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DEPARTMENT OF EARTH AND CLIMATE SCIENCES

IMPACT OF CLIMATE CHANGE AND LAND USE/LAND COVER DYNAMICS ON SMALL-SCALE FARMING SYSTEM IN GEDAREF STATE, SUDAN

By

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Climate Change and Adaptation in the department of Earth and Climate Sciences of the University of Nairobi

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PLAGIARISM STATEMENT

I, Maysoon Abdelhameid Abdelhai Osman, declare that this thesis is my original work and has not been previously submitted by me or any other person for a degree to this or any other tertiary institution.

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DEDICATION

I dedicate this achievement to my beloved mother, late father, brothers, and sisters, who have always supported and loved me unconditionally. Above all, I thank Almighty Allah, the source of my strength throughout this journey.

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ABSTRACT

Rainfed agriculture is generally the principal activity for the economy of Sudan. However, this sector is severely affected by climate change due to shifting in rainfall patterns, rising temperatures, and extreme weather events such as floods and droughts. Consequently, this has resulted in reduced crop production and increased hunger. Specifically, climate change coupled with changes in land use/ land cover (LULC), as a proxy for landscape structure, land fragmentation, degradation, and reduction in soil fertility have threatened small-holder livelihood in Sudan. Therefore, the aim of this study was to investigate the impacts of climate trends and LULC changes on crop production of small-holder farmers in Gedaref state, Sudan. To achieve this, four objectives were defined; i) to determine the relationship between climate trends and the level of crop yields; ii) to determine farmers' perception of climate variability and change and their choice of adaptation measures; iii) to assess and quantify LULC changes and their intensities between 1988 and 2018, and to project LULC structure in 2028 and 2048; iv) to assess the local farmers' perception of LULC change trends; and determine their drivers in Gedaref state. Historical records of rainfall and temperature, crop (sorghum, sesame, millet, cotton and sunflower) production, and population data for Gedaref state were obtained from Sudan Meteorological Authority, Ministry of Agriculture, and Sudan Central Bureau of Statistics, respectively. Semi-structured questionnaire, key informant interviews and focus group discussions were used to collect data on small-holder farmers' perception of climate and LULC trends. These datasets were subjected to various analysis including Mann–Kendall trend test, multiple linear regression, correlation and multinomial regression model. In addition, satellite-based data were used to map LULC changes between 1984 and 2018 using the machine learning random forest algorithm and future LULC for 2028 and 2048 utilizing the cellular automata-artificial neural network model. Trends in annual maximum and minimum temperatures significantly ($p < 0.0001$) increased in Gedaref state by 0.03°C and 0.05°C per year, respectively, with fluctuations in the amount of rainfall. The rainfall amount and duration of the rainy seasons were the only climatic factors that positively affected crop yields. The small-scale farmers were aware about climate change, and they used crop rotation, early cultivation and cultivation of short-maturing crop varieties as adaptation measures to climate change and variability. The analysis of LULC change showed a decline in forest and grassland cover and an increase in cropland and settlement. Local

land users perceived a similar trend and ranked firewood collection, agricultural expansion, and charcoal production as the top proximate drivers, while poverty and rapid population growth were the most vital drivers for LULC changes in Gedaref landscape structure. However, future prediction of LULC showed an overall increase in cropland and settlement areas at the expense of forest and grassland areas by 2048. These findings have shown that crop yields are affected by climate change and variability and changes in LULC would significantly affect future crop production. Therefore, there is a need to raise awareness among different stakeholders, especially policymakers to provide sustainable interventions for small-holder farmers against climate and LULC changes in Gedaref state and other similar farming systems.

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LIST OF ABBREVIATIONS

AD	Allocation Disagreement
ANN	Artificial Neural Network
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CA	Cellular Automata
CA-ANN	Cellular Automata-Artificial Neural Network Model
CV	Coefficient of Variation
DSSAT	Decision Support System for Agrotechnology Transfer
DTR	Diurnal Temperature Range
ENVI	Environment for Visualising Images
ERDAS	Earth Resources Data Analysis System
ETM+	Enhanced Thematic Mapper Plus
FAO	Food and Agriculture Organization
FGDs	Focus group discussions
GDP	Gross Domestic Product
GEE	Google Earth Engine
GMT	Greenwich Mean Time
ENVI	Environment for Visualising Images
IPCC	Intergovernmental Panel on Climate Change
LULC	Land Use and Land Cover
ML	Maximum Likelihood Classifier
NGOs	Non-Governmental Organisation

OA	Overall Accuracy
OLI	OLI Operational Land Imager
PA	Producer's Accuracy
QD	Quantity Disagreement
RF	Random Forest
SPSS	Statistical Package for Social Sciences
TD	Transdisciplinarity Approach
TM	Thematic Mapper

CHAPTER ONE

INTRODUCTION

1.1. Background

In the last century, the global air temperature has risen by 2–6°C due to greenhouse gas emissions, resulting in what is known as climate change (IPCC, 2014). With the continuous increase of greenhouse gases in the Earth's atmosphere, it is estimated that by the end of the twenty-first century the mean atmospheric temperature will increase by 1.4 to 5.8°C (IPCC, 2014). This temperature increase is expected to significantly affect crop production, resulting in food insecurity, particularly in developing countries (Zewdie, 2014). Therefore, climate change is rapidly becoming one of the most threatening and toughest global challenges.

Changing temperatures, shifting rainfall, sea-level rise, and increased experience of extreme climate events will highly decrease global food production in this century, unless an effort is made to address these adverse effects of climatic change (Ewert *et al.*, 2015). Furthermore, it has been projected that by 2050, the world will require to raise agriculture production by 60–110% to meet the ever growing human population and increasing demand for food (Ray *et al.*, 2013). Consequently, this will also exert pressure on available natural resources such as water, energy, and land. Therefore, increasing agricultural production in the near future will be one of the biggest challenges facing humanity (Godfray *et al.*, 2010; Licker *et al.*, 2010). Water availability for agricultural production is a critical factor of the many dimensions of this challenge (Fereres *et al.*, 2011). Although it is argued that agricultural output needs to be increased to meet the growing demand for food and to ensure the sustainability of natural resources, agricultural expansion is not a choice, but rather a strategy that need to be considered (i.e., increasing crop efficiency and closing yield gaps on underperforming land) (Elagib *et al.,* 2019).

Besides the impact of climatic change, human activities also influence ecosystem services through continuous land use/ land cover (LULC) changes. The combination of human population increase and competitive land usage due to climate change results in land scarcity, conversion of natural areas to agricultural lands, and other uses such as settlements (Kanianska, 2016). Indeed, humans have modified approximately one-third to half of the Earth's surface, and the extent of land use is expected to grow to meet the increasing demand for land, especially for agricultural production (Brovkin *et al.,* 2013; Ellis, 2011). Increased agricultural intensity puts a strain not just on land resources but also on the whole ecosystem. Accordingly, many scientists have stressed the significance of incorporating LULC studies into climate change research (de Chazal & Rounsevell, 2009; Mahmood *et al.,* 2010).

In Africa, millions of people depend on agricultural activities; thus, land is considered the most critical livelihood source. However, climate change has become a concerning issue due to its effects on agricultural production and land use, threatening livelihoods and food security (Akudugu *et al.,* 2012). Sub-Saharan Africa is one of the poverty-stricken areas facing considerable variation and decrease in food production due to climate variability and change (Schmidhuber & Tubiello, 2007). Yet, agricultural production is still tiny compared to the tremendous growth in agricultural output in many regions of the world over the past decades (Pretty *et al.,* 2011). Therefore, to meet the high demand for food in changing climate, the agricultural area has been dramatically expanded in sub-Saharan Africa (Kleemann *et al.,* 2017). This expansion led to the loss of bio(geo)diversity, severe erosion and land degradation, soil infertility and deforestation (Akinyemi & Speranza, 2022). On the other hand, the increase in the human population as well as other non-agricultural activities and urbanization, has resulted in a loss of productive agricultural lands in sub-Saharan Africa (Creutzig *et al.,* 2019). The rapid increase in human population coupled with a dramatic change in LULC, and this might aggravate climate change impact in the future.

In Sudan, agriculture remains a vital sector of the economy as the primary source of food, raw materials, income, and foreign exchange (Mahgoub, 2014). It supports livelihood for about 60% to 80% of the population in the country (Hussein *et al.,* 2022). It also plays a vital role in economic growth through the industrial sector and trade, thus, it contributes 27% of the country's Gross Domestic Product (GDP) (Hussein *et al.,* 2022). The agricultural sector in Sudan is split into two sub-sectors: irrigated and rainfed agriculture. The rainfed sector is the most important in Sudan and it occupies around 90% of the total cultivated land in the country and provides livelihoods to most of the population, especially in the rural areas. However, Sudan is highly vulnerable to climate variability and change, as like other African countries. This situation is exacerbated by several pressures at different levels, such as poverty, institutional deficiencies, and restricted access to finance, market and infrastructure. Indeed, in the last decades, the country has witnessed rainfall fluctuations, rising temperatures, increasing floods, and recurrent droughts, which highly affected agricultural production (Siddig *et al.,* 2020). This has affected the livelihood of millions of people in rural areas as the substantial rainfed cultivation is the primary source of their livelihood and income.

Gedaref state is the most important and largest rainfed agricultural area in Sudan, located in the eastern part of the country (Yousif & Babiker, 2015). This state is characterized by a semi-arid climate with medium to low rainfall and high temperature, which are the most critical direct factors to agricultural production (Mohmmed *et al.,* 2018). The rainfed sector in Gedaref State is divided into semi-mechanized farming and traditional farming, which is practiced only by small-holder farmers, who largely depend on farming activities for their livelihoods and contribute much to agricultural outputs (Ayoub, 1999). Degraded soils, erratic climate conditions, and weak adaptive capability enhances the vulnerability of small-scale farmers to climate variability and change (Mohmmed *et al.*, 2018). Furthermore, LULC changes at local scales have a major role in climate variability and change (Deng *et al.*, 2013). Therefore, LULC change analysis at the local scale over an extended timescale helps to reveal important basics that can explain future projections of new LULC changes (Sulieman & Elagib, 2012).

1.2. Problem statement

In Sudan, the agriculture sector remains the mainstay of the country's economy, where rainfed agriculture is the most important sector. However, climate change, evidently seen by rising temperatures and erratic rainfall in the country has significantly affected the agricultural sector, especially rainfed agriculture (Ayoub, 1999; Elagib & Elhag, 2011; Eldredge *et al.*, 1988; Siddig *et al.*, 2020). Given the projection that the population of Sudan (approximately 43 million people) will be doubled by the year 2050 (Nath *et al.*, 2001), hence the agricultural production, especially in rainfed areas such as Gedaraef state, needs to be doubled as well to ensure food and nutrition security. This increment will create pressure on available natural resources to produce sufficient agricultural output to meet the rising demand for food. Indeed, Gedaref state is the main rainfed agricultural area in Sudan, where thousands of people practice traditional small-holding farming, which their livelihoods mainly depend on. However, many farmers in this state have experienced different climate change effects over the last decades, which sometimes appear as increased intensity and recurrence of extreme climate events like floods, droughts, long dry spells, and unpredictable onset of the rainy season. As a result, agricultural productivity has been largely affected. Nevertheless, there is a lack of science-led evidence and assessment of climate effects on crop yield in the Gedaref region. Understanding the responses of crops to the shifts in inter-and intra-seasonal rainfall patterns is useful for agricultural planning and designing adaptation measures. Furthermore, how small-holder farmers in Gedaref state perceive climate and LULC changes and what adaptation measures they use to cope with the negative impacts of these changes are questions that have not yet been evaluated.

The immigration of many people within the country as well as from the neighbouring countries to Gedaref has led to expansion of agricultural land and settlements, affecting other natural resources. Indeed, Gedaref area has witnessed a remarkable large-scale land degradation indicated by reduced vegetation coverage, and loss of soil fertility (Glover & Elsiddig, 2012). This has aggravated the negative impacts of climate variability and change on rainfed farming (Morgan, 2019), coupled with LULC changes, which are triggered mainly by malpractices such as the removal of a large area of natural forest by people who engages in charcoal burning and illegal tree cutting and wood harvesting (Abdalla, 2015). However, LULC changes and factors that drive these changes for the whole Gedaref state are still largely unknown. Therefore, the emerging challenges of climate variability and change and LULC changes should not be considered independently; instead, their integrated effect should be evaluated in a holistic manner to support policy mainstreaming on mitigation of climate impacts. Hence, more attention on the impact of climate and LULC changes on the traditional rainfed agricultural sector is needed to minimize the negative impacts and achieve food and nutrition security in the Gedaref area and Sudan at large.

1.3. Justification

In Sudan, agriculture is one of the significant pillars of the country's economy. Notwithstanding, in recent years, rainfed agriculture has been affected significantly by climate variability and change and land degradation. This might result in a reduction in agricultural production by reducing suitable agricultural areas and quantities. In the country, one of the main states that rely on agriculture as the main the agriculture activity is Gadaref state. Agriculture in the state provides employment and livelihood for about 80% of the population (Mahgoub, 2014). Although Gadaref state is the main rainfed area in Sudan that is characterised by a semi-arid climate, little attention has been paid to assessing the effect of climate change on small-scale crop farming. It is speculated that fluctuation in the timing and duration of the rainy season could have an important negative influence on crop yield (Murenzi, 2019). Therefore, improved understanding of climate change impacts and land use changes can lead to the development of better farming practices. Also, introduction of climate-resilient crops and efficient land use techniques can increase yield and income for small-scale farmers. Without addressing climate change impacts and land use dynamics, agricultural productivity may decline due to increased vulnerability to extreme weather events and land degradation. Farmers may also continue using unsustainable practices, leading to further soil depletion and lower yields. Therefore, this study will provide much-needed information for decision-makers, extension officers, researchers, non-governmental organizations (NGOs), and fiscal development planners to adopt measures that enable reduction of the vulnerability of small-scale farmers to climate change and variability and LULC changes.

1.4. Objective of the study

1.4.1. General objective

The general objective of this study was to investigate the impacts of climate trends and variability and LULC changes on small-holder farmers' crop production in Gedaref State, Sudan.

1.4.2. Specific Objectives

The specific objectives of this study were to:

1. Determine the relationship between climate trends and the level of crop yields,

2. Determine farmers' perception of climate variability and change and choice of adaptation measures,

3. Assess and quantify the LULC changes and their intensities between the years 1988 to 2018 and forecast future LULC outlook in 2028 and 2048, and

4. Evaluate the local farmers' perception of LULC change trends; and determine the main drivers of such changes.

1.5. Research questions

1) What are the climate trends in Gedaref state?

2) What are crop farmers' perceptions on LULC changes in Gedaref state?

3) What is the relationship between climate trends and crop yields in Gedaref state?

4) What is the trend of LULC changes in Gedaref state over the last thirty years?

5) What are the factors that trigger LULC changes in Gedaref state?

6) What are the factors that influence farmers' choices of adaptation measures for climate change?

1.6. Scope and limitations of the study

1.6.1. Scope

Gedaref state in Sudan was selected for this study due to its importance as Sudan's largest rainfed agricultural area, with a few large and many small-scale farmers. It is largely recognized as the country's land of sorghum and sesame, where about one-third of these two crops are produced under a rainfed mechanized farming system (Elagib *et al.*, 2019). Other crops such as cotton, groundnut, millet, and sunflower are also cultivated in the area under rainfed conditions. Sorghum and millet are grown for food consumption, with sorghum being the staple food in the entire country. Sesame and sunflower are grown mainly for oil production and export, while cotton is an industrial cash crop. However, climate variability and change may significantly impact crops yield and, consequently, livelihoods, especially for small-holder farmers and the entire state’s economy. Additionally, LULC changes have aggravated the effects of climate variability and change on rainfed farming (Morgan, 2019) in Gedaref state. Therefore, food security and sustainable livelihoods are in danger for the highly vulnerable groups whose livelihoods depend largely on natural resources.

1.6.2. Limitations

The temperature data used for this study were obtained for one meteorological station in Gedaref state. This is due to the fact that Sudan meteorological authority from which these data were obtained has only one meteorological station in Gedaref state. In addition, the limited resources that could allow collection of ground LULC observations to train and test the models developed for detecting LULC changes and their intensities. Hence, on-screen reference LULC data was collected from the Google Earth Pro platform and used for training and testing the LULC models.

1.7 Structure of the thesis

This thesis contains eight chapters. The first chapter provides the background information about the study. The second chapter presents a detailed state-of-the-arts in relation to LULC and climate changes and their impact on crop production. The chapter also provides information in relation to farmers' perceptions of LULC and climate changes and their adaptation measures. A synthesis of the state-of-the-arts that shows the gaps in knowledge that needs to be filled was also highlighted. Chapter three describes the study area and provides a detailed methodological framework that employed to address each of the study objective. Chapter four provides results and discussion on climate and crop yield trends and the impact of climate variability and change on the main crops yield in Gedaref state. Chapter five provides results and discussion on farmers' perceptions of climate variability and change in Gedaref state, and the adaptation measures they use at the local scale to cope with the negative impact of climate change on crop production. Chapter six presents results and discussion on LULC dynamics and their intensities and future prediction of LULC outlook in Gedaref state. Chapter seven provides results and discussions on farmers' perception of LULC dynamics and the approximate and underlining drives that caused the changes in the landscape structure. Chapter eight presents the general conclusions for various objectives of the study and list of recommendations for further research, policy change and support for extension services.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter explores a relevant literature review on climate variability and change and its impact on crop yields, farmers' perception of climate change and adaptation measures they use to cope with the impacts of climate change in Sudan. It also reviews literature on land use/ land cover change and their driving factors.

2.2 Empirical review of farming system in Sudan

Farming systems face complex, dynamic, and interconnected changes in the production context as a result of climate change, rising food demand, scarcity of natural resources, volatile input and output prices, rising energy costs, and administrative regulation (Martin *et al.,* 2013). Farming systems differ from one location to another depending on many factors such as climatic conditions, water availability, level of farming and soil type. However, among these, water availability is the most important factor that plays a crucial role in determining the type of farming system in a specific location. Three farming systems namely rainfed, irrigation and supplementary irrigation are used in different parts of the world depending on the water supply for crop production (Pathak *et al.,* 2009). In Africa however, most of the farmers depend only on the amount of rainfall to cultivate their crops during the rainy season. Although farmers use different cropping systems such as maize mixed farming, agro-pastoral farming, cereal-root crop mixed farming, among others to ensure food security (Garrity *et al.,* 2012), the crop yields under rainfed conditions remain 50% lower than yields gained from the irrigated system (Jaramillo *et al.,* 2020).This is mainly due to the poor infrastructure in Africa, uncertainty in the amount of rainfall and the lower supply of solar energy during the rainy season that limits photosynthesis, leading yield reduction (Jaramillo *et al.*, 2020). Indeed, the low crop yield under rainfed conditions is the key factor that causes hunger, unemployment, poverty, and migration to cities in developing countries (Jaramillo *et al.,* 2020) including SSA. Therefore, a sustainable food supply needs to be achieved through sustainable agriculture using irrigation systems and agricultural technologies to ensure food and nutrition security, especially under climate change.

Sudan is empowered with large cultivable land areas located between the White Nile and the Blue Nile, and between the Blue Nile and the Atbara River, beside the wide cultivated regions of Kordofan and Darfur. Arable land constitutes about one-third of the total area of the country, of which 21% is cultivated, with fluctuating productivity, but the output remains far below potential performance (Mahgoub, 2014). More than 40% of the country's area consists of forests and pastures (Mahgoub, 2014). Commercial production and small-crop farming are practiced for local consumption and export. Two types of crop cultivation systems are used in Sudan: irrigated and rainfed cultivation. The irrigated system is located along the River Nile and its tributaries, including the area between Blue and White Niles and Atbara River. The farmers in these areas use different irrigation forms, including floods, pumps, gravities, and from seasonal streams (N. M. E. Ahmed & Elsaied, 2017). The irrigated area covers approximately 1.8 million hactares and produces cotton, wheat, beans, lentil, faba bean, and a significant portion of sorghum and groundnuts (FAO, 2015b). Although it occupies only about 10% of the total cultivated area, it contributes about 14% of the added value of agriculture and 40% of the added value of the crop sector in the country (FAO, 2015b). Nevertheless, poor infrastructure, lack of agricultural technologies, lack of financial support, change of government policies, and poor maintenance of irrigation channels in the major schemes such as Gezira, Al Rahad and New Halfa are the major challenges that are facing the irrigation farming system in Sudan. This has forced many farmers' especially, small-scale farmers to abandon crop cultivation or reduce the areas under crop cultivation.

On the other hand, rainfed cultivation is Sudan's widely practiced by small-scale farmers in Kordofan, Darfour, Gezira, Gedaref, Kasala, Blue and White Nile states covering around 80-90% of the total cultivated area (FAO, 2015b). In Sudan, a small-scale farmer typically refers to an individual or family who operates a relatively small piece of agricultural land, often less than 5 hectares. These farmers rely primarily on manual labor and traditional farming methods. The farming system in the rainfed sector is divided into semi-mechanised and traditional rainfed agriculture. The semi-mechanised covers nearly 6.7 million ha and is found in the central clay plains of Sudan in Gedaref, Blue and White Nile states and some parts of Gezira and South Kordafan states (Mahgoub, 2014). Mechanised activities are primarily limited to operations of tillage and harvesting. In contrast, the traditional rainfed farming system covers around 10 million ha; it is by far the biggest crop cultivation sector in Sudan (FAO, 2015b; Mahgoub, 2014). This farming system includes traditional practices for land preparation and sowing with rarely use of modern inputs. It is based on the use of hand-made tools that are locally made (Marizin *et al.*, 2017). Overall, the rainfed agricultural system produced the largest quantity of sorghum (44%), the major staple food in the country (FAO, 2015b). The main crops that are cultivated under rainfed conditions include sorghum, sesame, short-staple cotton, sunflower, millet, groundnut and cowpeas (FAO, 2015b). Although rainfed farming is the most important sector in Sudan where approximately 65-70% of the population is involved, agricultural productivity remains low and the majority of the farmers have abandon farming activities and migrated to the cities. This is due to fact that rainfed sector receive little attention from the local and national governments as well as the ongoing confilicts in Kordofan and Darfour has largely affect rainfed agricultural in Sudan. Furthermore, lack of technologies, inputs, access to credit, soil degradation and infertility and pests and disease remain the major challenges that are affecting rainfed cultivation in Sudan. This, coupled with climate variability and change, causes variations in the amount of rainfall leading to a huge impact on crop production.

2.3 Empirical review on climate variability and change

Climate variability and change pose a great challenge to natural resources in arid and semi-arid conditions (Singh & Chudasama, 2021). Variability in precipitation and increased frequency of droughts can lead to crop failures, affecting food security and the livelihoods of communities dependent on rainfed agriculture. Climate variability refers to a year-to-year fluctuation or the variations in the mean state of climate statistics on all spatial and temporal scales over a given period of time (e.g. a month, season or year). Variability may result from natural internal processes within the climate system or variations in human activities as external forces (Thornton *et al.*, 2014). While climate change refers to any change in climate over a long period of time (at least 30 years) or for an extended period, typically decades or longer, over a given region of the world, whether due to natural variability or human activities (Thornton *et al.*, 2014). According to IPCC report, land is already under growing human pressure and climate change is adding to these pressures, affecting food and nutrition security, especially in developing countries (IPCC, 2014). Hence it is necessary to develop appropriate adaptation and mitigation measures to cope with the negative impact of climate change. Concurrently, keeping global warming to well below 2ºC can be achieved only by reducing greenhouse gas emissions from all sectors, including land and food (IPCC, 2014). Therefore, climate change is considered to be one of the most significant difficulties confronting mankind in the 21st century, and its impacts pose a tremendous and real threat to all people around the world.

The Intergovernmental Panel on Climate Change (IPCC) states that the average annual temperature will increase by 2–6°C in Africa under high emission scenarios (RCP8.5) by the end of the 21st century (IPCC, 2014). This increment is expected to be higher within the arid regions of the African continent compared to the rate of global average temperature increment (Almazroui *et al.*, 2020; Déqué *et al.*, 2017). The effect of rising temperature combined with fluctuating rainfall and scarcity of water for irrigation is argued to have a pronounced negative impact on crop yield, particularly in semi-arid and arid regions in Africa (Kangalawe & Lyimo, 2013; Raza *et al.*, 2019). Consequently, this threatens the food and nutrition security situation in agriculture-based economies, which is the main source of livelihood for the resource-poor communities, especially in sub-Saharan Africa, where millions of people depend on agriculture for their livelihood support. Africa's development and climate are closely linked: if climate change is unaddressed, it will endanger Africa's hard-won development achievements and its ambitions for poverty reduction and further growth (The World Bank Group, 2016).

Sudan is one of the most vulnerable countries to climate variability and change. In the last decades, extreme climatic events, such as floods, droughts, and heat and cold waves, have been reported in Sudan (Elagib & Elhag, 2011). A study by Elagib and Mansell (2000) showed an increase in annual temperature in Sudan between 1941 and 1996 by 0.076–0.20°C per decade. Another study by Elagib and Elhag (2011) reported that the amount of rainfall significantly decreased between 1975 and 2008, with frequent drought occurrences ranging from 44.1% to 70.6%. Future projections also showed an increase in temperature between 2.5–3.0°C by 2065, with an increasing rainfall trend (Chen *et al.*, 2013). Although these are clear indicators of climate change in Sudan, the impact of climate variability and change on agricultural production and other sectors has been poorly documented. For instance, the seasonal temperature and annual rainfall trends in main rainfed agricultural areas like Gedaref have not been evaluated. Assessing and understanding the climate trend of a specific area is useful in determining the consequences of the social and economic impacts of climate change. Further, evaluating climate trends is essential for future agricultural production planning.

2.4 Impact of climate trends on crop yields

Climate variability and change severely threaten agriculture and food security (Rezaei *et al.,* 2015). From the perspective of climate change predictions, both natural systems and humans are at risk. However, developing countries are more at risk because they depend primarily on natural resources for their livelihoods and have lower adaptive capacity (Mumtaz *et al.*, 2019). Agriculture is critical to most sub-Saharan African economies, which provide about 70% - 80% of employment and contribute an average of 30% and 40% to GDP and exports, respectively (Calzadilla *et al.*, 2013). However, the uneven distribution of rainfall patterns, reported high temperatures, and extreme weather events negatively impact agricultural production (Ahmed ***et al.,*** 2018). This is because an estimated 97% of existing arable lands in sub-Saharan African are under rainfed agriculture (You *et al.,* 2011). In general, several studies have reported that crop yield under rainfed agriculture is considerably influenced by climate variables, with rainfall being associated with a higher impact on the level of yield. Specifically, Sawa and Adebayo (2018) argued that both frequencies of occurrence and length of dry spells are the main variables influencing crop yield under rainfed production systems. Furthermore, lack of sound adaptation measures coupled with the vulnerability of the rainfed agricultural sector in Sub-Saharan Africa has major effects on crop production (Mertz, Halsnæs, *et al.*, 2009). Poor access to services, limited knowledge, and small farm sizes have limited agricultural development in Sub-Saharan Africa. In this regard, urgent climate adaptation and mitigation measures are needed to minimise the risk and negative impact of climate change in Africa to achieve food and nutrition security.

