those engaged in farming, menial jobs and the self-employed have higher perceptions of various pull factors, such as good climate, available land, fertile farmlands, and good crop yield. It suggests that individuals with lower educational attainment and specific occupations are more attracted to environmental and agricultural opportunities as reasons for migration.

5.3.5 Analysis of Regional and District Variations in Migration Drivers in Northern Ghana

This section discusses the significance of the factors influencing migrants from the five different regions in the north, namely, the Northern Region (NR), North East Region (NER), Upper West Region (UWR), Upper East Region (UER), and Savannah Region (SR), as well as the three selected districts (Tamale, Wa, and Bole).

Table 5.15 Influence of Push Factors on Migrants from Various Regions and Districts in the North

	Region					District		
Push factors	**NR**	**NER**	**UWR**	**UER**	**SR**	**Tamale**	**Wa**	**Bole**
Reducing rainfall	76	83	80	86	84	87	94	92
Increasing temperature	69	70	70	69	70	78	76	62
Increasing drought	67	66	70	71	68	73	76	65
Land tenure system	22	17	28	27	35	22	30	46
Reducing farmland	19	21	25	22	28	20	21	31
Soil degradation	61	53	62	57	61	67	64	69
Reducing crop yield	56	53	60	65	61	56	61	73
Displacement due to disaster	22	36	30	20	16	31	52	8
Family related	24	43	31	20	17	31	52	8
Conflicts	47	21	26	27	23	44	30	23

Source: Authors' computation

The findings indicate that decreases in rainfall, rising temperatures, and increasing drought conditions are widely recognized as significant push factors across all Regions. The land tenure system and reduced available farmland are also acknowledged as influential push factors. However, regional and district-level variations exist (see Figures 5.7 and 5.8).

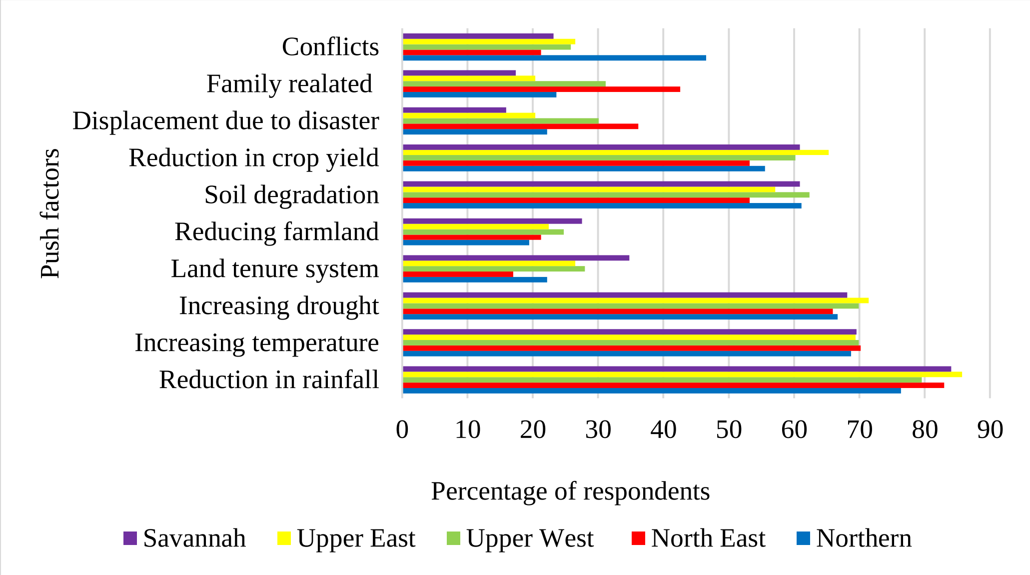


Figure 5.7 Distribution of Regional Migrant Perceptions on Push Factors for Migration
Source: Authors' construction

From Figure 5.7, climate variability factors such as reducing rainfall, temperature, drought, and LULCC-related aspects like soil degradation and crop yield were identified as highly significant drivers of migration, as found by Khavarian-Garmsir et al. (2019). When comparing the regions, most migrants from the Upper East region cited rainfall as the primary factor (Azumah and Ahmed, 2023), followed by those from the Savannah, North East, Upper West, and Northern regions, respectively.

On the other hand, a higher percentage of migrants in the North East region identified increasing temperature as a significant factor, followed by those from the Upper East, Upper West, Savannah, and Northern regions, respectively. Regarding drought-related migration, the Upper East Region had the highest relative percentage, followed by the Upper West region, Savannah, Northern, and North East regions. Furthermore, migrants from the Northern region and the Tamale metropolis showed the highest perception of conflicts as a push factor.

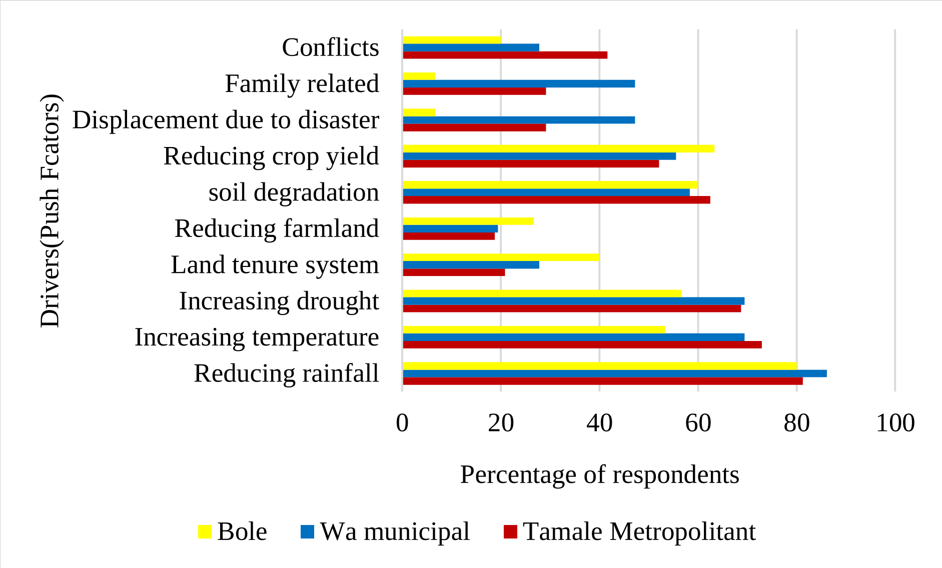


Figure 5.8 Push Factors Propelling Migration in Selected Northern Districts
Source: Authors' construction

From Figure 5.8, at the district level, reasons for migration were related to climate variability factors, followed by LULCC and socio-economic factors. Among the climate variables, reducing rainfall emerged as the dominant factor, particularly in Wa municipal, signifying its significant influence on migration decisions in that district. Interestingly, this finding contrasts with the results from the scientific analysis of climate variability, which indicated a better rainfall trend in Wa compared to the other two districts (see section 3.4.5). This discrepancy could be attributed to most respondents living in their migration destinations for over a decade (see Figure 5.2) and reporting on their experiences at departure. Furthermore, respondents in Wa cited drought, disasters, and family-related reasons for their migration, which might suggest that their livelihoods are negatively affected, given that many are farmers who rely on rain-fed agriculture for survival. Respondents in the Tamale Metropolis attributed their migration reasons to increasing temperature, soil degradation, and conflicts (Crippa et al., 2022; Khavarian-Garmsir et al., 2019; Mueller et al., 2014). On the other hand, those in Bole mentioned the land tenure system, reducing farmland, and decreasing crop yield as the main factors influencing their migration decisions.

Table 5.16 Impact of Pull Factors on Migrants from Various Regions and Districts

	Region					District		
Pull factors	NR	NER	UWR	UER	SR	Tamale	Wa	Bole
Good climate	83	81	84	90	80	89	94	85
Available farmland	57	68	47	84	65	62	61	65
Employment opportunities	65	55	69	80	68	69	76	73
Fertile farmlands	62	62	59	73	59	67	67	65
Good cropyield	67	68	57	71	55	73	67	50
Family	19	17	13	20	20	29	9	23
Ancestral attachment	5	11	5	4	3	4	0	0
No conflicts	61	53	53	57	58	71	61	73

Source: Authors' computation

Table 5.16, Figure 5.9, and Figure 5.10 illustrate the regional and district distribution of pull factors influencing migration in northern Ghana. The data reveals significant variations in the perceptions of pull factors among migrants from different regions and districts. Across all Regions, good climate, available land, and employment opportunities are commonly perceived as significant pull factors. Good soil nutrients and favourable crop yield are also recognized as influential pull factors, although with some regional and district variations.

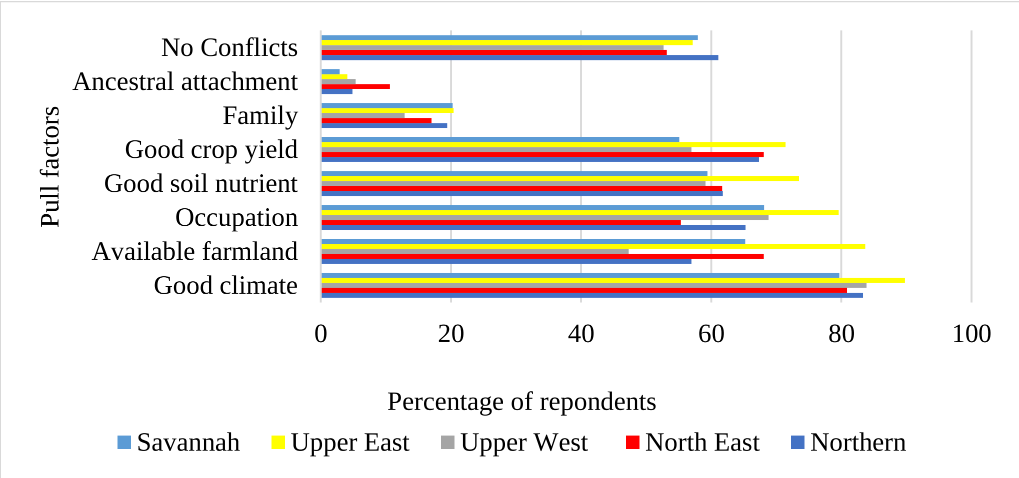


Figure 5.9 Regional Distribution of Migrants' Perceptions Regarding Pull Factors in Migration

Source: Authors' construction

Based on Figure 5.8, the primary pull factor for migration to the south of Ghana among most migrants from the Upper East region is good climate, followed by those from the Upper West, Northern Region, North East, and Savannah Regions, respectively. Additionally, many Upper East migrants mentioned available farmland, fertile farmland, and good crop yield as pull factors for their migration to the south of Ghana compared to migrants from other regions. However, it is interesting to note that most migrants from the Northern Region cited the absence of conflicts as the main pull factor for their migration.

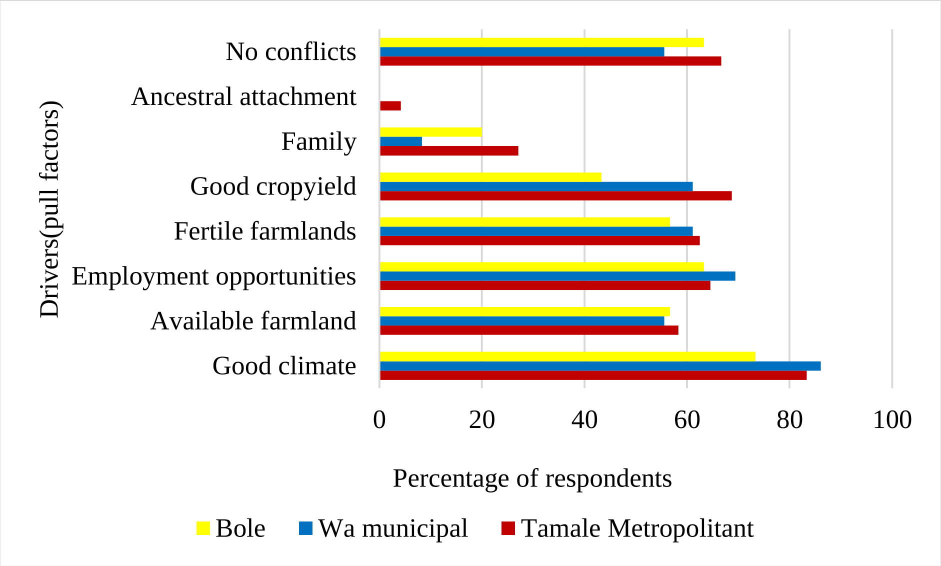


Figure 5.10 Pull Factors Influencing Migration in Selected Northern Districts
Source: Authors' construction

Regarding migrants from the districts, significant pull factors for those from Wa Municipal include good climate and employment opportunities. Conversely, migrants from the Tamale Metropolis mentioned good crop yield and no conflicts as prominent pull factors. Moreover, the absence of conflicts was more significant for migrants from Tamale and Bole than those from Wa, similar to the pattern observed in the Northern and Savannah regions.

5.3.6 Analysing the Complex Dynamics of North-South Migration in Ghana: A Principal Component Analysis Approach

This section employed Principal Component Analysis (PCA), utilizing Varimax with Kaiser Normalization Rotation (VKNR), to evaluate the significance of the identified push and pull factors affecting North-South Migration in Ghana.

The cross-factor loadings obtained through PCA yield insightful perspectives into the underlying forces steering migration concerning the distinct push and pull factors (refer to tables 5.20 and 5.22), aiding in comprehending the intricate interplay among diverse factors influencing migration trends.

Table 5.17 Summary of Case Processing for Push and Pull Factors in North-South Migration

Case Processing Summary					
		Push Factors		**Pull Factors**	
		N	%	N	%
Cases	**Valid**	402	100	402	100
	Excluded	0	0	0	0
	Total	402	100	402	100

Source: Authors' computation

Table 5.17 underscores the completeness and reliability of the dataset used for the study or investigation. The data includes 402 cases and each category's corresponding percentage (%). Both push and pull factors indicate that 402 cases were processed, and all were valid, representing 100% of the cases analysed. No cases were excluded from the analysis, meaning all the available data was considered and evaluated for both Push and Pull Factors.

Table 5.18 KMO and Bartlett's Test for Push and Pull Factors in North-South Migration

KMO and Bartlett's Test			
		Push Factors	**Pull Factors**
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.804	0.657
Bartlett's Test of Sphericity	**Approx. Chi-Square**	824.083	231.219
	df	45	28
	Sig.	0	0
	Determinant	0.038	0.082

Source: Authors' computation

Table 5.18 provides the KMO, which assesses the adequacy of the data for factor analysis and chi-square values for Bartlett's Test, which are used to determine whether the variables in the dataset are correlated and suitable for factor analysis (Kudeshia et al., 2016; Oh, et al., 2020). From the table, the high KMO value and significant Bartlett's Test support the appropriateness of conducting factor analysis on the dataset (Kudeshia et al., 2016).

The total variance explained by push factors

The analysis of the total variance acquired for push factors is presented in Table 5.19.

Table 5.19 Total Variance Explained by Push Factors in North-South Migration

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% Variance	Cumulative %	Total	% Variance	Cumulative %	Total	% Variance	Cumulative %
1	3.20	31.99	31.99	3.20	31.99	31.99	2.81	28.12	28.12
2	1.25	12.46	44.45	1.25	12.46	44.45	1.44	14.44	42.55
3	1.09	10.87	55.32	1.09	10.87	55.32	1.29	12.78	55.32
4	0.97	9.74	65.07						
5	0.81	8.07	73.14						
6	0.78	7.84	80.98						
7	0.62	6.16	87.14						
8	0.52	5.19	92.33						
9	0.40	4.02	96.36						
10	0.36	3.64	100.00						

Source: Authors' computation

Table 5.19 reveals that Component 1 accounted for a more significant proportion (32%) of the total variance, followed by Component 2 (12%). This highlights the significance of the first two components, which collectively explain 44.452% of the total variance.

Cross-factor loadings of Push factors

The analysis of the cross-factor loading results obtained for push factors, as presented in Table 5.20, underscores the interplay of three components with factors extracted under them.

Table 5.20 Cross-Factor Loadings of Push Factors in North-South Migration

Items	Climate-related	LULCC	Social
Reducing rainfall	0.785	0.073	-0.052
Increasing temperature	0.831	0.036	-0.069
Increasing drought	0.841	0.054	0.022
Land tenure system	-0.043	0.814	-0.079
Reducing farmland	0.319	0.685	0.093
Soil degradation	0.465	0.353	0.191
Reducing crop yield	0.589	0.335	0.214
Displacement due to disaster	0.361	0.204	0.387
Family reasons	0.004	-0.118	0.736
Conflicts	-0.04	0.093	0.694

Source: Authors' computation

From Table 5.20, the elements loading in the first component are climate-related. This component significantly influences the decision to migrate, with drought being the primary driver. Temperature dominated rainfall as a driver of North-South Migration, consistent with studies by Thiede et al. (2016), which revealed that temperature changes tend to have more robust effects on migration than rainfall changes. Reducing rainfall can lead to increasing temperatures and result in drought severity increases. These findings align with results from the scientific analysis of climate variability trends in this study (see sections 3.4.5 and 3.4.7) and other studies confirming decreasing rainfall, increasing temperatures and a corresponding increase in drought severity in northern Ghana. These negatively impact crop yield, causing a reduction and, hence, the people's livelihoods and ultimately driving them out (Isaacman et al., 2018).

In the second component, the Land tenure system had a substantial loading in indicating its categorization as a key LULCC factor influencing North-South Migration. From the focus group discussions, most respondents attributed land ownership in the north to the family land tenure system (See section 4.3.5). As a result, owning land is problematic since the family is increasing. It hinders the people's access to and utilization of land, motivating them to migrate to places (usually the South) where they think they can have more favourable land rights. Also, due to the patrilineal family system (Fuseini and Kalule-Sabiti, 2015) practised in northern Ghana, women are the most affected, as revealed in section 5.3.5. In addition to the problems associated with land rights, arable farmlands are reducing due to LULCC. When arable farmlands are reduced, the people's livelihood gets affected, thus driving them to migrate to regions with more arable farmland (Van der Geest, 2011).

The factor loadings in the last component relate to social factors that can impact the North. Family-related reasons significantly influence North-South Migration. The responses from migrants during FGDs underscore the importance of family-related challenges, such as young adults seeking independence from parents as playing a crucial role in their migration decisions (Kwankye et al., 2009). Also, the responses from some migrants (FGDs) revealed that their movement to the south was in search of safety and stability since some parts of the north of Ghana have consistently been saddled with conflicts. Indeed, it is widely acknowledged that many regions in northern Ghana are susceptible to conflicts (Tonah, 2012; Mbowura, 2014). For instance, there have been numerous enduring disputes, including but not limited to the Dagbon crisis, the Konkomba Nanumba war, chieftaincy conflicts in Bawku, and succession disputes among the Dagara of Nandom which have led to the flight of women and young adults seeking safety (Tonah, 2012; Mbowura, 2014). Further to the loss of lives and property, these conflicts disrupt economic and sociocultural activities and result in the displacement of people (Tonah, 2012; Mbowura, 2014). In summary, the data from the PCA on push factors presented in Table 5.20 indicates that climate-related factors are the primary drivers of North-South Migration, followed by LULCC-related factors. In terms of what propels migration, socio-economic factors rank the lowest.

The total variance explained by pull factors

Table 5.21 Total Variance Explained by Pull Factors in North-South Migration

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% Variance	Cumulative %	Total	% Variance	Cumulative %	Total	% Variance	Cumulative %
1	1.99	24.89	24.89	1.99	24.89	24.89	1.86	23.30	23.30
2	1.07	13.38	38.27	1.07	13.38	38.27	1.16	14.54	37.85
3	1.07	13.34	51.61	1.07	13.34	51.61	1.10	13.77	51.61
4	.98	12.24	63.86						
5	.92	11.52	75.37						
6	.80	9.94	85.32						
7	.64	7.98	93.30						
8	.54	6.70	100.00						

Source: Authors' computation

From Table 21, components 1,2 and 3 explain 51.612% of the total variance, with component 1 giving a greater explanation than the other two.

PCA factor loadings on Pull factors

Table 5.22 presents factor loadings obtained and categorized into three components.

Table 5.22 Factor Loadings for Pull Factors in Migration

Items	Climate and LULCC	Social	Economic
Good climate	0.668	0.122	-0.081
Available farmland	0.761	0.183	-0.074
Employment opportunities	0.012	0.003	0.861
Good soil nutrient	0.680	-0.131	0.323
Good crop yield	0.473	0.230	0.296
Family reasons	0.092	0.782	-0.194
Ancestral attachments	0.067	0.619	0.238
No conflicts	-0.373	0.222	0.249

Source: Authors' computation

The initial component reveals the interconnectedness between climate and land-related factors, illustrating their combined influence on migration decisions. Given that agriculture constitutes the primary livelihood for individuals in northern Ghana, a lack of a favourable climate and fertile farmlands drives them to seek better opportunities elsewhere (Van der Geest, 2011; Jha et al., 2018). Consequently, a positive environment, suitable climate, and fertile land significantly impact the migration from north to south, as noted by the study Thet (2014). They suggest regions with favourable climates can allure migrants to improved living conditions, agricultural prospects, and overall environmental comfort (Imoro, 2017; García Fernández and Peek, 2023; Thorn et al., 2023). In discussions held during focus groups in northern Ghana, farmers indicated that areas with abundant fertile farmland hold appeal due to their potential for enhanced agricultural prospects and livelihood opportunities and, hence, have a greater pull on them, as Imoro (2017) noted in his study.

In contrast, components two and three highlight socio-economic factors as pivotal pull factors of North-South Migration in Ghana. This finding is corroborated by the International Water Management Institute (2018) and the study of Teye et al. (2019).

Family-related reasons and Employment opportunities were represented in components 2 and 3. These extracted components signify their varied roles as attractions for northern migrants, as related by Thet (2014). When uncertainties arising from weather conditions and loss of arable land due to LULCC changes jeopardize the livelihood of residents of the north, seeking better prospects becomes more appealing. Similarly, as conflicts compel some migrants to leave, the allure of a secure and stable environment gains prominence.

From the PCA analysis on pull factors of North-South Migration, it can be seen that contrary to push factors, socio-economic factors attract northern migrants to the south than the push factor counterparts. These results agree with Tanner (2014), who found in his study that pull is more important than push, especially existing diasporas and the welfare state.

5.4 Conclusion

Climate and LULCC are more significant push factors driving North-South Migration than socio-economic factors. These environmental and land-related influences have a more substantial impact on migration decisions in the region.

Socio-economic factors in southern Ghana hold greater significance in attracting migrants compared to pushing them from northern Ghana.

5.5 Recommendations

Policymakers and stakeholders should develop targeted interventions and policies that address the identified push factors, such as climate-related challenges and socio-economic hardships in the northern regions.

Sustainable land management practices and climate adaptation strategies should be implemented to mitigate the impact of climate variability on migration decisions.

Efforts to enhance educational and employment opportunities in the northern regions can help reduce migration driven by economic considerations.

Policymakers should consider the importance of environmental factors, including good climate and farmland availability, in attracting migrants to the south and focus on promoting sustainable land use practices and agricultural opportunities.

CHAPTER SIX

CONCLUSIONS, RECOMMENDATIONS, POLICY INTERVENTIONS, LIMITATIONS AND FUTURE RESEARCH.

6.1 Introduction

This research offered an integrated analysis of climate variability, LULCC, and North-South Migration patterns in Ghana, focusing on the vulnerable northern regions. By examining the drivers of migration through climate variability trend analysis, LULCC mapping, and perception surveys, the study sheds light on the complex interplay between climate, land-related, and socio-economic factors influencing North-South Migration decisions.

The research used an integrated analysis to investigate the intricate relationships among climate variability, LULCC, and North-South Migration patterns in Ghana. The complex interplay of environmental and societal factors was explored through objective and subjective approaches.

Three specific objectives guiding the investigation were formulated. Firstly, the spatio-temporal patterns of climate variability in northern Ghana were examined. By integrating objective data analysis and subjective perspectives, a comprehensive understanding of the evolution of climatic conditions and their potential implications for the region's ecosystems and communities was gained. Secondly, the changes in northern Ghana's land use and land cover patterns were evaluated. Both objective and subjective viewpoints were considered to capture the multifaceted nature of human-environment interactions in shaping the landscape.

Lastly, the perception of climate variability and LULCC as critical factors influencing North-South Migration in Ghana was assessed in conjunction with other push and pull factors. By exploring the human dimension of migration decisions and considering the broader context of environmental changes, the underlying drivers that influence North-South Migration patterns within Ghana were uncovered.

The objectives were addressed by formulating three research questions. Firstly, the trend of climate variability in northern Ghana from 1990 to 2020 was uncovered, relying on historical climate data to identify potential patterns and shifts in the region's climatic conditions. It allowed gaining insights into the environmental dynamics that may have influenced land use decisions and migration patterns.

Secondly, the pattern of LULCC in northern Ghana was investigated. Through meticulous analysis and on-the-ground assessments, the transformations in the landscape and how human activities have contributed to these changes over time were understood.

Lastly, the significance of climate variability and LULCC as drivers of North-South Migration in Ghana was comprehended. The complexities of migration dynamics in the country were grasped by integrating these environmental factors with other socio-economic and demographic factors.

6.2 Conclusions and Recommendations

6.2.1 Conclusions on Climate Variability in Northern Ghana

The analysis of climate datasets, including precipitation, maximum and minimum temperatures, revealed consistent monthly variations of precipitation and temperature variables across all years and locations.

Notably, the study revealed a decrease in rainfall, particularly during April and August, which are crucial for the farming season and an increase in temperatures (maximum and minimum) and drought severity in northern Ghana over the last decade.

The perceptions of farmers regarding changes in rainfall patterns, temperature, and drought severity were broadly consistent with scientific analysis. Farmers acknowledged the shift in rainfall timing and observed increased temperature and drought severity, aligning with the research findings.

6.2.2 Recommendations on Climate Variability in Northern Ghana

Enhance weather data collection and monitoring across the region by installing adequate weather stations and adopting advanced remote sensing technologies by the Ghana Meteorological Agency to improve data accuracy and reliability.

Encourage farmers to adopt climate-smart agriculture practices using drought-resistant crops, irrigation, and soil conservation techniques. Through the Ministry of Agriculture, the government can provide support through subsidies and incentives to facilitate the adoption of these practices.

Given the irregular changes in precipitation and temperature, reinforce disaster preparedness and response mechanisms to reduce the vulnerability of communities to climate-related disasters. The National Disaster Management Organization (NADMO) should be central to this endeavour.

Increase education and awareness about climate change and its impacts by developing climate change education programs in schools and conducting training and awareness-raising activities for community members. Informed and empowered communities can better adapt to changing climatic conditions.

6.2.3 Conclusions on LULCC Patterns in Northern Ghana

There is a significant transformation in land cover, with cropland being the dominant land use that has undergone significant changes, followed by shrub/grassland, woodland, water, and settlement/bare. Notably, there has been a considerable increase in woodland and a progressive decrease in water in the study area.

Cropland, shrub/grassland, and woodland experienced higher conversion rates, with the conversion of cropland into shrub/grassland and woodland, and vice versa, being the significant changes observed.

Most farmers recognise land use and land cover changes and believe these changes negatively affect their crop yields and farmland. They attribute these changes to human activities, underscoring the need for sustainable land management practices to address these challenges.

Climate variability changes do not directly correspond to the conversion of land use and land cover classes. Human activities are the primary drivers of land use and land cover change in the study area.

6.2.4 Recommendations on LULCC Patterns in Northern Ghana

Efforts should be made to promote sustainable land management to mitigate the adverse effects of land use and land cover change on crop yield and livelihoods in the region.

Implementation of land-use planning strategies could help optimise agricultural production and manage the changing land cover dynamics, ensuring long-term sustainability and resilience of farming systems in the study area.

Given the perception of farmers about the impact of land use and land cover change on their crop yield, extension services and capacity-building programs should be organised to educate farmers on climate-smart agriculture and sustainable land use practices that can mitigate the adverse effects of land use and land cover change on agricultural productivity.

To ensure the accuracy and reliability of land use and land cover maps for future studies and decision-making, using classifiers with high overall accuracy and kappa values and considering visual inspection for quality assessment is essential.

6.2.5 Conclusions on Drivers of North-South Migration in Ghana

LULCC and Climate variability are the primary drivers of North-South Migration. These environmental factors have a more significant push impact on migration decisions than socio-economic factors.

In contrast to push factors, socio-economic factors such as economic opportunities and improved living conditions are central in attracting northern migrants to southern regions. These factors act as significant incentives for migration.

Gender plays a crucial role in shaping perceptions of migration factors. Females have distinct perspectives on push and pull factors, highlighting the need for gender-specific approaches in migration-related policies and interventions.

Additionally, individuals with lower educational levels and specific occupations exhibited greater vulnerability to specific push and pull factors.

6.2.6 Recommendations on Drivers of North-South Migration in Ghana

Given the significant influence of climate variability and land use change on North-South Migration, it is crucial to prioritize environmental resilience and adaptation strategies in the northern regions. These strategies could include sustainable land management, water resource conservation, and climate-resilient agriculture to reduce the need for migration due to environmental stressors by government agencies such as MOFA.

Efforts should be made to promote economic development and job creation in the northern areas by the Government of Ghana **to** address the pull factors associated with socio-economic opportunities in southern regions. Investment in infrastructure, skills development, and the diversification of economic sectors can enhance local opportunities and reduce the appeal of migration.

Recognizing the gender-specific perceptions of migration factors, policies and programs should be designed to cater to the unique needs of both male and female migrants. These policies and programs could include ensuring access to education, healthcare, and economic opportunities and addressing gender-based discrimination and violence.

Initiatives should focus on improving educational access and quality in the northern regions to mitigate vulnerabilities related to education and occupation. Vocational training and skill development programs can empower individuals with the skills needed to access better employment opportunities, reducing the vulnerability of specific occupational groups.

Continual data collection and monitoring of migration patterns, including the reasons for migration, can provide valuable insights for policymakers. Regular assessments of the evolving factors influencing migration can inform adaptive policy responses.

Collaboration between local communities, government agencies, and non-governmental organizations is essential for effective policy implementation. Cross-sectoral approaches that integrate environmental, economic, and social considerations can lead to more holistic solutions to migration challenges.

Raising public awareness about the impacts of migration and the opportunities available within the northern regions can help dispel misconceptions and encourage informed decision-making among potential migrants.

6.3 Policy Interventions

Climate-resilient agriculture: Implementing policies and practices that promote climate-smart agriculture techniques, such as crop diversification, water conservation, and soil management, to enhance agricultural resilience in the face of climate variability.

Land-use planning and management: Develop comprehensive land-use plans that consider the potential impacts of LULCC on migration patterns. This can involve regulating land conversions, promoting sustainable land management practices, and identifying areas for conservation and restoration. Integrated planning can help minimize conflicts over land and resources, promote sustainable urbanization, and preserve ecosystems.

Rural development and livelihood diversification: Support programs that promote alternative income-generating activities and livelihood options in rural areas, reducing the dependence on agriculture alone. It can include investments in agro-processing industries, tourism, renewable energy projects, and skill development programs to enhance employment opportunities and improve rural livelihoods.

Enhancing social safety nets: Implement social protection measures and safety nets that support vulnerable populations affected by climate variability, land degradation, and migration. It can include targeted interventions such as cash transfers, insurance schemes, and capacity-building programs to enhance resilience and protect the well-being of affected communities.

Strengthening climate information and early warning systems: Enhance the capacity of local communities and relevant stakeholders to access and utilize climate information and early warning systems. It can enable timely decision-making, adaptation planning, and response strategies to mitigate the impacts of climate variability and reduce the need for migration.

Integrated policy frameworks: Develop integrated policy frameworks that acknowledge the interconnected nature of climate variability, LULCC, and migration. Encourage collaboration among sectors such as agriculture, land management, migration, and climate change to foster coordinated approaches that address the root causes and holistically promote sustainable development.

6.4 Limitations of the Study and Suggestions for Future Research

6.4.1 Availability and Quality of Data

The study relies on historical climate data, satellite data, and perception surveys, which may have limitations regarding accuracy, coverage, and completeness. Inaccurate or incomplete data could impact the findings' robustness and constrain the analysis's depth.

Future studies could focus on improving data collection and quality assurance processes. This could involve establishing more regional weather stations and adopting advanced remote sensing technologies to enhance data accuracy and reliability. Additionally, longitudinal studies that collect data over an extended period could provide a more comprehensive understanding of climate variability and its impact on migration.

6.4.2 More Extensive Qualitative Research

While the chosen Push-Pull theory provides a valuable framework, it may oversimplify the intricate decision-making processes. Capturing the full complexity of these decisions requires more extensive qualitative research and a deeper exploration of individual and community motivations for migration.

Future studies could consider conducting longitudinal studies that track individuals and communities over time to provide insights into how these motivations evolve and influence migration patterns.

6.4.3 Challenges in Land Use Classification Accuracy for Settlements

The land use maps generated in this study revealed an unexpected decreasing trend of the settlement/bare class across epochs in the land use maps. This decrease may be due to potential misclassification from factors such as the quality of the utilized images and the unique nature of built-up areas in the study area. Consequently, this limitation affects the reliability of the calculated settlement sizes in accurately representing their real-world dimensions.

Future research can enhance the reliability of land use classifications by employing higher-resolution imagery, diversifying training samples, and implementing advanced machine learning algorithms. Collaboration with local experts and the integration of ancillary data can further improve the accuracy of land use mapping.

APPENDICES

Appendix 1A: Computations of aired t-Test of GMet and satellite datasets

t-Test for 1990 precipitation Wa

	1990_Gmet	1990_Satellite
Mean	75.525	73.34104
Variance	7161.837	5422.85
Observations	12	12
Pearson Correlation	0.956746	
Hypothesized Mean Difference	0	
Df	11	
t Stat	0.294519	
P(T<=t) one-tail	0.386922	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.773845	
t Critical two-tail	2.200985	

t-Test for 1990 precipitation Tamale

	1990_Gmet	1990_satellite
Mean	94.15	81.18732
Variance	8359.765	6740.808
Observations	12	12
Pearson Correlation	0.844559	
Hypothesized Mean Difference	0	
df	11	
t Stat	0.912662	
P(T<=t) one-tail	0.190494	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.380988	
t Critical two-tail	2.200985	

t-Test for 1990 precipitation Bole

	1990_Gmet	1990_satellite
Mean	125.7417	84.53896
Variance	23671.19	5364.778
Observations	12	12
Pearson Correlation	0.495333	
Hypothesized Mean Difference	0	
df	11	
t Stat	1.067648	
P(T<=t) one-tail	0.154275	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.30855	
t Critical two-tail	2.200985	

t-Test for 2000 precipitation Wa

	2000_Gmet	2000_Satellite
Mean	95.1	83.2318
Variance	8596.705	5981.108
Observations	12	12
Pearson Correlation	0.932043	
Hypothesized Mean Difference	0	
df	11	
t Stat	1.181339	
P(T<=t) one-tail	0.131189	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.262379	
t Critical two-tail	2.200985	

t-Test for 2000 precipitation Tamale

	2000_Gmet	2000_Satellite
Mean	85.33333	100.6128
Variance	7751.488	11173.3
Observations	12	12
Pearson Correlation	0.883444	
Hypothesized Mean Difference	0	
df	11	
t Stat	-1.06256	
P(T<=t) one-tail	0.155377	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.310753	
t Critical two-tail	2.200985	

t-Test for 2000 precipitation Bole

	2000_Gmet	2000_Satellite
Mean	102.1917	83.55831
Variance	7270.261	5554.301
Observations	12	12
Pearson Correlation	0.841833	
Hypothesized Mean Difference	0	
df	11	
t Stat	1.400075	
P(T<=t) one-tail	0.094529	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.189059	
t Critical two-tail	2.200985	

t-Test for 2010 precipitation Wa

	2010_Gmet	2010_Satellite
Mean	86.01667	89.33058
Variance	9220.252	7996.279
Observations	12	12
Pearson Correlation	0.851957	
Hypothesized Mean Difference	0	
df	11	
t Stat	-0.22575	
P(T<=t) one-tail	0.412768	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.825536	
t Critical two-tail	2.200985	

t-Test for 2010 precipitation Tamale

	2010_Gmet	2010_Satellite
Mean	108.9	113.6229
Variance	11451.81	11442.69
Observations	12	12
Pearson Correlation	0.843053	
Hypothesized Mean Difference	0	
df	11	
t Stat	-0.27293	
P(T<=t) one-tail	0.39498	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.78996	
t Critical two-tail	2.200985	

t-Test for 2010 precipitation Bole

	2010_Gmet	2010_Satellite
Mean	116.9667	99.64535
Variance	15799.24	7423.252
Observations	12	12
Pearson Correlation	0.845356	
Hypothesized Mean Difference	0	
df	11	
t Stat	0.856079	
P(T<=t) one-tail	0.205107	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.410215	
t Critical two-tail	2.200985	

t-Test for 2020 precipitation Wa

	2020_Gmet	2020_Satellite
Mean	96.05	84.35864
Variance	11567.21	6695.141
Observations	12	12
Pearson Correlation	0.905368	
Hypothesized Mean Difference	0	
df	11	
t Stat	0.83949	
P(T<=t) one-tail	0.209533	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.419066	
t Critical two-tail	2.200985	

t-Test for 2020 precipitation Tamale

	2020_Gmet	2020_Satellite
Mean	86.89167	88.80731
Variance	5826.055	7420.034
Observations	12	12
Pearson Correlation	0.913022	
Hypothesized Mean Difference	0	
df	11	
t Stat	-0.18845	
P(T<=t) one-tail	0.426978	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.853957	
t Critical two-tail	2.200985	

t-Test for 2020 precipitation Bole

	2020_Gmet	2020_Satellite
Mean	80	77.41667
Variance	5046.909	4758.992
Observations	12	12
Pearson Correlation	0.833457	
Hypothesized Mean Difference	0	
df	11	
t Stat	0.221206	
P(T<=t) one-tail	0.414493	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.828985	
t Critical two-tail	2.200985	

t-Test for 1990 Maximum Temperature Wa

	1990_Gmet	1990_Satellite
Mean	33.975	32.36648
Variance	7.572955	6.786968
Observations	12	12
Pearson Correlation	0.981083	
Hypothesized Mean Difference	0	
df	11	
t Stat	10.29813	
P(T<=t) one-tail	2.75E-07	
t Critical one-tail	1.795885	
P(T<=t) two-tail	5.51E-07	
t Critical two-tail	2.200985	

t-Test for 1990 Maximum Temperature Tamale

	1990_Gmet	1990_satellite
Mean	34.49167	33.28456
Variance	7.862652	7.412576
Observations	12	12
Pearson Correlation	0.991275	
Hypothesized Mean Difference	0	
df	11	
t Stat	11.18174	
P(T<=t) one-tail	1.2E-07	
t Critical one-tail	1.795885	
P(T<=t) two-tail	2.4E-07	
t Critical two-tail	2.200985	

t-Test for 1990 Maximum Temperature Bole

	1990_Gmet	1990_satellite
Mean	33.15	31.99424
Variance	8.03	8.597692
Observations	12	12
Pearson Correlation	0.962116	
Hypothesized Mean Difference	0	
df	11	
t Stat	5.007537	
P(T<=t) one-tail	0.000199	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.000398	
t Critical two-tail	2.200985	

t-Test for 2000 Maximum Temperature Wa

	2000_Gmet	2000_Satellite
Mean	33.56667	32.66807
Variance	6.973333	7.368948
Observations	12	12
Pearson Correlation	0.979416	
Hypothesized Mean Difference	0	
df	11	
t Stat	5.677924	
P(T<=t) one-tail	7.14E-05	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.000143	
t Critical two-tail	2.200985	

t-Test for 2000 Maximum Temperature Tamale

	2000_Gmet	2000_Satellite
Mean	34.18333	33.383
Variance	8.339697	7.153076
Observations	12	12
Pearson Correlation	0.956839	
Hypothesized Mean Difference	0	
df	11	
t Stat	3.285121	
P(T<=t) one-tail	0.003634	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.007267	
t Critical two-tail	2.200985	

t-Test for 2000 Maximum Temperature Bole

	2000_Gmet	2000_Satellite
Mean	32.975	32.33363
Variance	7.4275	7.69971
Observations	12	12
Pearson Correlation	0.973322	
Hypothesized Mean Difference	0	
df	11	
t Stat	3.487104	
P(T<=t) one-tail	0.002542	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.005084	
t Critical two-tail	2.200985	

t-Test for 2010 Maximum Temperature Wa

	2010_Gmet	2010_Satellite
Mean	34.50833	33.83325
Variance	9.989924	10.93763
Observations	12	12
Pearson Correlation	0.981572	
Hypothesized Mean Difference	0	
df	11	
t Stat	3.666901	
P(T<=t) one-tail	0.001855	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.00371	
t Critical two-tail	2.200985	

t-Test for 2010 Maximum Temperature Tamale

	2010_Gmet	2010_Satellite
Mean	34.58333	34.03048
Variance	10.69242	9.408486
Observations	12	12
Pearson Correlation	0.984079	
Hypothesized Mean Difference	0	
df	11	
t Stat	3.190003	
P(T<=t) one-tail	0.004303	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.008606	
t Critical two-tail	2.200985	

t-Test for 2010 Maximum Temperature Bole

	2010_Gmet	2010_Satellite
Mean	33.675	33.21667
Variance	9.962045	8.225902
Observations	12	12
Pearson Correlation	0.992189	
Hypothesized Mean Difference	0	
df	11	
t Stat	3.351062	
P(T<=t) one-tail	0.003233	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.006465	
t Critical two-tail	2.200985	