In Sudan, changes in rainfall patterns and rising temperatures affect agricultural production of both rainfed and irrigated sectors, consequently impacting livelihoods and food security (Nelson *et al.*, 2010). For example, following the severe drought in Sudan in the year 1984, crop production, particularly in the main crop production areas such as the Gedaref rainfed region, substantially decreased; consequently, the country was exposed to a severe famine (Eltohami, 2016). As a result of such a famine, it was reported that about 55 thousand people died, while the survivors were recorded to have suffered socio-economic loss, especially in communities that rely on crop farming and agro-ecosystem services (Elhag & Zhang, 2018). It has been documented that the optimal temperature for the production of most crops in Sudan, such as sorghum and millet, ranges between 26ºC and 32ºC (Mahgoub, 2014). However, in some parts of the country, temperature exceeds 47ºC, causing stress and heat-related diseases to crops. This indicates that an increase in temperature trend not only affects the plant physiology but also increases crop pest and disease incidence. Furthermore, the rainfall fluctuation from the North to the South, besides its concentration into a short growing season, has increased the vulnerability of rainfed farming systems (Mahgoub, 2014). According to the world resources report 2011, the humid agroclimatic zones in Sudan will shift to the South, making northern areas increasingly unsuitable for farming (Lim *et al.*, 2011). For example, millet production in Kordofan region is predicted to decline between 15% and 62%, sorghum between 29% and 71%, and gum Arabic between 25% and 30% under future climatic conditions between 2030 to 2060 (Lim *et al.*, 2011). Though these are significant findings, how climate variability and change affect crop yield in the Gedaref state and

Sudan at large has not been understood. It is speculated that the fluctuation in the timing and duration of the rainy season could have an important influence on crop yield (Murenzi, 2019). However, there is a lack of science-led evidence and assessment of climate effects on crop yield in the Gedaref region. This is due to the fact that determining the relationship between climatic factors and crop yield is rather difficult. Separating the effect of overlapping factors such as climate, agricultural inputs, soil fertility, technologies and management practices on crop yields remains the major challenge in assessing the impact of climate change on crop yield. Nevertheless, elucidating the relationships between climate variables such as temperature and rainfall patterns provides fundamental information that helps in agricultural planning and designing appropriate adaptation measures.

2.5 Farmers' perception of climate change and determinants of adaptation measures

Perception is defined as a process by which information is received and transformed to create psychological awareness (Qiong, 2017). People's perception of climate change varies from one place to another depending on their cultural and socio-economic differences that expose people to various values, interests, and attitudes (Ayal & Filho, 2017; Wolf *et al.*, 2013). Therefore, farmers' perceptions of climate change and its impacts are influenced by socio-economic and psychological differences that limit their response to climate change. For farmers to choose adaptation measures, they must first perceive that the climate is changing and acknowledge that it poses a challenge to their farming activities and consequently their livelihoods (Bryan *et al.*, 2013). Recently, studies on farmers' perceptions of climate change have elicited significant research interest. Literature has shown that there are different variables like age, farm size, and annual income influence farmers' perceptions of climate change. In one such study, Maddison (2007) states that farmers' perception of climate change depends on their farming experience and accessibility of extension guidance related to climate change. In line with this finding, Foguesatto and Machado (2021) concluded that the help provided by extension offers can be like a proxy for different kinds of information. Therefore, getting extension services has significant positive impacts on the farmers' perception of climate change. In Ethiopia, the study by Tesfahunegn et al. (2016) revealed that some biophysical and institutional factors positively influence farmers' perceptions regarding climate change. Similarly, in Chile, Roco et al. (2015) found that age, income, and weather information from mass media and the internet influenced farmers' perceptions.

In Sudan, a thorough literature search on farmers' perception of climate variability and change yielded only one related study in Bahar Alarab locality of East Darfur state (Younis *et al.,* 2022). The study revealed that 69% of the respondents perceived climate change indicated by increased temperature, while 49.4% indicated a decrease in the amount of rainfall (Younis *et al.,* 2022). This clearly shows the huge gap in climate research in Sudan, particularly climate change perception. The ongoing conflicts, coupled with fragile governments and poor institutional capacity, have contributed to the lack of climate research in Sudan. Therefore, it is necessary to evaluate how farmers perceive climate change and its impact on their farming activities in order to enhance their adaptive capacity. However, perception is not enough condition for adaptation since farmers who have recognised the change in climate might not adapt or the type of their adaptation response may differ as a result of a complex interaction among environmental, social, economic, and institutional factors (Maharjan *et al.,* 2011; Mertz, Mbow, *et al.,* 2009). Thus, it is crucial to evaluate the adaption measures that farmers use in their localities to cope with climate change.

Adaptation to climate change includes all adjustments in behaviour or economic structure that reduce society's vulnerability to climate change impacts (Gyampoh *et al.,* 2009). According to

Shongwe and Manyatsi (2014), adaptation measures include changing crop varieties, shifting crop planting dates, selecting different cropping technologies, and changing irrigation systems. Some studies reported that soil conservation practices, the use of improved crop varieties, agroforestry, and adjusting planting dates are the most important adaptation measures by small-holder farmers in East Africa (Asrat & Simane, 2018; Bryan *et al.*, 2013; Deressa *et al.*, 2008). Although Elramlawi et al. (2020) stated that soil and water management are important adaption options for sorghum production in Gedaref state in Sudan, other adaptation measures that farmers use to cope the negative impact of climate change are still unknown. Mohmmed et al. (2018) reported that farming communities in Alfushqa and Alfaw regions in Gedaref state have a low adaptive capacity to climate change, especially for drought vulnerability. These regions are characterized by low crop diversity, productivity, and agricultural insurance (Mohmmed *et al.*, 2018). Shifting in the onset of the rainy season coupled with a short duration of rain could be the critical factors for the farmers to adapt to climate change. However, the adaptation measures that farmers use could vary from one location to another depending on the socio-economic characteristics of the farmers. Indeed, understanding local perceptions and adaptive behavior provide relevant information for policies that help to address the challenge of sustainable agricultural development in the face of climate change (Simane *et al.*, 2016).

2.6 Land use and land cover change

Land use and land cover (LULC) patterns on the Earth reflect the relationship between human activities and the natural environment (Alonso-Pérez *et al.*, 2003). Competitive land use, together with human population growth, causes land scarcity, turning wildlands into farmland and other uses (Kanianska, 2016). Land use and land cover change is one of the main drivers of climate change globally and is of major concern due to its effects on different economic sectors (Wondie *et al.*, 2011). These changes occur temporally over different times, such as months or years and spatially, such as the size of the area and the land-use intensity (Houghton, 1994). In light of this, long-term changes probably are the most significant factors for global environmental change and are useful in evaluating natural resource sustainability (Lambin & Ehrlich, 1997; Tian *et al.*, 2019) . Hence, understanding LULC dynamics provide a vital factor for developing strategies for monitoring, evaluating, and conserving natural resources that are required for sustainable development (Lambin & Meyfroidt, 2011; Twisa & Buchroithner, 2019).

Historically, LULC changes are linked to variation in the biophysical environment, while recent changes are primarily associated with anthropogenic factors (Verburg *et al.*, 2004). Consequently, an area's climate pattern plays a major role in controlling human land use and land cover (Matlhodi *et al.*, 2019). Globally, human activities have been considered as a driver of environmental changes with an unprecedented rate, magnitude, and spatial size (Seto *et al.*, 2011). These changes are related to rapid population growth, economic development, and technological progress, while human land use links to different cultivation forms, grazing, protected land, timber extraction, and settlement (Matlhodi *et al.*, 2019). In developing countries, understanding land-use change dynamics is critical for sustainable land resource management, especially in sub-Saharan Africa, where most people rely on natural resources for their livelihoods.

In Africa, LULC has been highly affected by severe and recurrent droughts, anthropic/human activities, and armed conflicts, among others (Barnieh *et al.*, 2020; Mbaabu *et al.*, 2019). Particularly, the sub-Saharan Africa region is projected to be highly susceptible to the effects of LULC changes, where many parts of the region experienced a diverse pattern of LULC dynamics, with significant transformations of forest and grassland into cropland (Näschen *et al.*, 2019;

Petersen *et al.,* 2021). In addition, high levels of poverty, harvesting of fuelwood, charcoal production, agricultural expansion, settlements, unfavourable climatic events and land degradation in various agro-ecological zones are considered to be the major contributors to LULC changes in sub-Saharan Africa (Kamwi *et al.*, 2015; Mekuyie *et al.*, 2018; Munthali *et al.*, 2019). Therefore, more research on the location, extent, magnitude and rate of LULC dynamics is still needed in sub-Saharan Africa, where the population is growing rapidly, coexisting with soil infertility and overuse of nature-based resources such as forests and water.

2.7 Land use and land cover mapping

Detection of LULC changes using satellite remote sensing is one of the approaches that has been intensively used to assess and understand various land-use dynamic forces at various spatio-temporal scales (Dubovik *et al.*, 2021). Despite the recent advancement in remote sensing and geospatial tools, there is an inconsistency and a lack of standards in LULC mapping and detection products, particularly at global and regional scales (Chang *et al.*, 2018). At a local scale, several studies have successfully assessed the dynamics of LULC and their drivers (i.e., Mertz et al. 2009b; Rahman et al. 2017; Bonilla-Moheno and Aide 2020). Most of these studies have utilized commercial geospatial analytical tools like ArcGIS, Environment for Visualising Images (ENVI) and Earth Resources Data Analysis System (ERDAS), among others, for mapping and detecting LULC changes. However, in resource-limited countries, such analytical tools might not be feasibly used. Also, these tools require computers with high-performance capability to analyze 'big' satellite data. That also comes with time and cost implications in many developing countries. Moreover, most commercial geospatial tools do not allow automation of satellite data acquisition, processing and analysis. To overcome these challenges, cloud-based remote sensing and geospatial analytical tools like Google Earth Engine (GEE) have recently been introduced as freely available platforms for providing terabytes of images and advanced machine learning and artificial intelligence analytical tools (e.g., random forest (RF)) (Floreano & de Moraes, 2021). This could allow the development of relatively accurate semi- or fully automated LULC change detection approaches.

Furthermore, accurate LULC change layers could be efficiently used to predict future LULC patterns, which are also helpful for forecasting the vulnerability of ecosystems to, for instance, climate change. This requires a different set of tools that use artificial intelligence to simulate and mimic such future LULC dynamics. One of these tools is the cellular automata (CA) model, which has a high potential to effectively perform nonlinear spatially complex LULC change processes (Qiang & Lam, 2015). Cellular automata is a valuable approach for understanding LULC dynamics and their integral systems, especially when combined with other machine learning techniques, such as artificial neural networks (ANN) (Abbas *et al.,* 2021; Basse *et al.*, 2014). The CA-ANN is an artificial intelligence algorithm commonly used for simulating LULC change patterns and works on what-if scenarios (Abbas *et al.*, 2021; Baig *et al.*, 2022). In spite of the complexity of LULC set up in any ecosystem, the CA-ANN model provides comparatively accurate future predictions that could deliver to stakeholders and policymakers future LULC outlooks for informed planning (Buğday & Erkan Buğday, 2019; Qiang & Lam, 2015; Saputra & Lee, 2019).

2.8 Land use and land cover change in Sudan

In Sudan, the natural resources are continuously diminishing, where forests and natural woodlands are lost as agricultural land expands (Arfat, 2010). Also, about 80% of the energy consumed in Sudan is produced from biomass, i.e., fuelwood, charcoal, and crop residues (Hassan *et al.*, 2009). These activities have primarily reformed LULC structure, especially in the main agricultural areas.

Many studies attempted to map LULC changes in different regions of Sudan (i.e., Mohamed 2006; Zakaria 2010; Dafalla et al. 2014; Mohmmed et al. 2018). However, these studies have mainly utilized the maximum likelihood (ML) classifier with Landsat and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) datasets to characterize LULC dynamics in rainfed agricultural areas. Subsequently, LULC changes in these areas were estimated using different periods. For instance, in the Northern Kordofan region, LULC change was assessed between the periods 1973 – 2001 (Dafalla *et al.*, 2014; Mohamed, 2006) and 1972 – 2007 (Zakaria, 2010). In West Kordofan, LULC changes were mapped for 2000 – 2005 (Mohmmed *et al.*, 2018). Negative vegetation cover changes were reported in the two regions, mainly due to desertification and socio-economic effects.

Gedaref state has been exposed to large-scale land degradation indicated by reduced vegetation coverage, and loss of soil fertility, among others (Biro *et al.*, 2013; E. K. Glover & Elsiddig, 2012). This is basically due to unsuccessful land-use policies and practices used, such as sorghum mono-cropping system and inappropriate methods of soil preparation and conservation (Biro *et al.*, 2013; Glover, 2017; Glover & Elsiddig, 2012). Additionally, the expansion of rainfed mechanized agricultural schemes in Gedaref has played a significant role in LULC changes, which resulted in land degradation, environmental deterioration, and a decline in agricultural productivity (Sulieman and Elagib, 2012). As a consequence, livelihood in this region has been highly affected. For instance, many pastoralists have lost their livestock or are forced to abandon livestock-rearing activities due to the loss of a considerable proportion of the traditional grazing lands (Sulieman and Elagib, 2012). Therefore, mapping LULC changes in Gedaref state could enable the quantification of trends in agriculture, grassland, forest cover, and freshwater resources. This can help manage agro-natural systems and improve land use policies (Midekisa *et al.*, 2017).

Although many studies have been conducted in Gedaref state on LULC dynamics, these studies were done in specific areas and did not cover the whole Gedaref state, which is the country's food basket. For example, a study by Sulieman (2010) detected a large expansion of mechanised agriculture in Southern Gedaref using Landsat satellite imagery between 1972 and 2003. Issa (2018) reported a decrease in grassland and frost areas by 80% and 2.9%, respectively, in Qala El-Nahal locality in Gedaref state between 1972 and 2018. Similarly, Adam (2019) reported a decline in forest area in El-Rawashda locality in Eastern Gedaref between 1988 and 2018. The studies found drastic changes in natural vegetation, mainly due to the areal extent of mechanized rainfed farming in Gedaref state. Despite the relatively high LULC classification accuracy obtained in the previously-mentioned studies using maximum likelihood classifier, the transferability of such a parametric mapping approach to other points in space and time could be hindered by overfitting due to limited training dataset; studies have yet to predict the future LULC changes in high productive rainfed agricultural areas in Sudan like Gedaref. Moreover, no study has utilized a machine learning algorithm to classify LULC in rainfed agricultural areas in Sudan. In this regards, it is crucial to evaluate LULC change for the whole Gedaref state using such tools to assess LULC trends and their intensities to determine the underlining dynamics that caused the change in landscape structure. A survey conducted by Adam (2019) showed that the local communities identified the collection of firewood, charcoal and building materials as the main drivers that have negatively affected El-Rawashda forest in Gedaref state. However, other factors such as rapid population growth, agricultural expansion and climate change should be considered in such studies for a better understanding LULC drivers. Furthermore, future prediction of LULC change based on natural and anthropogenic drivers could help in developing land use polices and a better resource management in Gedaref state. Therefore, LULC in Gedaref state and their underlining drivers need to be evaluated using a holistic approach including satellite imagery, ground truth data and local land users' perception.

2.9 Summary

The literature review in this chapter has demonstrated the challenges of rainfed farming system in Gedardef state, Sudan. This includes climate variability and change, change in LULC structure that affect natural resources. Although these are important topics that are directly linked to food and nutrition security, they have received little priority in research, especially climate change studies and its impact on crop yield. Few studies have assessed climatic trends (temperature and rainfall) in Sudan (Elagib & Elhag, 2011; Elagib & Mansell, 2000; Sulieman & Elagib, 2012). However, the impact of climate change on crop yield is still has not been quantitatively measured, especially in the main rainfed areas of Sudan. Despite the fact that the traditional rainfed farming is the biggest crop cultivation sector in Sudan (FAO, 2015a; Mahgoub, 2014), it has been neglected by researchers compared to the mechanized sector. Traditional rainfed farming is occupied mainly by small-holder farmers, who are the most vulnerable group to the impact of climate change. Hence, it is important to assess their perceptions of climate change and the adaptation measures they use to minimize the negative impact on their farming activities. Assessing the local perceptions and adaptive behavior of small-holder farmers is essential in providing relevant information for developing policies to address the challenge of sustainable agriculture, food security and livelihood under climate change. On the other hand, LULC change is one of the main drivers of climate change and is of major concern due to its effects on different economic sectors (Wondie *et al.*, 2011). Many studies have assessed LULC changes in Gedaref state in specific areas focusing on the mechanized agricultural expansion (Sulieman, 2010), change in vegetation cover (Issa, 2018; Sulieman, 2008; Yagoub *et al.*, 2017), and the impact of LULC changes on pastoral communities (H. M. Sulieman & Elagib, 2012). However, less attention has been given to the underlining dynamics of LULC changes, factors that drive these changes and future prediction of LULC structure. In other words, studies of LULC change should involve a holistic approach, including satellite imagery, ground truth data and local land users' perception. Understating LULC change and the approximate and underlining factors that drive these changes could help develop land use policies and better resource management in Gedaref state. To this end, it was critical to conduct this study to investigate the impacts of climate trends and variability and land use/land cover changes on crop production of small-holder farmers in Gedaref State, Sudan. The findings would provide a clear picture of the impact of climate change on crop yield, historical and future LULC change and the approximate and underlining drivers that caused LULC dynamics in Gedaref state.

CHAPTER THREE

STUDY AREA AND METHODS

3.1 Introduction

This chapter provides a comprehensive description of the study site that includes the location of the study area, biophysical and socio-economic settings, and the study's conceptual framework. It also presents a detailed overarching methodological description for the study objectives including methods of data collection, data management, analytical approaches, algorithms and tools used for analysis.

3.2 Location

Gedaref is one of the states in the Eastern part of Sudan; it is located between 33 – 37° E Longitudes and 12 – 16° N Latitudes, with an area of about 78.228 km^2 and its average altitude is 600 meters above sea level (Figure 3.1). It is bordered on the South by Blue Nile state, in the North by Kassala and Khartoum states, in the West by Gezira and shared a border with Ethiopia from the East. Gedaref state is the main rainfed agricultural area in Sudan and is largely recognized as the land of sorghum (primary staple food) and sesame in Sudan, where about one-third of sorghum and sesame produced are cultivated in this region. Other crops such as cotton, groundnut, millet, wheat, and sunflower are also cultivated. Gedaref state was selected as a study area because it is Sudan's hub of rainfed crop production. Also, the state has a long history (about 77 years) of a well-established rainfed mechanized farming system where secondary data on crop yield and climate variables can be readily obtained.

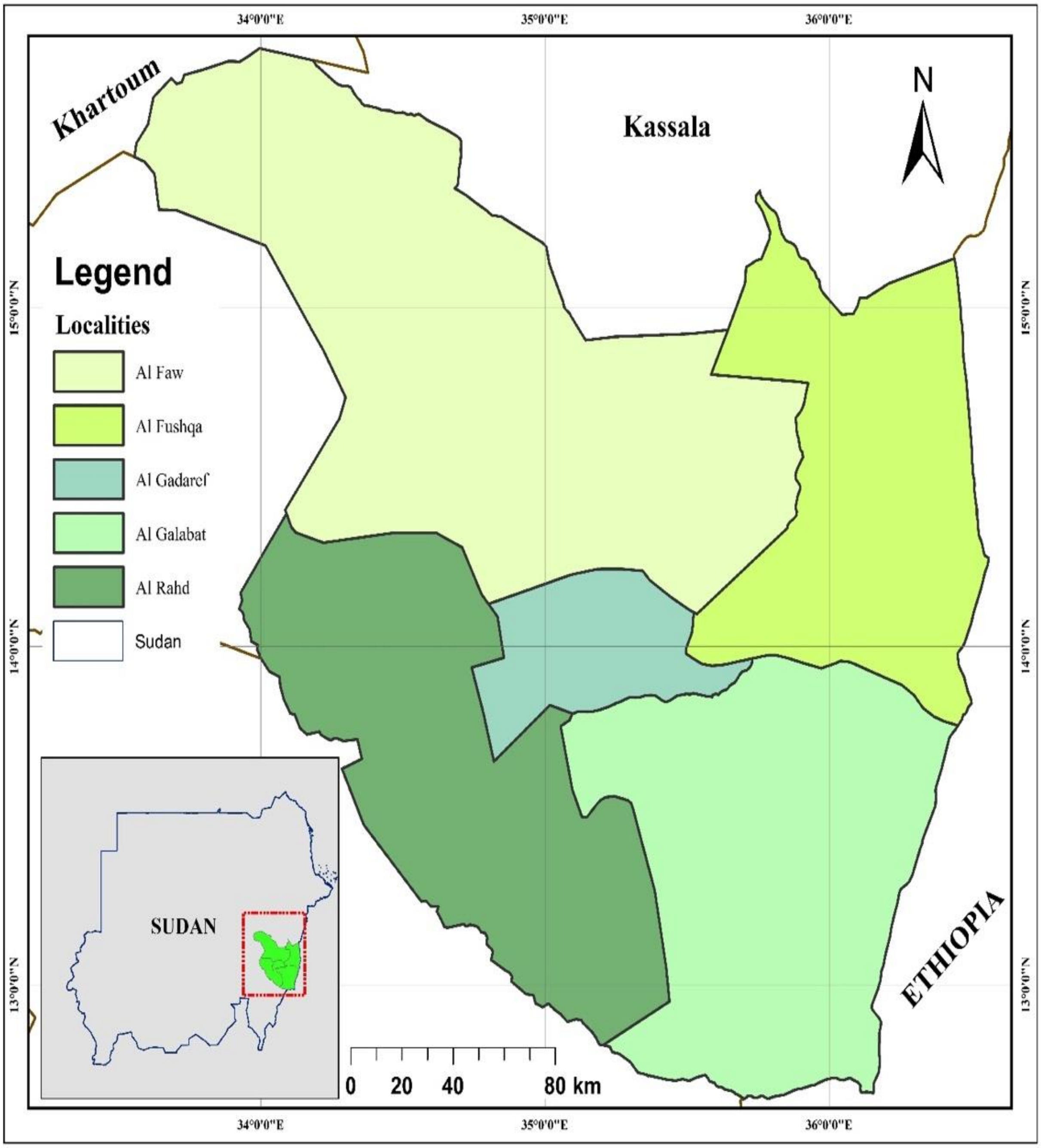

Figure 3.1: Location of Gedaref State in Sudan (Source: Author)

3.2.1 Population in Gedaref state

The population in Gedaref state was estimated to be about 2,208,385 in 2018 (Idreas, 2015). Due to the introduction of semi-mechanized rainfed farming in 1944, Gedaref state has become an important economic market, attracting more people in the area. In early 1940's Gedaref area was estimated to have a population of less than 20,000 people, while in 1968 the population of the state increased to 483,032 people. Generally, in this state, the population grows by a rate of 4.7 % annually, which is even higher than the national growth rate of 2.2 % (Idreas, 2015). In addition, the migration of people from other states in Sudan as well as refugees from the neighboring countries due to political conflicts has increased the population in Gedaref state.

3.3 Biophysical setting in Gedaref state

3.3.1 Climate

Gadaref state is characterized by semi-arid climatic conditions. The rainy season starts from June and ends in October, with a peak in August and September (Figure 3.2), while the dry season extends from November to May (Elagib *et al.*, 2019). The mean annual rainfall ranges between 200-800 mm (Idreas, 2015). However, the amount of rainfall increases from the North toward the South parts of the state with an average annual rainfall amount of 175, 570, and 650 mm in North, Center, and South Gedaref, respectively. The average annual temperature in Gedaref area is 30℃, with the hottest season occurring between the months of April and May (Yagoub *et al.*, 2017). Rainfall is considered as a very important climatic variable in Gedaref state because the majority of the population rely on rainfall to grow food and cash crops and support livestock production. The growing season in the state extends from June to October, which corresponds to the rainy season in Sudan (Figure 3.2). The planting dates range between from June to mid of July while the harvesting time range from October to November, depending on the type of the crop.

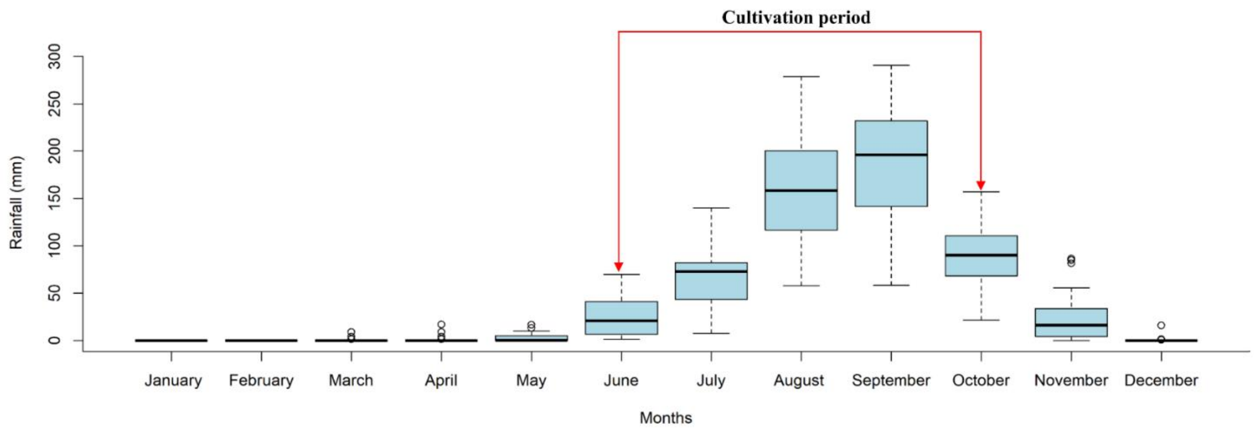

Figure 3.2: Boxplot showing the monthly rainfall in Gedaref state, Sudan between 1984 2018. The red arrows show the main crop cultivation period. Median rainfall values are shown by the bold lines within the boxes and the circles show outliers.

Source: Author

3.3.2 Soil types in Gedaref state

The area is dominated by Vertisols soil, which is characterized by dark and heavy clay. Its clay content about 60%, which it tends to increase from South to East, coinciding with the pattern of rainfall increment. The fertile clay soils coupled with and vast suitable land for crop production led to the development of the well-established and highly profitable rainfed grain cultivation system in the state (Sulieman & Elagib, 2012).

3.3.3 Agriculture as a livelihood source in Gedaref state

Agriculture is the major economic activity in Gedaref State. It provides employment and supports livelihood for around 80% of the people in the state (Mahgoub, 2014). Agricultural systems are generally rainfed, which are divided into semi-mechanized and traditional farming systems. The semi-mechanized farming systems depend mainly on machines for land preparation and sowing and it was introduced in Gedaref state in 1944. It is practiced by large-scale farmers with farm sizes larger than 420 ha, while traditional farming dominated by small-scale farmers with an average farm size of approximately 2 ha (Mohmmed *et al.*, 2018). The principal crops cultivated in Gedaref region are sesame, sorghum, cotton, groundnut, millet, and sunflower. Sorghum and millet are grown for food consumption with sorghum being the stable food in the entire country. Sesame and sunflower are grown mainly for oil production as well as export, while cotton farming is primarily grown as an industrial and cash crop.