t-Test for 2020 Maximum Temperature Wa

	2020_Gmet	2020_Satellite
Mean	34.11667	33.68954
Variance	10.12152	11.10749
Observations	12	12
Pearson Correlation	0.987819	
Hypothesized Mean Difference	0	
df	11	
t Stat	2.790147	
P(T<=t) one-tail	0.008791	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.017582	
t Critical two-tail	2.200985	

t-Test for 2020 Maximum Temperature Tamale

	2020_Gmet	2020_Satellite
Mean	34.95	34.10197
Variance	9.871818	9.202102
Observations	12	12
Pearson Correlation	0.94247	
Hypothesized Mean Difference	0	
df	11	
t Stat	2.790312	
P(T<=t) one-tail	0.008788	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.017577	
t Critical two-tail	2.200985	

t-Test for 2020 Maximum Temperature Bole

	2020_Gmet	2020_Satellite
Mean	33.41667	33.52607
Variance	10.26515	9.104018
Observations	12	12
Pearson Correlation	0.950271	
Hypothesized Mean Difference	0	
df	11	
t Stat	-0.37968	
P(T<=t) one-tail	0.355705	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.71141	
t Critical two-tail	2.200985	

t-Test for 1990 Minimum Temperature Wa

	1990_Gmet	1990_Satellite
Mean	22.6	22.83147
Variance	2.087273	1.785025
Observations	12	12
Pearson Correlation	0.994547	
Hypothesized Mean Difference	0	
df	11	
t Stat	-4.42292	
P(T<=t) one-tail	0.000512	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.001024	
t Critical two-tail	2.200985	

t-Test for 1990 Minimum Temperature Tamale

	1990_Gmet	1990_satellite
Mean	23.03333	23.90449
Variance	2.486061	1.011361
Observations	12	12
Pearson Correlation	0.845218	
Hypothesized Mean Difference	0	
df	11	
t Stat	-3.33875	
P(T<=t) one-tail	0.003304	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.006608	
t Critical two-tail	2.200985	

t-Test for 1990 Minimum Temperature Bole

	1990_Gmet	1990_satellite
Mean	21.24167	22.48932
Variance	1.919015	1.081519
Observations	12	12
Pearson Correlation	0.831658	
Hypothesized Mean Difference	0	
df	11	
t Stat	-5.55981	
P(T<=t) one-tail	8.51E-05	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.00017	
t Critical two-tail	2.200985	

t-Test for 2000 Minimum Temperature Wa

	2000_Gmet	2000_Satellite
Mean	22.53333	22.44167
Variance	2.769697	3.581587
Observations	12	12
Pearson Correlation	0.923301	
Hypothesized Mean Difference	0	
df	11	
t Stat	0.434042	
P(T<=t) one-tail	0.336324	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.672649	
t Critical two-tail	2.200985	

t-Test for 2000 Minimum Temperature Tamale

	2000_Gmet	2000_Satellite
Mean	22.95833	23.57477
Variance	4.355379	3.532908
Observations	12	12
Pearson Correlation	0.930227	
Hypothesized Mean Difference	0	
df	11	
t Stat	-2.77913	
P(T<=t) one-tail	0.008966	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.017932	
t Critical two-tail	2.200985	

t-Test for 2000 Minimum Temperature Bole

	2000_Gmet	2000_Satellite
Mean	20.275	22.30916
Variance	3.565682	1.953936
Observations	12	12
Pearson Correlation	0.914063	
Hypothesized Mean Difference	0	
df	11	
t Stat	-8.45718	
P(T<=t) one-tail	1.92E-06	
t Critical one-tail	1.795885	
P(T<=t) two-tail	3.84E-06	
t Critical two-tail	2.200985	

t-Test for 2010 Minimum Temperature for Wa

	2010_Gmet	**2010_Satellite**
Mean	23.375	23.29119
Variance	3.874773	5.876725
Observations	12	12
Pearson Correlation	0.971747	
Hypothesized Mean Difference	0	
df	11	
t Stat	0.420197	
P(T<=t) one-tail	0.341216	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.682432	
t Critical two-tail	2.200985	

t-Test for 2010 Minimum Temperature for Tamale

	2010_Gmet	2010_Satellite
Mean	22.975	24.21769
Variance	7.636591	5.013774
Observations	12	12
Pearson Correlation	0.980435	
Hypothesized Mean Difference	0	
df	11	
t Stat	-5.98695	
P(T<=t) one-tail	4.55E-05	
t Critical one-tail	1.795885	
P(T<=t) two-tail	9.1E-05	
t Critical two-tail	2.200985	

t-Test for 2010 Minimum Temperature for Bole

	2010_Gmet	2010_Satellite
Mean	22.15833	22.98483
Variance	6.631742	3.078388
Observations	12	12
Pearson Correlation	0.967622	
Hypothesized Mean Difference	0	
df	11	
t Stat	-2.91285	
P(T<=t) one-tail	0.007058	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.014117	
t Critical two-tail	2.200985	

t-Test for 2020 Minimum Temperature Wa

	2020_Gmet	2020_Satellite
Mean	22.64167	23.4607
Variance	4.569924	4.547927
Observations	12	12
Pearson Correlation	0.961721	
Hypothesized Mean Difference	0	
df	11	
t Stat	-4.80233	
P(T<=t) one-tail	0.000276	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.000551	
t Critical two-tail	2.200985	

t-Test for 2020 Minimum Temperature Tamale

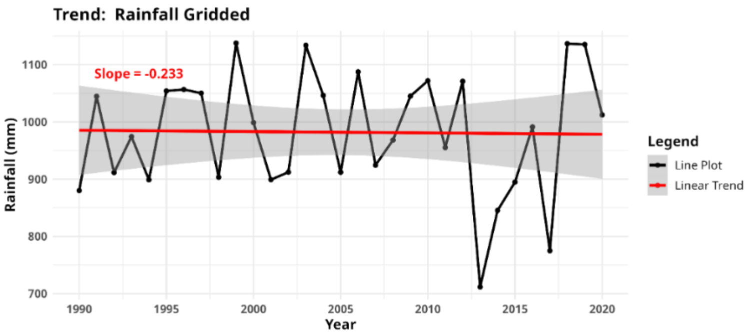
	2020_Gmet	2020_Satellite
Mean	24.10833	24.5064
Variance	3.309924	4.072018
Observations	12	12
Pearson Correlation	0.980559	
Hypothesized Mean Difference	0	
df	11	
t Stat	-3.23058	
P(T<=t) one-tail	0.004004	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.008007	
t Critical two-tail	2.200985	

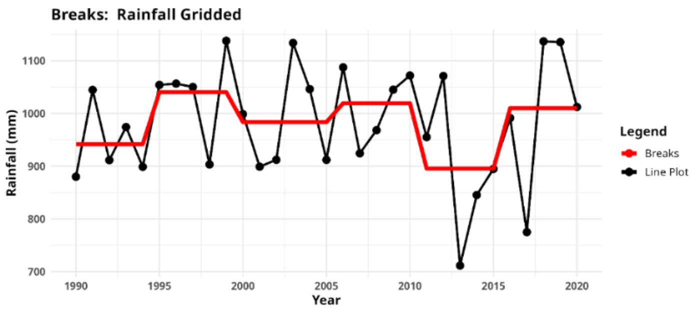
t-Test for 2020 Minimum Temperature Bole

	2020_Gmet	2020_Satellite
Mean	22.25	23.23131
Variance	6.204545	2.067505
Observations	12	12
Pearson Correlation	0.81279	
Hypothesized Mean Difference	0	
df	11	
t Stat	-2.17184	
P(T<=t) one-tail	0.026304	
t Critical one-tail	1.795885	
P(T<=t) two-tail	0.052608	
t Critical two-tail	2.200985	

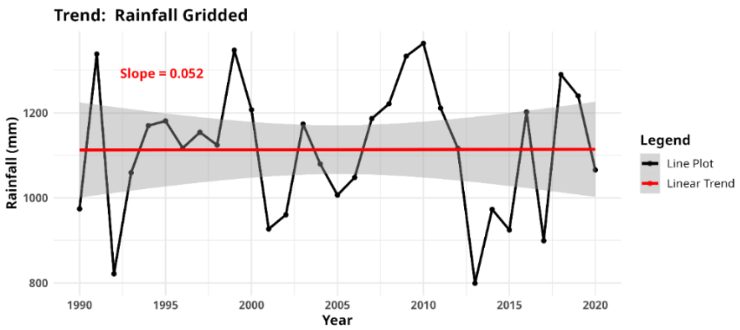
Appendix 1B: Time series plot of precipitation, Maximum, and Minimum Temperatures from GMet and CHIRPS/ERA5 data for all stations

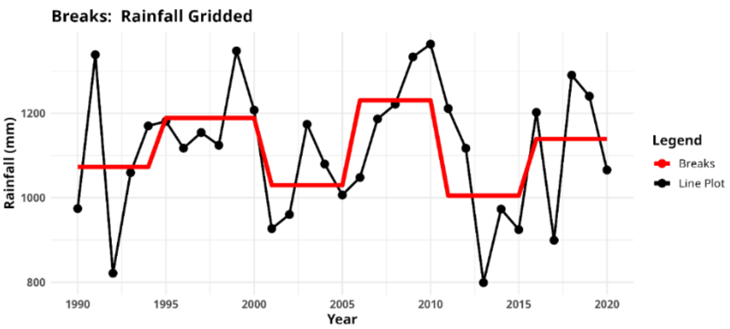
CHIRPS precipitation and breakpoints Wa Municipal



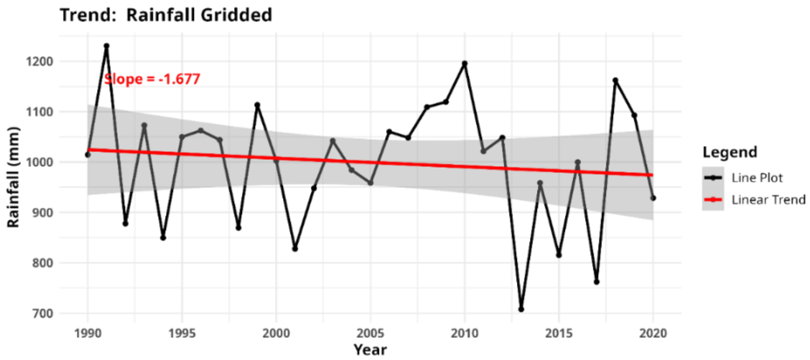


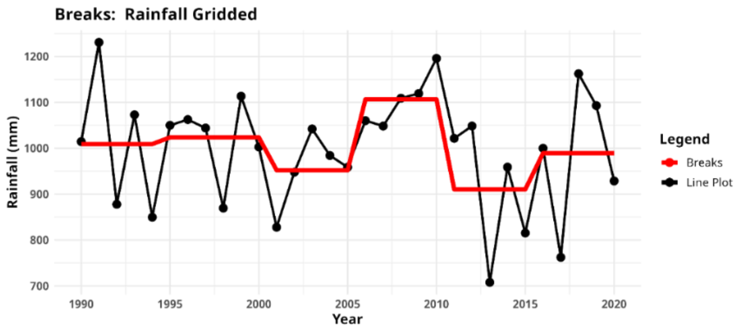
CHIRPS precipitation and breakpoints Tamale Metropolis



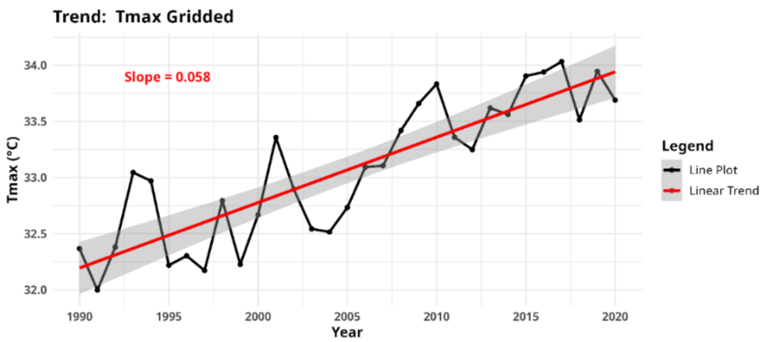


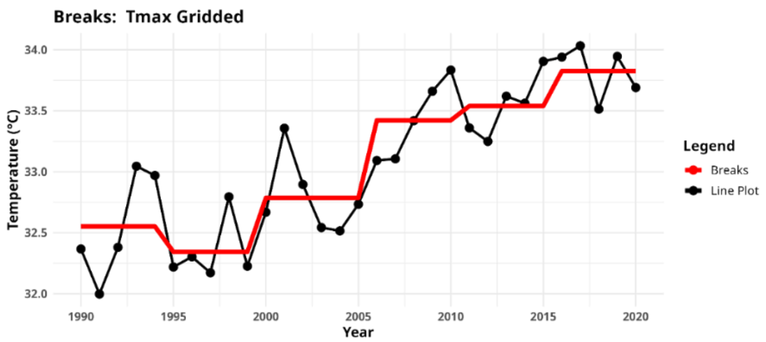
CHIRPS precipitation and breakpoints Bole District



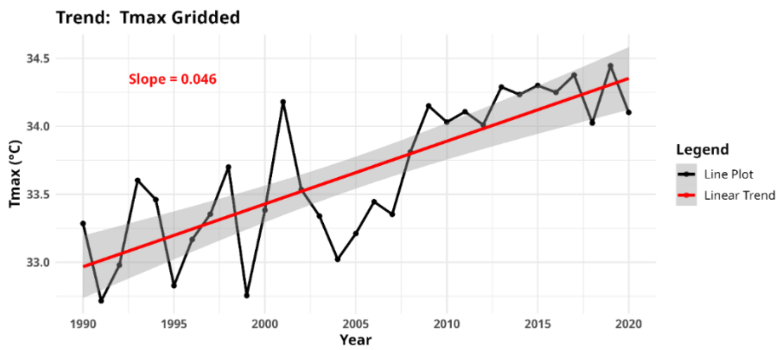


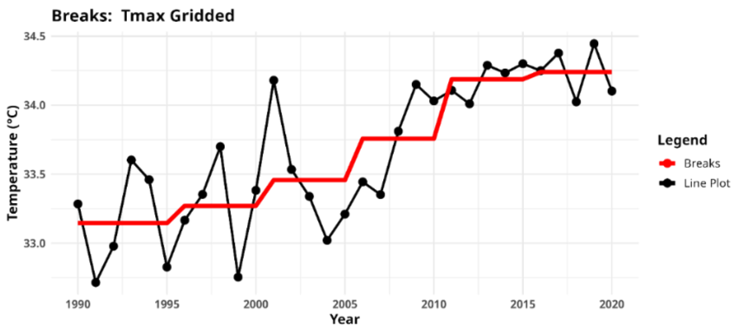
ERA5 Maximum temperature and breakpoints Wa Municipal



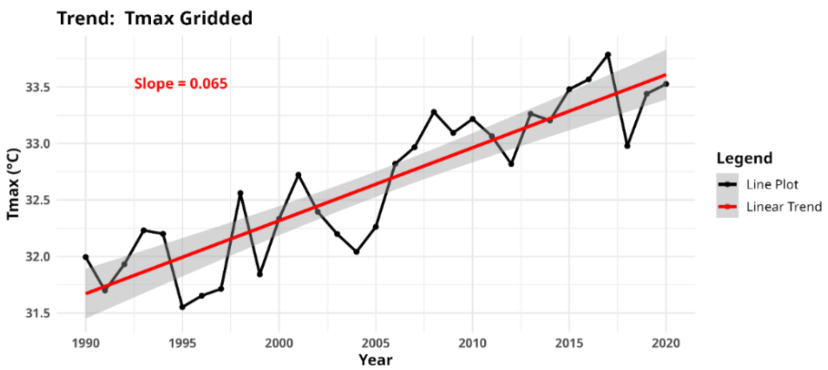


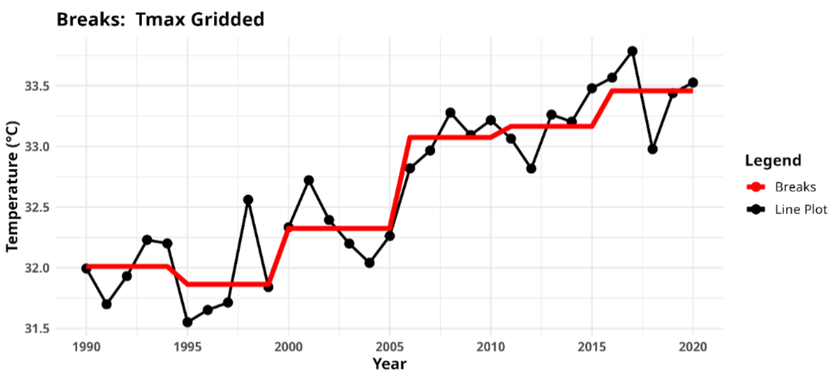
ERA5 Maximum temperature and breakpoints Tamale Metropolis



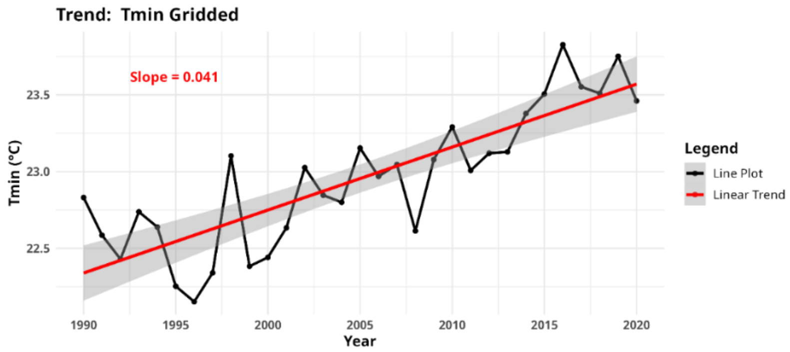


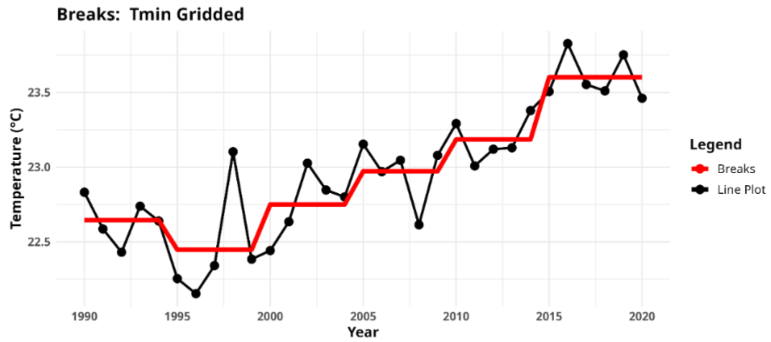
ERA5 Maximum temperature and breakpoints Bole District



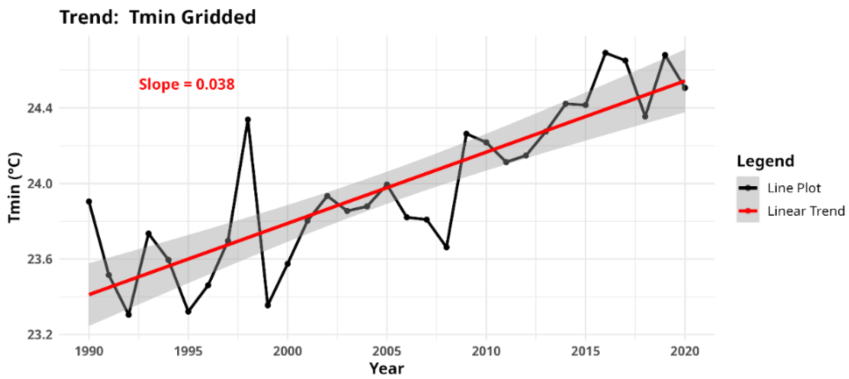


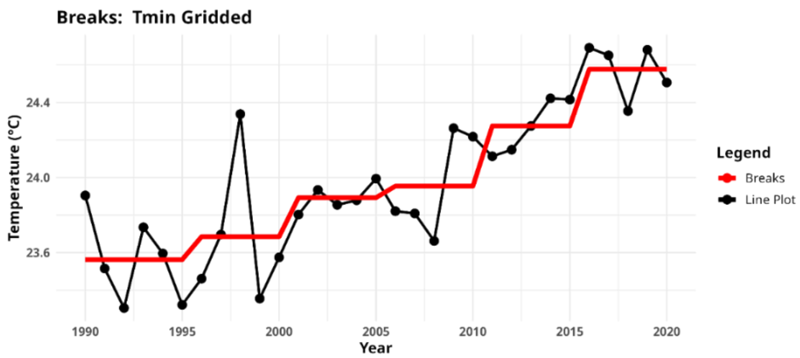
ERA5 Minimum temperature and breakpoints Wa Municipal