3.3.4 Land use/ land cover (LULC) in Gedaref state

The land use in Gedaref state is mainly dominated by agriculture, followed by livestock keeping in villages in traditional seasonal transhumance patterns. Also, as a recent feature, the large-scale mechanized merchant-farmers keep cattle as the main livestock investment enterprises. Some traditional forms of economic activity in the state are trading forest products like gum tapping and charcoal burning. Therefore, people obtain their income from a set of three different major systems of land use in Gedaref state; farming, grazing, and forestry (H. M. Sulieman & Elagib, 2012). While the main land cover features in Gaderef area according to the Food and Agricultural Organization (FAO) of the United Nations are trees, shrubs, herbaceous, cropland, bare rocks and soil, water bodies, and urban areas.

3.4 Conceptual framework for the study

The conceptual framework (Figure 3.3) developed for his study shows how climate variability and change, LULC changes, adaptation measures interact with each other and how they affect small-holder rainfed farming in Gedaref State. Therefore, this interaction can impact the livelihood and food security of small-scale farmers in the enter State as rainfed farming being the main source of income and food in the region.

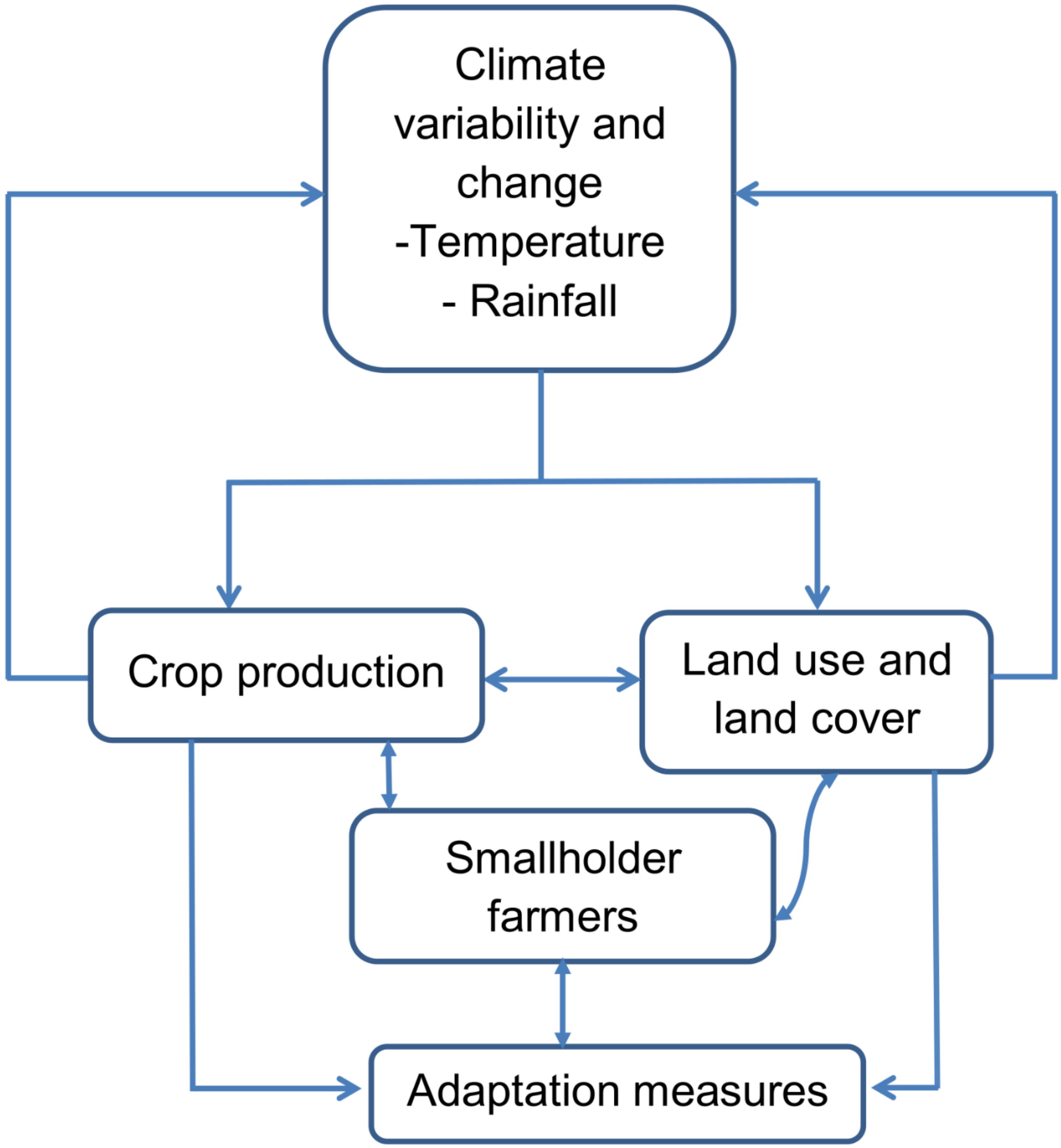

Figure 3.3: Conceptual framework of the study

Source: Author

3.5 Methods

3.5.1 The study design

This study used a transdisciplinarity (TD) approach involving collection of both qualitative and quantitative datasets. This includes impact of climate change, LULC change, crop production and yield and the perceptions of the farmers of the drivers of such changes in the study area. The TD approach is holistic and robust method in solving research problems as it allows an in-depth analysis of the problem under study. This is done through collaboration between different groups of experts and the societies that are affected by problem to find sustainable solutions to such complex challenges like climate and LULC changes (Klenk & Meehan, 2015). The present study involved both primary and secondary datasets. The primary data were obtained through 400 questionnaires for the household survey, 16 focus group discussions (FGDs), and key informant interviews. These data were supplemented with secondary datasets, which consisted of climatic data (temperature and rainfall), crop production and yield for five major crops cultivated in Gedaref state (sorghum, sesame, sunflower, millet and cotton) and remotely sensed Landsat images to address the objectives of this study.

3.5.2 Determination of the relationship between climate trends and the level of crop yields

3.5.2.1 Desktop studies and secondary data

Daily minimum (Tmin) and maximum (Tmax) temperature, which refer to the lowest and highest values of the daily temperature records, respectively, as well as daily rainfall data from 1984 to 2018 were obtained from Gedaref meteorological station (latitude 14.03° N; longitude 35.40° E;

altitude 600 m). The Tmin and Tmax were estimated every three hours daily using an alcohol thermometer. On the other hand, the daily rainfall was measured and recorded every six hours daily using rain gauges where a rainy day starts from 8:01 am and ends on the following day at 8:00 am local time (Greenwich Mean Time: GMT + 2). In addition, annual rainfall data for the same period (i.e., 1980 to 2018) were obtained from different locations in Gedaref state, namely Elghadambliya (latitude 14.023° N; longitude 35.012° E; altitude; 497 m), Um Seinat (latitude 12.845° N; longitude 35.864° E; altitude; 572 m), Samsam (latitude 12.838° N; longitude 35.733° E; altitude; 527 m), and Elhawata (latitude 13.431° N; 34.629° E; altitude; 444 m), where rainfall data were also measured using rain gauges. Data on yield for five major crops, viz., sorghum, sesame, cotton, sunflower, and millet at the Gedaref state scale were obtained from the Ministry of Agriculture, Gedaref. Basically, the crop yield data were collected from some representative farmers' fields. Crop production (ton) data and harvested area (ha) were obtained for the period 1970–2018, except for millet and sunflower, which were only available between 1982 and 2018, and 1987 and 2018, respectively. Annual yield (kg ha^{-1}) for each crop was calculated by dividing the total crop production by the harvested area.

3.5.2.2 Data analysis

A) Data quality assessment

Complete records were obtained for climate and crop yields, and these datasets were measured during the above-mentioned periods with no missing values. Since these are secondary datasets, we subjected them to a descriptive statistical analysis (skewness coefficient, mean, range, and confidence interval) and Shapiro–Wilk test (*p*-value and *W* value) of inferential statistics prior to trend and regression analyses to evaluate their quality. A summary of descriptive statistics provides useful information about the data quality. For instance, a mean value that describes the center of a dataset distribution can be an indicator of data quality since there is prior knowledge (e.g., expert knowledge) about the dataset itself. Additionally, a close to zero skewness value indicates a moderately skewed dataset that can fit a normal distribution, which is a good indicator of data quality (Klayman, 2022). Normally distributed data imply that the observations were collected with less bias and errors that hinder the quality of the data (Klayman, 2022). Among the climatic datasets, rainfall was normally distributed (skewness = 0.33, $W = 0.97$ and $p = 0.629$), while Tmax (skewness = 0.199, $W = 0.98$ and $p = 0.001$) and Tmin (skewness = -0.34, $W = 0.98$ and $p = 0.001$) slightly deviated from a normal distribution (Figure 3.4). On the other hand, all crop yield datasets were normally distributed (sorghum: skewness = 0.31, $W = 0.97$ and $p = 0.242$, cotton: skewness = 0.46, $W = 0.97$ and $p = 0.242$, millet: skewness = 0.59, $W = 0.95$ and $p = 0.227$, and sunflower: skewness = 0.30, $W = 0.95$ and $p = 0.126$), except sesame: skewness = 1.97, $W = 0.85$, and $p = 0.000$ (Figure 3.5). Furthermore, the climate and crop yield datasets had a few outliers in the Tmin, rainfall, and sesame, millet, and sunflower yield observations. These statistical metrics ensured the quality of the data that met the assumption for the present study.

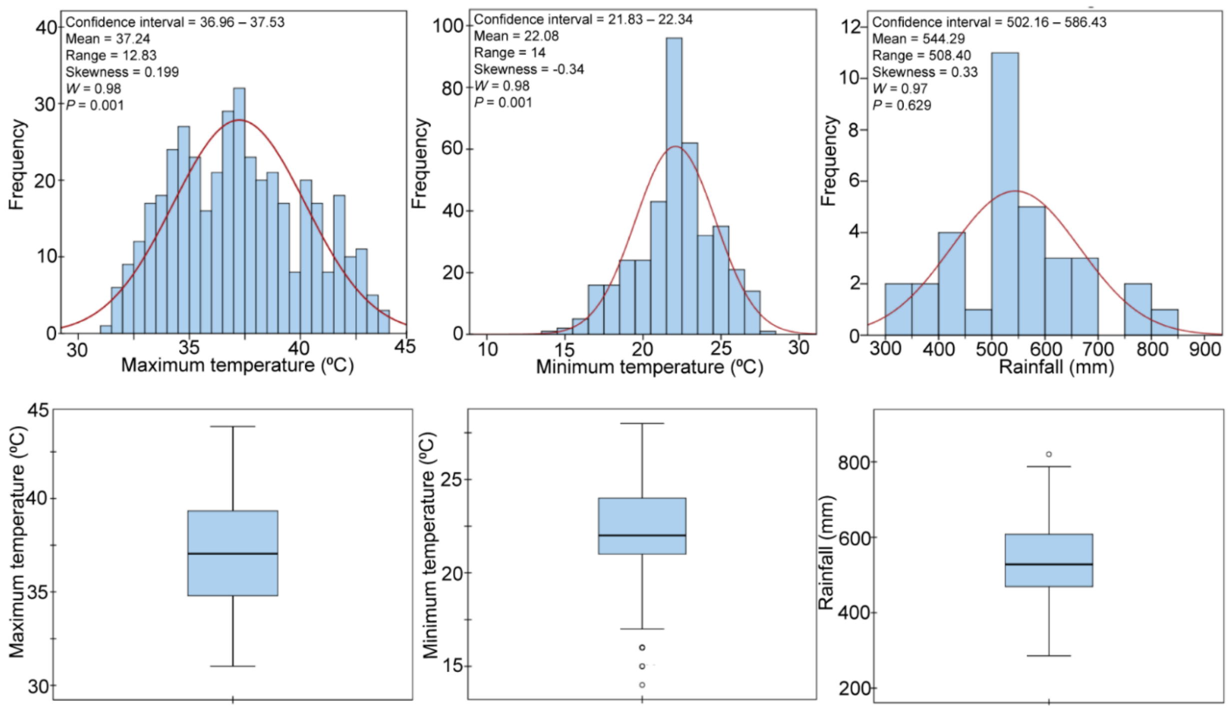

Figure 3.4: Histogram, normal distribution, and boxplot fitted for minimum (Tmin) and maximum (Tmax) temperatures (1984–2018) and rainfall (1980–2018) data obtained from the Gedaref meteorological station, Sudan. Circles in some boxplots represent individual outlier observations.

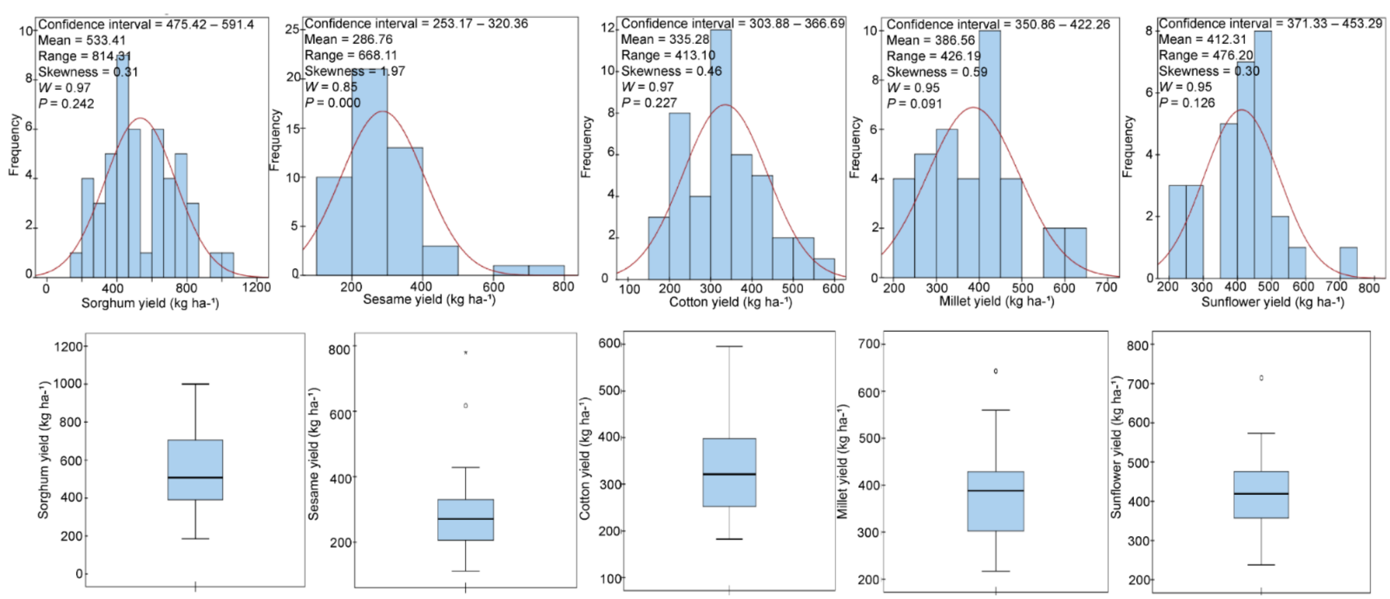

Figure 3.5: Histogram, normal distribution, and boxplot fitted for crop yield data obtained from the Ministry of Agriculture, Gedaref, Sudan. The crop yield data were collected in 1970–2018, except for millet and sunflower, which were only available between 1982–2018 and 1987–2018, respectively. Circles in some boxplots represent individual outlier observations.

B) Trend Analysis

The average annual Tmax, Tmin, and diurnal temperature range (DTR: which refers to the range between Tmax and Tmin) were calculated from the daily temperature records of Gedaref metrological station for each year (1984–2018) and season of the year (i.e., summer: March to May, winter: February to November, and autumn: June to October). Afterward, Tmax, Tmin, and annual rainfall and temperature variables were subjected to Mann–Kendall trend analysis to assess the positive or negative trend in temperature and rainfall. A Mann–Kendall trend test is a nonparametric test (distribution-free) that is not sensitive to outliers (Kendall, 1948; Mann, 1945), and is widely used for analyzing time-series historical data to assess if there is a significant increasing or decreasing trend in variables of interest (e.g., temperature and rainfall) over time. In the present study, the Mann–Kendall trend test was computed using Equation (1):

$$\sum_{i=1}^{n-1} \sum_{j=1+i}^{n} \mathrm{sign} = (x_j - x_i) \qquad (1)$$

where: x_j= the data value at time j; x_i= the data value at time i; n = the length of the time-series data; sign $(x_j - x_i)$ = the sign function which can be defined as follows:

$$Sign\left(x_j - x_i\right) = \begin{cases} 1\ if\ (x_j - x_i) > 0 \\ 2\ if\ \left(x_j - x_i\right) = 0 \\ -1\ if\ \left(x_j - x_i\right) < 0 \end{cases} \qquad (2)$$

The increasing trend is explained by a very high positive value of the Mann–Kendall test, while the decreasing trend is explained by a very low negative value. To statistically quantify the significance of the trend in the temperature and rainfall data, Sen‘s slope estimator test was applied (Sen, 1968). In specific, the slope (Q), which is the change in the temperature and rainfall as a function of time (i.e., years), was calculated for all possible data pairs as follow (Equation 3):

$$\mathrm{Q} = \frac{\mathrm{x_j} - \mathrm{x_i}}{\mathrm{j} - \mathrm{i}} \tag{3}$$

where x_j and x_i are the data value in the time series at time j and i, respectively.

Since there are a number of Qs (N), they are ranked from smallest to largest in the time-series data, then Sen's slope was estimated as the median of these values (Equation 4):

$$Q_i = \begin{cases} Q\left(\frac{N+1}{2}\right) & if N\ is\ odd \\ \frac{1}{2}\left(Q\ \frac{N}{2} + Q\,\frac{N+2}{2}\right) & if\ N\ is\ even \end{cases} \tag{4}$$

On the other hand, simple linear regression was employed to assess the trend of crop yield over time. This is because crop yield data depend on many factors rather than climatic variables; a reason that does not meet the assumption of the Mann–Kendall trend analysis test (Kendall, 1948; Mann, 1945). In addition, the yield data were normally distributed (Figure 3.5), hence linear regression was preferred over a Mann–Kendall trend analysis.

C) Temperature and rainfall variability analysis

To assess the annual temperature and rainfall variabilities in the study area over 35 years (1984–2018), the standardized anomaly index was calculated. Standardized anomaly index is a common index used to indicate temperature and rainfall fluctuations in regional climate change studies (Koudahe *et al.*, 2017). The standardized anomaly index was calculated as follows (Equation 5):

$$SAI = \frac{X - X_i}{\sigma} \tag{5}$$

where X is the mean temperature or rainfall of a year, X_i is the mean value over the long-term, and σ is the standard deviation value over the long-term. Years with an above long-term average were indicated as the most warming periods, while the years with values below the long-term average were considered as cold periods. Similarly, years with above long-term average rainfall were indicated as the years with surplus rainfall, while years with below long-term average rainfall were indicated as the years with deficit rainfall.

Moreover, the coefficient of variation (*CV*) was calculated as follows (Equation 6) to assess the variability (fluctuation) in each temperature and rainfall variable and crop yield data:

$$CV = \frac{\sigma}{\mu} * 100 \qquad (6)$$

where *CV* is the coefficient of variation; σ is standard deviation; μ is the mean of the time series data set of each climatic variable (i.e., Tmin, Tmax, DTR, and rainfall) and crop yield.

D) Characteristics of rainy season

The onset and cessation dates and length of the rainy season were analysed using R INSTAT software version 0.6.6 (Stern *et al.,* 2021). This was done by applying the threshold procedure to determine variations in the rainy season characteristics such as onset, cessation, and the length of the rainy season. The threshold for a rainy day was set at 0.85 mm (Ngetich *et al.,* 2014; Ntirenganya, 2018) and the mean rainfall was calculated for every 5 days (pentads) of the rainy season. This threshold value is appropriate for agricultural purposes in the tropical region because the accumulation of such an amount of rain contributes greatly to soil moisture (Ngetich *et al.,* 2014; Ntirenganya, 2018; Ojara *et al.,* 2020). Furthermore, the onset of the rainy season was defined as a "date when the amount of rainfall accumulation is 20 mm in 1 or 2 days within 3 dekads (dekad = 10 days), but not followed by more than 10 consecutive dry days in the next 3 dekads" (Sibanda *et al.,* 2020). This amount of rainfall is sufficient for germination and growth of the crop during the first month after planting. The cessation of the rainy season has several definitions. Here, the approach proposed by (Tadross *et al.*, 2005) was adopted for this study, which defines the cessation of the rainy season as the date when the rain is less than 20 mm within 3 dekads followed by 2 dekads of dry days. This approach was widely used to determine the end of the rainy season (Moyo *et al.*, 2017; Setiawan, 2020). Rainfall is the most significant factor affecting crop growth and yield, particularly in semi-arid regions where rainfall is limited to only a few months per year (Laux *et al.*, 2009). Therefore, simple linear regression analysis was used to determine the relationship between the length of the rainy season and crop yield. The following steps were taken to determine this relationship: (1) the first difference approach was used to generate anomalies in crop yield and length of the rainy season and (2) in a second step, simple linear regression analysis was employed to test the impact of the length of the rainy season on crop yield anomalies.

E) Analysis of relationships between the climate variables and crop yield

Due to the effect of non-climatic factors such as crop management practices and new cultivars on crop yield, some statistical methods such as the first difference approach (Nicholls, 1997) and crop simulation models such as decision support system for agro-technology transfer (DSSAT) (Jones *et al.*, 2003) are used to evaluate the effect of climate change on crop yield (Ding *et al.*, 2021). However, models such as DSSAT require some settings and parameters, such as crop genetic coefficient, that might not have been estimated to simulate crop yield under Gedaref climatic conditions. Hence, in this study, the first difference approach was used to remove the effects of non-climatic factors on crop yield. The first difference approach was initially introduced by Nicholls (1997) and thereafter adopted by studies that evaluated the effect of climate change on crop yield (El-Maayar & Lange, 2013; Peltonen-Sainio *et al.*, 2010; Zhang *et al.*, 2014). The first difference values for crop yield and climatic variables (i.e., anomalies) for the period 1984–2018 were generated as follows (Equation 7):

$$\Delta Y = Y_t - Y_{t-1}$$
$$\Delta X = X_t - X_{t-1} \tag{7}$$

where ΔY is the yield difference in two consecutive years; that is the yield in year t and $t-1$, respectively, while ΔX is the difference in the climatic variable in two consecutive years; that is the climatic variable during crops growing season (June–October) in year t and $t-1$, respectively.

To estimate quantitative relationships between climate variables and crop yield, the anomalies generated from the first difference for climate variables and crop yield were subjected to a Pearson's correlation analysis to determine the association between the crop yield and climatic variables. In addition, a multiple linear regression model was used to quantify the impact of climate change on crop yield using the anomalies of the first difference (Poudel & Shaw, 2016). The following linear equation (equation 8) was used to determine such a relationship for each crop:

$$Y = a + b_1 * Tmin + b_2 * Tmax + b_3 * DTR + b_4 * Rainfall \tag{8}$$

where, Y is the observed change in yield (kg ha^{-1}) due to climatic variables, a is the intercept of the regression model, and b_1, b_2, b_3, and b_4 are the regression coefficients of Tmin, Tmax, DTR, and rainfall, respectively.

F) Models validation

A leave-two-out cross-validation procedure was used to validate the simple and multiple linear regression models. In specific, the data were divided into k samples (k = total number of crop yield samples) and then samples were removed two-by-two. Yield predictive models were fitted k times using all k data points, except for the removed ones, and validated using these omitted (holdout) ones. A cross-validated R^2 between the observed and predicted yield data was then calculated to test the certainty of the models.

3.5.3 Determination of farmers' perception of climate variability and change and the choice of adaptation measures.

3.5.3.1 Desktop studies and secondary data

Temperature and rainfall data are presented in section *3.5.2.1*. For this section, the mean annual temperature and rainfall were used for further analysis on farmers' perceptions and choice of adaptation measures.

3.5.3.2 Household survey, key informant interview and focused group discussion

A) Household data collection

To assess farmers' perception of climate change, face-to-face interviews were conducted in Gedaref state, Sudan, between January and February 2021, using a semi-structured questionnaire. The questionnaire was divided into two parts; the first part of the questionnaire included open and closed-ended questions to collect in-depth data on the local communities' perception of climate change and the adaptation measures they use. The second part consisted of questions of LULC perceptions. Data collected in the first part of the questionnaire were used for this objective. The respondents were selected randomly for the interviews using random sampling techniques. A total of 400 respondents were selected for the interview using Yamane's, (1967) equation:

$$n = \frac{N}{1+N(e)^2} \qquad (9)$$

Where n = the selected sample size for the study, N = the total number of small-holder farmers in Gederaf state (total population) e = the standard error.

The questionnaire was tested with 20 respondents in Gedaref state who were not included in the study. The questionnaires' responses enabled to make the necessary adjustments before the actual interviews were conducted. Additionally, the selected respondents for the interview had the following criteria (i) small-scale farmers (ii) the respondents are at least 20 years old and above, and (iii) had resided in the Gedaref state for ≥10 years. Each respondent was interviewed for about 40 to 60 minutes.

B) Key informant interviews and focus group discussions

In addition, focus group discussion (FGD) and key informant interviews were also conducted to confirm the information generated from the household survey. This helped in gathering the necessary information and understanding the perception of the local community on climate variability and change, its impacts on their agricultural activities, and the adaptation measures used to adapt to these changes in Gedaref state. Two FGDs were held in each study village (n = 8) at the same time as household interviews. A total of 16 FGDs were conducted in the eight villages; all participants in the FGD were not included in the household interviews. The FGDs were facilitated in accordance with Hennink (2007), and were guided by a checklist of questions about climate variability and change, its impacts on their agricultural activities, and the adaptation measures used to adapt to these changes. Each FGD lasted between 120 and 180 minutes and involved between 10 and 15 people. Key informants were identified using a purposive sampling method based on their experience and knowledge of the study area. Interviews with the key informants included elders, researchers and officers from the ministry of agriculture, meteorological authority, environmental and research institutions, natural resource conservation and agro-dealers at the state level.

3.5.3.3 Data management and analysis

The trend analysis for mean annual temperature and rainfall was conducted as describe above in section *3.5.2.2 (B)*. This trend of the metrological station was compared with farmers' perception to understand whether the local communities in Gedaref state perceive climate change correctly. The data generated from the questionnaire were coded, entered, and analyzed using Statistical Package for Social Sciences (SPSS) version 20. Descriptive statistics were used to describe the socio-economic characteristics, institutional characteristics, farmers' perceptions of climate variability and change, and their adaptation measures. A multinomial logistic regression model (equation 10) was used to examine the factors influencing farmers' choice of adaptation measures. The socio-economic characteristics of the small-holderfarmers were designated as independent variables in the model, while the adaptation measures were the dependent variables. The following equation was used:

$$logit(Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad (10)$$

where Y = dependent variable, α = the intercept, $\beta_1 ... \beta_n n$ = coefficients of associated independent variables, while X_1 . . . X_n = independent variables.

3.5.4 Assess and quantify LULC changes and their intensities for 30 years (1988-2018) and project LULC in 2028 and 2048

3.5.4.1 Desktop studies and secondary data

A) Satellite remotely sensed data acquisition and pre-processing

Figure 3.6 shows the methodological approach used in this study. Landsat multispectral images are the most widely used for time series analysis of LULC classification due to the long historical data that are readily available (Qu *et al.*, 2021). Multi-date Landsat imagery were used for the years 1988, 1998, 2008 and 2018 acquired by Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) sensors from the freely available data catalog in Google Earth Engine (GEE) at a spatial resolution of 30 m in the World Geodetic System (WGS84). Standard image pre-processing, including cloud filtering, topographic, atmospheric, and geometric corrections, layer stacking and re-sizing was performed in GEE. A yearly (from 1st January to 31st December) median value was used to create a composite image for the selected years (i.e., 1988 and 1998 for Landsat 5, 2008 for Landsat 7, and 2018 for Landsat 8) (Griffiths *et al.*, 2013; Hermosilla *et al.*, 2015).

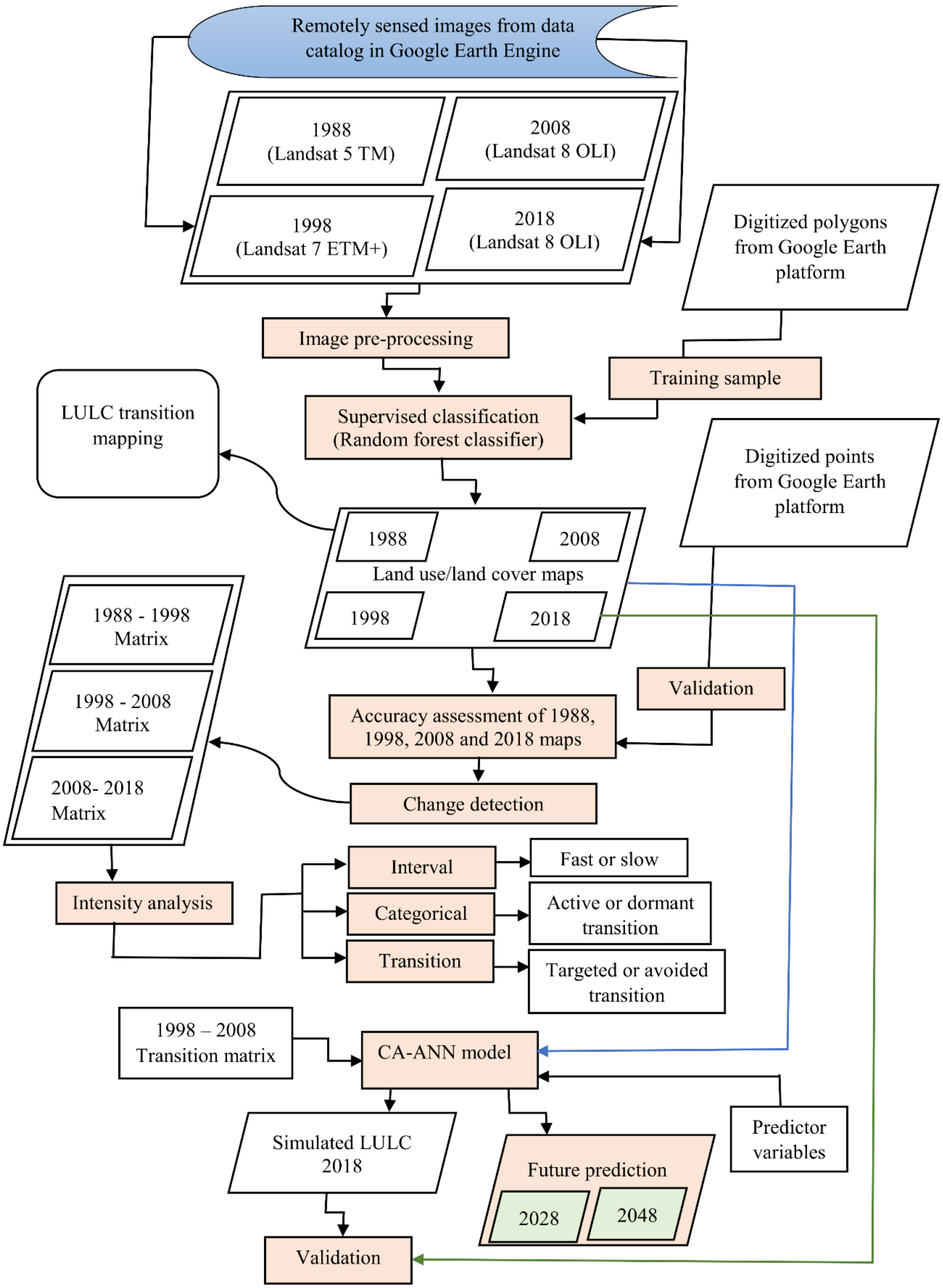

Figure 3.6: Methodological flowchart for the land use/ land cover (LULC) mapping, transition, intensity and future prediction.

B) Training and testing data

Five of the defined Intergovernmental Panel on Climate Change (IPCC) classes (Penman *et al.*, 2003), namely cropland, forest land, grassland, water, and settlements were used for the classification experiment. Polygon-based training data for each class were obtained through onscreen digitization using historical high-resolution images on the Google Earth Pro platform. This method has been widely used and reported in the literature for LULC analysis, as it provides high and reliable classification accuracy (De Sousa *et al.*, 2020; Hansen *et al.*, 2008; Phan *et al.*, 2020). A total of 1000 samples were selected for each year (1988, 1998, 2008 and 2018) to train and validate the LULC maps, 70% of the samples collected were used for training the classification model (700 polygons) and 30% were used for testing the model (300 points). The defined polygons, which were relatively small in size, each containing many comparatively homogeneous pixels of a specific LULC type, were used as a training dataset to reduce the influence of spatial autocorrelation. The polygons also capture the colour gradient of each LULC type (e.g., deep water against shallow water; high, medium, and low grassland coverage) to avoid confusion between the classes. On the other hand, point-based data were utilized to test the LULC maps accuracy. These points were randomly selected at a minimum distance of 100 m from the nearest training polygon to minimize overfitting and spatial multi-correlation (Phan *et al.*, 2020).

3.5.4.2 Data analysis

A) Landsat image classification

There are many advanced non-parametric machine-learning classification algorithms in GEE for supervised classification, such as random forest (RF), support vector machines, and classification and regression tree, among others (Lin *et al.*, 2020). Also, a meta-analysis of more than 300 peer-reviewed articles published in the last ten years before 2018 showed that the most used classifier for classifying satellite data in GEE is the RF (Tamiminia *et al.*, 2020). The RF classification algorithm was employed in GEE to classify and distinguish among the LULC classes of Gedaref state in Sudan using the multi-date Landsat images. Many studies have reported that RF algorithm achieved higher classification accuracy and reliability compared to other machine learning algorithms (Pelletier *et al.*, 2016; Tong *et al.*, 2020; Zurqani *et al.*, 2018). This is because RF is a user-friendly algorithm that requires settings and optimization of two parameters only. It also can handle large and noisy data as well as outliers, and reduce overfitting. The algorithm can simulate missing values through the calculation of proximity among samples (Feng *et al.*, 2020). This algorithm is a combination of learning methods, which includes many individual decision trees (Breiman, 2001; Fonseka *et al.*, 2019). Each single decision tree (ntree) has many splits (mtry, i.e., number of randomly selected variables) and nodes that predict the final class label based on the large number of votes from all decision trees. Considering the recommendations of other studies (Cánovas-García *et al.*, 2017; Ghimire *et al.*, 2012), 100 trees (ntree = 100) were used, and a default mtry value (the square root of the number of predictor variables). The strength of RF is that it can efficiently process a huge number of input variables without being affected by outliers and noise in the data, and is highly robust against overfitting (Ge *et al.*, 2019; Lin *et al.*, 2020; Phan *et al.*, 2020).

B) Assessment of classification accuracy

The reliability of a thematic LULC map relies on the overall and individual accuracies of the map and the individual classes, respectively (Warrens, 2015). Commonly, several metrics like kappa coefficient, producer's accuracy (PA), user's accuracy (UA) and overall accuracy (OA) are utilized to validate the accuracy of the thematic maps. In this study, these accuracy metrics were calculated, except kappa coefficient, to assess the accuracy of the LULC classification experiment. Subsequently, a class-wise accuracy metric was developed by applying the F1-score formula (equation 11). This score combines PA and UA into a single fused accuracy measure ranging from 0 to 100% (Mudereri *et al.*, 2022), and it was calculated using the equation below.

$$(F1)_i = \frac{2\times PA_i \times UA_i}{PA_i + UA_i} \qquad (11)$$

Additionally, due to many concerns regarding the use of kappa coefficient in evaluating the reliability of thematic maps (Foody, 2020), two more suitable measures of disagreement were performed *viz.*, quantity disagreement (QD) and allocation disagreement (AD) that were proposed by (Pontius & Millones, 2011). The QD measures the difference between the observed and modelled class instances, whereas AD assesses the variance in the localities of the observed class samples.

C) Detection of Land use/ land cover (LULC) changes

LULC patterns of different time periods in the study area were assessed to detect the change in each class category. The change (%) for various LULC types in different point in time was calculated according to Anand and Oinam, (2020) as expressed in following equation:

$$\frac{C_2 - C_1}{C_1} \times 100 \qquad (12)$$

where C_1 and C_2 are LULC class areas during the first (1988) and last of the study time period (2018), respectively.

The transition matrix produced in this analysis provided a general overview of the LULC stocks (amount and composition). Also, the transfers among LULC categories every 10 years during the study period, 1988–1998, 1998–2008 and 2008–2018 were evaluated.

D) Land use/ land cover (LULC) transitions mapping

In order to visually and quantitatively examine the nature of LULC transitions in Gedaref state and the transformation of each LULC class (Barnieh *et al.,* 2020; B. Nath *et al.*, 2018), we used the Semi-Automatic Classification plugin that embedded in QGIS software version 2.18.15. The thematic LULC maps between 1988 and 2018 were used to create LULC transitions maps and their corresponding transition matrixes, where we used the LULC maps for the years 1988, 1998, and 2008 as reference layers to detect the transitions in each class in 30, 20 and 10 years (i.e., till 2018), respectively.

E) Intensity analysis in land use/ land cover (LULC) transitions

Overall, the thematic LULC maps do not mimic the pattern and magnitude of the change that cause the landscape transformation (Asante-Yeboah *et al.*, 2022). To address this, Aldwaik and Pontius (2012) proposed the so-called 'intensity analysis', which is a qualitative approach for better understanding the magnitude of the transformation in landscape structure. LULC intensity analysis was performed using the contingency table for each period to look at the extent and intensity of change at various scales; interval, category, and transition. The analysis of the interval level computes the rate and size of change over a specific point in time. Whereas the categorical level analysis examines differences in the intensity of change across LULC classes. Lastly, the analysis of the transition level emphasises on the magnitude and direction of the change between the LULC categories in each time interval (Asante-Yeboah *et al.,* 2022; Zhou *et al.,* 2014).

The uniform intensity lines provided by all three levels of analysis depict a theoretical situation in which uniform transformation takes place across all LULC classes. The predicted class area from the interval level experiment defines the period that has annual fast or slow changes compared to the uniform intensity line. When the intensity of a category exceeds the uniform line, it is called an active category; when it falls lower than the uniform line, it is called a dormant category. Similarly, in the transition intensity, a targeted class is the one that its loss or gain exceeds the uniform intensity line. On the other hand, if a category does not reach the uniform intensity line, it is regarded as avoided (Asante-Yeboah *et al.,* 2022). Initially, transition matrices of the periods 1988-1998, 1998-2008, and 2008-2018 were generated for the thematic LULC maps. Thereafter, a tool developed by Aldwaik and Pontius (2013) was used to compute the three intensity levels at different time intervals using the following equations and their description provided in Table 3.1: Firstly, the transitions at the interval level were computed (Equation 13), through dividing the magnitude of change by the length of time interval, generating percentage of spatial extent. The categorical annually gross loss intensity in a time interval was calculated by dividing the size of the category's annual gross loss by the size of the category at the beginning of each interval (Equation 14). On the other hand, the category's annually gross gain intensity in a time interval was calculated by dividing the size of the category's annually gross gain with the size of the category at the final stage of each time interval (Equation 15). The common hypothesis for each interval's category level proposes that all categories experience gross loss and gross gain with the same annually intensity. This sum is equal to the transition rate in the interval (S_t). If L_{ti} < S_t, the loss of i, is paused during the interval t. In contrast, if G_{tj}< S_t, the gain of j is withheld during the interval t. In the case L_{ti} > S_t, loss of i is considered to be active during the interval t; similarly, if G_{tj}> S_t, gain of j is considered active during that time interval. Equation (16) computes the annual transition intensity of the gain in a specific category n from other categories$i$, that is the amount of the annually transition to the specific category n from the other category divided by amount of another category at the beginning of each interval. The hypothesis at the level of transition for intervals states that particular category n moves to all other categories with a comparable annual intensity. This amount is calculated by dividing the size of the yearly gain of category n by the total quantities of sizes of all other categories at the beginning time of intervals (Equation 17). Hence, if R_{tin} < W_{tn}, the gain of n pause i during the interval t. If R_{tin} > W_{tn}, the gain of n targets i within interval t.

Table 3.1: Mathematical symbols used to calculate different intensities as illustrated in equations 3-7 as described by Aldwaik and Pontius (2012).

Symbol	Description
T	number of time points
γ_t	year at time point t
t	index for the initial time point of an interval $[\gamma_t - \gamma_{t+1}]$,where t ranges from 1 to $T - 1$
J	number of categories
i	index for a category at the initial time point of an interval
j	index for a category at the latter time point of an interval
n	index of the gaining category for the selected transition
C_{tij}	size of transition from category i to category j during interval $[\gamma_t - \gamma_{t+1}]$
S_t	annual change during interval $[\gamma_t - \gamma_{t+1}]$
G_{tj}	intensity of annual gain of category j during interval $[\gamma_t - \gamma_{t+1}]$ relative to size of category j at time $t+1$
L_{ti}	intensity of annual loss of category i during interval $[\gamma_t - \gamma_{t+1}]$ relative to size of category i at time t
R_{tin}	intensity of annual transition from category i to category n during interval $[\gamma_t - \gamma_{t+1}]$ relative to size of category i at time t
W_{tn}	uniform intensity of annual transition from all non-n categories to category n during interval $[\gamma_t - \gamma_{t+1}]$ relative to size of all non-n categories at time t

$$S_t = \frac{Change\ during\ [\gamma_t,\gamma_{t+1}]}{(Duration\ of\ [\gamma_t,\gamma_{t+1}])(Extent\ Size)} 100\% = \frac{\sum_{j=1}^{J}[(\sum_{i=1}^{J} C_{tij}) - C_{tij}}{(\gamma_{t+1}, \gamma_t)(\sum_{j=1}^{J}\sum_{j=1}^{J} C_{tij})} 100\% \tag{13}$$

$$L_{ti} = \frac{Annual\ loss\ o\ f\ i\ during\ [\gamma_t,\gamma_{t+1}]}{Size\ o\ f\ i\ at\ \gamma_t} 100\% = \frac{[\sum_{i=1}^{J} C_{tij}) - C_{tij}]/(\gamma_{t+1} - \gamma_t)}{\sum_{j=1}^{J} C_{tij}} 100\% \tag{14}$$

(4)$$G_{tj} = \frac{Annual\ gain\ of\ j\ during\ [\gamma_t,\gamma_{t+1}]}{Size\ of\ j\ at\ \gamma_{t+1}} 100\% = \frac{[(\sum_{i=1}^{J} C_{tij}) - C_{tij}]/(\gamma_{t+1} - \gamma_t)}{\sum_{i=1}^{J} C_{tij}} 100\% \tag{15}$$

$$R_{tin} = \frac{Annual\ transition\ from\ i\ to\ n\ during\ [\gamma_t,\gamma_{t+1}]}{Size\ of\ i\ at\ \gamma_t} 100\% = \frac{C_{tin/}(\gamma_{t+1} - \gamma_t)}{\sum_{i=1}^{J} C_{tij}} 100\% \tag{16}$$

$$W_{tn} = \frac{Annual\ gain\ of\ n\ during\ [\gamma_t,\gamma_{t+1}]}{Size\ of\ non{-}n\ at\ \gamma_t} 100\% = \frac{[(\sum_{i=1}^{J} C_{tin}) - C_{tnn}]/(\gamma_{t+1} - \gamma_t)}{\sum_{j=1}^{J}[(\sum_{i=1}^{J} C_{tij}) - C_{tnj}} 100\% \tag{17}$$

F) Future land use/ land cover (LULC) prediction and validation

After generating LULC maps from Landsat data for the period 1988 to 2018 with 10 years intervals, future simulation of LULC change was performed using Cellular Automata Artificial Neural Network (CA-ANN) algorithm in MOLUSCE plugin that embedded in QGIS software version 2.18.15. Studies have shown that the CA-ANN model is more powerful and robust in simulating future LULC as compared to other models like linear regression and Marcov (Abbas *et al.*, 2021; El-Tantawi *et al.*, 2019; Rahman *et al.*, 2017). Moreover, the MOLUSCE plugin effectively processes LULC change analyses and is suitable for evaluating spatio-temporal LULC changes and predicting future scenarios (Gismondi, 2013; Muhammad *et al.*, 2022). For future LULC predictions, the same resolution was retained (30 x 30 m) and WGS 84 coordinate system.

To simulate future LULC, it is recommended that a number of predictor variables, which play a major role in LULC change and transition should be considered (McCarthy *et al.*, 2001). Based on LULC change drivers that were reported in previous studies (Gounaridis *et al.*, 2019; Kafy *et al.*, 2021; Wu *et al.*, 2022), and the availability of such factor datasets, 8 predictor variables (Figure

3.6) were selected to describe the LULC change processes that occurred in Gadaref state between 1988 – 2018. These predictors include topographic variables such as slope, aspect and elevation; and human disturbance variables like distance from Gedaref state center, towns, highways, roads and the railway line (Figure 3.7). These variables are frequently used to predict LULC because they provide reproducible data on the natural and human disturbances in LULC processes (Muhammad *et al.,* 2022).

Prediction of future potential LULC for a prospective project can be only reliable if the simulation outcome is validated using existing datasets. Accordingly, in the first step, we predicted LULC for the year 2018 using the transition matrix generated from the thematic maps of the years 1998 and 2008 and the selected predictor variables that are presented in Figure 3.7. Thereafter, the validation process was performed using a comparative analytical procedure of the overall correctness percentage and kappa coefficient in the MOLUSCE plugin. Specifically, to validate the performance of CA-ANN model, the simulated LULC map for 2018 that was generated using CA-ANN algorithm was compared with one that generated for the same year using the multi-date Landsat images and RF classifier. After obtaining adequate validation metrics, LULC data from 2008 and 2018 maps (herein referred to as prediction data) were utilized to simulate future LULC in 2028 and 2048.

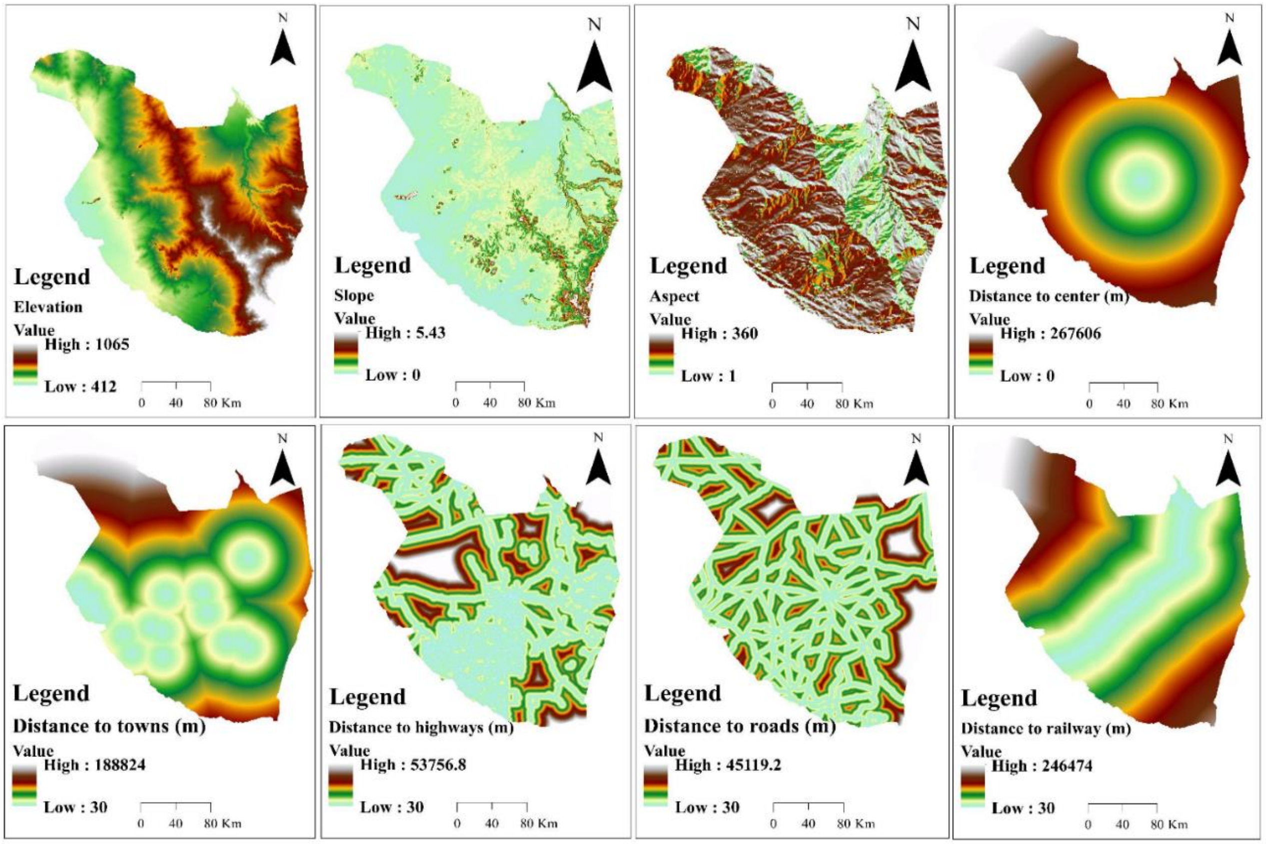

Figure 3.7: Predictor variables used for land use/ land cover (LULC) future predictions

Source: Author

3.5.5 Assess the local farmers' perception of land use/ land cover (LULC) change trends; and determine LULC drivers in Gedaref state.

3.5.5.1 Desktop studies and secondary data

Remote sensing and geospatial data have been identified as trustworthy sources for determining and understanding LULC change drivers of homogenous and heterogeneous landscapes (Daba & You, 2022). Therefore, the LULC maps for the years 1988, 1998, 2008, and 2018 generated using the methodology of objective 3, were used to determine the land cover trend. The change in the

LULC classes (area in ha) for each year was extracted from the classified maps and then compared with farmers' perceptions.

Temperature and rainfall data for the years 1988 to 2018 obtained in section *3.5.2.1* of objective 1 were used for this objective. However only annual mean temperature and rainfall were used for the analysis. The total cultivated area, production, and yield for the five main crops, namely sorghum, sesame, millet, sunflower and cotton, were acquired from the Ministry of Agriculture in Gedaref state. While population datasets for the state were acquired from the Sudan Central Bureau of Statistics. Sudan has undertaken three population censuses before and during the study period (1983, 1993 and 2008). The census population for the years 1988, 1998 and 2018 were estimated from the nearest census data of Gedaref state and annual population growth rates in Gedaref state based on the following equation adopted by Kindu et al. (2015) and Munthali et al. (2019):

$$P_2 = P_1 e^{rt} \qquad (18)$$

Where P_1 = total population size of the nearest census; P_2 =the estimated total populations for the given year; e = exponential constant (2.718); t = number of years between the initial census (nearest census P_1) and estimated enumeration (P_2); and r = the rate of the annual population growth in Gedaref state (4.7%).

3.5.5.2 Household survey, key informant interview and focused group discussion.

A) Household data collection

The second part of the questionnaire that was described in section *3.5.3.2* of objective 2, was basically contained questions to assess farmers' perception of LULC change and the underlying factors that driver these dynamics in Gedaref state. This part of the questionnaire included questions that were designed to collect in-depth data on the local land users' perception of LULC dynamics, the driving factors of these changes and crop yield in Gedaref state during the study period (1988–2018). The same 400 respondents that were selected in section *3.5.3.2* were interviewed.

B) Key informant interview and focus group discussion

A total of 16 FGDs were conducted in the eight villages using the same procedure described in section *3.5.3.2.2* of objective 2. These FGDs were done separately from the ones that were done in objective 2. The FGDs were conducted to generate the necessary information and understanding the perception of the local land users on LULC changes that occurred in Gedaref state and the underlying causes that have contributed to these changes. Discussions with the key informants including elders, researchers and officials from agricultural, environmental institutions, and natural resource conservation at the state level.

3.5.5.3 Data management and analysis

The generated data from the questionnaires on the perception of LULC were entered, coded and cleaned before the analysis. Thereafter, descriptive statistics was used to describe the socio-economic and demographic characteristics of the respondents. In addition, the perceived LULC change drivers by the local land users were ranked based on their weighted average using the ranking index adopted by Musa et al. (2006) and Solomon et al. (2017):

$$\text{Index} = \frac{R_n C_1 + R_{n-1} C_2 \ldots\ldots + R_1 C_n}{\sum R_n C_1 + R_{n-1} C_2 \ldots\ldots + R_1 C_n} \qquad (19)$$

Where R_n = value assigned to the lowest rank (for instance, if the lowest rank is the 5th, then R_n= 5, R_{n-1} = 4, R_1 = 1; C_1 = counts of the lowest ranked level (in the above example, the count of the 5th rank = C_5, and the count of the 1st rank =C_1).

Multinomial logistic regression model (equation 10 in objective 2) was used to determine the key factors that drive LULC dynamics in Gedaref state at the household level. The identified perceived drivers for LULC changes were the dependent variables for the model, while socio-economic variables such as sex, sex of the household, age, education level and land tenure were the independent variables.

This study only focused on three LULC classes, namely cropland, forest, and settlement. Therefore, the cropland, forest and settlement areas estimated from the satellite images and the actual total cultivated area for the five main crops that are cultivated in Gedaref state were subjected to Mann–Kendall trend analysis to assess the increase or decrease trends in their coverage based on Sen's slope value. In addition, we employed simple linear regression to assess the trends in the production of the five crops over time. This is due to the fact that crop production is largely related to crop harvested area rather than climatic and other variables. Hence, the Mann-Kendall trend analysis is not appropriate for such data as crop production data do not meet the assumption of this analysis (Kendall, 1948; Osman *et al.*, 2021). Moreover, the association between each of the LULC drivers (temperature, rainfall and population) and the change (area in ha) in LULC classes (cropland, forest and settlement) was determined using Pearson's correlation test. The same correlation analysis was also employed to assess the association between the actual total cultivated areas and crop yields for the five major crops during the studied period (1988–2018). This analysis was done to get insights into whether crop acreage and yield were changed simultaneously in Gedaref state. Furthermore, a multiple linear regression model was used to determine the effect of LULC drivers (temperature, rainfall and population) on the area (in ha) of LULC classes (cropland, forest and settlement).