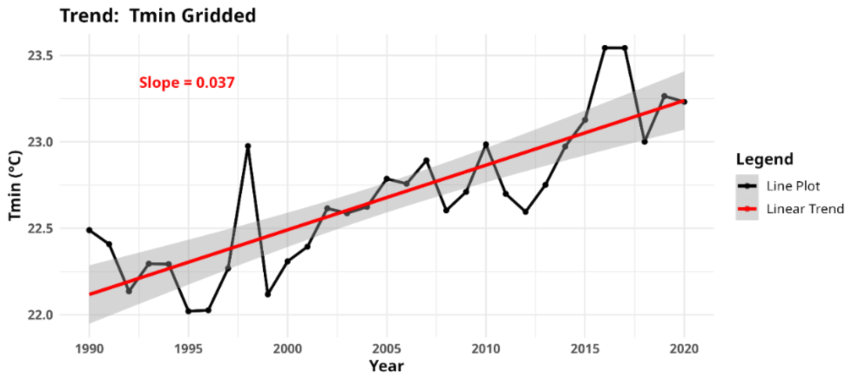


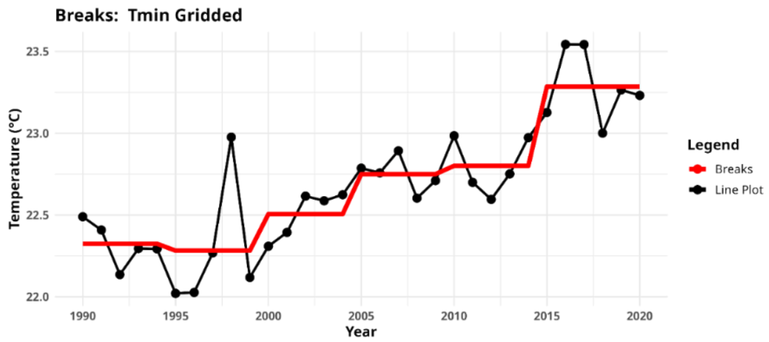
ERA5 Minimum temperature and breakpoints Tamale Metropolis





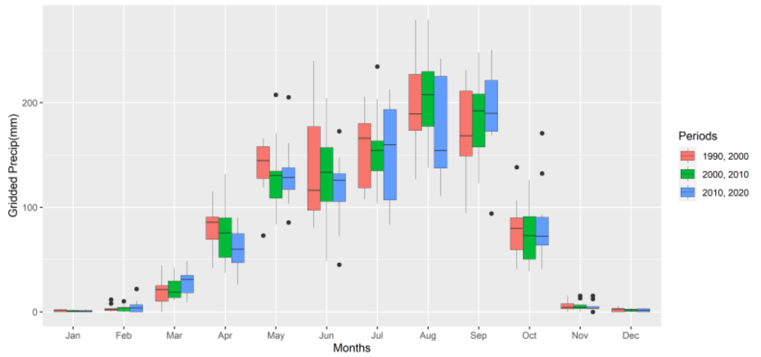
ERA5 Minimum temperature and breakpoints Bole District



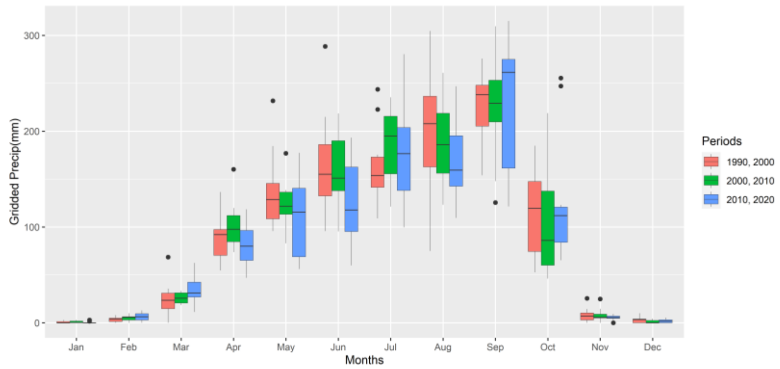


Appendix 1C: Results of monthly variations of climate variability for specific periods using satellite data

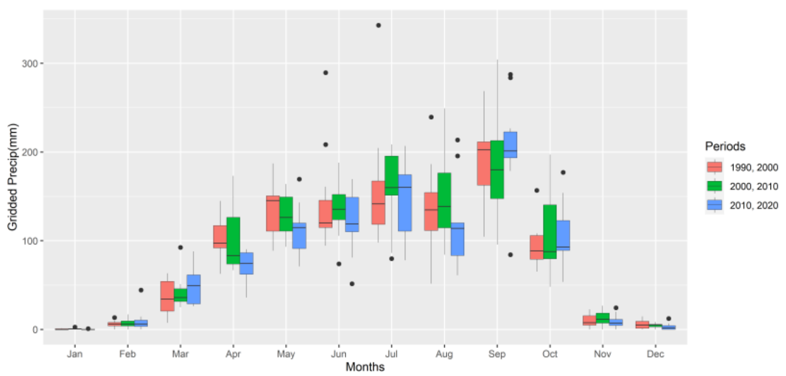
Periodic monthly precipitation trend of CHIRPS for Wa Municipal



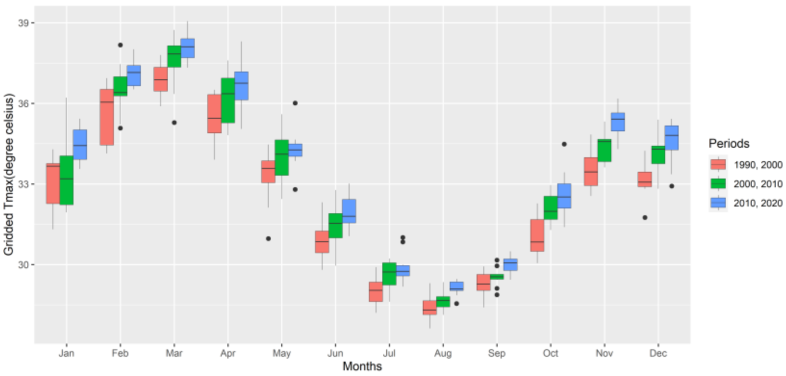
Periodic monthly precipitation trend CHIRPS for Tamale Metropolis



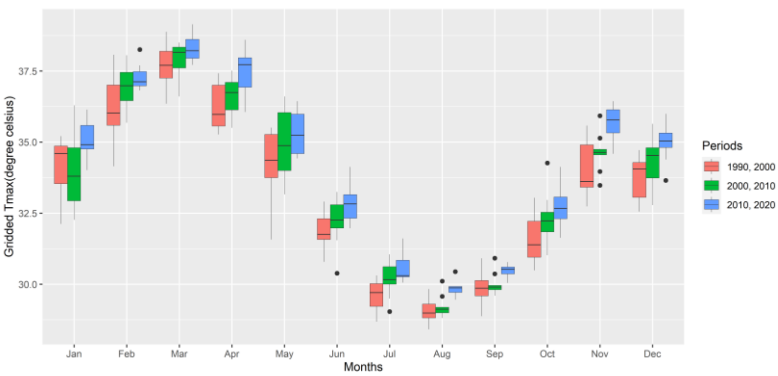
Periodic monthly precipitation trend of CHIRPS for Bole District



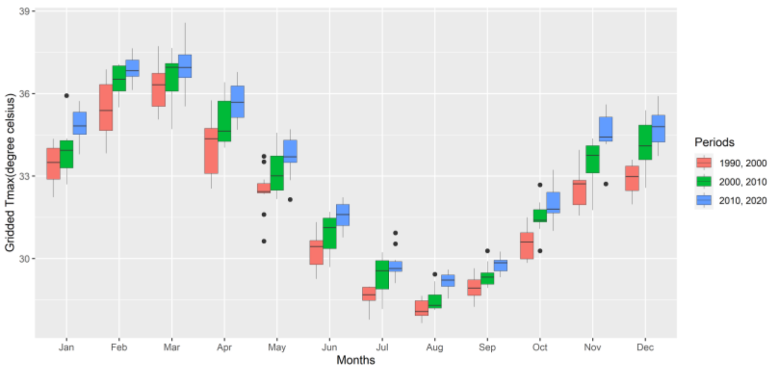
Periodic monthly Maximum temperature trend from ERA5 for Wa municipal



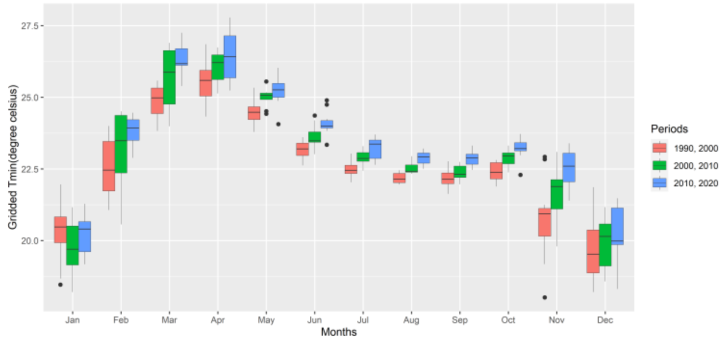
Periodic monthly Maximum temperature trend from ERA5 for Tamale Metropolis



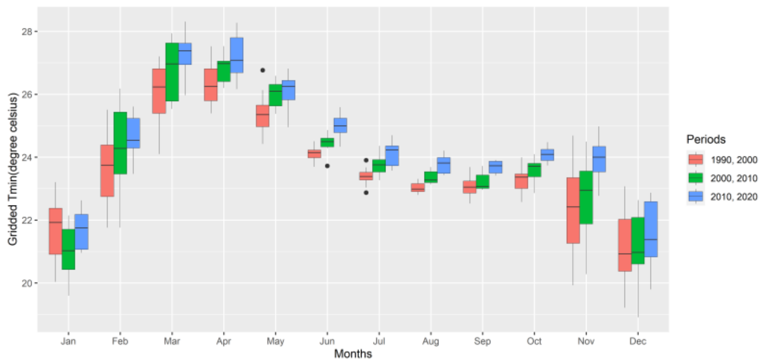
Periodic monthly Maximum temperature trend from ERA5 for the Bole district



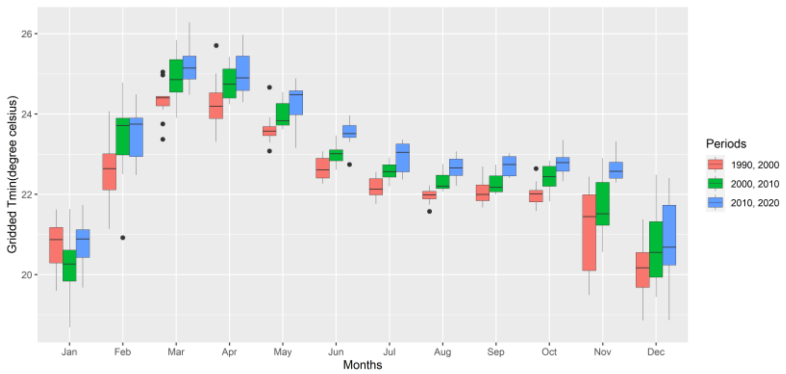
Periodic monthly Minimum temperature trend from ERA5 for Wa municipal



Periodic monthly Minimum temperature trend from ERA5 for Tamale Metropolis

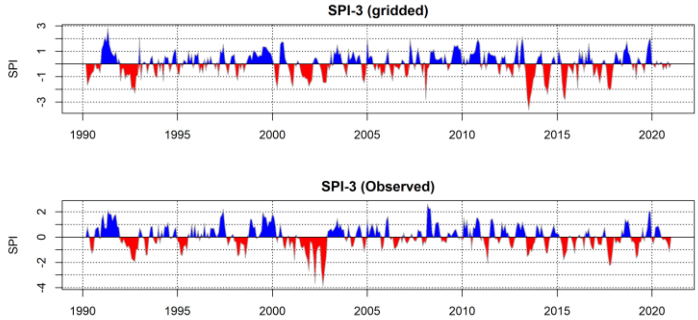


Periodic monthly Minimum temperature trend from ERA5 for the Bole district

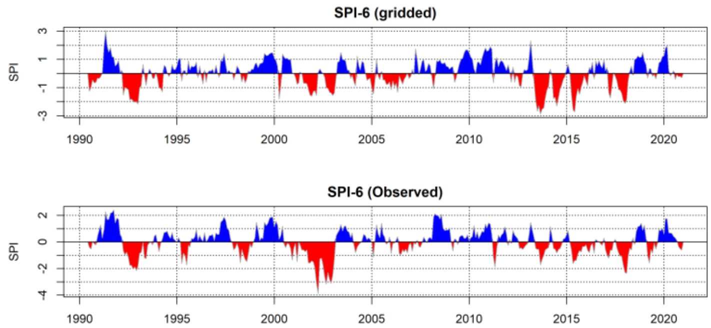


Appendix 1D: Results of SPI and SPEI using GMet and CHIRPS data

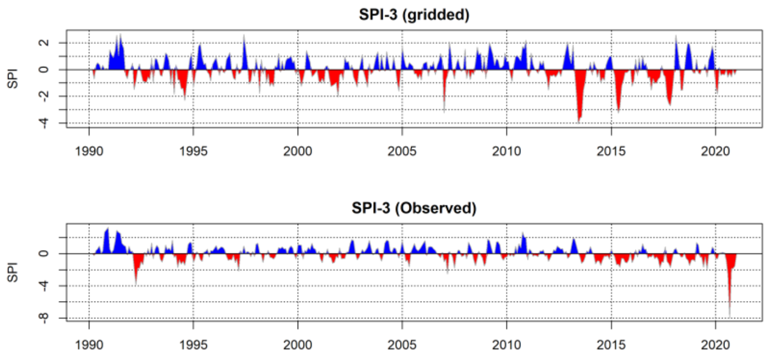
Three months SPI calculated from GMet and CHIRPS data for Tamale Metropolis



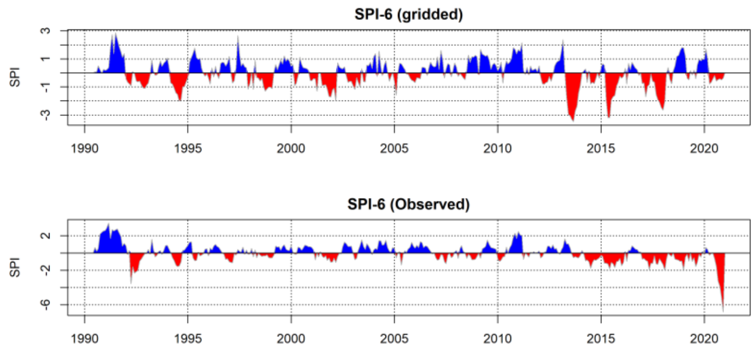
Six months SPI calculated from GMet and CHIRPS data for Tamale Metropolis



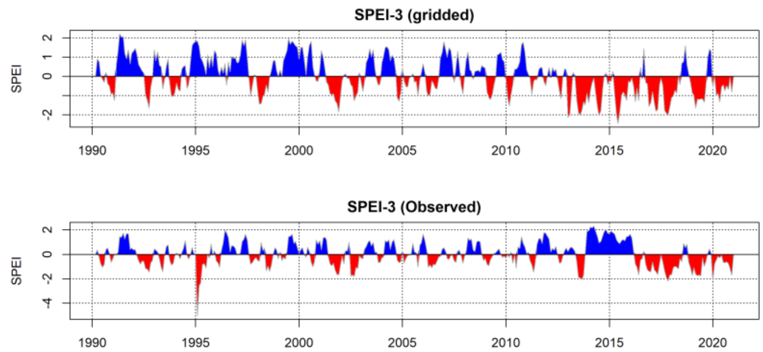
Three months SPI calculated from GMet and CHIRPS data for Bole District



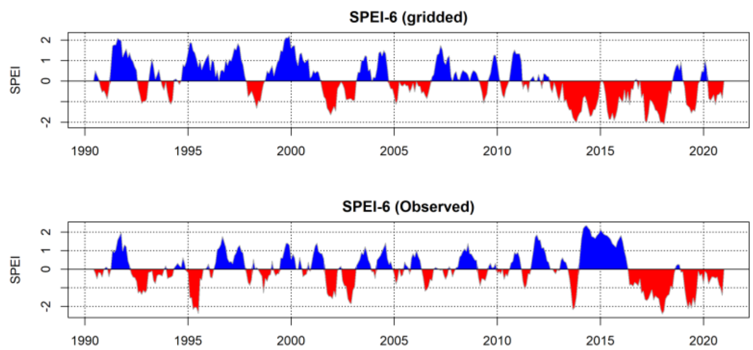
Six months SPI calculated from GMet and CHIRPS data for Bole District



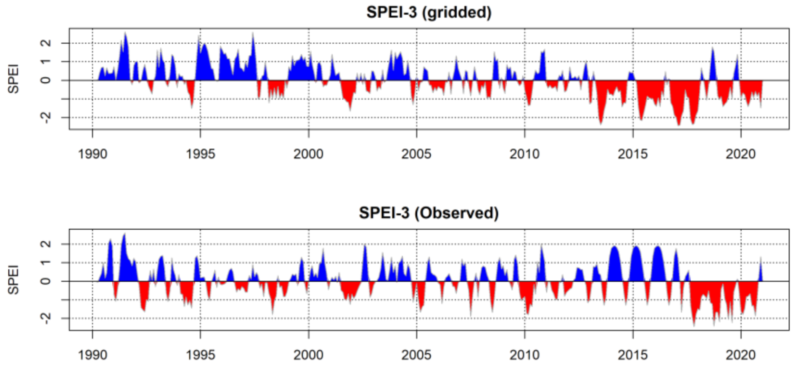
Three months of SPEI calculated from GMet and CHIRPS data for Tamale Metropolis



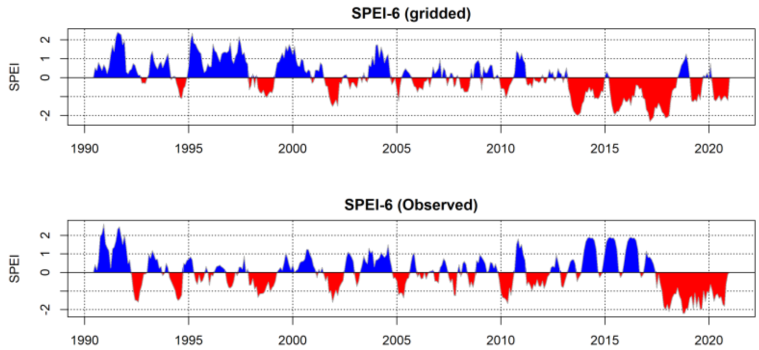
Six months of SPEI calculated from GMet and CHIRPS data for Tamale Metropolis



Three months of SPEI calculated from GMet and CHIRPS data for Bole District



Six months of SPEI calculated from GMet and CHIRPS data for Bole District



Appendix 2A: Accuracy assessments of LULCC maps

Classification scheme: 1-Settlement/Bare, 2-Water, 3-Cropland, 4-Shrub/Grassland and 5-Woodland

Random Forest (RF)

Classified Data		1	2	3	4	5	Total	PA (%)	UA (%)	EC (%)
1990-Overall Classification Accuracy= 93.14%, Kappa Coefficient= 91.05%										
	1	75	0	5	0	0	**80**	93.75	98.68	6.25
	2	0	83	7	0	0	**90**	92.22	100.00	7.78
	3	1	0	160	8	0	**169**	94.67	86.49	5.33
	4	0	0	12	141	1	**154**	91.56	92.76	8.44
	5	0	0	1	3	57	**61**	93.44	98.28	6.56
Total		**76**	**83**	**185**	**152**	**58**	**554**			
EO (%)		1.32	0.00	13.51	7.24	1.72				
2000-Overall Classification Accuracy= 94.28%, Kappa Coefficient= 92.54%										
	1	72	0	6	2	0	**80**	90.00	100.00	10.00
	2	0	89	5	0	1	**95**	93.68	100.00	6.32
	3	0	0	162	5	2	**169**	95.86	89.01	4.14
	4	0	0	6	147	1	**154**	95.45	94.84	4.55
	5	0	0	3	1	57	**61**	93.44	93.44	6.56
Total		**72**	**89**	**182**	**155**	**61**	**559**			
EO (%)		0.00	0.00	10.99	5.16	6.56				
2010-Overall Classification Accuracy=94.81%, Kappa Coefficient= 93.25%										
	1	78	0	2	0	0	**80**	97.50	98.73	2.50
	2	1	93	1	0	0	**95**	97.89	100.00	2.11
	3	0	0	164	5	0	**169**	97.04	89.62	2.96
	4	0	0	14	139	1	**154**	90.26	94.56	9.74
	5	0	0	2	3	56	**61**	91.80	98.25	8.20
Total		**79**	**93**	**183**	**147**	**57**	**559**			
EO (%)		1.27	0.00	10.38	5.44	1.75				
2020-Overall Classification Accuracy=96.78%, Kappa Coefficient= 95.82%										
	1	80	0	0	0	0	**80**	100.00	100.00	0.00
	2	0	95	0	0	0	**95**	100.00	100.00	0.00
	3	0	0	163	6	0	**169**	96.45	95.32	3.55
	4	0	0	8	146	0	**154**	94.81	93.59	5.19
	5	0	0	0	4	57	**61**	93.44	100.00	6.56
Total		**80**	**95**	**171**	**156**	**57**	**559**			
EO (%)		0.00	0.00	4.68	6.41	0.00				