CHAPTER FOUR

CLIMATE VARIABILITY AND CHANGE AFFECT CROPS YIELD UNDER RAINFED CONDITIONS: A CASE STUDY IN GEDAREF STATE, SUDAN

4.1 Introduction

This chapter presents results on an assessment of the trends in minimum and maximum temperatures (Tmin and Tmax), diurnal temperature rang (DTR) and rainfall in Gedaref state, Sudan, between 1984 and 2018. It also characterizes the onset, cessation and length of the rainy season in Gedaref state for the same period. In addition, this chapter also presents an assessment of the trends in crops yield of five major cultivated crops in Gedaref state: sorghum, sesame, sunflower, millet and cotton. Furthermore, the chapter investigates the impact of rainfall and temperature-based variables (Tmin, Tmax and DTR) on the yield of the main crops in Gedaref state.

4.2. Results

4.2.1. Estimation of annual and seasonal temperature trends in Gedaref state

The Mann–Kendall and Sen's slope trend analysis showed that the annual Tmax significantly ($p < 0.01$) increased in Gedaref state by 0.03°C per year, between the years 1984 and 2018, with a confidence interval ranged between 0.014 and 0.043°C (Table 4.1; Figure 4.1A). Similarly, the annual Tmin significantly ($p < 0.0001$) increased by 0.05°C per year, with a confidence interval ranging between 0.031 and 0.061°C (Table 4.1; Figure 4.1B). Between the years 1984 and 2018, the Tmin in Gedaref state ranged between 20.81 and 23.26°C per year, while the values of the Tmax ranged from 36.10 to 38.34°C (Table 4.1). The annual DTR had significantly ($p < 0.01$) decreased by 0.02°C per year, with a confidence interval between −0.234 and 0.142°C for the study period (Table 4.1; Figure 4.1C). The seasonality trend showed that the Tmax increased by 0.02 and 0.04°C per year in winter and summer, respectively, with no change reported in autumn (Table 4.1; Figure 4.1A), while the Tmin in winter, summer, and autumn has significantly ($p < 0.001$) increased by 0.05°C, 0.06 °C, and 0.04 °C per year, respectively (Table 4.1; Figure 4.1B). The highest decrease in DTR was reported in winter, with an estimated value of 0.03 °C per year ($p < 0.001$).

Table 4.1: Estimated Sen's slope values for the annual and seasonal temperature (°C) trends at Gedaref state, Sudan between 1984 and 2018.

Parameter	**Range**		**Sen's Slope**	**95% Confidence interval**	**Coefficient of Variation (*CV* %)**	***p*−Value**
	Minimum	**Maximum**				
Annual Tmin	20.817	23.266	0.045	0.031–0.061	2.65	<0.0001
Annual Tmax	36.100	38.343	0.030	0.014–0.043	4.33	0.001
Annual DTR	14.064	16.090	−0.023	−0.234–0.142	6.82	<0.003
Winter Tmin	17.248	21.283	0.048	0.025–0.070	4.29	<0.001
Winter Tmax	34.687	37.548	0.017	−0.001–0.039	1.74	0.069
Winter DTR	15.661	18.350	−0.037	−0.207–0.192	3.38	<0.001
Summer Tmin	22.957	25.838	0.056	0.036–0.071	2.83	<0.0001
Summer Tmax	38.809	41.771	0.039	0.014–0.63	3.19	0.003
Summer DTR	15.034	17.174	−0.009	−0.304–0.246	3.19	0.288
Autumn Tmin	21.349	23.637	0.038	0.023–0.051	2.33	<0.0001
Autumn Tmax	33.228	36.676	0.002	−0.026–0.034	2.58	0.809
Autumn DTR	11.073	15.207	−0.026	−0.001–0.312	6.81	0.045

Tmin, Tmax and DTR are minimum temperature, maximum temperature and diurnal temperature range, respectively.

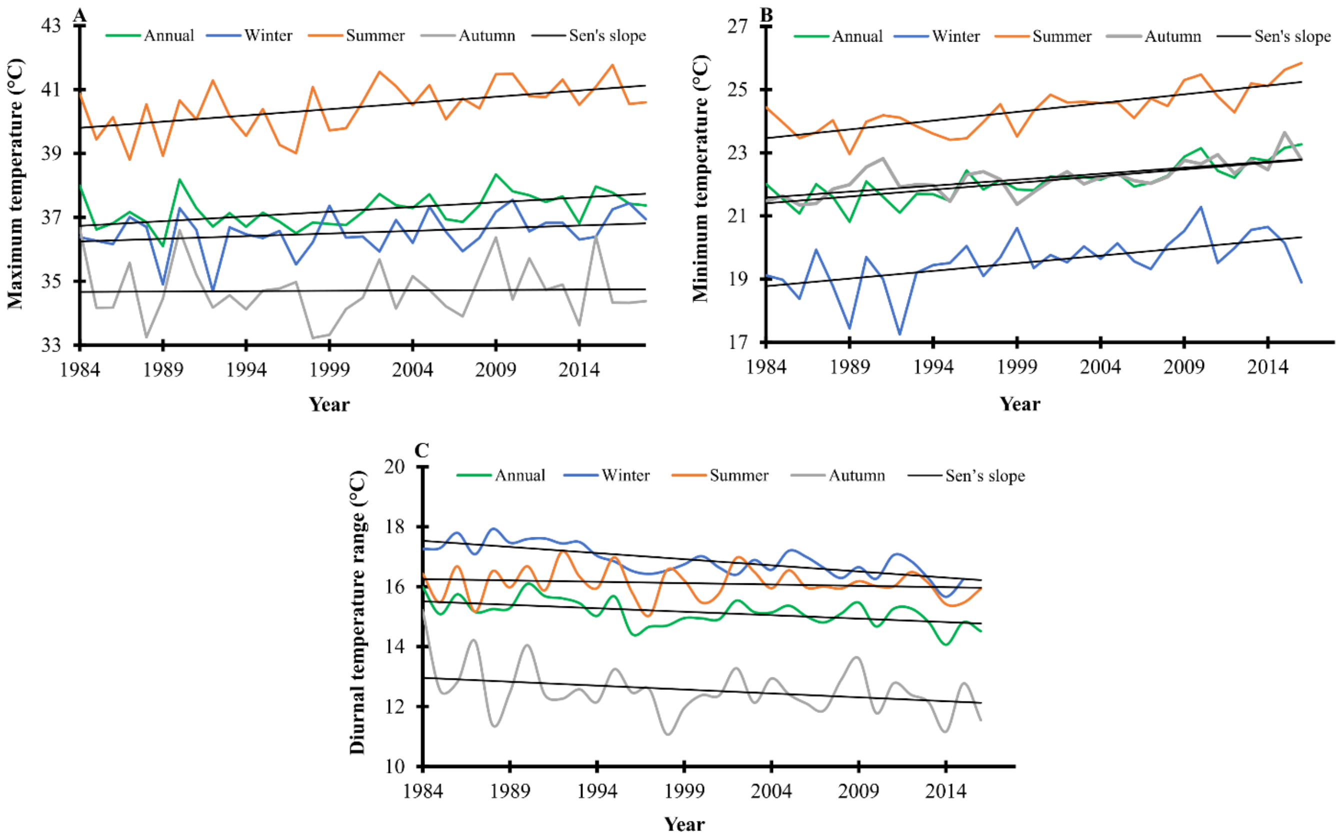

Figure 4.1: Annual and seasonal temperature trends in Gedaref state, Sudan between 1984 and 2018. (A): maximum temperature, (B): minimum temperature, and (C): diurnal temperature range.

4.2.2. Determination of annual rainfall trends in Gedaref state

Mann–Kendall and Sen's slope trends for the annual rainfall data for the five different stations are presented in Table 4.2 and Figure 4.2, respectively. Overall, there was a variation in the annual rainfall trends between 1980 and 2018, with no significant (p ranged between 0.131 and 0.841) increase or decrease in the amount of rainfall within this period in the five locations. Rainfall decreased in Gedaref and Samsam by about 0.3 mm per year and increased in the other three locations by about 2.5–3.1 mm per year (Table 4.2) during the study period, with high variability in El hawata (CV = 26.57%) and low variability in Samsam (CV = 20.59%). The highest decrease in rainfall was recorded at the Samsam location, fluctuating from 420 to 1023 mm (Table 4.2;

Figure 4.2D). The overall trend of the average rainfall recorded in the five locations revealed that the rainfall has increased by ≈ 1.0 mm in Gedaref state between 1980–2018, with *CV* of 14.73% (Table 4.2; Figure 4.2F).

Table 4.2: Estimated Sen's slope values for annual rainfall (mm) trends reported at different stations in Gedaref State, Sudan between 1980 and 2018.

Location	**Range**		**Sen's slope**	**95% Confidence interval**	**Coefficient of Variation (*CV* %)**	***p*-Value**
	Minimum	**Maximum**				
Gedaref	322.000	871.000	−0.323	−3.967–3.636	21.29	0.841
El gadabalea	285.000	755.000	2.571	1.032–5.533	21.63	0.217
Am Senat	435.000	1070.000	3.100	−1.250–7.091	22.35	0.150
Samsam	420.000	1023.000	−3.222	−7.757–0.769	20.59	0.131
El hawata	222.000	809.000	2.611	−1.679–7.152	26.57	0.183
Mean for all five locations	425.4000	753.8000	0.9627	−34.200–41.080	14.73	0.4135

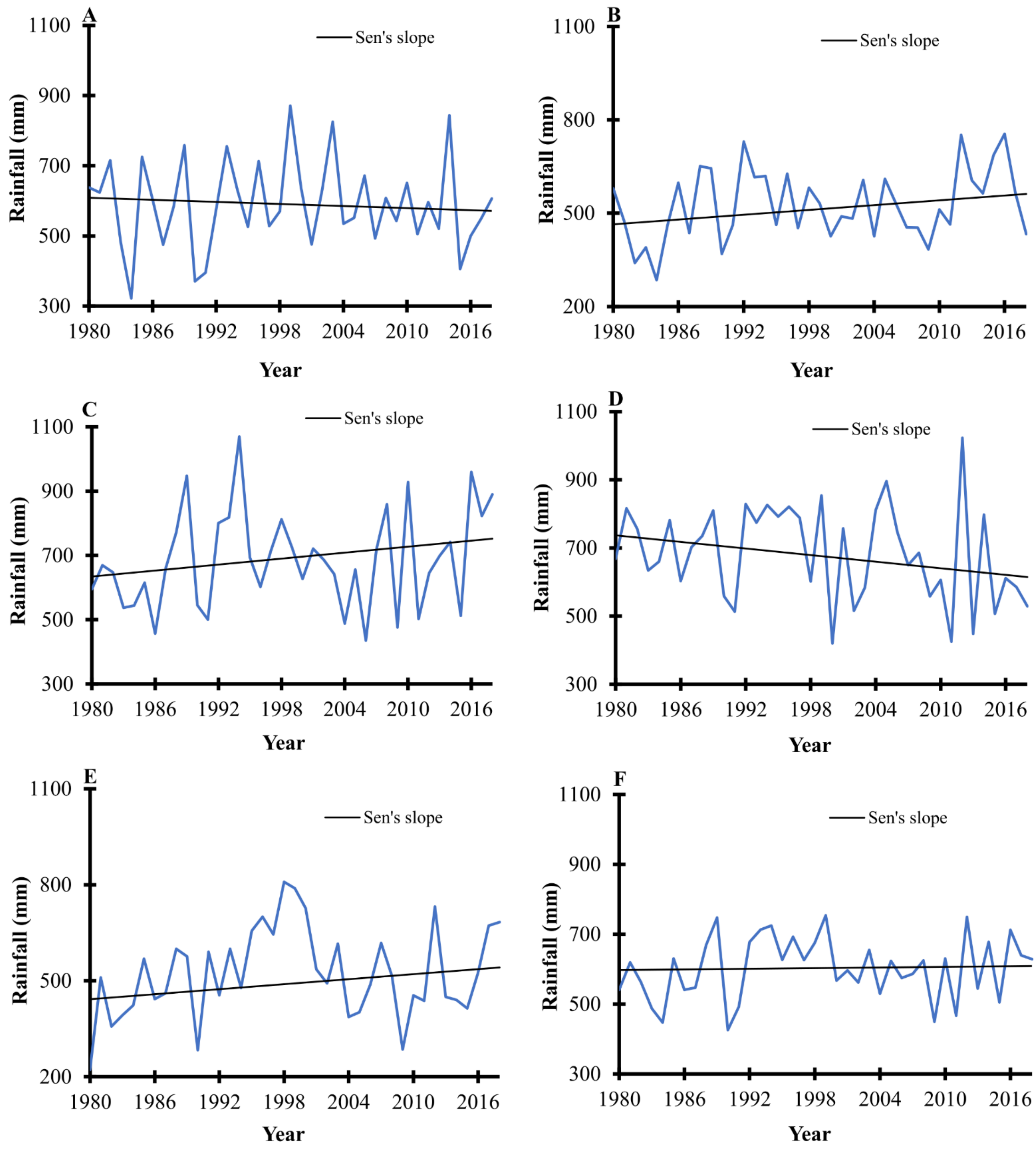

Figure 4.2: Annual rainfall trends in five locations in Gedaref state, Sudan between 1980 and 2018. **(A):** Gedaref, **(B):** El gadabalea, **(C)**: Am Senat, **(D):** Samsam, **(E)**: El hawata, and **(F):** Average rainfall for all five locations.

4.2.3. Assessment of annual crop yield trends in Gedaref state

The trend analysis showed a decrease in the annual yield of the five studied crops between 1970 and 2018, with the exception of sunflower and sesame, which had a yield increment (Table 4.3; Figure 4.3). However, there was a significant yield change for sorghum ($p< 0.01$) and sunflower ($p < 0.001$) only (Table 4.3; Figure 4.3). In particular, sorghum and cotton, respectively recorded the highest (0.41 kg ha^{-1} per year) and lowest (0.02 kg ha^{-1} per year) yield decrement, while sunflower recorded a yield increment of about 0.61 kg ha^{-1} per year (Table 4.3; Figure 4.3).

Table 4.1: Estimated slope of linear regression for the annual yield trends for five crops (sesame, sorghum, cotton, millet, and sunflower) in Gedaref state, Sudan from 1970–2018.

Crop Yield	**Range**		**Slope**	**95% Confidence interval**	**Coefficient of Variation (*CV* %)**	***p*-Value**
	Minimum	**Maximum**				
Sorghum	185.718	1000.020	−0.409	−0.676–−0.141	37.85	0.003
Sesame	111.907	780.016	0.163	−0.127–0.453	40.78	0.263
Cotton	58.096	1190.500	−0.018	−0.311–0.276	55.49	0.905
Millet	216.671	642.870	−0.025	−0.368–0.318	29.29	0.883
Sunflower	238.100	833.350	0.607	0.310–0.903	30.16	0.000

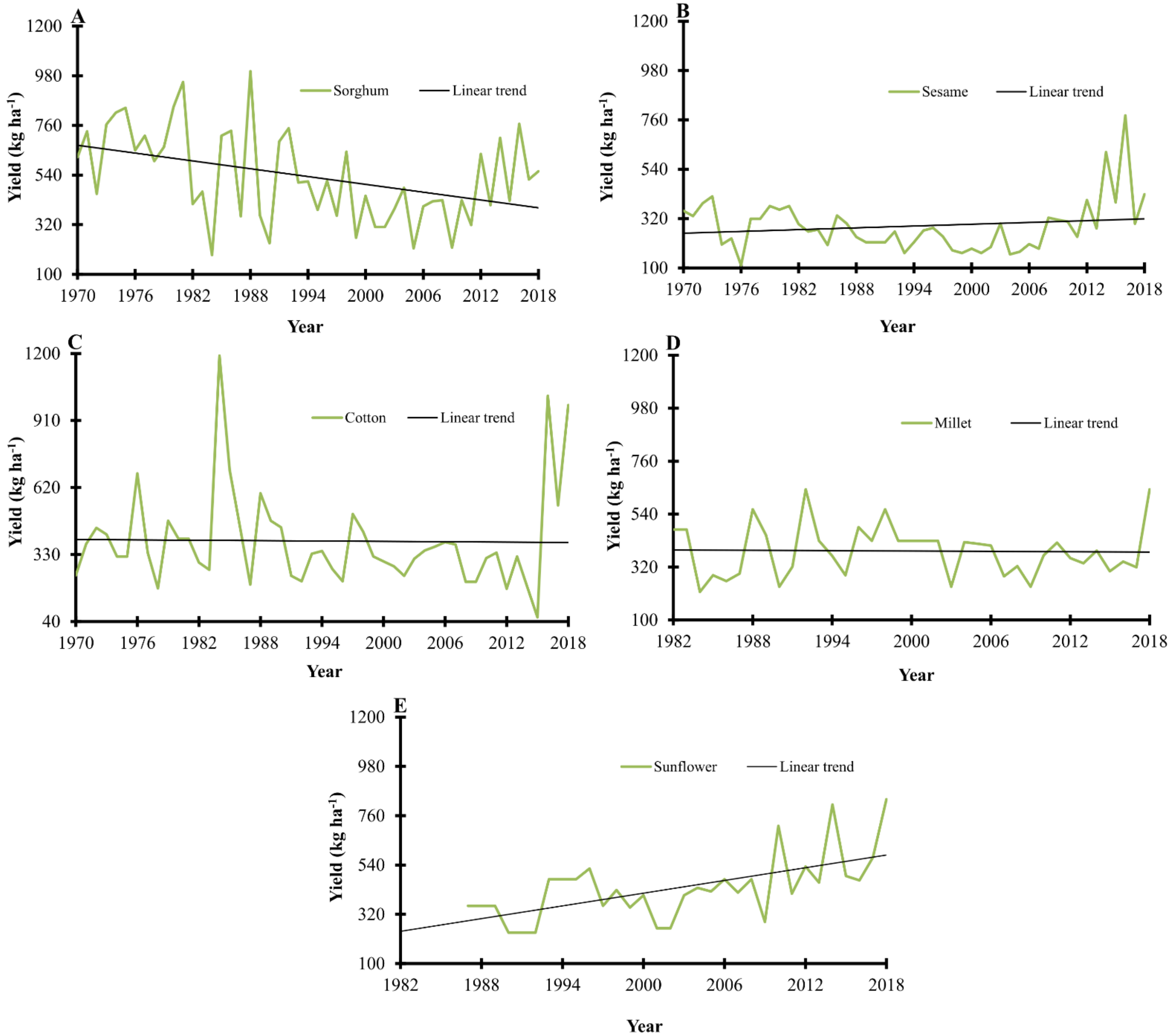

Figure 4.3: Annual crop yield trends for the major crops grown in Gedaref State, Sudan from 1970–2018, (**A**): sorghum, (**B**): sesame (**C**): cotton, (**D**): millet and (**E**): sunflower yield trends.

4.2.4. Estimation of temperature and rainfall variability indices

The temperature and rainfall anomalies that occur in Gedaref state for the period 1984–2018 were described by mean annual temperature and rainfall. Standardized anomaly index for the mean annual temperature in Gedaref state was characterized by the below long-term average between 1984 and 2000, indicating cold years (Figure 4.4A). The cold years started in 1985 and continued with only one warm year (i.e., 1990) until 2000. Afterward, there were warm years which continued until 2018, which are characterized by being above the long-term average with two breaks of cold years (Figure 4.4A). Standardized rainfall anomaly index for long-term annual rainfall of Gedaref for the period 1984–2018 was used to identify the years with rainfall deficit and the years with surplus rainfall. The coefficient of variation for annual rainfall was 23%, which indicates that there was no high variation in the amount of rainfall between the years. The year 1984 experienced the highest rainfall deficit occurrence, followed by 1990, 1991, 2013, 2011, and 1987, in decreasing order of magnitude (Figure 4.4B). In contrast, the years with the highest surplus rainfall were 1999, 2014, 2003, and 2002, as can be observed in Figure 4.4B.

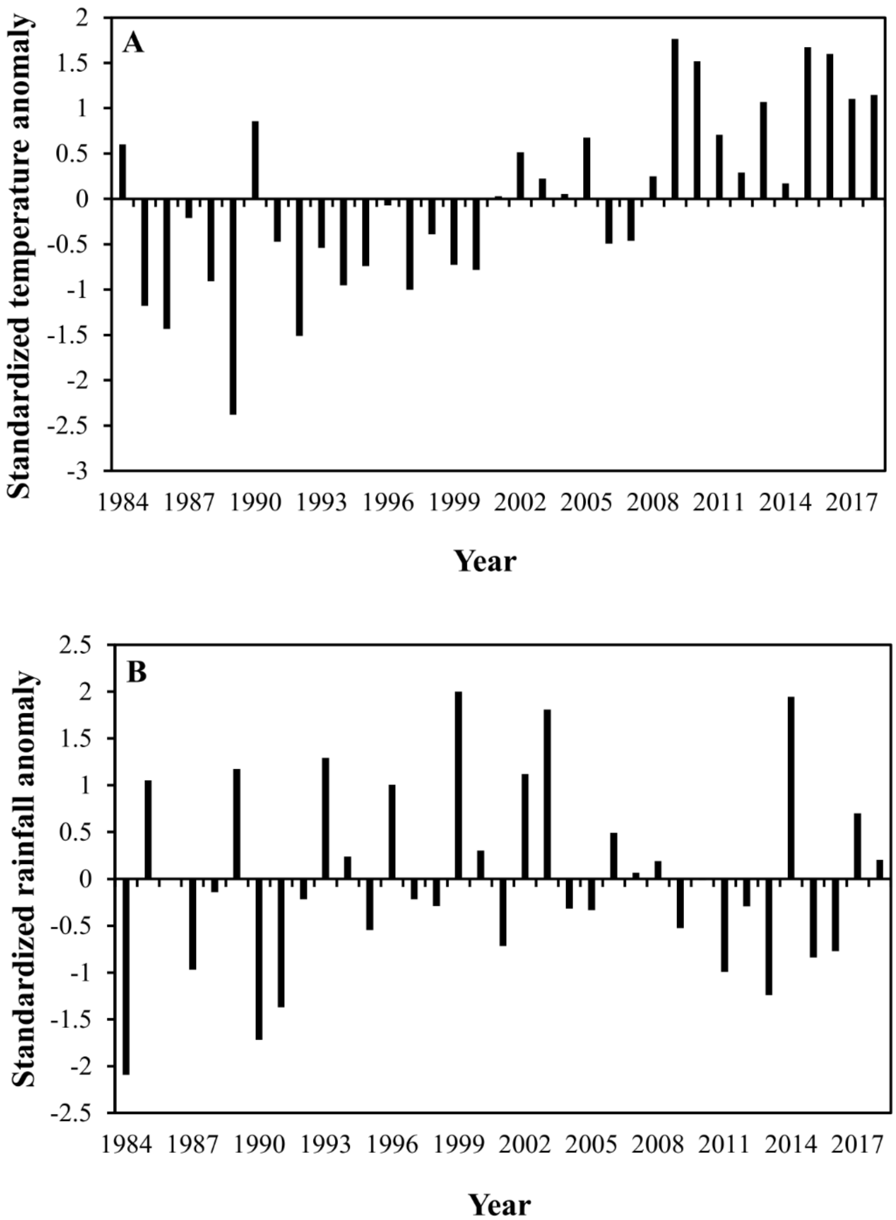

Figure 4.4: Standardized anomaly index for mean temperature (**A**), and annual rainfall (**B**) in Gedaref State, Sudan from 1984–2018.

4.2.5. Characteristics of rainy seasons in Gedaref state

On average, the starting dates of the rains in Gedaref state were estimated to range between the second and third dekad of June, which corresponds to the 166–176 days of the year. The cessation dates estimated between the second and third dekad of September and the first and second dekad of October, which falls between the 250–287 days of the year (Table 4.4). The length of the rainy season in Gedaref state ranged between 57 days (2013 season) and 117 days (2016 season) (Table 4.4). Some exceptions are noticed in the years 1991, 1998, and 2013 when onset dates occurred within the second and third dekad of July, while cessation date exceptions are 2007 and 2012 in the first dekad of September and the year of 2017 in the third dekad of August (Table 4.4). The total amount of rainfall ranged between 286 and 820 mm, with an average of 539.7 mm per season (Table 4.4).

Linear regression analysis showed that an increase in the length of the rainy season significantly increased the yield of sesame ($p < 0.001$ and $R^2 = 0.47$), sorghum ($p < 0.001$ and $R^2 = 0.43$), sunflower ($p < 0.001$ and $R^2 = 0.49$), and cotton ($p < 0.05$ and $R^2 = 0.22$) (Figure 4.5). However, the yield of millet was not significantly ($p = 0.432$ and $R^2 = 0.02$) affected by the length of the rainy season (Figure 4.5).

Table 4.2: Estimated length of the rainy season (1984–2018) for Gedaref State, Sudan.

Season	Onset date	Day of the year for onset	Cessation date	Day of the year for cessation	Length of the rainy season (Day)	Total rain (mm)
1984	7-July	189	16-September	260	76	286
1985	20-June	171	12-October	285	114	669
1986	29-June	180	3-October	275	96	525
1987	19-June	170	12-October	285	115	445
1988	29-June	181	18-September	262	81	532
1989	22-June	173	19-September	262	89	682
1990	15-June	166	25-September	268	102	335
1991	13-July	129	1-October	274	80	308
1992	4-July	186	13-October	287	101	520
1993	18-June	169	28-September	271	102	693

Table 4.4(cont.):

Season	Onset date	Day of the year for onset	Cessation date	Day of the year for cessation	Length of the rainy season (Day)	Total rain (mm)
1994	17-June	168	24-September	267	99	579
1995	17-June	168	19-September	262	94	499
1996	22-June	174	30-September	274	100	576
1997	25-June	166	24-September	267	91	505
1998	17-July	198	10-October	283	85	552
1999	20-June	171	8-October	281	110	766
2000	24-June	176	1-October	275	99	621
2001	23-June	174	7-October	280	106	430
2002	10-July	191	21-September	264	73	629
2003	21-June	172	2-October	275	103	820
2004	20-June	172	10-October	284	112	579
2005	22-June	173	20-September	263	90	504
2006	19-June	170	28-September	271	101	626
2007	24-June	175	7-September	250	75	575
2008	23-June	175	12-September	256	81	528
2009	2-July	183	15-September	258	75	510
2010	23-June	174	14-October	287	113	544
2011	19-June	170	13-September	256	86	408
2012	23-June	175	28-August	241	66	511
2013	21-July	202	16-September	259	57	418
2014	24-June	175	4-October	277	102	787
2015	9-July	190	28-September	271	81	399
2016	18-June	170	13-October	287	117	440
2017	18-June	169	6-September	249	80	535
2018	29-June	180	29-September	272	92	556

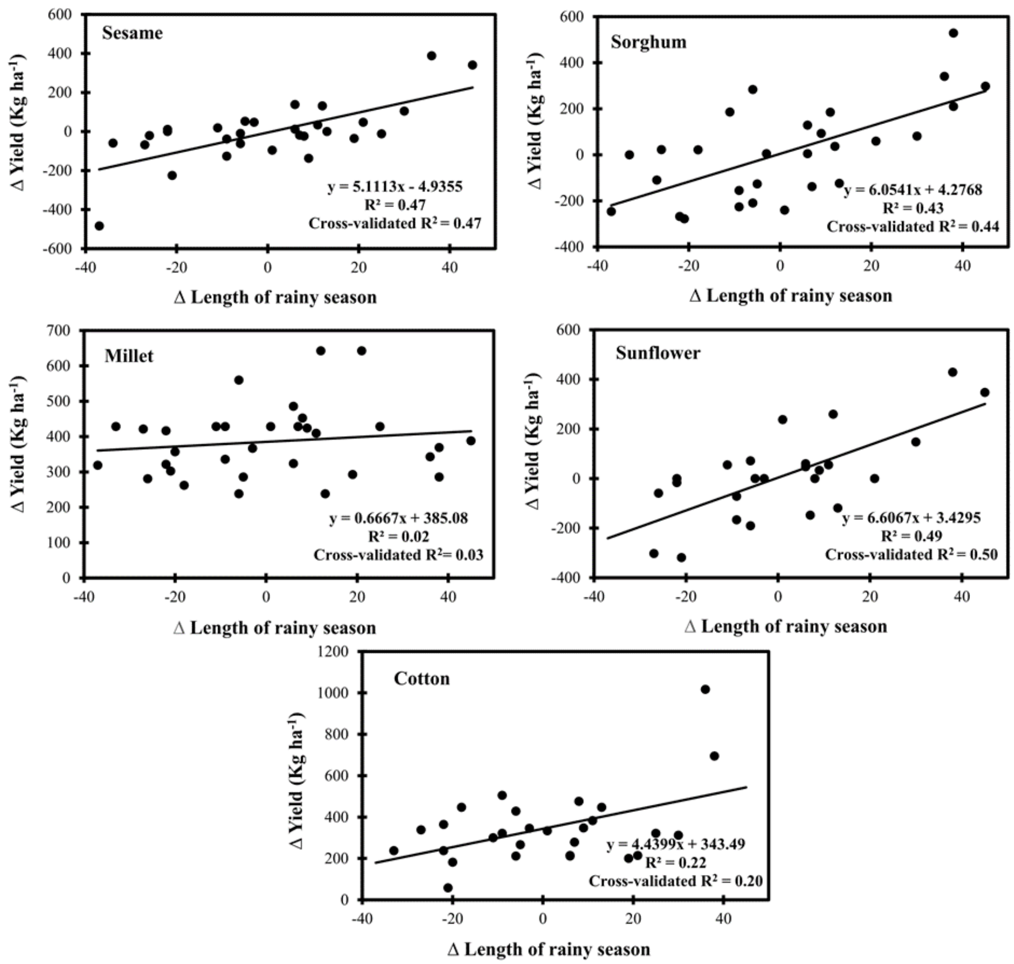

Figure 4.5: Relationships between the length of the rainy season and yield of five major crops grown in Gedaref state, Sudan. R^2 is coefficient of determination.

4.2.6. Assessment of the relationship between climatic variables and crop yield in Gedaref

The result of the relationships among crop yield and temperature variables as well as rainfall, as assessed using Pearson's correlation, are presented in Figure 4.6. There were negative relationships among the temperature-based variables (Tmin, Tmax, and DTR) and crop yield, whereas the relationships among rainfall and crop yield were positive. The associations among all studied climate variables and most of the crop yields were significantly correlated (p < 0.01), with correlation coefficient values of above 0.5, except for millet and Tmin and rainfall, cotton and all climate variables, and sesame and DTR (Figure 4.6).

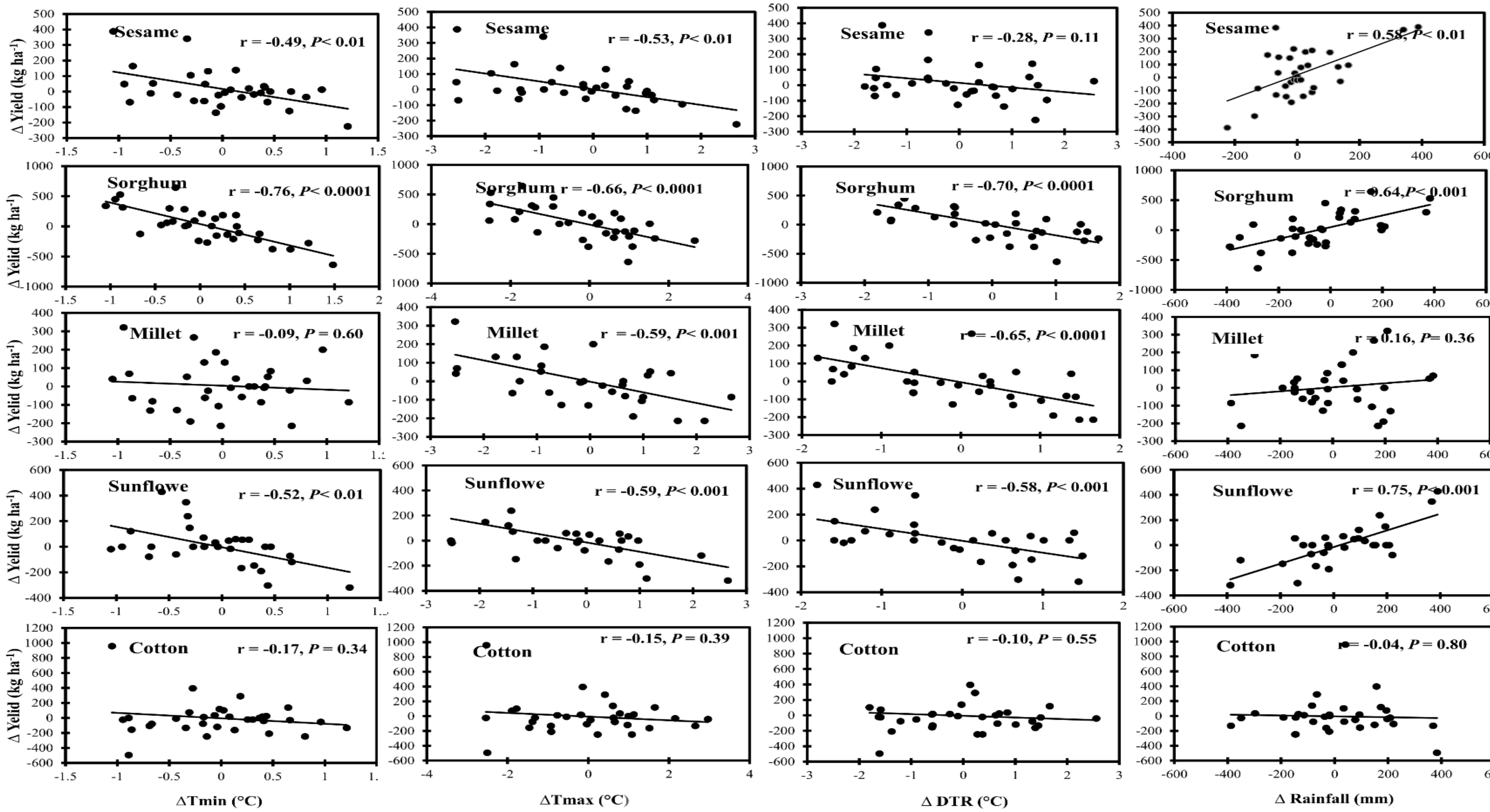

Figure 4.6: Associations, as assessed by a Pearson's correlation analysis, among climatic variables and yield of five major crops grown in Gedaref State, Sudan. r is correlation coefficient.

The results of the multiple linear regression analysis estimating the changes in yield of each of the five crops as a function of temperature-based and rainfall predictor variables are presented in Table 4.5. When all the climate variables were combined in one linear model, the result showed that 50% to 70% of sorghum, millet, and sunflower yield variabilities could be explained by the studied climatic variables. This was also confirmed by the cross-validated R^2, which ranged between 0.54 and 0.69, attesting to the certainty of the crop yield estimate models (Table 4.5). However, the regression coefficients were only significant ($p < 0.05$) for Tmin and DTR on sorghum yield changes. In addition, the coefficients of Tmin and Tmax were significant ($p < 0.05$) for the change in millet yield model, and rainfall in the sunflower yield model (Table 4.5). For sesame and cotton, only 41% and 6% of their yield variability, respectively, could be explained by the climatic predictor variables, indicating a very weak relationship between these variables and the change in yield of these two crops.

Table 4.3: Multiple linear regression terms and R^2 values for estimating yield, as a function of climatic variables, of five major crops grown in Gedaref state, Sudan.

Crop		Intercept	Tmin (°C)	Tmax (°C)	DTR (°C)	Rainfall (mm)	R^2	Cross-Validated R^2
Sesame	Coefficient	−0.734	−23.337	−32.206	10.891	0.239	0.41	0.38
	p−value	0.96	0.59	0.22	0.64	0.07		
Sorghum	Coefficient	33.980	−260.213	40.452	−132.345	0.110	0.70	0.69
	p−value	0.293	<0.001	0.42	<0.05	0.65		
Millet	Coefficient	−8.578	217.319	−191.497	102.271	−0.021	0.54	0.54
	p−value	0.61	< 0.05	< 0.05	0.19	0.84		
Sunflower	Coefficient	−16.746	9.8571	−16.042	−25.435	0.536	0.61	0.62
	p−value	0.43	0.87	0.65	0.49	<0.01		
Cotton	Coefficient	−3.610	−93.661	−17.070	0.000	−0.277	0.06	0.08
	p−value	0.93	0.40	0.67	-	0.33		

4.3. Discussion

This study provides information on climate trends and their effect on the yield of five main crops grown in Gedaref state, which is the most important rainfed agricultural area in Sudan that lies in the semi-arid region. The crops were grown under rainfed conditions during the rainy season (June–October). The results showed that there is an increasing trend in annual temperature over the last 35 years. These results agree with the findings of Loh et al. (2020), who reported an increase in the mean annual temperature trend by 0.06°C per year for the period between 1985–2015 in the Eastern part of Sudan. A similar trend was also reported for semi-arid regions of Iran where Tmin and Tmax increased over the last 50 years (Bannayan *et al.*, 2020). However, this study showed that the DTR annual trend decreased by 0.23°C per decade, which was indicated by a narrowing range of Tmin and Tmax. The trends of Tmin for all seasons of the year (winter, summer, and autumn) increased, while the DTR trend decreased between 1984 and 2018. The results of this study are also following the findings of Elagib (2010), who reported a rise in temperature in Sudan with a warming rate of 0.424, 0.357, and 0.451°C per decade for summer, winter, and autumn seasons, respectively, between 1941 and 2005. Yet, it has been argued that an increase in mean temperature by 2.6°C should be expected in the study area in 2070 (Platts1 *et al.*, 2015) and that might have a serious impact on crop production. The rainfall trend analysis for the five locations in Gedaref state showed variation in annual rainfall, which could be explained by the fact that rainfall varies from one location to another. Nevertheless, coefficient of variation for rainfall amongst the five locations was almost similar except for El hawata, where rainfall variation was slightly higher. The trend of the overall mean for the five locations showed an increase in rainfall trend in Gadaref by ≈1 mm for the years between 1980 and 2018. However, the projected regional climatic model showed that the annual amount of rainfall in Gadaref state might decrease by 50 mm by the end of this century (Platts1 *et al.*, 2015).

The standardized anomalies of annual mean temperature revealed that there was a cold period between 1984 and 2000 in the study area, which is indicated by anomalies below the long-term temperature average. However, after the year 2000, temperatures above the long-term average were detected, indicating a warm period. In fact, temperature had increased by 1.5°C above average in the years spanning 2009, 2010, 2015, and 2016, and this warming continued until the year 2018. The year-to-year departures were not reported for temperature anomalies, suggesting that the changes for some years were slightly around the mean (Koudahe *et al.*, 2017). Similarly, the standardized anomalies of annual rainfall indicated that the year 1984 took the first highest position of rainfall deficit occurrence, followed by the years 1990, 1991, 2013, 2011, and 1987, respectively. These anomalies in annual rainfall showed that the years with rainfall deficit corresponded to the true occurrence of droughts in Sudan. For example, the rainfall deficit in 1984 led to drought throughout the country, which resulted in famine and the death of thousands of people within the country (Hamid & Eltayeb, 2017). Overall, it is clear that the mean annual temperature between 1984 and 2018 was characterized by variability at a decadal scale, unlike the annual rainfall series, which is characterized by variability between the years. The results showed that an increase in the length of the rainy season significantly increased the yield of sesame, sorghum, sunflower, and cotton. These results agree with the findings of Murenzi (2019), who showed a positive relationship between the length of the rainy season and maize yield in Rwanda. However, the relationship between the length of the rainy season and cotton yield should be interpreted with caution as it could have been affected by the outliers when the change in the rainy season was above 36 days and cotton yield was more than 600 kg ha^{-1} (Figure 4.5). In addition, there was no clear relationship between the length of the rainy season and the yield of millet. This could be attributed to the fact that millet is a drought-tolerant crop with low water requirements, a characteristic that enables the crop to tolerate the terminal drought that usually occurs towards the end of the growing season during the grain-filling stage (Tadele, 2016).

The yield trend of sorghum, millet, and cotton decreased by 0.409 kg ha^{-1}, 0.025 kg ha^{-1}, and 0.018 kg ha^{-1}, respectively; however, the decreases in yields have fluctuated over the years. Obviously, the fluctuating rainfall trend is associated with the fluctuation and decrease in yield of sorghum, millet, and cotton. This suggests that there is a meaningful trend in the association between these crops' yield and rainfall. In the case of sorghum, the results were consistent with a previous study in the Gedaref region, which showed that rainfall shortage or flood can lead to a reduction in sorghum yield (Khalifa, 2016). The findings of this study are similar to those reported by Rowhani et al. (2011), who found a positive correlation between rainfall and sorghum yield in Tanzania, with intra-seasonal variability having a negative impact on yield. Likewise, the results agree with previous results from a study by Ibrahim (2015), who concluded that the fluctuations in the amount of rainfall were the most important factor that influenced the yield of sesame in Sudan. In the case of millet, the yield trend decreased with the decrease in rainfall trend, as reported by Traore et al. (2017). However, the trend showed that the yield reduction of millet was only −0.025 kg ha^{-1} compared to the other crops that require a high amount of water, such as sorghum. Similarly, correlation analysis revealed that the association between the amount of rainfall and millet yield was weak and not significant, which, again, confirms the low water requirements of this crop. The fluctuation in cotton yield was previously attributed to the variation in the amount of rainfall (Sultan *et al.,* 2008) when the crop is grown under rainfed conditions. Indeed, in the present study, rainfall amount was positively correlated with the yield of all crops except cotton.

When compared to other crops, water requirement by cotton depends on the length of the growing period and the favorite climatic conditions. In addition, continuous rain during the flowering and boll opening stages of cotton crop impairs pollination and thus the final crop yield (Cetin & Basbag, 2010). The trend analysis also showed an increase in sunflower yield over time. This could be attributed to expansion in sunflower cultivation as an industrial crop. The crop is also relatively drought-tolerant and can be grown in various soil types, making it a viable option for areas where other crops may not perform well.

In this study, temperatures were negatively correlated with crop yield regardless of the crop type. A study by Rowhani et al. (2011) in Tanzania reported that the variability in the mean seasonal temperature had a negative effect on sorghum yield. This previous finding agrees with the results of this study, which showed a negative correlation between sorghum yield and the studied temperature-based variables. It has also been reported by Hammer et al. (2015) that high temperature shortens the development time of sorghum, but it also leads to a significant reduction in plant height, pollen viability, and seed set, and, as a consequence, a reduction in crop yield. Therefore, temperature rise, in light of global warming, might reduce the yield of sorghum in Sudan and this may have a serious consequence on food and nutrition security countrywide. The present study also shows that temperature-based variables (Tmin, Tmax, and DTR) were negatively correlated with sesame yield in Gedaref state. This is consistent with the report of Nath et al. (2001), who showed that the ambient temperature of 30°C can negatively affect sesame yield in India. In addition, Kumazaki et al. (2008) showed that day and night temperatures of 23 and 18°C, respectively, affected the stem growth of sesame and that flowering of the crop also did not occur under these unfavorable conditions. Similarly, the temperature had a negative effect on the yield of millet, sunflower, and cotton. It is anticipated that this could be due to the effects of increased temperature on vegetative growth, flowering, and grain or boll-filling stages.

Although the multiple linear regression results showed few significant relationships among climate variables and crop yield, the regression coefficients can be used to determine the effects of the studied climatic variables on the yield changes of the five crops (Poudel & Shaw, 2016). For example, an increase in Tmin by 1°C led to a reduction in the yield of sesame and sorghum by 23.3 and 260.2 kg ha^{-1}, respectively. In addition, the sign of the regression coefficients in the regression model can indicate the direction of change in the yield versus climate variable changes (Nicholls, 1997). The multiple linear regression model captured between 6% and 70% variability in crop yield as a function of climatic factors. This indicates that the variation in the yield is well explained by climatic variables, except for cotton and sesame, where the model captured only 6% and 41% of their yield variations. The rest of the variations in yield that the model could not capture as a function of the climatic variables could be explained by the variance that is due to other factors, such as fertilizer and pesticide application and weed control, among other confounding factors. Also, it has been demonstrated that plant density on the farm is one of the most important factors that influence sesame yield (Öztürk & Şaman, 2012). A study by Ali et al. (2020) in Gedaref showed that planting sesame at 5 cm between rows could increase its yield by 210.18 kg ha^{-1}. For sorghum, the results showed that the climatic variables were responsible for 70% of the variation in its yield. This finding is in agreement with several studies, which revealed that climatic variables are the most important factors affecting sorghum yield, particularly rainfall (Msongaleli *et al.*, 2017; Mundia *et al.*, 2019). Indeed, the model showed that an increase in rainfall amount by 1 mm led to an increase in sorghum yield by 0.11 kg ha^{-1}. Also, the results depicted 54% in millet yield change, which is explained by the studied climatic variables. For the sunflower, the results proved that 61% of its yield change variation could be due to climatic variables. This result corroborates the findings of Mijić et al. (2012), who indicated that rainfall before and during the vegetation period has a great effect on sunflower yield.

Overall, the present study has utilized secondary data and no ground survey was conducted for primary data collection. As assessed by the descriptive statistical and normal disruption analyses, the quality of the secondary data met the hypothesis that secondary data should not be highly skewed, with a few outliers, and somewhat fit a normal distribution (Figures 3.4 and 3.5). However, some data, such as Tmin and yield of sesame, were either slightly skewed or deviated from a normal distribution. It is worth noting that the long-term (≥35 years) secondary data were consistently collected with no missing values. This study promotes the movement of open data science, data sharing, and re-use for addressing further research questions. However, the study focused only on climatic factors rather than incorporating other factors that influence yields, such as soil properties and farming practices. Such factors could be included in other modelling approaches such as DSSAT and production function. Hence, the crop yield estimate models should be interpreted with some caution, as their certainties (Cross-validated R^2) were not high. In this context, it is recommended that the crop yield estimate models should further be assessed using an independent test dataset collected at different points in time (e.g., 2019–2021).

4.4. Conclusions

In conclusion, this study shows that the annual Tmin and Tmax had increased by 0.04°C and 0.03 °C per year in the period between 1980 and 2018, while DTR decreased by 0.02°C per year in Gedaref state. Furthermore, the state had cold and warm years between 1984 and 2000 and 2001 and 2018, respectively, and the length of the rainy season in Gedaref state ranged between 57 and

117 days. The trend of annual yield for sorghum had significantly decreased, while sunflower yield had increased in the period between 1970 and 2018. Temperature variables had a negative relationship with the yield of all crops, while an increase in the amount of rainfall significantly increased the yield of sorghum, sesame, and sunflower. Moreover, the increase in the length of the rainy season significantly increased the yield of sesame, sorghum, sunflower, and cotton. There was high variability in crop yields, for example, over 50% variability in the yield of sorghum (R^2 = 0.70 and cross-validated R^2 = 0.69), millet (R^2 = 0.54 and cross-validated R^2 = 0.54) and sunflower (R^2 = 0.64 and cross-validated R^2 = 0.62), which could be related to climatic variables. These findings could be used to support awareness creation amongst different stakeholders and policymakers on the impacts of climate variability and change on crop production and the need for resource allocation to support the uptake of adaptation practices that ensure resilience amongst agricultural communities within the state.

4.5. Summary

It is projected that, on average, annual temperature will increase between 2°C to 6°C under high emission scenarios by the end of the 21st century, with serious consequences in food and nutrition security, especially within semi-arid regions of sub-Saharan Africa. This study aimed to investigate the impact of historical long-term climate (temperature and rainfall) variables on the yield of five major crops *viz*., sorghum, sesame, cotton, sunflower, and millet in Gedaref state, Sudan over the last 35 years. Mann–Kendall trend analysis was used to determine the existing positive or negative trends in temperature and rainfall, while simple linear regression was used to assess trends in crop yield over time. The first difference approach was used to remove the effect of non-climatic factors on crop yields. On the other hand, the standardized anomaly index was calculated to assess the variability in both rainfall and temperature over the study period (i.e., 35 years). Correlation and multiple linear regression (MLR) analyses were employed to determine the relationships between climatic variables and crops yield. Similarly, a simple linear regression was used to determine the relationship between the length of the rainy season and crop yield. The results showed that the annual maximum temperature (Tmax) increased by 0.03°C per year between the years 1984 and 2018, while the minimum temperature (Tmin) increased by 0.05°C per year, leading to a narrow range in diurnal temperature (DTR). In contrast, annual rainfall fluctuated with no evidence of a significant ($p > 0.05$) increasing or decreasing trend. The yields for all selected crops were negatively correlated with Tmin, Tmax (r ranged between -0.09 and -0.76), and DTR (r ranged between −0.10 and −0.70). However, the annual rainfall had a strong positive correlation with yield of sorghum (r = 0.64), sesame (r = 0.58), and sunflower (r = 0.75). Furthermore, the results showed that a longer rainy season had significant ($p < 0.05$) direct relationships with the yield of most crops, while Tmax, Tmin, DTR, and amount of rainfall explained more than 50% of the variability in the yield of sorghum ($R^2 = 0.70$), sunflower ($R^2 = 0.61$), and millet ($R^2 = 0.54$). These results call for increased awareness among different stakeholders and policymakers on the impact of climate change on crop yield, and the need to upscale adaptation measures to mitigate the negative impacts of climate variability and change. The next chapter will present findings on small-holder farmers' perceptions of climate variability and change, observed climate trends and adaptation measures of climate change in Gedaref state, Sudan.

CHAPTER FIVE

SMALL-HOLDER FARMERS' PERCEPTIONS OF CLIMATE VARIABILITY AND CHANGE, OBSERVED CLIMATE TRENDS AND ADAPTATION MEASURES IN GEDAREF STATE, SUDAN

5.1. Introduction

This chapter presents results on assessment of farmers' perceptions of climate variability and change in Gedaref state, Sudan, and the adaptation measures they use at the local scale to cope with the negative impact of climate change on their agricultural activities. The perception of the small-holder farmers was compared with the meteorological data (rainfall and temperature) to determine how farmers' perceptions mirror climatic trends. The chapter also presents results on the socio-economic factors that influence the choice of climate adaptation measures by the small-holder farmers in Gedaref state, Sudan.

5.2. Results

5.2.1. Demographic and socio-economic characteristics of small-holder farmers

The summary of the demographic and socio-economic characteristics of the sampled respondents is presented in Table 5.1. Out of the 400 sampled small-holder farmers, 58.2% were males, while 41.7% were females. The average age of the respondents was 43.4 years old, with an average of 38.9 years for the respondents live in the village. The average family size of the households comprised six members, with most households headed by men (79.7%) and an average land size of 5.2 hectares. The marital status of the respondents indicated that 73.0% were married, 20.3%

were single, while 6.0% were widowed, separated, or divorced. Among the total sampled respondents, 27% had never attended school, 34.7% had primary school level, 20.5% had attained secondary school education and 17.5% went to college or university education. Farming was the primary source of income and livelihood for 61% of the respondents, followed by 18.5% of whom are in salaried employment, 18.3 % were self-employed, and 2.3% were selling forest products. In addition, the average farming experience for the respondents was 19.2 years.

Table 5.1: Socio-economic characteristics of surveyed households in the study area (N = 400)

Household characteristics	Statistics
Mean age of the respondent (year)	43.35
Mean of the years of the respondent live in the villages	38.98
Mean family size of the respondents	06.00
Mean land size of the respondent (hectare)	05.21
Gender (%)	
Male	58.25
Female	41.75
Gender of the head of the household (%)	
Male	79.75
Female	20.25
Marital status (%)	
Married	73.00
Single	20.25
Divorced	02.75
Separated	01.00
Widowed	03.00
Education (%)	
Illiterate	27.00
Primary	34.75

Table 5.1 (cont.):

Education (%)	
Secondary	20.75
Graduate	17.50
Main sources of income (%)	
Farming	61.00
Salaried employment	18.50
Self-employed	18.25
Selling of forest produce	02.25
Experience in agriculture (years) (%)	
< 11	40.75
11 – 20.99	24.25
21 - 40.99	26.50
41 and above	08.50

5.2.2. Small-holder farmers' perception of climate variability and change

More than 90% of the respondents had perceived climate variability and change, while 5.75% disagreed that climate change had not occurred in Gedaref state (Figure 5.1). Among those who perceived that climate change had occurred, 31.4% of them indicated fluctuations/erratic patterns in rainfall trend, while 16.9%, 12% and 11%, respectively, indicated a decrease in rainfall amount, an increase in rainfall amount and late onset of the rainy season (Figure 5.2). The least perception by the farmers was for frequent drought, increase in the length of the dry period and frequency of flooding (Figure 5.2).