PA-Producer's Accuracy, UA-User's Accuracy, EC-Error of Commission, EO-Error of Omission

Classification and Regression Trees (CART)

Classified Data	1	2	3	4	5	Total	PA (%)	UA (%)	EC (%)

1990-Overall Classification Accuracy= 91.16%, Kappa Coefficient= 88.48%

	1	74	0	5	1	0	**80**	92.50	93.67	7.50
	2	0	85	5	0	0	**90**	94.44	95.51	5.56
	3	5	2	150	10	2	**169**	88.76	87.21	11.24
	4	0	2	9	143	0	**154**	92.86	89.94	7.14
	5	0	0	3	5	53	**61**	86.89	96.36	13.11
Total		**79**	**89**	**172**	**159**	**55**	**554**			
EO (%)		6.33	4.49	12.79	10.06	3.64				

2000-Overall Classification Accuracy= 93.56%, Kappa Coefficient= 91.63%

	1	74	0	3	3	0	**80**	92.50	97.37	7.50
	2	0	90	2	1	2	**95**	94.74	98.90	5.26
	3	2	1	158	7	1	**169**	93.49	91.33	6.51
	4	0	0	8	145	1	**154**	94.16	91.19	5.84
	5	0	0	2	3	56	**61**	91.80	93.33	8.20
Total		**76**	**91**	**173**	**159**	**60**	**559**			
EO (%)		2.63	1.10	8.67	8.81	6.67				

2010-Overall Classification Accuracy=91.59%, Kappa Coefficient= 89.07%

	1	77	0	2	1	0	**80**	96.25	95.06	3.75
	2	0	93	2	0	0	**95**	97.89	100.00	2.11
	3	4	0	153	11	1	**169**	90.53	85.47	9.47
	4	0	0	16	136	2	**154**	88.31	90.67	11.69
	5	0	0	6	2	53	**61**	86.89	94.64	13.11
Total		**81**	**93**	**179**	**150**	**56**	**559**			
EO (%)		4.94	0.00	14.53	9.33	5.36				

2020-Overall Classification Accuracy=96.24%, Kappa Coefficient= 95.14%

	1	80	0	0	0	0	**80**	100.00	100.00	3.75
	2	0	95	0	0	0	**95**	100.00	98.95	2.11
	3	1	0	159	5	4	**169**	94.08	95.88	9.47
	4	0	0	6	146	2	**154**	94.81	93.04	11.69
	5	0	0	0	3	58	**61**	95.08	100.00	13.11
Total		**81**	**95**	**165**	**154**	**64**	**559**			
EO (%)		4.94	0.00	14.53	9.33	5.36				

PA-Producer's Accuracy, UA-User's Accuracy, EC-Error of Commission, EO-Error of Omission

Gradient Tree Boosting (GTB)									
Classified Data	1	2	3	4	5	**Total**	**PA (%)**	**UA (%)**	**EC (%)**
1990-Overall Classification Accuracy= 93.86%, Kappa Coefficient= 92.01%									
1	75	0	5	0	0	**80**	93.75	100.00	6.25
2	0	85	5	0	0	**90**	94.44	98.84	5.56
3	0	0	160	8	1	**169**	94.67	89.39	5.33
4	0	1	8	142	3	**154**	92.21	93.42	7.79
5	0	0	1	2	58	**61**	95.08	93.55	4.92
Total	**75**	**86**	**179**	**152**	**62**	**554**			
EO (%)	0.00	1.16	10.61	6.58	6.45				
2000-Overall Classification Accuracy= 94.81%, Kappa Coefficient= 93.26%									
1	75	0	2	3	0	**80**	93.75	94.94	6.25
2	0	90	3	1	1	**95**	94.74	100.00	5.26
3	2	0	161	6	0	**169**	95.27	92.53	4.73
4	2	0	5	146	1	**154**	94.81	93.59	5.19
5	0	0	3	0	58	**61**	95.08	96.67	4.92
Total	**79**	**90**	**174**	**156**	**60**	**559**			
EO (%)	5.06	0.00	7.47	6.41	3.33				
2010-Overall Classification Accuracy=95.35%, Kappa Coefficient= 93.95%									
1	76	0	3	1	0	**80**	95.00	96.20	5.00
2	2	93	0	0	0	**95**	97.89	100.00	2.11
3	1	0	164	4	0	**169**	97.04	92.13	2.96
4	0	0	9	144	1	**154**	93.51	94.74	6.49
5	0	0	2	3	56	**61**	91.80	98.25	8.20
Total	**79**	**93**	**178**	**152**	**57**	**559**			
EO (%)	3.80	0.00	7.87	5.26	1.75				
2020-Overall Classification Accuracy=96.60%, Kappa Coefficient= 95.59%									
1	80	0	0	0	0	**80**	100.00	100.00	0.00
2	0	94	0	1	0	**95**	98.95	98.95	1.05
3	0	0	163	6	0	**169**	96.45	95.88	3.55
4	0	0	7	147	0	**154**	95.45	93.04	4.55
5	0	1	0	4	56	**61**	91.80	100.00	8.20
Total	**80**	**95**	**170**	**158**	**56**	**559**			
EO (%)	0.00	1.05	4.12	6.96	0.00				

PA-Producer's Accuracy, UA-User's Accuracy, EC-Error of Commission, EO-Error of Omission

Support Vector Machine (SVM)									
Classified Data	1	2	3	4	5	**Total**	**PA (%)**	**UA (%)**	**EC (%)**
1990-Overall Classification Accuracy= 80.32%, Kappa Coefficient= 74.34%									
1	73	0	4	3	0	**80**	91.25	91.25	8.75
2	0	85	5	0	0	**90**	94.44	94.45	5.56
3	6	3	133	13	14	**169**	78.70	70.05	21.30
4	1	0	32	118	3	**154**	76.62	83.69	23.38
5	0	2	16	7	36	**61**	59.02	67.92	40.98
Total	**80**	**90**	**190**	**141**	**53**	**554**			
EO (%)	8.75	5.56	30.00	16.31	32.08				
2000-Overall Classification Accuracy= 84.43%, Kappa Coefficient= 79.63%									
1	63	0	6	11	0	**80**	78.75	84.00	21.25
2	0	85	8	2	0	**95**	89.47	96.59	10.53
3	6	2	153	4	4	**169**	90.53	77.27	9.47
4	5	0	21	127	1	**154**	82.47	85.23	17.53
5	1	1	10	5	44	**61**	72.13	89.80	27.87
Total	**75**	**88**	**198**	**149**	**49**	**559**			
EO (%)	16.00	3.41	22.73	14.77	10.20				
2010-Overall Classification Accuracy=87.84%, Kappa Coefficient= 84.15%									
1	71	0	4	5	0	**80**	88.75	93.42	11.25
2	0	92	2	1	0	**95**	96.84	97.87	3.16
3	5	0	148	9	7	**169**	87.57	82.68	12.43
4	0	1	15	136	2	**154**	88.31	86.62	11.69
5	0	1	10	6	44	**61**	72.13	83.02	27.87
Total	**76**	**94**	**179**	**157**	**53**	**559**			
EO (%)	6.58	2.13	17.32	13.38	16.98				
2020-Overall Classification Accuracy=90.88%, Kappa Coefficient= 88.15%									
1	79	0	1	0	0	**80**	98.75	97.53	1.25
2	0	92	2	1	0	**95**	96.84	97.87	3.16
3	2	1	152	6	8	**169**	89.94	86.86	10.06
4	0	0	15	138	1	**154**	89.61	90.20	10.39
5	0	1	5	8	47	**61**	77.05	83.93	22.95
Total	**81**	**94**	**175**	**153**	**56**	**559**			
EO (%)	2.47	2.13	13.14	9.80	16.07				

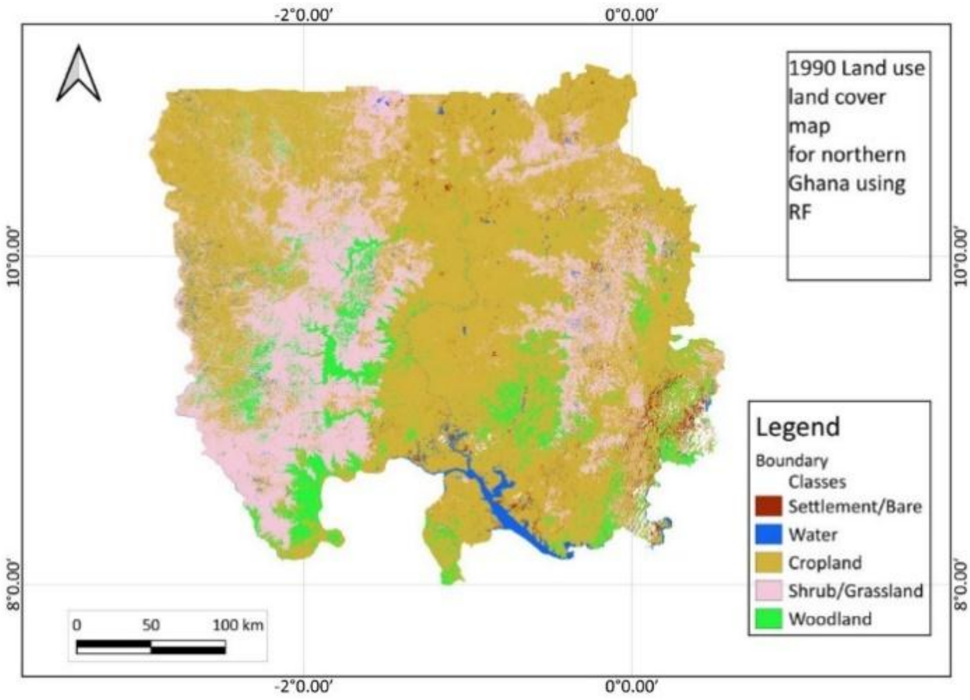
PA-Producer's Accuracy, UA-User's Accuracy, EC-Error of Commission, EO-Error of Omission

Majority Filtering (MajF)									
Classified Data	1	2	3	4	5	**Total**	**PA (%)**	**UA (%)**	**EC (%)**
1990-Overall Classification Accuracy= 94.04%, Kappa Coefficient= 92.23%									
1	77	0	3	0	0	**80**	96.25	97.47	3.75
2	0	85	5	0	0	**90**	94.44	100.00	5.56
3	2	0	161	6	0	**169**	95.27	88.95	4.73
4	0	0	11	143	0	**154**	92.86	92.86	7.14
5	0	0	1	5	55	**61**	90.16	100.00	9.84
Total	**79**	**85**	**181**	**154**	**55**	**554**			
EO (%)	2.53	0.00	11.05	7.14	0.00				
2000-Overall Classification Accuracy= 94.99%, Kappa Coefficient= 93.49%									
1	76	0	2	2	0	**80**	95.00	97.44	5.00
2	0	90	3	1	1	**95**	94.74	100.00	5.26
3	2	0	161	6	0	**169**	95.27	91.48	4.73
4	0	0	7	146	1	**154**	94.81	94.19	5.19
5	0	0	3	0	58	**61**	95.08	96.67	4.92
Total	**78**	**90**	**176**	**155**	**60**	**559**			
EO (%)	2.56	0.00	8.52	5.81	3.33				
2010-Overall Classification Accuracy=95.35%, Kappa Coefficient= 93.95%									
1	79	0	1	0	0	**80**	98.75	97.53	1.25
2	1	93	1	0	0	**95**	97.89	100.00	2.11
3	1	0	166	2	0	**169**	98.22	89.73	1.78
4	0	0	14	139	1	**154**	90.26	97.20	9.74
5	0	0	3	2	56	**61**	91.80	98.25	8.20
Total	**81**	**93**	**185**	**143**	**57**	**559**			
EO (%)	2.47	0.00	10.27	2.80	1.75				
2020-Overall Classification Accuracy=96.78%, Kappa Coefficient= 95.82%									
1	80	0	0	0	0	**80**	100.00	100.00	0.00
2	0	95	0	0	0	**95**	100.00	98.96	0.00
3	0	0	164	5	0	**169**	97.04	95.35	2.96
4	0	0	8	146	0	**154**	94.81	94.19	5.19
5	0	1	0	4	56	**61**	91.80	100.00	8.20
Total	**80**	**96**	**172**	**155**	**56**	**559**			
EO (%)	0.00	1.04	4.65	5.81	0.00				

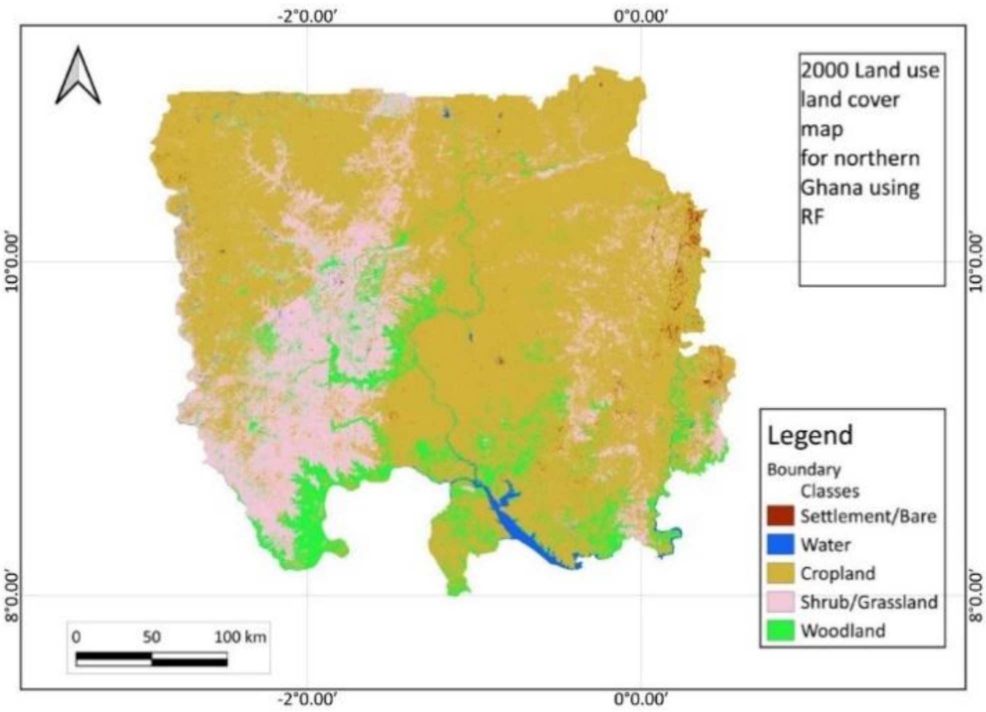
PA-Producer's Accuracy, UA-User's Accuracy, EC-Error of Commission, EO-Error of Omission