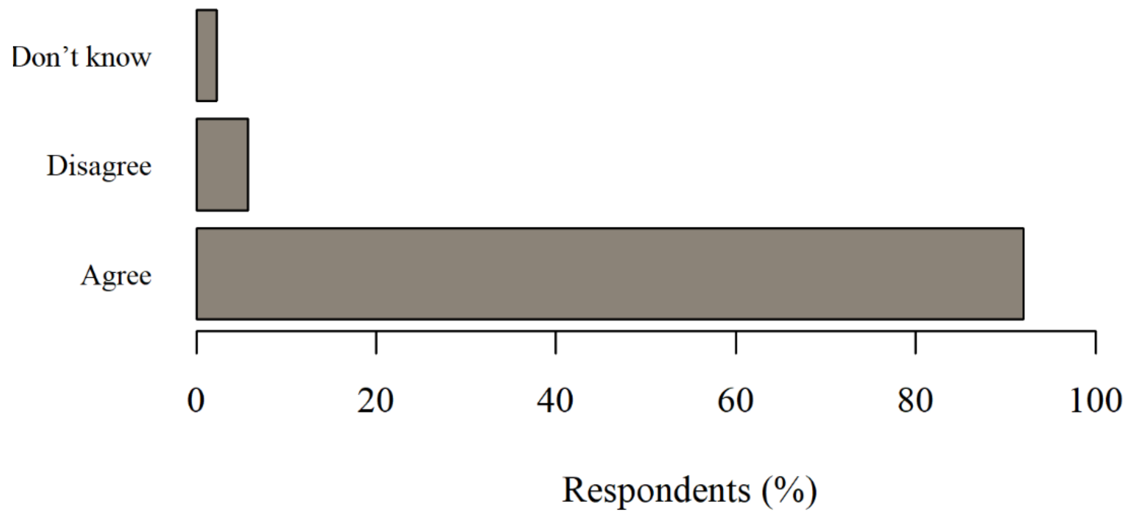

Figure 5.1: Farmers' perception of climate change

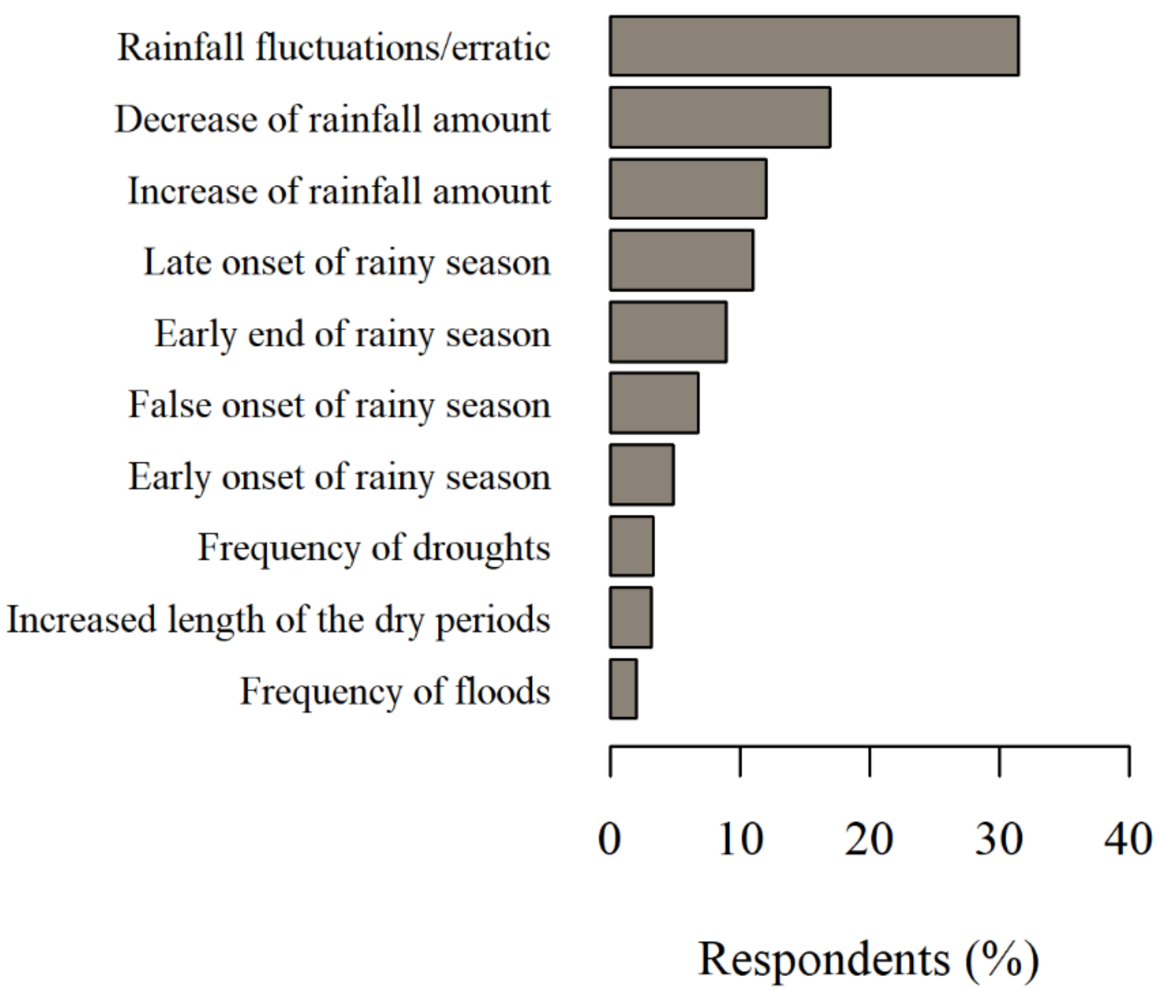

Figure 5.2: Indicators that support farmers' perceptions of fluctuations in rainfall.

Figure 5.3 presents farmers' perceptions of temperatures during the summer and winter seasons. About 61% of the respondents indicated an increase in daytime temperature, while 17.7% testified to a decrease in nighttime temperature during the summer (Figure 5.3). Parallel to this, 42% and 28.4% of the respondents perceived an increase in daytime temperature and a decrease in nighttime temperature, respectively during winter (Figure 5.3). The FGDs and key informant interview results revealed that the local communities in Gedaref state were aware of climate change and variability, which were indicated by unpredictable rainfall patterns and amounts, shifting of the onset of the rainy season, reoccurring of dry spells, decrease in rainfall amount, and rise in temperatures.

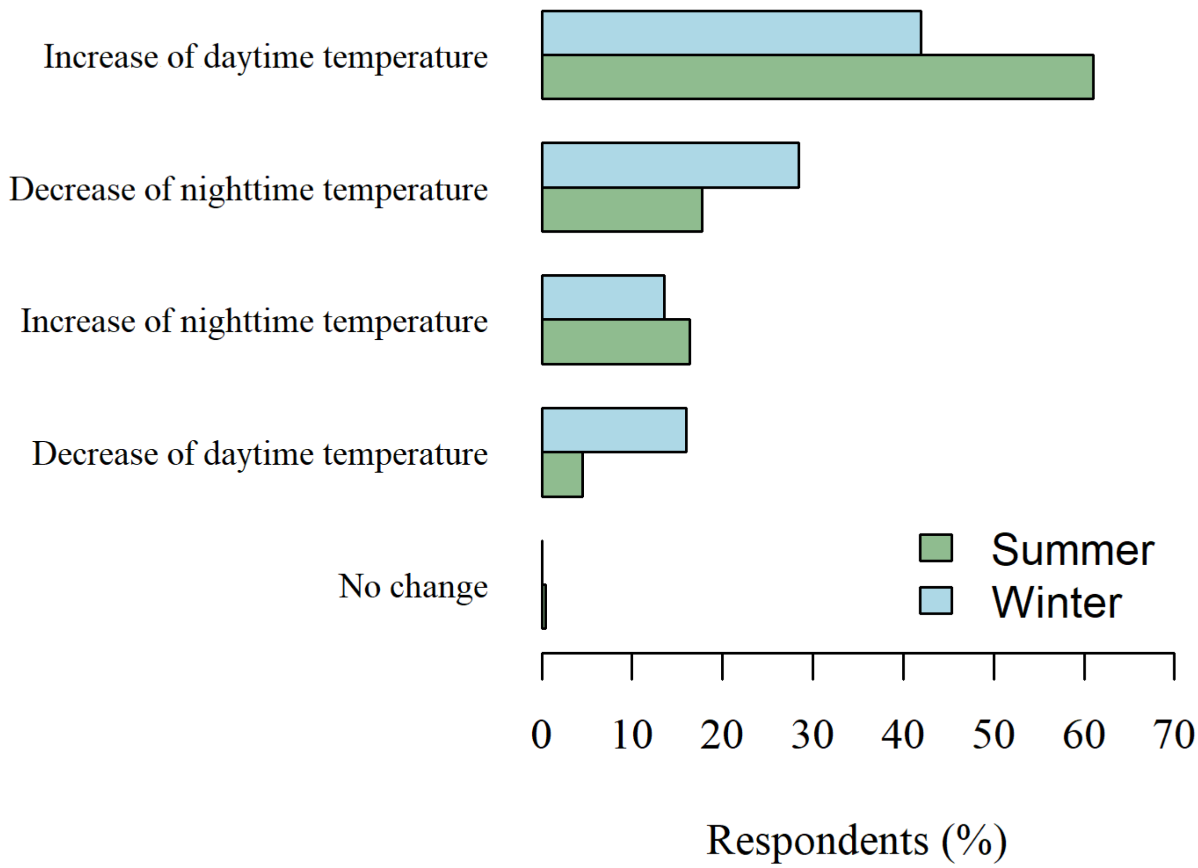

Figure 5.3: Indicators that support farmers' perceptions of increasing temperatures in summer and winter seasons

5.2.3. Access and source of climate information

Figure 5.4 represents the percentage of respondents who had access to climate information and sources of information within the community. The results showed that 62% of the respondents had access to climate information, while 38% had no access to climate information (Figure 5.4A). Among those who had access to climate information, the majority of them (66.2%) relied on the radio to access the information (Figure 5.4B). While 14.5% of respondents obtained their climate information from different channels like Televion sets, newspapers, indigenous knowledge and opinion leaders. This was followed by 11.9% who obtained their climate information through mobile phones (Figure 5.4B). During the FGDs, farmers stated that they did not receive advice on climatic conditions and agricultural practices through government extension services to help them to adapt to climate change.

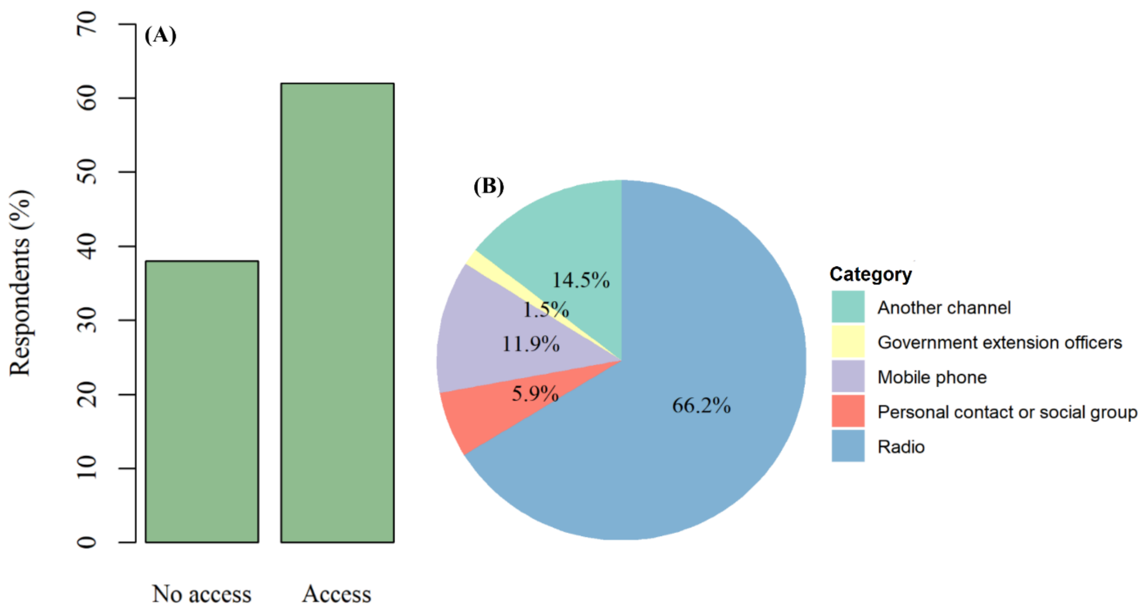

Figure 5.4: A) small-holder farmers' access to climate information and **B)** source that farmers used to access climate information

5.2.4. Trends in climatic variables (rainfall and temperature) of the metrological station

Mann–Kendall and Sen's slope trends for the annual rainfall and mean temperature data for Gedaref state between 1984 and 2018 are presented in Table 5.2 and Figure 5.5. The metrological data showed that annual rainfall trends increased by 0.96 mm per year. However, this increment was not significant (p = 0.41), indicating fluctuation in the amount of rainfall over the years (confidence interval 34.200 – 41.080). In contrast, the annual mean temperature significantly increased by 0.04°C per year, with a confidence interval ranging between 0.02 and 0.05°C (p = 0.05).

Table 5.2: Estimated Sen's slope values for annual rainfall (mm) and mean annual temperature (°C) trends in Gedaref State, Sudan, between 1984 and 2018.

Climatic variable	Range		Sen's slope	95% Confidence Interval	*p*-Value
	Minimum	Maximum			
Rainfall	425.400	753.8000	0.9627	-34.200 – 41.080	0.41
Mean temperature	28.458	30.609	0.038	0.022– 0.052	0.05

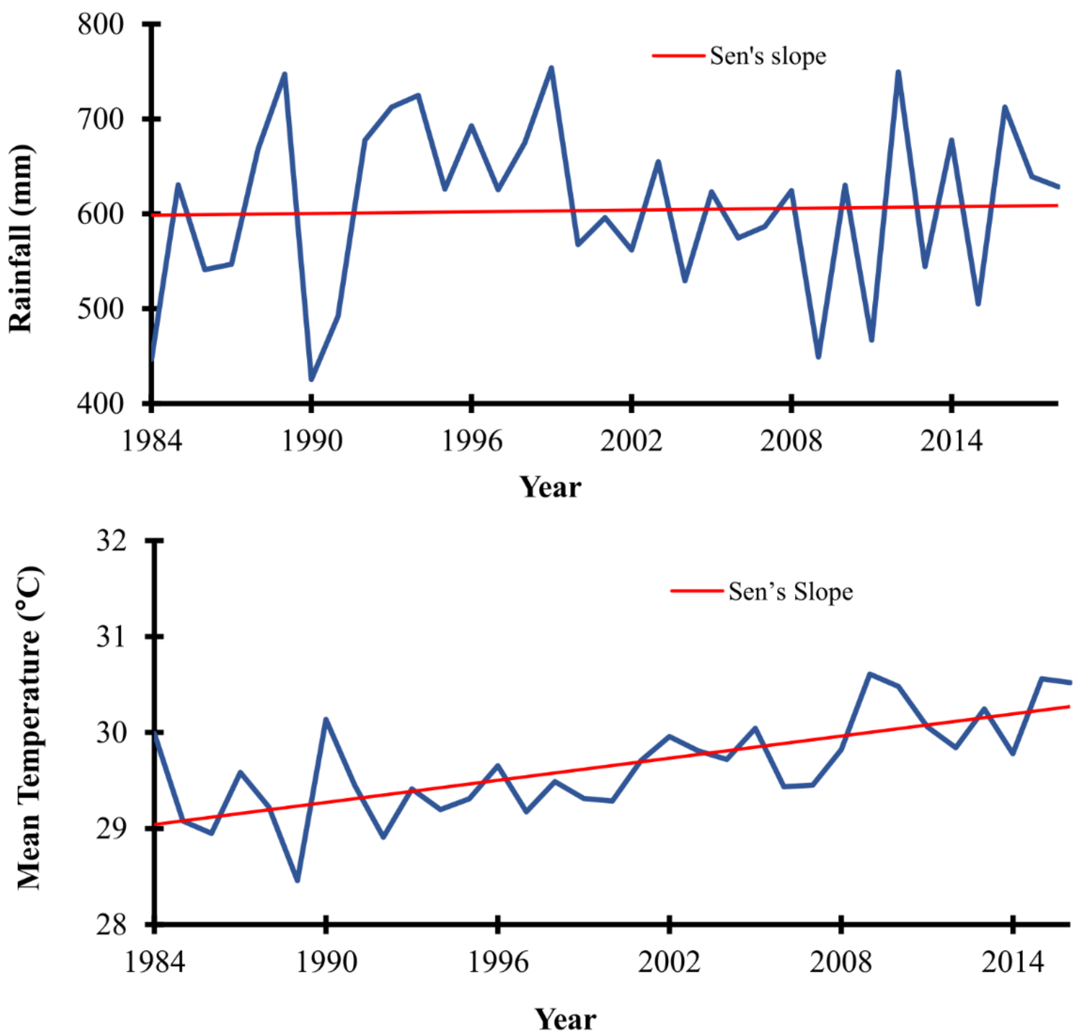

Figure 5.5: Annual rainfall and mean temperature trends in Gedaref state, Sudan, between 1984 and 2018.

5.2.5. Small-holder farmers' adaptation measures

Farmers in Gedaref state used different adaptation measures to adapt to climate variability and change (Table 5.3). The most used adaptation measure was crop rotation (18.6%), followed by early cultivation (17.2%), mixing farming (14.5%) and cultivation of short-maturing crop varieties (14.2%). The use of underground water, rainwater harvesting, and practice of supplementary irrigation were the least adaptation measures used by the small-holder farmers in Gedaref state (Table 5.3).

Table 5.3: Adaptation measures used by the respondents to adapt to climate change (N= 400)

Adaptation measures	**Responses**		**% of Cases**
	N	**%**	
Early cultivation	305	17.2	76.4
Delayed cultivation	115	6.5	28.8
Cultivation of short-maturing varieties	253	14.2	63.4
Intercropping	19	1.1	4.8
Crop rotation	330	18.6	82.7
Soil conservation	103	5.8	25.8
Practice supplementary irrigation	4	0.2	1.0
Use of technologies as fertilizers and pesticides	130	7.3	32.6
Introduce drought-tolerant varieties	106	6.0	26.6
Use of improved varieties	58	3.3	14.5
Rainwater harvesting	9	0.5	2.3
Cover the soil around the plant with straw, stone, plastic and/or crop residues to facilitate water infiltration and decreased water evaporation	78	4.4	19.5
Mixing farming	258	14.5	64.7
Use of underground water	10	0.6	2.5

Total	**1778**	**100**	**445.6**

5.2.6. Factors influencing small-holder farmers' choice of adaptation measures

Factors influencing farmers' choice of adaptation measures to adapt to climate variability and change are presented in Table 5.4. The result depicted that the sex of the respondent significantly influenced the choice of early cultivation ($p < 0.05$), cultivation of short maturation variety, soil conservation, use of technology such as fertilizer and pesticide, introducing drought tolerant variety and mixing farming (Table 5.4). Farming experience positively affected soil conservation, introducing drought tolerant varieties and the use of improved varieties. The number of years that the respondent lived in the village significantly influenced the probability of adopting early cultivation and introduction of drought tolerant as adaptation measures ($p < 0.05$).

Table 5.4: Multinomial logistic regression estimates for the factors that influence the choice of adaptation measures by small-holder farmers in Gedaref state

Adaptation Option	Independent Variable	Estimate	Std. Error	Wald	*p*-Value	95% Confidence Interval	
						Lower Bound	Upper Bound
Early cultivation	Sex	0.740	0.327	5.111	**0.024**	1.103	3.982
	Number of years living in the village	-0.025	0.011	5.437	**0.020**	0.955	0.996
Delay cultivation	Education	0.347	0.125	7.681	**0.006**	1.107	1.809
Cultivation of short maturation variety	Sex	-0.862	0.354	5.931	**0.015**	0.211	0.845
	Head of the household	2.287	0.394	33.650	**0.000**	4.545	21.313
Intercropping	Age	-0.048	0.023	4.357	**0.037**	0.911	0.997
Soil conservation	Sex	2.379	0.371	41.181	**0.000**	5.221	22.336
	Farming experience	0.053	0.013	15.471	**0.000**	1.027	1.082
	Main sources of income	0.461	0.162	8.144	**0.004**	1.155	2.177
	Family size	-0.088	0.043	4.146	**0.042**	0.841	0.997
Use of technology such as fertilizer and pesticides	Sex	-1.007	0.316	10.166	**0.001**	0.197	0.678
	Head of the household	1.315	0.369	12.696	**0.000**	1.807	7.672
	Education	-0.275	0.116	5.590	**0.018**	0.605	0.954
	Main sources of income	0.340	0.140	5.867	**0.015**	0.541	0.937
	Access to climate information	0.730	0.233	9.843	**0.002**	1.315	3.276

Table 5.4 (cont.):

Adaptation Option	Independent variable	Estimate	Std. Error	Wald	*p*-Value	95% Confidence Interval	
						Lower bound	Upper bound
Introduce drought tolerant variety	Sex	1.581	0.340	21.634	**0.000**	2.496	9.460
	Number of years living in the village	-0.030	0.016	3.646	**0.056**	0.941	1.001
	Age	0.034	0.018	3.604	**0.058**	0.999	1.073
	Farming experience	0.027	0.012	4.998	**0.025**	1.003	1.053
	Main sources of income	0.401	0.156	6.634	**0.010**	1.101	2.028
Use of improved varieties	Farming experience	0.042	0.016	6.686	**0.010**	1.010	1.076
Rainwater harvesting	Age	0.204	0.106	3.717	**0.054**	0.997	1.508
Cover soil around the plant	Family size	0.119	0.048	6.096	**0.014**	1.025	1.237
Mixing farming	Sex	-0.987	0.311	10.059	**0.002**	0.203	0.686
	Land tenure	0.664	0.188	12.512	**0.000**	1.345	2.807
	Family size	-0.084	0.039	4.562	**0033**	0.851	0.993

5.3. Discussion

This study assessed small-holder farmers' perceptions of climate variability and change in Gedaref state and the factors that influence their choice of a specific adaptation measure. The results indicate that the local communities in Gedaref state perceived changes in climate variables (rainfall and temperature) over time. About 31.4% of the farmers were aware of rainfall fluctuation, while 11% perceived late onset of the rainy season over the last decades. These perceptions in rainfall align with the actual annual rainfall trend between 1984 and 2018, which showed a fluctuation in the amount of rainfall ranging from 425.4 to 753.8 in Gedaref region. These results agree with the findings of Glover and Elsiddig (2012) who reported that annual rainfall in Gedaref state was erratic and scarce in the past decades, ranging between 400 and 800 mm. However, 16.9% and 12%, respectively, indicated a decrease and increase in rainfall, which could be attributed to the variation in the rainfall amount from one location to another. Apart from the rainfall, farmers also correctly perceived increased temperature during the summer and winter seasons, confirming the results from the annual mean temperature trends of the metrological records in Gedaref between 1984 and 2018. These results were also supported by Issa (2018) who reported a significant increase in temperature in the study area between 1972 and 2017. This was further confirmed by key informant interviews and FGDs who highlighted similar rainfall and temperature trends in the study area. The FGDs also pointed out that these changes negatively affected agricultural activities in Gedaref state.

The majority of respondents who were aware of climate change (92%) had adopted some adaptation practices to minimize the impacts of climate change on their agricultural activities. These farmers used one or more adaptation measures to cope with the negative impact of climate change in Gedaref state. The majority (18.6%) of the farmers practiced crop rotation as an adaptation measure. Crop rotation improves soil nutrients, increasing the biomass that enhances soil health water holding capacity as well as interrupts the life cycles of the pests. Marini et al. (2020) reported that crop rotation is one of the adaptation measures that increase cereal yields under a changing climate. In Gedaref state, sorghum is the most dominant cultivated crop and the main staple food crop for the entire country. This may be one factor that leads small-holder farmers to mostly practice crop rotation, compared to other adaptation measures to increase yield (Marini *et al.*, 2020). The use of crop rotation might also be attributed to the fact that small-holder farmers had limited access to agricultural technologies and inputs that were unaffordable to most of them. Apart from crop rotation, 17.2% of the farmers applied early cultivation as a measure to adapt to climate change. These findings are in line with the earlier result of Mohmmed et al. (2018), who reported that the farmers in Gedaref state had changed their planting dates as an adaptation option to deal with climate change and variability. In addition, 14.5% of respondents practiced mixed farming, which includes crop farming and livestock raising, as an adaptive strategy. The farmers during the FGDs explained that keeping livestock was a buffer against crop losses during drought or flooding events. For example, they sell milk or chicken that could support the household in overcoming a poor crop harvest as well as contributes to household food security. Moreover, 14.2% of the farmers indicated that adoption of the cultivation of short-maturing varieties as a climate adaptation measure. This could be explained by rainfall being limited to a short period in Gedaref state (Osman *et al.*, 2021).

Although farmers listed various adaptation measures to climate change, the choice of a specific adaptation option by a farmer was dependent on several factors. In this study, the choice of the cultivation of short maturation variety and the use of technology such as fertilizer and pesticide were significantly influenced by the sex of the head of the household. This mainly could be attributed to the fact that most farmers (79.8%) were male-headed. These findings agreed with the study by Abdalla et al. (2013) who stated that male-headed households were the predominant group in Sudan. The FGDs have highlighted that most key decision-makers in Gedaref were men on when what and where to plant and use during the cultivation season. Also, the results of the present study indicated that the age of respondents was strongly related and affected the choice of intercropping, introducing drought tolerant variety and rainwater harvesting. This suggests that older farmers were more likely to adopt these adaptation measures, which could be explained by long farming experiences that allow them to perceive environmental changes. Deressa et al. (2008) reported that the age of the farmers could be used to detect the farming experience in the Nile Basin of Ethiopia. The authors also indicated that the age of the farmers had a positive relationship with taking up adaptation measures. In this study, the number of years farmers lived in their villages significantly influenced the choice of early cultivation and the use of drought tolerant variety. Farmers with a higher number of years living in the villages had adequate knowledge about the area and the nature of rainfall. This could help them select an appropriate adaptation measure depending on the onset of the rainy season.

In this study, 62% of the respondents had access to climate information and more than half of them (66.2) received climate information through the radio. This is due to the fact that radio was the most accessible and popular medium of communication in rural areas because even illiterate farmers can access and understand climate information in their local language. This result confirmed the finding of Ndavula and Lungahi (2018) who concluded that radio played a crucial role in many African countries as an effective information dissemination means. The authors further stated that rural populations favor radio and consider it to be the most significant and accessible media.

Furthermore, farmers with more extended farming experience were more likely to adopt soil conservation, use of drought tolerant varieties and improved varieties. Many previous studies had reported similar funding. For instance, Adimassu and Kessler (2016) concluded a significant positive relationship between years of experience in agriculture and farmers' adoption of improved agricultural technologies such as drought tolerant and improved varieties. While Alhassan et al. (2019) and Mwungu et al. (2020) reported that farmers with more farming experience were more likely to use adaptation methods to increase their resilience under environmental changes. The mono-cropping of sorghum in Gedaref state coupled with fluctuation in the amount of rainfall might be the major factors that contributed to the adoption of soil conservation, the use of drought tolerant varieties and improved varieties by small-holder farmers. The main source of income was significantly and positively related to soil conservation, use of technology such as fertilizer and pesticide and introducing drought tolerant variety. About 60% of the respondents occupied farming as a primary source of their income, and this could be the reason of the use of these adaptation measures to increase their crop yield and consequently, income. The results of the present study also showed that education level significantly influence the adoption of delayed cultivation and the use of technology such as fertilizer and pesticides. These results were consistent with a study in Kenya where the farmers' education had a significant relationship with adopting practices to adapt to climate change (Nyang'au *et al.*, 2021). This is due to the fact that more educated farmers had more access to information about agricultural inputs such as fertilizers and pesticides as well as climate information that could help them to adapt accordingly.

In this study, family size significantly influenced farmers' choice of soil conservation and covering the soil around the plant with straw, stone, plastic and crop residues to facilitate water infiltration and decrease water evaporation. This could be linked to the fact that soil conservation needs sufficient family labor (Tesfaye *et al.,* 2014). Therefore, households with enough family labor to execute soil conservation measures were more likely to participate in the implementation of soil conservation as an adaptation measure. The result of this study depicted that land tenure had a significant positive relationship with adopting mixed farming to adapt to climate change and variability. This is mostly because land tenure was critical to adaptation due to the fact that landowners embraced new technology faster than renters (Fosu-Mensah *et al.,* 2012). Furthermore, the results reveal that access to climate information significantly influenced the use of technology such as fertilizer and pesticides as adaptation practices. Zamasiya et al. (2017) reported similar results that access to climate information increased small-holder farmers' adoption of climate change adaptation measures. During the key informant interviews and FGDs, the local community highlighted that applying manure to their farms as a climate change adaptation measure to conserve soil fertility and moisture because of the high cost of fertilizers, which they could not afford.

5.4 Conclusions

The findings of this study revealed that farmers in Gedaref state, Sudan are aware of climate variability and change, and they used different adaptation measures to cope with its negative impacts on their farming activities. The most used adaptation measures by the farmers were crop rotation, early cultivation, mixed farming and cultivation of short-maturing varieties. Age, sex of the respondent, education level, sex of the head of the household, number of years living in the village, farming experience, main sources of income, family size, access to climate information and land tenure were the main factors that significantly influenced the choice of adaptation measures. Therefore, government policies that promote climate adaptation strategies in Gedaref state should consider these factors to increase the likelihood of smallholder farmers’ adoption of climate adaptation measures to cope with the negative impact of climate change on crop yield. In addition, the findings of this study will be useful in implementing and monitoring adaptation measures through the integration of farmers' perceptions with the scientific findings to improve crop yield in Gedaref state and other rainfed agricultural areas in Sudan.