Appendix 2B: LULC maps created with different classifiers

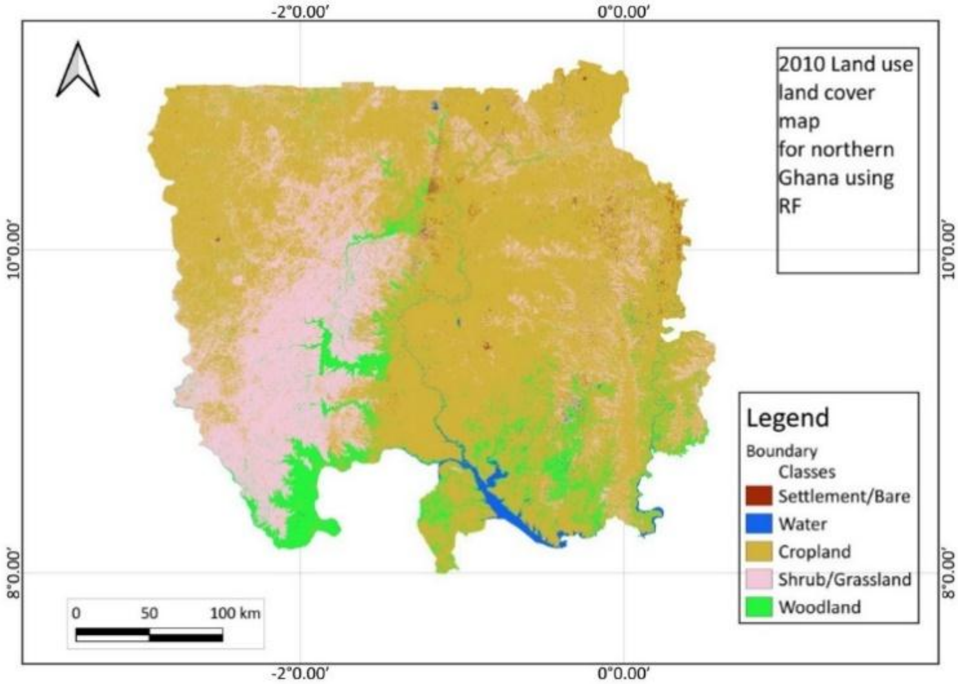
LULC map for 1990 using RF



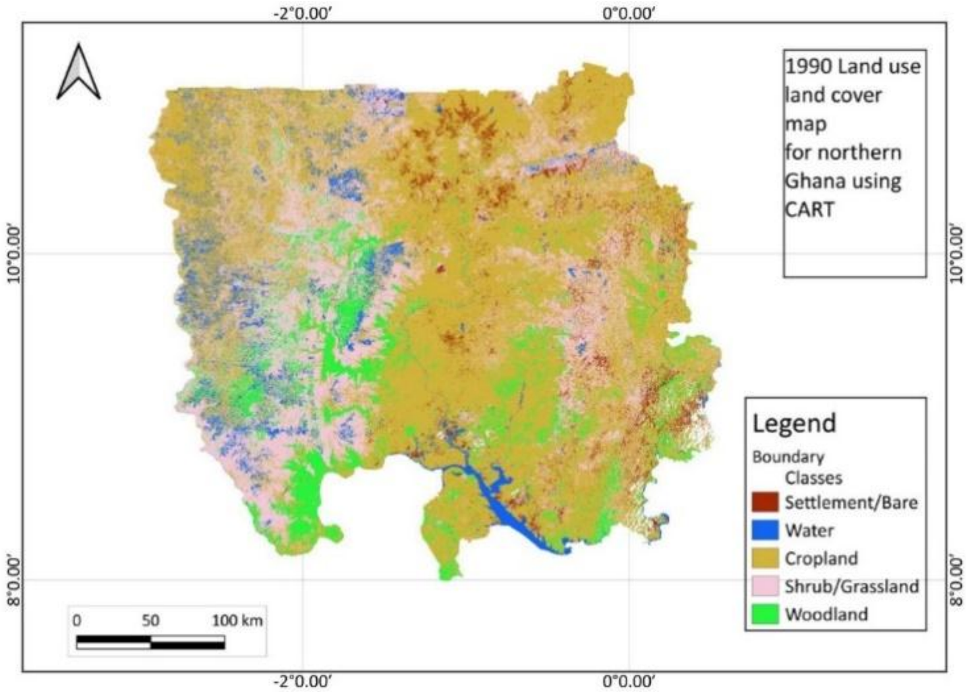
LULC map for 2000 using RF



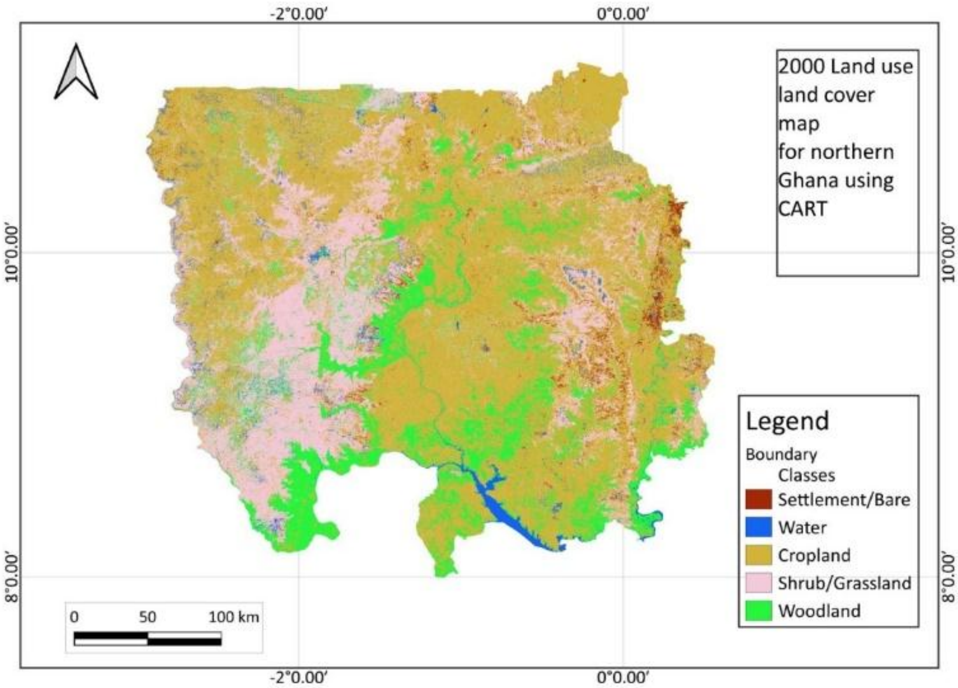
LULC map for 2010 using RF



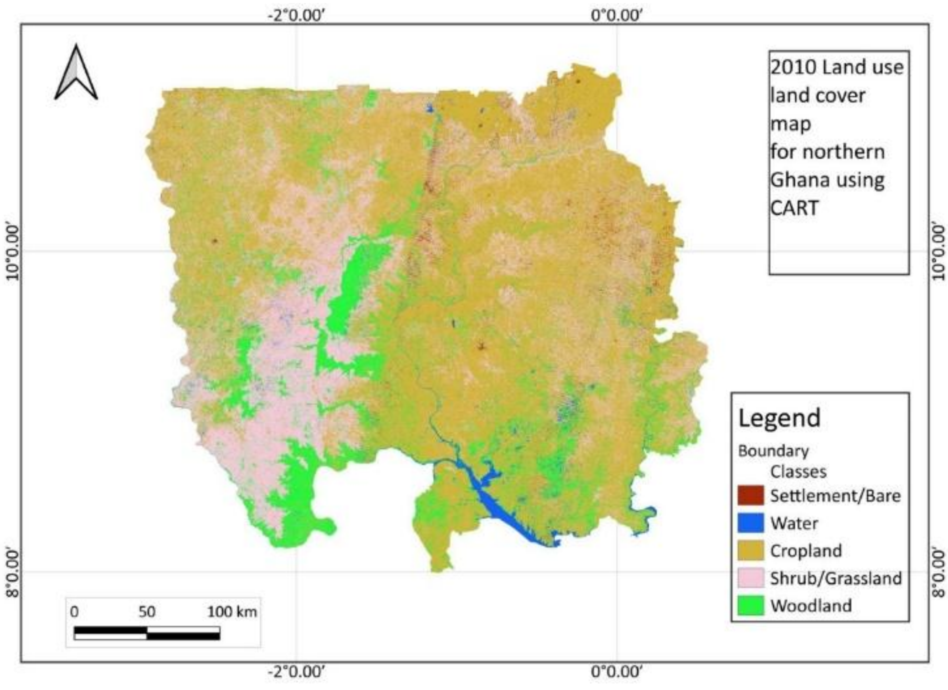
LULC map for 1990 using CART



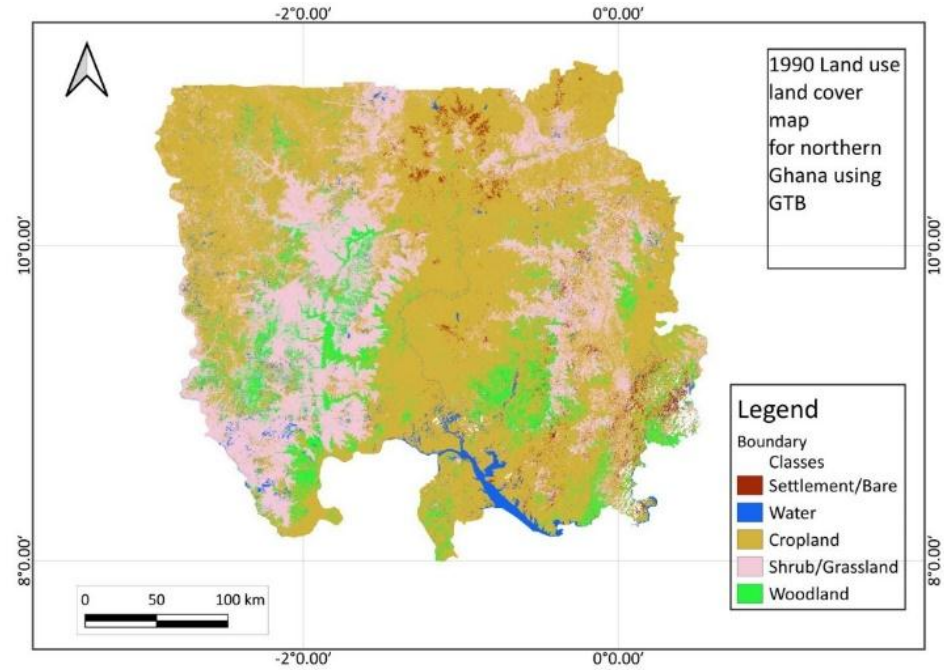
LULC map for 2000 using CART



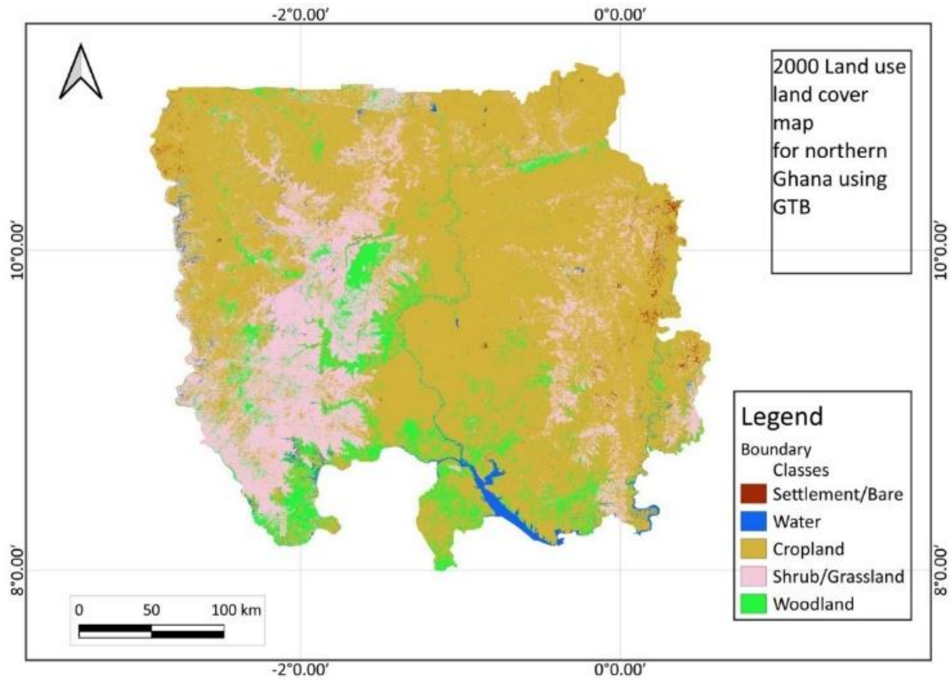
LULC map for 2010 using CART



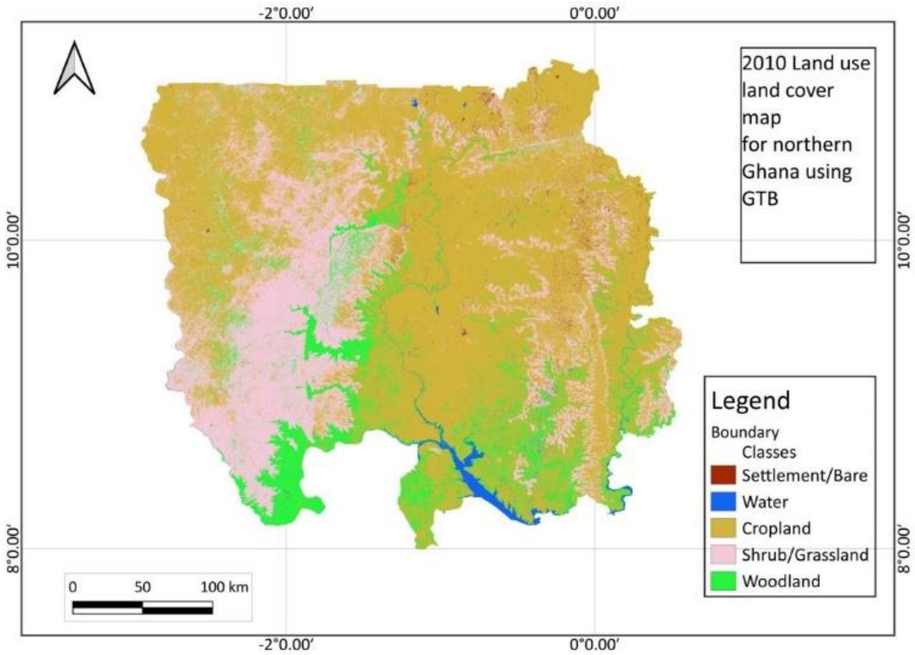
LULC map for 1990 using GTB



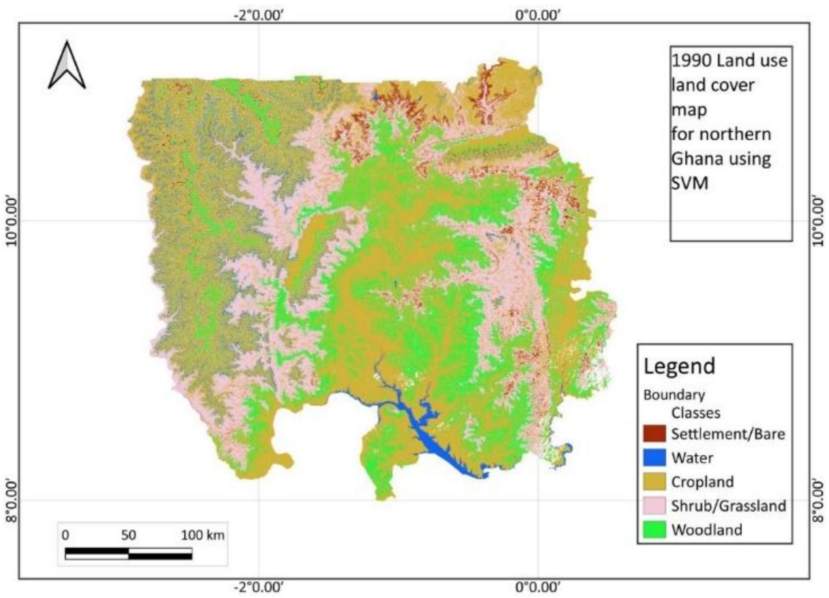
LULC map for 2000 using GTB



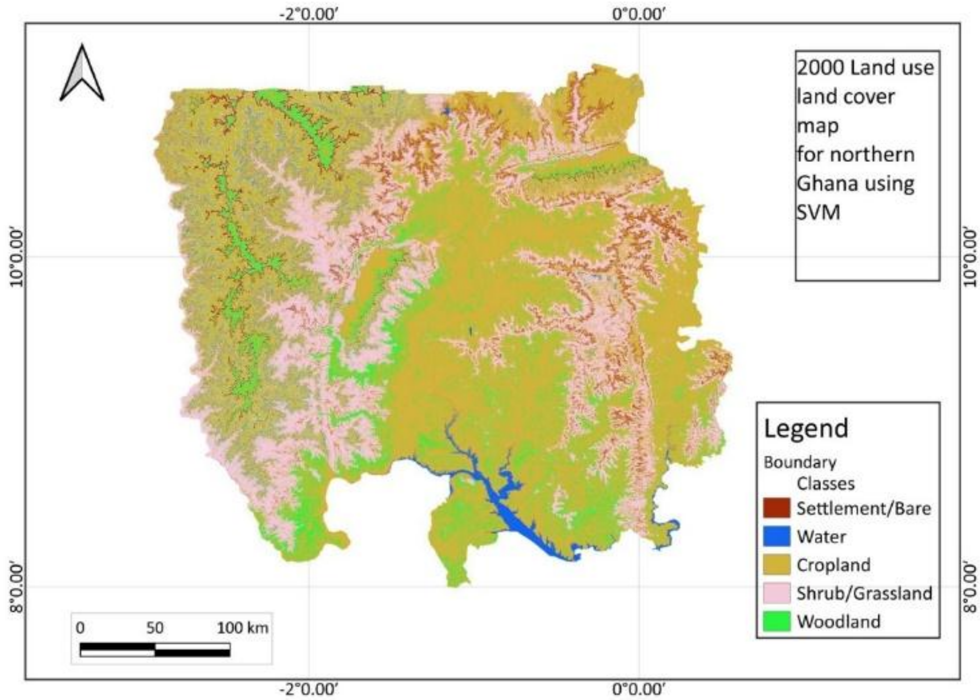
LULC map for 2010 using GTB



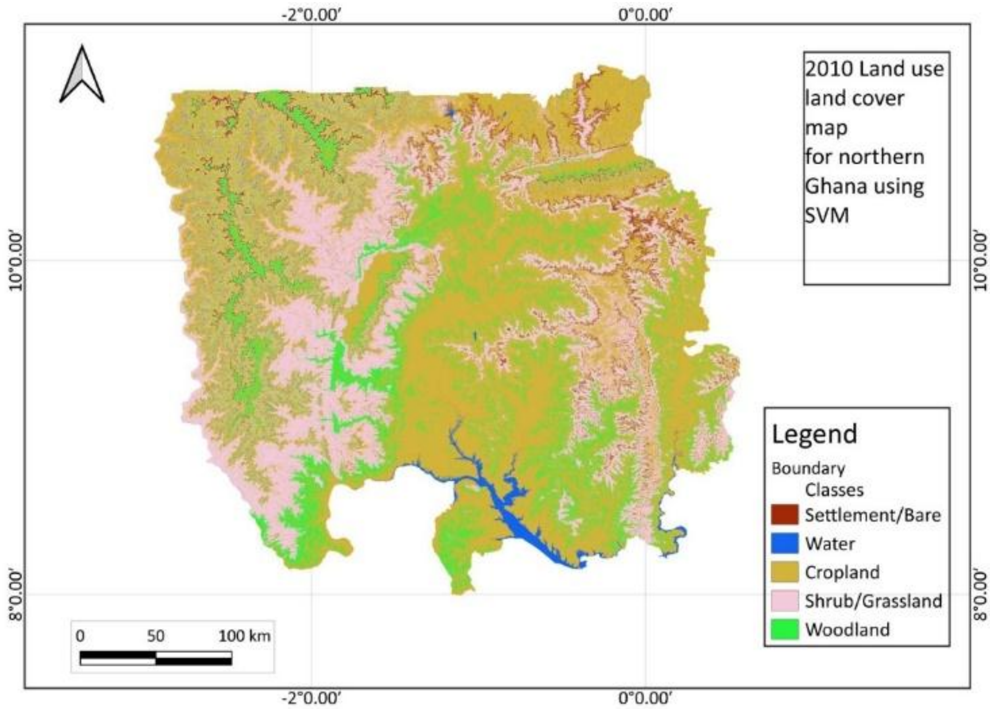
LULC map for 1990 using SVM



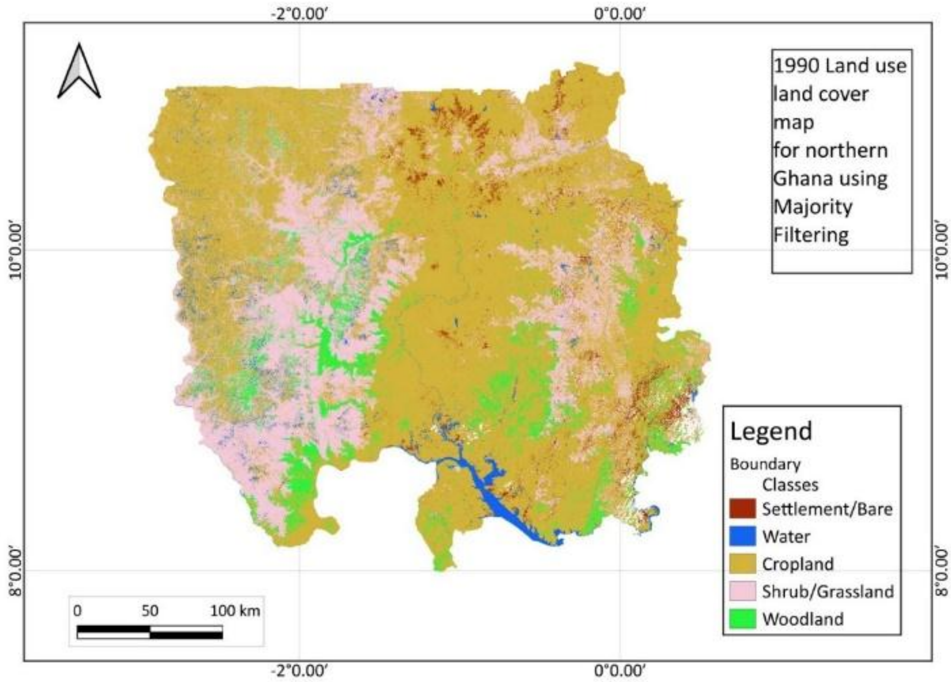
LULC map for 2000 using SVM



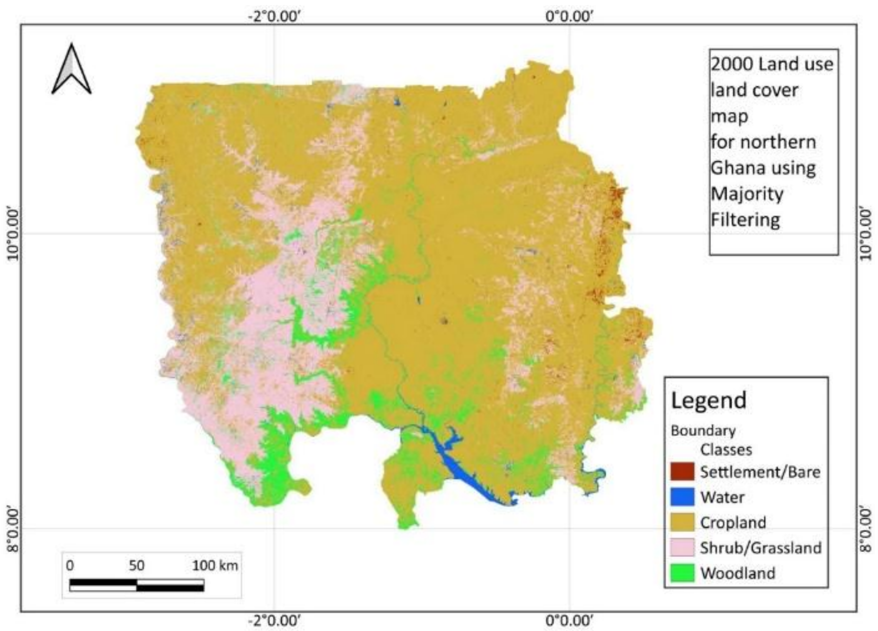
LULC map for 2010 using SVM



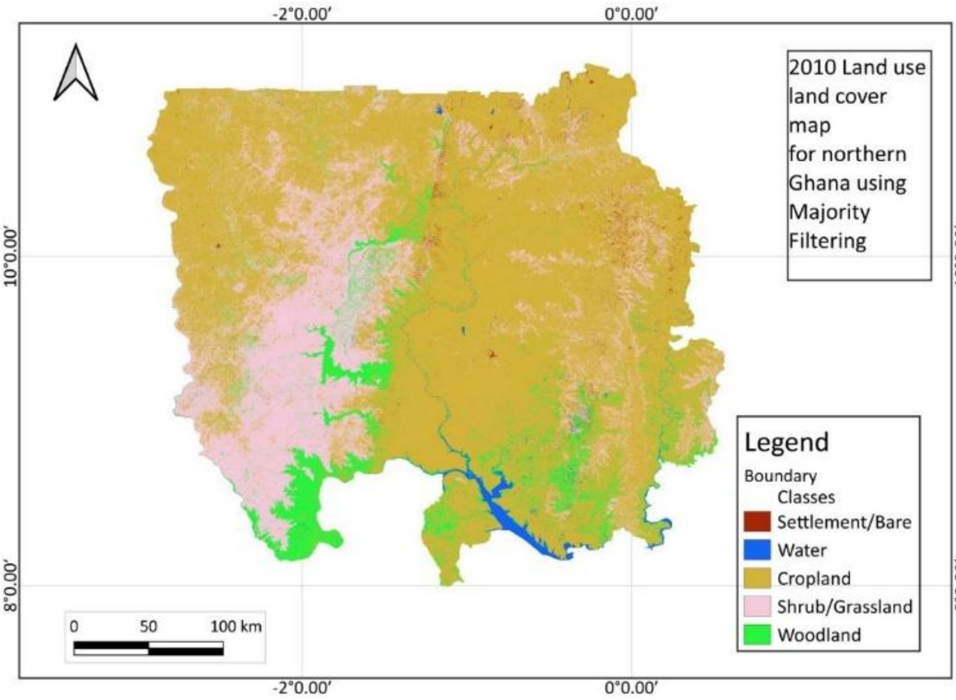
LULC map for 1990 using Majority filtering



LULC map for 2000 using Majority filtering



LULC map for 2010 using Majority filtering



Appendix 2C: Change statistics

Class changes from 1990 to 2000

LULC Change	Changed Area (Sq.km.)
Settlement/Bare (No Change)	42.07
Water to Settlement/Bare	8.16
Cropland to Settlement/Bare	455.00
Shrub/Grassland to Settlement/Bare	86.77
Woodland to Settlement/Bare	8.54
Settlement/Bare to Water	21.96
Water (No Change)	905.28
Cropland to Water	367.33
Shrub/Grassland to Water	208.62
Woodland to Water	38.93
Settlement/Bare to Cropland	1674.08
Water to Cropland	1167.54
Cropland (No Change)	54807.20
Shrub/Grassland to Cropland	9264.55
Woodland to Cropland	2802.92
Settlement/Bare to Shrub/Grassland	222.90
Water to Shrub/Grassland	675.66
Cropland to Shrub/Grassland	4568.51
Shrub/Grassland (No Change)	13571.13
Woodland to Shrub/Grassland	1218.99
Settlement/Bare to Woodland	46.30
Water to Woodland	221.59
Cropland to Woodland	3716.66
Shrub/Grassland to Woodland	680.97
Woodland (No Change)	2020.58

Class changes from 2000 to 2010

LULC Change	Changed Area (Sq.km.)
Settlement/Bare (No Change)	46.22
Water to Settlement/Bare	2.62
Cropland to Settlement/Bare	504.41
Shrub/Grassland to Settlement/Bare	83.03
Woodland to Settlement/Bare	3.59
Settlement/Bare to Water	6.50
Water (No Change)	879.28
Cropland to Water	307.76
Shrub/Grassland to Water	95.26
Woodland to Water	109.79
Settlement/Bare to Cropland	469.05
Water to Cropland	387.60
Cropland (No Change)	58238.17
Shrub/Grassland to Cropland	6021.29
Woodland to Cropland	2684.94
Settlement/Bare to Shrub/Grassland	75.99
Water to Shrub/Grassland	236.25
Cropland to Shrub/Grassland	7500.84
Shrub/Grassland (No Change)	13770.30
Woodland to Shrub/Grassland	822.69
Settlement/Bare to Woodland	3.38
Water to Woodland	67.33
Cropland to Woodland	3590.74
Shrub/Grassland to Woodland	427.84
Woodland (No Change)	3150.70

Class changes from 2010 to 2020

LULC Change	Changed Area (Sq.km.)
Settlement/Bare (No Change)	48.87
Water to Settlement/Bare	15.71
Cropland to Settlement/Bare	169.59
Shrub/Grassland to Settlement/Bare	16.95
Woodland to Settlement/Bare	4.273
Settlement/Bare to Water	4.298
Water (No Change)	903.26
Cropland to Water	90.04
Shrub/Grassland to Water	119.00
Woodland to Water	148.57
Settlement/Bare to Cropland	449.58
Water to Cropland	199.26
Cropland (No Change)	46917.29
Shrub/Grassland to Cropland	3594.04
Woodland to Cropland	2712.91
Settlement/Bare to Shrub/Grassland	131.46
Water to Shrub/Grassland	143.63
Cropland to Shrub/Grassland	16268.00
Shrub/Grassland (No Change)	18149.19
Woodland to Shrub/Grassland	847.72
Settlement/Bare to Woodland	5.64
Water to Woodland	136.75
Cropland to Woodland	4356.14
Shrub/Grassland to Woodland	526.90
Woodland (No Change)	3526.59

Conversion of classes between 1990-2000

	1990-2000			
Class	**Change to other Classes**	**Change from other Classes**	**Area no Change**	**Area after Change**
Settlement/Bare	1965.23	558.47	42.07	600.54
Water	2072.96	636.83	905.28	1542.11
Cropland	9107.51	14909.09	54807.20	69716.28
Shrub/grassland	10240.92	6686.07	13571.13	20257.19
Woodland	4069.36	4665.52	2020.58	6686.09

Conversion of classes between 2000-2010

2000-2010				
Class	**Change to other Classes**	**Change from other Classes**	**Area no Change**	**Area after Change**
Settlement/Bare	554.92	593.64	46.22	639.85
Water	693.80	519.32	879.28	1398.59
Cropland	11903.76	9562.90	58238.17	67801.07
Shrub/grassland	6627.42	8635.77	13770.30	22406.07
Woodland	3621.02	4089.29	3150.70	7231.00

Conversion of classes between 2010-2020

2010-2020				
Class	**Change to other Classes**	**Change from other Classes**	**Area no Change**	**Area after Change**
Settlement/Bare	590.99	206.52	48.87	255.39
Water	495.36	361.91	903.26	1265.16
Cropland	20883.78	6955.79	46917.29	53873.08
Shrub/grassland	4256.88	17390.82	18149.19	35540.01
Woodland	3713.47	5025.44	3526.59	8552.03

Appendix 2D: Sample data for the Relationship between Climate variability and LULCC

Maximum/minimum temperatures (degrees Celsius)								Precipitation (mm)				Classes lulc maps:1-settlement/bare, 2-water, 3-cropland, 4-shrub/grassland and 5-woodland			
Tmin1990	Tmin2000	Tmin2010	Tmin2020	Tmax1990	Tmax2000	Tmax2010	Tmax2020	1990	2000	2010	2020	2020	2010	2000	1990
22.2	21.9	22.5	22.7	32.5	32.7	32.6	33.5	1022.7	987.7	1145.3	940.9	4	4	4	4
23.8	23.1	23.8	23.8	34.5	34.1	34.4	34.6	854.5	972.6	1106.9	1025.4	3	3	3	3
23.8	23.1	23.8	23.8	34.5	34.1	34.4	34.6	861.5	983	1115.4	1049.6	3	3	3	3
23.2	22.8	23.3	23.5	32.8	32.8	32.8	33.2	1009.3	1210.5	1321.3	1134.7	4	3	3	3
23.7	23.4	24.1	24.2	33.7	33.8	33.9	34.5	1032	1108.9	1223.9	855	3	3	5	3
23.4	23	23.5	23.5	34.2	34.1	34.3	34.3	748.5	873.8	1023.1	1037.3	3	4	3	3
23.1	22.7	23.4	23.5	32.6	32.9	32.9	33.5	1255.4	1317.2	1536.8	1465.4	4	3	3	4
23.4	22.8	23.5	23.6	34.4	34	34.4	34.6	842	921.3	1083.3	1059.6	3	3	3	3
23.2	22.7	23.5	23.5	32.9	33	33.1	33.5	1157.1	1318.8	1357.8	1401.2	5	5	3	5
22.6	22.3	22.8	22.8	33.4	33.2	33.4	33.5	754.5	942.4	1054.9	1071.7	4	4	3	3
23.3	23.1	23.8	23.9	33.2	33.6	33.6	34.2	1000	1114.4	1221.3	980.2	3	3	3	3
22.9	22.5	23.1	23.1	33.4	33.2	33.4	33.5	866.8	1061.1	1063.8	1209	3	3	3	3
22.6	22.2	22.8	22.9	33	32.9	33.2	33.2	852.4	1019.2	1083.9	1115.5	3	3	3	1
23.8	23.4	24	24.2	33.6	33.5	33.6	34.1	884.4	1081.5	1211.8	905.6	3	3	3	3
23.2	22.7	23.5	23.5	32.9	33	33.1	33.5	1166.5	1310.6	1368.8	1430.3	3	3	3	3
23	22.5	23.1	23.3	33.5	33.4	33.7	34.1	909.9	990	1152.9	1023	4	4	4	4
23.6	23.2	23.8	24.1	34	34	34	34.7	961.4	1039.6	1239.5	854.3	3	3	3	3
22.8	22.2	22.9	22.9	33.9	33.4	33.8	33.9	833.3	883.7	1053.4	1127.8	3	3	3	3

22.7	22.3	22.8	23.2	32.9	33	32.8	33.5	970.1	979.8	1195.7	896.9	4	4	4	4
23.8	23.4	24	24.2	33.9	33.8	33.9	34.5	951.3	1027.7	1211.6	870	3	3	3	3
23.5	23	23.5	23.5	34.4	33.9	34.1	34	758.7	895.7	1050.3	1082.4	3	3	3	3
23.2	22.8	23.3	23.4	34.1	34	34.1	34.1	816.9	1004	1114	1103.2	4	4	3	4
23.4	23	23.6	23.7	32.7	32.7	32.8	33.2	1045.2	1203.5	1346.1	1173.9	3	3	3	4
23	22.8	23.4	23.5	33.9	34.3	34.1	34.6	890.5	966.1	1238.9	810.1	5	5	5	5
22.5	22.1	22.7	22.9	32.8	32.8	32.8	33.4	1016	948	1254	1000.3	4	4	4	3
23.6	23.2	23.7	24	34	34	34	34.6	958.3	996.5	1254.4	816	4	4	4	3
24.5	24.3	25	24.9	32	32.3	32.5	32.9	1065.7	1227.7	1379	1054.2	3	3	3	5
22.6	22.2	22.7	22.9	32.9	33	32.8	33.5	987.9	950	1262.1	989.9	4	5	5	4
22.4	22	22.5	22.8	32.6	32.7	32.8	33.3	959	950.4	1176.6	1079.2	4	4	4	3
22.5	22.1	22.7	22.9	32.7	32.9	32.7	33.4	943.7	964	1221.9	926	3	4	4	5
23.6	23.1	23.7	23.9	33.5	33.3	33.3	33.9	994.3	1205.2	1333.8	1010	3	3	3	3
23.3	22.9	23.5	23.5	33.2	33.2	33.2	33.5	1049.3	1193.7	1279	1145.4	4	3	4	4
22.8	22.4	22.9	23.3	33.1	33.3	33.1	33.8	952.1	935.5	1223.1	817.3	4	4	4	4
23	22.4	23.1	23.1	34.1	33.6	33.9	34.1	825.9	957.5	1086.7	1028.9	4	4	3	3
22.8	22.1	22.9	22.9	34.1	33.4	33.8	33.9	819.1	890.6	1038.4	1066.6	3	3	3	4
23.1	22.8	23.4	23.6	33.3	33.5	33.4	34.1	926.4	911.5	1202.5	810.3	3	5	5	3
22.9	22.5	23.1	23.3	33.4	33.5	33.4	34.1	958.6	912.6	1211.5	990.1	4	4	4	4
22.6	22.3	22.9	23.2	32.7	33	32.9	33.6	1012.6	989.5	1140.1	841.5	4	4	4	4
23.8	23.4	24.1	24.2	32.1	32.4	32.4	33	1091	1287	1481.7	1191.1	3	5	3	5
22.9	22.3	23	23	33.6	33.1	33.6	33.7	856.2	914	1097.7	1052.3	4	3	3	3
23.5	22.9	23.6	23.7	34.5	34	34.5	34.8	738.4	913.2	1029.8	1095.1	4	4	3	3
23.4	23.1	23.8	23.8	32.1	32.4	32.4	33	1115.5	1250.4	1487.1	1189.5	4	3	3	0

22.6	22.3	22.8	22.8	33.4	33.2	33.4	33.5	757.3	940.9	1040.5	1077.9	3	3	3	3
22.8	22.1	22.8	22.9	33.8	33.4	33.7	34	772.6	819.2	900.5	783.7	1	3	3	3
23.4	22.8	23.5	23.6	34.4	34	34.4	34.6	761.2	886.6	1087.8	1094	3	3	3	3
22.9	22.2	22.9	23	34.1	33.5	33.8	34	781.4	909.3	1050.4	1051	3	3	3	3
23.8	23.5	24.2	24.2	32.2	32.5	32.7	33.1	1133.8	1316.6	1498.1	1099.8	3	3	3	3
23.5	23	23.5	23.5	34.4	33.9	34.1	34	740.9	841.5	1039.3	1071.4	3	3	3	3
23.2	22.8	23.4	23.5	32.7	32.7	32.9	33.2	988.7	1230.6	1335.9	1224.6	3	3	3	3
23.4	23	23.5	23.5	34.2	34.1	34.3	34.3	770.6	882.1	1046.4	1058.7	3	3	3	3
23.6	23.1	23.7	23.9	33.9	33.8	33.8	34.4	933.6	1049.1	1219.4	936.1	3	3	3	3
23.3	22.7	23.4	23.4	33.9	33.7	33.9	34.2	936.3	992.6	1109.3	1064.8	3	3	3	3
22.9	22.2	22.9	23	33.8	33.3	33.6	33.9	960.6	1006.2	1069.5	1030.1	4	3	3	3
23	22.4	23.1	23.1	34.1	33.6	33.9	34.1	862.2	951.7	1082.9	1006.3	4	3	3	3
24.5	24.3	25	24.9	32	32.3	32.5	32.9	1089.9	1245.1	1388.7	1113.7	5	5	5	3
23.3	22.7	23.4	23.4	33.9	33.7	33.9	34.2	924.4	1017	1203.8	1022.9	5	3	3	3
22.9	22.5	23.1	23.1	33.4	33.2	33.4	33.5	891.9	1103	1147.2	1190	3	3	3	3
23.8	23.3	23.8	24	34.1	33.7	33.8	34.1	1008	1039.6	1221.8	1111.6	3	3	3	3
22.6	22.2	22.7	22.9	32.9	33	32.8	33.5	1002.3	941.7	1257.8	967.4	4	4	5	3
22.9	22.3	22.9	23	33.7	33.3	33.5	33.9	898.9	982.5	1156.5	1004.8	4	3	5	4
23	22.5	23.1	23.3	33.5	33.4	33.7	34.1	973.8	1025.8	1189.2	1047.4	4	4	3	4
23.3	22.7	23.4	23.5	34.2	33.7	34.3	34.5	825.1	940.1	1108	1152.4	4	3	3	4
22.7	22.2	22.9	23	33.4	33.2	33.3	33.8	1059.8	946.7	1212.4	957.6	4	3	3	5
24	23.7	24.4	24.5	33.1	33.2	33.5	33.8	1081.1	1264.6	1410.5	974.2	3	2	5	2
23	22.4	23.1	23.1	34.1	33.6	33.9	34.1	833.1	961.2	1062.8	1014.2	3	3	3	3
22.6	22	22.7	22.8	33.3	32.9	33.3	33.5	838.7	984.9	1030.2	1001.6	3	3	3	3

22.5	22.1	22.7	22.9	32.8	32.8	32.8	33.4	1028.8	944.3	1209.5	983.7	4	3	5	3
23.8	23.5	24.1	24.3	33.8	33.7	33.9	34.4	990.4	1186.4	1285.3	880.9	3	3	3	3
23.7	23.1	23.6	23.7	34.3	33.8	33.9	34	948	1052.8	1168.5	1079.9	4	4	4	4
23.7	23.1	23.6	23.7	34.3	33.8	33.9	34	957.4	1011.5	1159.9	1092.8	4	3	3	3
22.9	22.3	23	23	33.6	33.1	33.6	33.7	875	913.3	1091.9	1094.7	4	3	3	3
22.9	22.2	22.9	23	34	33.5	33.7	34	906.3	986.7	1062.7	976.3	4	3	3	3
23.6	23	23.7	23.7	34.5	34.1	34.5	34.7	861.3	953.6	1103.7	1060	3	3	3	3
23.7	23.3	23.9	24	33.4	33.4	33.5	33.8	1049	1207	1305.7	1015.4	3	3	3	3
22.4	22	22.5	22.8	32.6	32.7	32.8	33.3	964.6	1018.8	1211.4	1034.1	4	4	4	4
23.3	22.9	23.4	23.5	33.3	33.1	33.1	33.4	1035.6	1096.4	1287.9	1105.7	4	3	3	3
23.4	22.9	23.5	23.5	33.7	33.6	33.7	33.8	1116.5	1121.6	1252	1259.1	4	4	3	4
22.8	22.1	22.8	22.9	33.8	33.4	33.7	34	821.7	879.2	966.1	834.4	3	3	3	3
22.9	22.5	23	23.2	33.5	33.3	33.3	33.8	920.4	984.3	1212.6	992.8	3	3	3	2

Appendix 3A: Questionnaires used for Perception surveys

Open-ended questionnaire

KNUST

OPEN-ENDED QUESTIONNAIRE

DORDAH A. George
PhD student in Climate Change and Land Use
KNUST, Kumasi, Ghana
gadordah@gmail.com

Research title: **Assessing Climate Variability, Land Use Land Cover Change (LULCC), And North-South Migration Patterns in Ghana: An Integrated Analysis.**

Overall objective

This questionnaire seeks to educe information to be used for student research work. The student's research aims to assess trends of climate variability and land use land cover (LULC) changes and their influence on North-South Migration in Ghana. Your responses will be anonymous.

SECTION ONE: DEMOGRAPHY OF RESPONDENT

1. **Name of Town/Village:** ……………………………………………………………..
2. **Gender of migrant:** ☐ Male ☐ Female
3. **Age:**……………………………………………………………………………………..
4. **Occupation**………………………………………………………………………………..
5. **Educational level:**…………………………………………………………………...
6. **Ethnic group** ………………….……………………………………………………..

SECTION TWO: MIGRATION RELATED INFORMATION

1.Where do you come from?..
………………………………………………………………………………………………..

2. How long have you lived in this community?
☐ Less than 10 years ☐ 11-30 years ☐ Above 30 years

3. What influenced/would influence your migration to the south (list in other of importance)?
(i). ………………………………………………………………………………………….....
(ii)…………………………………………………………………………………………….
(iii)…………………………………………………………………………………………....
(iv)…………………………………………………………………………………………....
(v)…………………………………………………………………………………………….

4. What was the impact of (Q3 i to iii on you)?
………………………………………………………………………………………………..
………………………………………………………………………………………………..

Date of the interview: ……/……/2021 Questionnaire type: Open-ended
Start Time: ……………………… End Time: ………………

Questionnaire for key informants

KNUST
INTERVIEW GUIDE FOR KEY INFORMANTS

DORDAH A. George
PhD Student in Climate Change and Land Use
KNUST, Kumasi, Ghana
gadordah@gmail.com

Research title: **Assessing Climate Variability, Land Use Land Cover Change (LULCC), And North-South Migration Patterns in Ghana: An Integrated Analysis.**

Overall objective

This questionnaire seeks to educe information to be used for student research work. The student's research aims to assess trends of climate variability and land use land cover (LULC) changes and their influence on North-South Migration in Ghana. Your responses will be anonymous.

SECTION ONE: DEMOGRAPHY OF STAKEHOLDERS

7. **Name of Town/Village:** …………………………………………………...
8. **Region:**………………………………………………………………
9. **District:**…………………………………………………………………....
10. **Name of Department:**……………………………………………………...
11. **Position held:**…………………………………………………………
12. **Gender:** ☐ Male ☐ Female

SECTION TWO: INFORMATION ON CLIMATE AND LAND TENURE AND ADAPTATION FOR FARMERS

GHANA METEOROLOGICAL SERVICES

1. Has the level and timing of rainfall in this area changed over the past 30 years?
i. Onset and Cessation, ii. Wet and dry spells iii. Volume

2. Has the temperature in this area changed over the past 30 years?
i. Increased or Decreased

MOFA/Agric Extension officers

3. Have changes in temperature and rainfall affected crop yield from farms?

4. Are farmers increasing their farmlands to adjust for poor yield due to the changes in weather patterns?
5. Are farmers increasing fertilizer application and other investments in the farmland compared to the past?
6. Are people in this area abandoning farming and migrating because the climate variability of the site is affecting yield and income?
7. Will many people in this area farm if the climate is good?
8. What is the average farm size per farmer in this community?

- Less than five

- Five to twenty Acres
- More than twenty acres
-

9. What type of crops do farmers in this community grow?
   - Cereals
   - Tubers
   - Vegetables
   - Commercial crops

10. Do farmers get good yields from their farms?
    - Yes
    - No

11. Are the sales from farm produce sufficient to keep farmers going throughout the year?
    - Yes
    - No

12. Are farmlands sufficient for the farming needs of farmers?
    - Yes
    - No
13. Can farmers acquire more land when the need arises?
    - Yes
    - No
14. Can the lack of available land cause people to migrate from here?
    - Yes
    - No

15. What is the typical tenure of land in this area?
    - Self-owned
    - Family land
    - Lease

16. Does this area's land tenure system adversely affect farmers and cause them to want to migrate?
    - Yes
    - No

17. What is the dominating land cover type in this area?
    - Grass
    - Woodland
    - Bare ground

18. Has the land cover in this area changed over the past 30 years?
    - Yes
    - No

19. Does the changes in land cover affect the use of land in this community?
    - Yes
    - No

20. What mainly causes changes in land cover in this community?

i. Natural impacts, e.g., Climate variability

ii. Human activities

21. Is this area prone to disasters?

22. Can land use and land cover change deterioration cause you to migrate from your current location?

- Yes
- No

23. How do farmers adapt to changes in land use, land cover, and climate variables?
i. Agric mechanization

ii. Changing my farming systems

iii. Support from elsewhere, e.g., NGOs, Cooperatives, banks

iv Migration

24. What are the causes of disasters in this community?
i. Natural impacts. Climate variability leading to LULCC

ii. Human activities

NADMO

25. What type of disaster/s is/are frequent in this community?

- Floods
- Bushfires
- Wind storms

26. Do these disasters from climate variability cause loss of farmlands and farm produce?
27. Do the disasters in this area lead to the displacement of people?
28. Do the disasters cause loss and damage of property?

29. How do People in this area adapt to such disasters?
i. Migrate
ii. Support from elsewhere, e.g., NADMO, NGOs, Cooperatives
iii. Stay and find other means of survival

Date of the interview: ……/……/2021 Questionnaire type: Key Informants

Questionnaire for Migrants

KNUST
MIGRANT QUESTIONNAIRE

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Research title: **Assessing Climate Variability, Land Use Land Cover Change (LULCC), And North-South Migration Patterns in Ghana: An Integrated Analysis.**

Overall objective

This questionnaire seeks to educe information to be used for student research work. The main aim of the student's research work is to assess trends of climate variability and land use land cover (LULC) changes and their influence on North-South Migration in Ghana. Your responses will be anonymous.

SECTION ONE: DEMOGRAPHY OF MIGRANT

1. **Name of Town/Village:** ….…………………………………………..........................
2. **Region:**…………………………………………………………………………….….
3. **District:**……………………………………………………….... ……………
4. **Migrant's House No. (Where applicable):** …………………………………………
5. **Coordinates of House. (Where applicable):** ……………………. /………………...
6. **Gender of Migrant** ☐ Male, ☐ Female
7. **Age of Migrant:** ☐ less than 18years ☐ 18-35years ☐ 36-60 years ☐ Above 60 years
8. **Occupation**……………………………………………………………….
9. **Phone no.:** ……………………… …………………………………
10. **Educational level:** ☐ No education ☐ below JHS ☐ JHS ☐ SHS ☐ Tertiary
11. **Ethnic group of Migrant:**…………………………………………………..
12. **The Religion of Migrant:**…**.** ……………………………………………...

SECTION TWO: MIGRATION RELATED INFORMATION

1. Where do you come from?

☐ In Ghana ☐ Abroad, where……………….

a. Region…

b. District….

c. Town……

2. Where were you born?

☐ In Ghana ☐ Abroad, where………………

a. Region…

b. District….

c. Town……

3. Who migrated to this community?

☐ Me ☐ Parents ☐ Ancestors

4. What is the name of the place you/your parents/ancestors migrated from?

☐ In Ghana ☐ Abroad, where………………

a. Region…

b. District….

c. Town……

5. If it was you who migrated, what was your occupation in the town you migrated from?

☐ Farming ☐ Self-employed ☐ An employee ☐ unemployed ☐ Menial jobs ☐

Others specify………………………………

6. If your parents/ancestors migrated, what was their occupation at the place they migrated from?

☐ Farming ☐ Self-employed ☐ An employee ☐ unemployed ☐ Menial jobs ☐

Others specify………………………

7. If it was you who migrated, why did you migrate from your former community?

i. Reducing rainfall

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree.

ii. Increasing temperature

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

iii. Increasing drought

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

iv. No land for farming

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

v. Reducing size of land for farming

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

vi. Reducing soil nutrient

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

vii. Reducing crop yield

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

viii. Displacement by natural disaster e.g., floods

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

ix. Your family

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

x. Poor living conditions

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

xi. Conflicts

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

8. If it was your parents/ancestors who migrated, why did they migrate from the former community?

i. Reducing rainfall

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

ii. Increasing temperature

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

iii. Increasing drought

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

iv. No land for farming

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

v. Reducing size of land for farming

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

vi. Reducing soil nutrient

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

vii. Reducing crop yield

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

viii. Displacement by natural disaster e.g., floods

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

ix. Your family

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

x. Poor living conditions

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

xi. Conflicts

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

9. Why did you/your parents/ancestors migrate to this community?

i. Good rainfall

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

ii. Good temperature

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

iii. Better drought conditions

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

iv. Available land for farming

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

v. Good soil nutrient

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

vi. Good crop yield

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

vii. Because my family is here

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

viii. Good living conditions

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

ix. Attachment because my ancestors ever lived here

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

10. How long have you stayed in this community?

☐ Less than 10 years ☐ 10-30 years ☐ More than 30 years

11. How long do you intend to stay in this place?

☐ For a season ☐ Permanently

12. If you consider to migrate from this community, where will migrate to?

☐ In Ghana ☐ Abroad, where………………

a. Region…

b. District….

c. Town……

13. What will make you consider to migrate from this community?

i. Reducing rainfall

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

ii. Increasing temperature

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

iii. Increasing drought

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

iv. No land for farming

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

v. Reducing size of land for farming

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

vi. Reducing soil nutrient

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

vii. Reducing crop yield

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

viii. Displacement by natural disaster e.g., floods

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

ix. Your family

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

x. Poor living conditions

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

xi. Conflicts

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

14. If you will want to stay in this community, why would you continue staying here?

i. The climate is good

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

ii. Available land for farming

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

iii. Your Occupation

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

iv. Good living conditions

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

v. Better crop yield

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

vi. My family lives here

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

vii. Attachment because my ancestors lived here

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

13. Do people at home depend on you to remit them?

■ Yes ■ No

14. Are you able to survive on your earnings from your current occupation?

■ Yes ■ No

15. Are you making enough money to enable you remit home?

■ Yes ■ No

16. How often do you remit home? Remittance

■ Regular ■ Sometimes ■ I don't remit home

17. What is your main problem staying in this town?

i. Language barrier

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

ii. Abuse from the Indigenous people

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

iii. Accommodation

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

iv. Poor living conditions

☐ Strongly agree ☐ agree ☐ disagree ☐ strongly disagree

v. Others, specify……………………………………...

SECTION THREE: INFORMATION ON CLIMATE, LAND TENURE AND ADAPTATION

1. The Onset and cessation of rainfall in this community is better than where I migrated from.

☐ Yes ☐ No

2. Comparatively, temperature in this community is better than where I migrated from.

☐ Yes ☐ No

3. I wouldn't have migrated if the temperature and rainfall patterns in my former community were as good as those in this area.

☐ Yes ☐ No

4. The changes in temperature and rainfall patterns in my former community have adverse effects on crop yield compared to this area.

☐ Yes ☐ No

5. I don't need to increase my farmland to make up for poor yield due to changes in climate variability.

☐ Yes ☐ No

6. I don't need to increase fertilizer application and other investments in my farmland to improve yield due to climate variability.

☐ Yes ☐ No

7. I abandoned farming in the area I migrated from because the climate variability of the area was affecting yield and income.

☐ Yes ☐ No

8. I moved out of my former community because the yield and income from my farm was decreasing due to climate variability.

☐ Yes ☐ No

9. If the climate had not changed to affect farming so much in my former community, I would have continued farming and not migrate to this community in search of other livelihood options.

☐ Yes ☐ No

10. If the climate variables change adversely in this community, will you migrate from here?

☐ Yes ☐ No

11. What is the size of your farm?

Please specify……………………………

12. What type of crops do you grow?

Please specify……………………………

13. Do you have good yield from your farm?

☐ Yes ☐ No

14. What is the estimated yield from your farm?

Please specify……………………………………………….

15. Are the sales from your farm produce sufficient to keep you going throughout the year?

☐ Yes ☐ No

16. How much do you make from the sale of your farm produce?

Please specify……………………………………………….

17. How much do you invest in your farm?

Please specify……………………………………………….

18. Is your land sufficient for your needs?

☐ Yes ☐ No

19. Are you able to acquire more land when the need arises?

☐ Yes ☐ No

20. If you cannot acquire enough land, will you migrate from here?

☐ Yes ☐ No

21. What is the tenure (who owns the land) on your land?

Please specify……………………………

22. Does the tenure on your land affect you adversely to cause you to want to migrate?

☐ Yes ☐ No

23. What was the cover of your land prior to cultivation?

☐ Grass ☐ woodland ☐ bare ground ☐ others …………………………………

24. Are you witnessing any changes in the land cover around your area?

☐ Yes ☐ No

25. Do the changes in land cover affect the use of land in this community?

■ Yes ■ No

26. Can land use and land cover change deterioration cause you to migrate from your current location?

■ Yes ■ No

27. The changes in land cover in this community is mostly caused by

i. Natural impacts, e.g., Climate variability

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

ii. Human activities

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

28. What are some of the activities that cause land cover change in this community

Please specify……………………………

29. How do you adapt to the changes in land use and land cover and climate variables?

i. Agric mechanization

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

ii. Changing my farming systems

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

iii. Changing crop types

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

iv. Support from elsewhere e.g., NGOs, Cooperatives, banks

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

v. Migration

■ Strongly agree ■ agree ■ disagree ■ strongly disagree

vi. Others, specify…………………………………………………………

30. Is this community prone to disasters?

■ Yes ■ No

31. What are type of disasters are very frequent in occurrence?

Please specify……………………………

32. What are the causes of disasters in this community?

Please specify……………………………

33. Disasters in this community have caused loss of farmlands and farm produce

☐ Yes ☐ No ☐ Not applicable if not a farmer

34. Disasters in this community have caused loss and damage of property

☐ Yes ☐ No

35. Disasters in this community have led to displacement of people

☐ Yes ☐ No

36. People in this community have adapted to disasters through migration

☐ Yes ☐ No

37. People survive through other means, please state them here

……………………………………………………………………….

Date of the interview: ……/……/2021 Questionnaire type: Migrants

Start Time: ……………………… End Time: ………………

Questionnaire for Household heads

KNUST

HOUSEHOLD QUESTIONNAIRE

DORDAH A. George
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Research title: **Assessing Climate Variability, Land Use Land Cover Change (LULCC), And North-South Migration Patterns in Ghana: An Integrated Analysis.**

Overall objective

This questionnaire seeks to educe information to be used for student research work. The main aim of the student's research work, is to assess trends of climate variability and land use land cover (LULC) changes and their influence on North-South Migration in Ghana. Your responses will be anonymous.

SECTION ONE: DEMOGRAPHY OF HOUSEHOLDS HEAD

13. **Name of Town/Village:** ……………………………………………...
14. **Region:**…………………………………………………………
15. **District:**……………………………………………………....
16. **House No:** ……………………………………………………………

17. **Coordinates of House:** ……………………. /………………...
18. **Gender of household head:** ☐ Male ☐ Female
1. **Age of Head:** ☐ less than 18years ☐ 18-35years ☐ 36-60 years ☐ Above 60 years
2. **Occupation**…………………………………………………………….
3. **Phone no.:** ………………………… …………………………………….
4. **Educational level:** ☐ No education ☐ below JHS ☐ JHS ☐ SHS ☐ Tertiary
5. **Ethnic group of households**……………………………………………
6. **Religion of Household head** ………………………………………….
7. **Household size (estimate for thirty years ago):** ……………………………… …...
8. **No. of Births (estimate for the last thirty years):**…………
9. **No. of deaths**:……………………………………….
10. **Household size (current):** …………………………………..................
11. **No. of Migrants**:……………………………………………………

INFORMATION OF HOUSEHOLD MIGRANTS

Gender	Age	Marital status	Education	Occupation	Reason for migrating	Destination	Remittance home
1.Male 2.Female		1.Married 2. Divorced 3. Seperated 4. Single	1.Yes 2. Non	a. Farming b. Entrepreneur c. An employee d. Unemployed e. Menial jobs f. Others specify	1.Weather 2.Land 3.Family 4.Occupation 5.Poverty	A. Another town within my region B. A place outside my region	A. Regular B. Sometimes C. No

SECTION TWO: MIGRATION RELATED INFORMATION

1. Are you from this community?

☐ Yes ☐ No

2. If you are not from this community, where do you come from?

In Ghana, where

a. Region….
b. District….
c. Town……

Abroad, where……………………………….

3. How long have you lived in this community?

☐ Less than 10 years ☐ 10-30 years ☐ Above 30years

4. Would you like to migrate from this community?

☐ Yes ☐ No

5. If you were to migrate from this community, where would you like to migrate to?

In Ghana, where

d. Region….
e. District….

f. Town……
Abroad, where……………………………….

6. What will cause you to migrate from this community?
i. Reducing rainfall
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
ii. Increasing temperature
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
iii. Increasing drought
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
iv. No land for farming
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
v. Reducing size of land for farming
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
vi. Reducing soil nutrient
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
vii. Reducing crop yield
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
viii. Displacement by natural disaster eg. floods
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
ix. Your family
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
x. Poor living conditions
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
xi. Conflicts
■ Strongly agree ■ agree ■ disagree ■ strongly disagree

7. If you prefer to stay in this community, why would you like to continue staying in this place?

i. The climate is good
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
ii. Available land for farming
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
iii. Your Occupation
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
iv. Good living conditions
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
v. Very good crop yield
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
vi. My family lives here
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
vii. Attachment because my ancestors come from here
■ Strongly agree ■ agree ■ disagree ■ strongly disagree

8. If you are not from this community, were you born here?
■ Yes ■ No

9. If you were born in this community, why did your parents migrate to this place?
i. Reducing rainfall
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
ii. Increasing temperature
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
iii. Increasing drought
■ Strongly agree ■ agree ■ disagree ■ strongly disagree
iv. No land for farming
■ Strongly agree ■ agree ■ disagree ■ strongly disagree

v. Reducing size of land for farming
Strongly agree agree disagree strongly disagree
vi. Reducing soil nutrient
Strongly agree agree disagree strongly disagree
vii. Reducing crop yield
Strongly agree agree disagree strongly disagree
viii. Displacement by natural disaster e.g., floods
Strongly agree agree disagree strongly disagree
ix. Your family
Strongly agree agree disagree strongly disagree
x. Poor living conditions
Strongly agree agree disagree strongly disagree
xi. Conflicts
Strongly agree agree disagree strongly disagree

10. If you were not born here, why did you migrate to this community?
i. Reducing rainfall
Strongly agree agree disagree strongly disagree
ii. Increasing temperature
Strongly agree agree disagree strongly disagree
iii. Increasing drought
Strongly agree agree disagree strongly disagree
iv. No land for farming
Strongly agree agree disagree strongly disagree
v. Reducing size of land for farming
Strongly agree agree disagree strongly disagree
vi. Reducing soil nutrient
Strongly agree agree disagree strongly disagree
vii. Reducing crop yield
Strongly agree agree disagree strongly disagree
viii. Displacement by natural disaster e.g., floods
Strongly agree agree disagree strongly disagree
ix. Your family
Strongly agree agree disagree strongly disagree
x. Poor living conditions
Strongly agree agree disagree strongly disagree
xi. Conflicts
Strongly agree agree disagree strongly disagree

11. Have you migrated from this community before?
Yes No

12. Why did you migrate?
i. Reducing rainfall
Strongly agree agree disagree strongly disagree
ii. Increasing temperature
Strongly agree agree disagree strongly disagree
iii. Increasing drought
Strongly agree agree disagree strongly disagree
iv. No land for farming
Strongly agree agree disagree strongly disagree
v. Reducing size of land for farming
Strongly agree agree disagree strongly disagree
vi. Reducing soil nutrient
Strongly agree agree disagree strongly disagree
vii. Reducing crop yield
Strongly agree agree disagree strongly disagree
viii. Displacement by natural disaster e.g., floods

Strongly agree agree disagree strongly disagree
ix. Your family
Strongly agree agree disagree strongly disagree
x. Poor living conditions
Strongly agree agree disagree strongly disagree
xi. Conflicts
Strongly agree agree disagree strongly disagree

13. How long did you stay away?
For a season 1-5 years above 5 years

14. Where did you migrate to?
In Ghana, where?
g. Region….
h. District….
i. Town……
Abroad, where………………………...

15. Why did you come back?
i. Reducing rainfall
Strongly agree agree disagree strongly disagree
ii. Increasing temperature
Strongly agree agree disagree strongly disagree
iii. Increasing drought
Strongly agree agree disagree strongly disagree
iv. No land for farming
Strongly agree agree disagree strongly disagree
v. Reducing size of land for farming
Strongly agree agree disagree strongly disagree
vi. Reducing soil nutrient
Strongly agree agree disagree strongly disagree
vii. Reducing crop yield
Strongly agree agree disagree strongly disagree
viii. Displacement by natural disaster e.g., floods
Strongly agree agree disagree strongly disagree
ix. Your family
Strongly agree agree disagree strongly disagree
x. Poor living conditions
Strongly agree agree disagree strongly disagree
xi. Conflicts
Strongly agree agree disagree strongly disagree

SECTION THREE: INFORMATION ON CLIMATE, LAND TENURE AND ADAPTATION FOR FARMERS

1. The Onset and cessation of rainfall in this area has changed over the past 30 years.
Yes No

2. Temperature in this area has increased over the past 30 years.
Yes No

3. In the past (i.e., 30years ago), the temperature and rainfall patterns in this area were better than now.
Yes No

4. The changes in temperature and rainfall have had adverse effects on crop yield from my farm and thus my income.
Yes No

5. I have had to increase my farmland to adjust to improve the poor yield due to the changes in climate.

Yes No

6. I have had to increase fertilizer application and other investments in my farmland to get the same yield I used to get in the past.

Yes No

7. People in my house have abandoned farming because climate variability of the area is affecting yield and income.

Yes No

8. People in my house have migrated to other parts of Ghana/abroad because climate variability of the area is affecting yield and income.

Yes No

9. I will move out of here for other options if the yield and income from my farm continue to decrease due to the climate variability.

Yes No

10. If the climate had not changed to affect farming so much, people would continue farming and not migrate to other areas in search of other livelihood options.

Yes No

11. What is the size of your farm?

Less than five Five to twenty Acres More than twenty acres

12. Is your land sufficient for your needs?

Yes No

13. Are you able to acquire more land when the need arises?

Yes No

14. If you cannot acquire enough land, will you migrate from here?

Yes No

15. What is the estimated yield from your farm?
Please specify……………………………………………………….

16. How much do you make from the sale of your farm produce?
Please specify……………………………………………………….

17. How much do you invest in your farm?
Please specify……………………………………………………….

18. What is the tenure (who owns the land) on your land?

Self-owned Family land Lease others…...

19. Does the tenure on your land affect you adversely to cause you to want to migrate?

Yes No

20. What was the cover of your land prior to cultivation?

Grass savanna woodland bare ground others

21. Has the land cover around your area changed over the past 30years?

Yes No

22. Does the changes in land cover affect the use of land in this community?

Yes No

23. The changes in land cover in this community is mostly caused by

i. Natural impacts e.g., Climate variability

Strongly agree agree disagree strongly disagree

ii. Human activities

Strongly agree agree disagree strongly disagree

24. What type of crops do you grow?

Cereals Tubers Vegetables Commercial crops

Others…………………...

25. Do you have good yield from your farm?

Yes No

26. Are the sales from your farm produce sufficient to keep you going throughout the year?

Yes No

27. How do you adapt to the changes in climate variables

i. Agric mechanization

Strongly agree agree disagree strongly disagree

ii. Changing my farming systems

Strongly agree agree disagree strongly disagree

iii. Support from elsewhere e.g., NGOs, Cooperatives, banks

Strongly agree agree disagree strongly disagree

iv Migration

Strongly agree agree disagree strongly disagree

v. Others, specify………………………………...

28. Can land use and land cover change deterioration cause you to migrate from your current location?

Yes No

29. This community is prone to disasters,

Yes No

30. What type of disasters are very frequent in occurrence?

i. Floods

Strongly agree agree disagree strongly disagree

ii. Bushfires

Strongly agree agree disagree strongly disagree

iii. Wind storms

Strongly agree agree disagree strongly disagree

iv. Others…………………………

31. Disasters in this community are mostly caused by
i. Natural impacts eg. Climate variability leading to LULCC
- Strongly agree - agree - disagree - strongly disagree

ii. Human activities
- Strongly agree - agree - disagree - strongly disagree

iii. Other specify……………

32. Disasters in this community have caused loss of farmlands and farm produce
- Yes - No

30. Disasters in this community have caused loss and damage of property
- Yes - No

33. Disasters in this community have led to displacement of people
- Yes - No

34. Over the years, people in this community have adapted to such disasters through
i. Migration
- Strongly agree - agree - disagree - strongly disagree

ii. Support from elsewhere e.g., NADMO, NGOs, Cooperatives
- Strongly agree - agree - disagree - strongly disagree

iii. Finding other means of survival, give example……………………………………

Date of the interview: ……/……/2021 Questionnaire type: Household Head
Start Time: ……………………… End Time: ………………

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