5.5 Summary

Climate projections indicate that sub-Saharan Africa will experience significant climatic changes, including extreme drying and warming, particularly in arid and semi-arid regions. Although many studies have reported the impact of climate change and variability on agricultural systems, few studies have examined perceptions of local communities on climate change and variability, and their roles in strategic decision making and developing appropriate adaptation measures for mitigation of local impacts on producers. Therefore, this study aimed to assess farmers' perceptions of climate change and their adaptation measures at the local level in Gedaref state; compare smallholder farmers' perceptions with the meteorological records to determine how farmers' perceptions mirror climatic trends. Four-hundred respondents were interviewed using semi-structured questionnaire to gather data on the local community's perception of climate variability and change, its impacts on agricultural activities, and adaptation measures employed to mitigate such impacts. This was followed by key informant interview and 16 focus group discussion. More than 90% of the respondents perceived that Gedaref state had experienced climate variability and change. About 61% of the respondents indicated an increase in daytime temperature, which was confirmed with meteorological records, which showed that annual mean temperature in Gedaref state had increased by 0.04°C per year. The adaptation measures practised by most farmers in Gedaref state were crop rotation, early cultivation, mixed farming and cultivation of short-maturing varieties. The main factors that significantly influenced choice of adaptation measures included age, sex of respondent, education level, sex of head of household, number of years live in villages, farming experience, main sources of income, family size, access to climate information and land tenure. Findings from this study are useful for policy formulation on mitigation of climate change impacts and enhancing farmers' resilience to climate change, consequently increasing crop productivity and sustained livelihoods.

CHAPTER SIX

MAPPING, INTENSITIES AND FUTURE PREDICTION OF LAND USE/ LAND COVER DYNAMICS USING GOOGLE EARTH ENGINE AND CA-ARTIFICIAL NEURAL NETWORK MODEL

6.1 Introduction

This chapter presents results on evaluation of LULC changes in the Gedaref state, Sudan for the period between 1988–2018 using Landsat imageries and the random forest classifier. It also determines the underlying dynamics that caused the changes in the landscape structure using intensity analysis. Moreover, this chapter predicts the future LULC outlook for the years 2028 and 2048 in Gedaref state using cellular automata-artificial neural network (CA-ANN) algorithm.

6.2 Results

6.2.1 Land use/ land cover (LULC) classification

The classified LULC maps and associated area statistics under each class category for 1988, 1998, 2008 and 2018 are presented in Figure 6.1 and Table 6.1. Among the LULC categories, cropland was the most dominant in 1988, followed by grassland; each occupying 78.64%, and 19.64% of the total area, respectively (Table 6.1). Whereas forest, water and settlement covered less than 2% of the studied landscape (Table 6.1). A similar trend was observed for the other studied years. Nevertheless, there was a distinct LULC change in Gedaref during the study period, where an expansion in cropland and settlement area and a decline in forest and grassland areas were observed (Figure 6.1 and Table 6.1). Water area increased in all study years except in 2008.

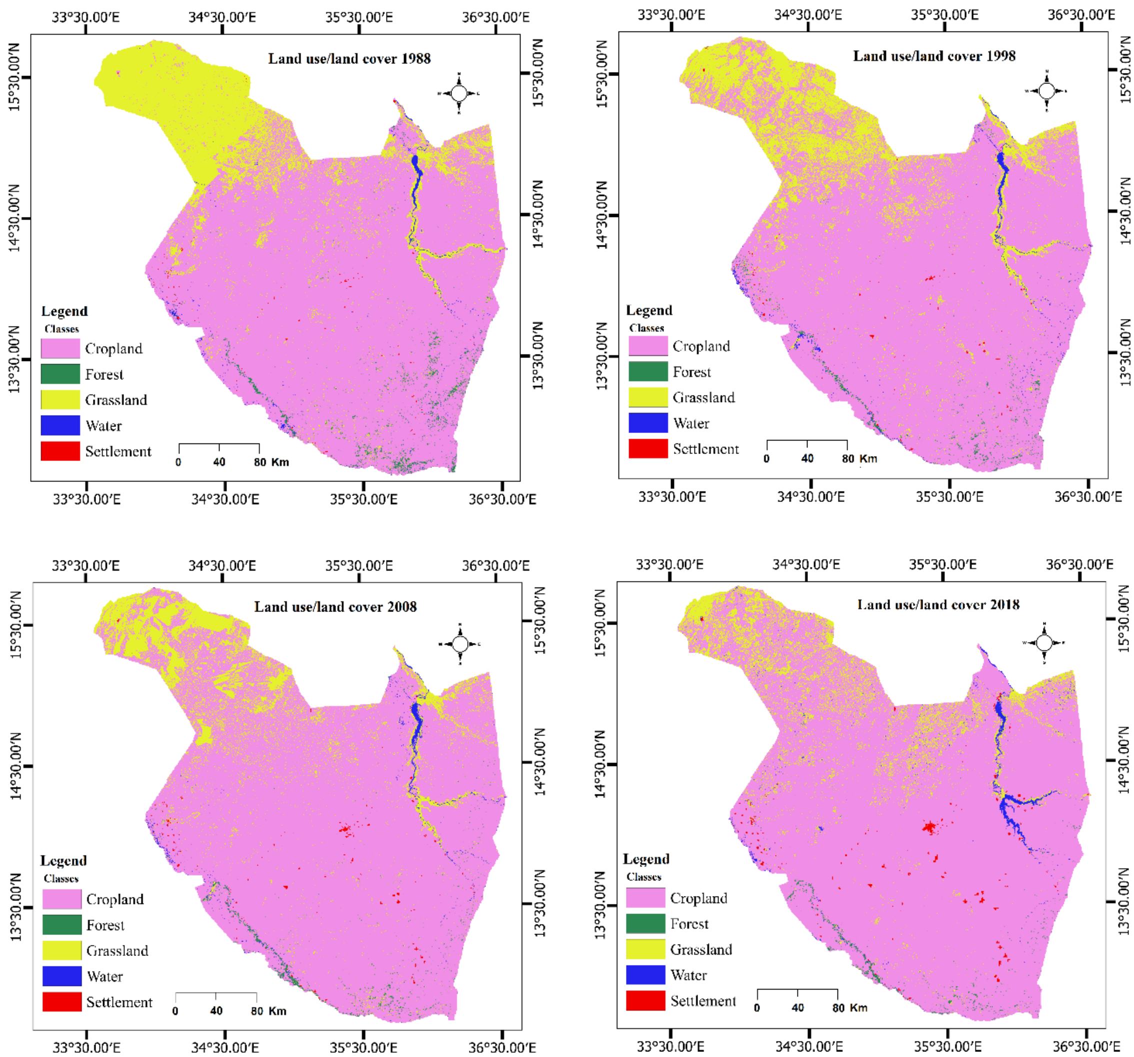

Figure 6.1: Classified Land use/ land cover (LULC) maps of Gedaref state for the years 1988, 1998, 2008 and 2018 produced using multi-date Landsat images and random forest classification algorithm

Table 6.1: Area (ha) and percent cover (%) of each land use/ cover (LULC) class in Gedaref state for the years 1988, 1998, 2008, and 2018 estimated using multi-date Landsat images and random forest classification algorithm

Year	**1988**		**1998**		**2008**		**2018**	
	Area		**Area**		**Area**		**Area**	
LULC	**ha**	**%**	**ha**	**%**	**ha**	**%**	**ha**	**%**
Cropland	5023958.04	78.64	5289566.13	82.8	5566904.46	87.14	5723662.45	89.59
Forest	0069053.13	01.08	0037217.16	00.58	0035406.99	00.55	0030056.44	00.47
Grassland	1254479.85	19.64	1012649.94	15.85	0734874.57	11.51	0548998.87	08.59
Water	0034132.05	00.53	0039363.12	00.62	0035961.84	00.56	0057366.22	00.89
Settlement	0006739.02	00.11	0009565.74	00.15	0015214.23	00.24	0028278.13	00.44
Total	**6388362.09**	**100**	**6388362.09**	**100**	**6388362.09**	**100**	**6388362.09**	**100**

6.2.2 Accuracy of land use/ land cover (LULC) classification

The accuracy evaluation metrics of the classified LULC maps generated from the confusion matrix is presented in Table 6.2. The overall accuracy of the 1988, 1998, 2008 and 2018 LULC maps was 81.75%, 83.28%, 85.15%, and 87.70%, respectively. While F1 score value for all LULC classes in all years ranged between 80% and 90% (Table 6.2). Additionally, the results of quantity disagreement for all the classified maps ranged between 3% and 4%, whereas allocation disagreement varied from 9% to 14% (Table 6.2).

Table 6.2: Overall and individual class accuracies of land use/ land cover (LULC) maps of Gedaref state for the years 1988, 1998, 2008 and 2018.

Class	**Producer's accuracy (%)**	**User's accuracy (%)**	**F1 score (%)**	**Overall accuracy (%)**	**Allocation disagreement (%)**	**Quantity disagreement (%)**
1988						
Cropland	88.88	77.41	82.75	81.75	14	4
Forest	81.13	81.39	81.39			
Grassland	85.29	80.55	82.85			

Table 6.2 (cont.):

Class	Producer's accuracy (%)	User's accuracy (%)	F1 score (%)	Overall accuracy (%)	Allocation disagreement (%)	Quantity disagreement (%)
Water	81.13	81.13	81.13	81.75	14	4
Settlement	73.13	89.09	80.32			
1998						
Cropland	83.07	83.07	83.07	83.28	14	3
Forest	83.13	87.34	85.18			
Grassland	84.48	77.77	80.99			
Water	86.66	81.25	83.87			
Settlement	78.78	86.66	82.53			
2008						
Cropland	95.23	82.19	88.23	85.15	11	4
Forest	86.07	85.00	85.53			
Grassland	76.56	87.50	81.63			
Water	88.88	87.67	88.27			
Settlement	76.92	83.33	80.00			
2018						
Cropland	89.28	80.64	84.74	87.70	9	3
Forest	89.07	88.33	88.70			
Grassland	84.78	81.25	82.97			
Water	79.20	94.11	86.02			
Settlement	92.40	88.48	90.40			

6.2.3 Land use/ land cover (LULC) change detection

Forest and grassland categories were considerably decreased by about 46% and 19%, respectively, in the first 1998 – 2008 interval (Table 6.3). On the other hand, there was an expansion in cropland area during the whole study period, which ranged between about 2.8% and 5% in the three intervals. Similarly, the settlement areas dramatically increased by 41.94% and 59.04% in the first and second intervals, respectively, with the third interval being drastically greater (85.86%) than that of the first and second intervals. Water class increased by 15.32% in the first period of the study and decreased during the second time period, with a sharp increase (85.86%) in the third interval compared to the increase in the first interval.

Table 6.3: Land use/ land cover (LULC) change estimates (area and percentage) for Gedaref state for the 1988–1998, 1998–2008, 2008–2018 and 1988–2018.

Year	**1988 - 1998**		**1998 - 2008**		**2008 - 2018**		**1988 - 2018**	
LULC	Area		Area		Area		Area	
	ha	%	ha	%	ha	%	ha	%
Cropland	265608.00	5.28	277338.30	05.24	156758	2.81	699704.35	13.92
Forest	-31835.97	-46.10	-1810.17	-04.86	-5350.55	-15.11	-38996.70	-56.47
Grassland	-241829.91	-19.27	-277775.37	-27.43	-185875.71	-25.29	-705480.98	-56.23
Water	5231.07	15.32	-3401.28	-8.64	21404.38	59.52	23234.17	86.07
Settlement	2826.72	41.94	5648.49	59.04	13063.9	85.86	21539.11	319.61

6.2.4 Land use/ land cover (LULC) transitions mapping

The results in Figure 6.2 indicate the transformation of each of the five LULC classes during 1988–2018, 1998–2018 and 2008–2018. The major LULC transition that took place over the study period (1988–2018) were forest to cropland, grassland to cropland, cropland to grassland, water to cropland, cropland to water, cropland to settlement and grassland. In particular, the dominant transition in Sothern and Western parts of Gedaref sate across the three transition periods (1988–2018, 1998–2018 and 2008–2018) was forest to cropland. Whereas the transition from grassland to cropland was mainly observed in Northern and Northeast of Gedaref state (Figure 6.2). The transition from cropland to settlement was mainly occurred in Central, Northwest, and Southern parts of Gedaref state.

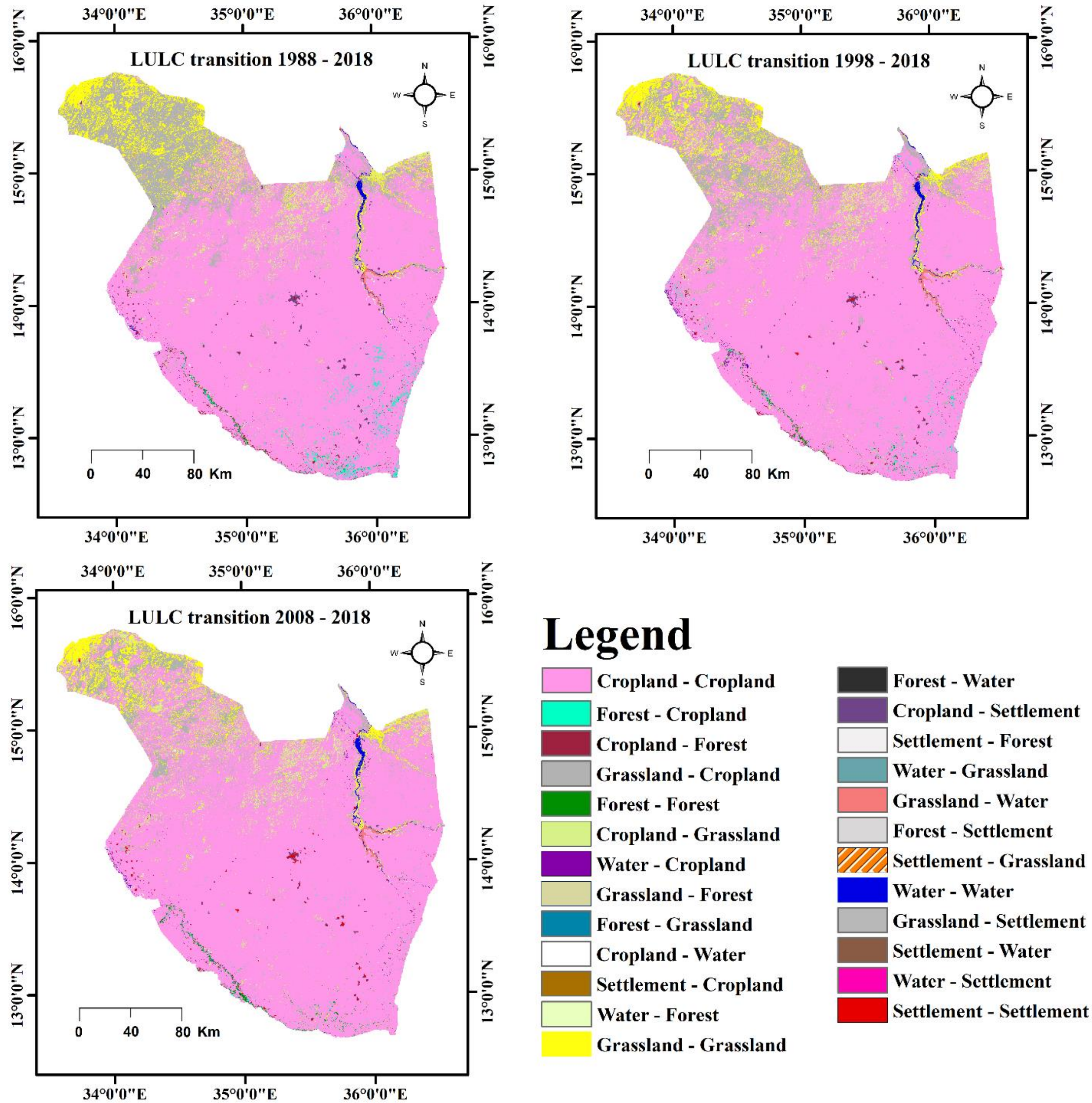

Figure 6.2: Land use/ land cover (LULC) transitions of Gedaref state during 1988–2018, 1998–2018 and 2008–2018

6.2.5 Intensity analysis in land use/ land cover (LULC) transitions

Interval level intensity results showed the changing intensity over each time period (Figure 6.3A) and the annual change between intervals (Figure 6.3B). Interval analysis revealed that the period 1988–1998 experienced fast LULC transitions and annual change rates. In the second interval, the observed and annual transitions were relatively equal to the uniform line but lower than in the third interval indicating slow LULC transitions.

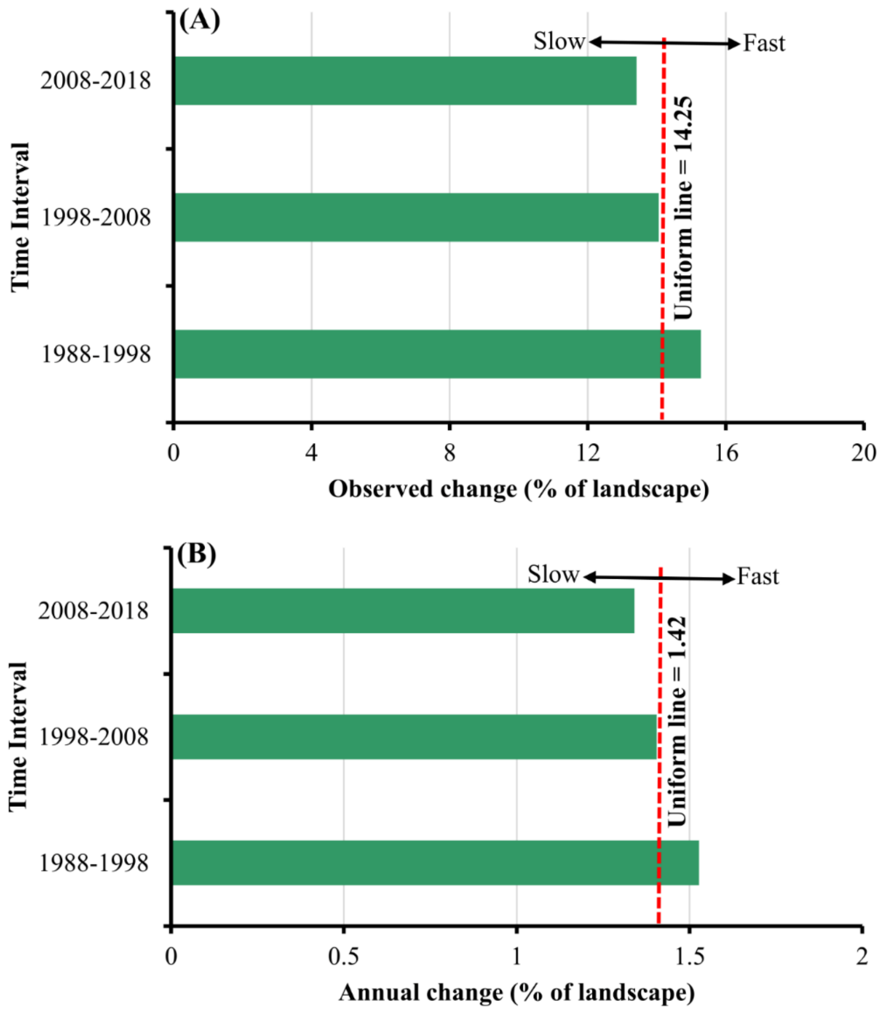

Figure 6.3: Interval level intensity of land use/ land cover (LULC) change for 1988 1998, 1998–2008 and 2008–2018. A) the percent of the area that changed over each interval and B) the percentage of the area that annually changed during each interval

Figure 6.4 illustrates that the LULC classes experienced dormant or active changes during the study period. Moreover, the figure shows that the active LULC classes were the ones that their gain or loss is crossing the uniform line. In contrast, the dormant categories are those of gain or loss that do not reach the uniform line. During the three intervals, forest, grassland, water and settlement categories were active gainers with relatively higher gains in the settlement, forest and water, respectively. However, cropland category was the dormant gainer throughout the study period. Three categories, i.e., forest, grassland and water, were active losers during the three intervals with relatively higher losses in forest and grassland respectively. Whereas settlement was an active loser during the first interval and a dormant loser during the second and third intervals. The cropland category was the dormant loser during the three intervals.

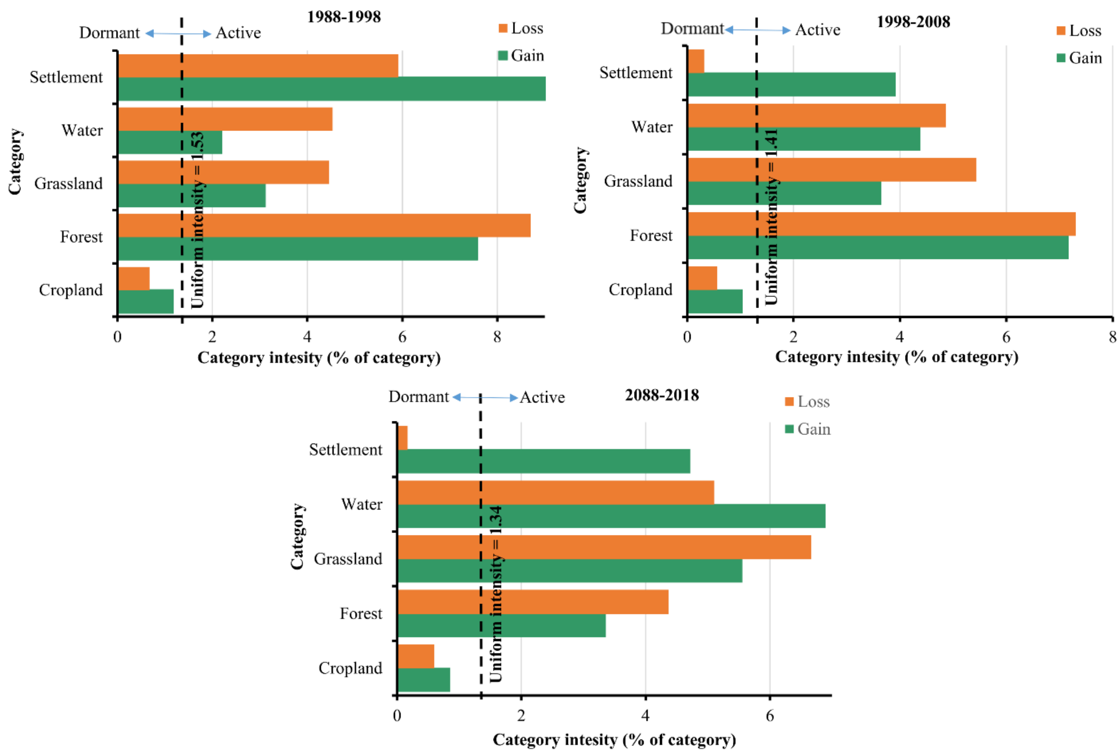

Figure 6.4: Land use/ land cover (LULC) category level intensity for 1988–1998, 1998–2008, 2008 and 2018

Figures 6.5–6.7 demonstrate the results of the transition level analysis for each of LULC category. The vertical dashed lines on both sides of the chart represent hypothetical uniform intensity lines. The left side of the uniform line explains the theoretical uniform value in the transition intensity that accounted for the losses in the specific LULC classes. While the side on the right represents the gains in transition intensity. The intensity showed that the expansions in cropland in 1998 targeted forest only and losses in cropland targeted both forest and settlement (Figure 6.5A). The gain and loss in forest areas targeted water and cropland (Figure 6.5B). Likewise, the transition to grassland in 1998 targeted settlement and avoided the other LULC categories, while the losses in grassland targeted water (Figure 6.5C). Losses in water targeted cropland and forest, whereas the gains in the water category targeted forest, grassland, and settlement (Figure 6.5D). The reductions and expansions in cropland between 1998 and 2008 followed a similar trend to that of 1988-1998, where this category targeted forest areas (Figure 6.6A). On the other hand, the expansions in settlements in the same period targeted cropland, but reductions in settlement area targeted grassland and water equally (Figure 6.6E). Gains in water targeted forest and slight grassland, and losses targeted forest (Figure 6.6D).

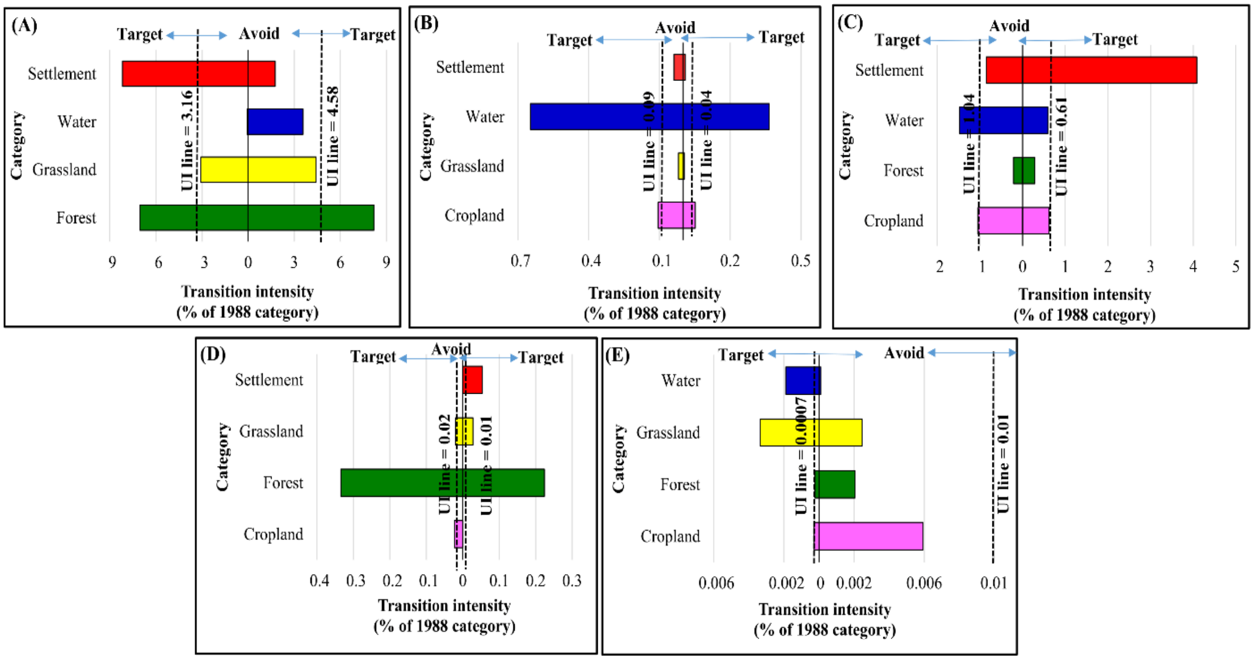

Figure 6.5: Transition level intensity of land use/ land cover (LULC) for the period 1988–1998. (A) cropland, (B) forest, (C) grassland, (D) water and (E) settlement (gains on the right and losses on the left)

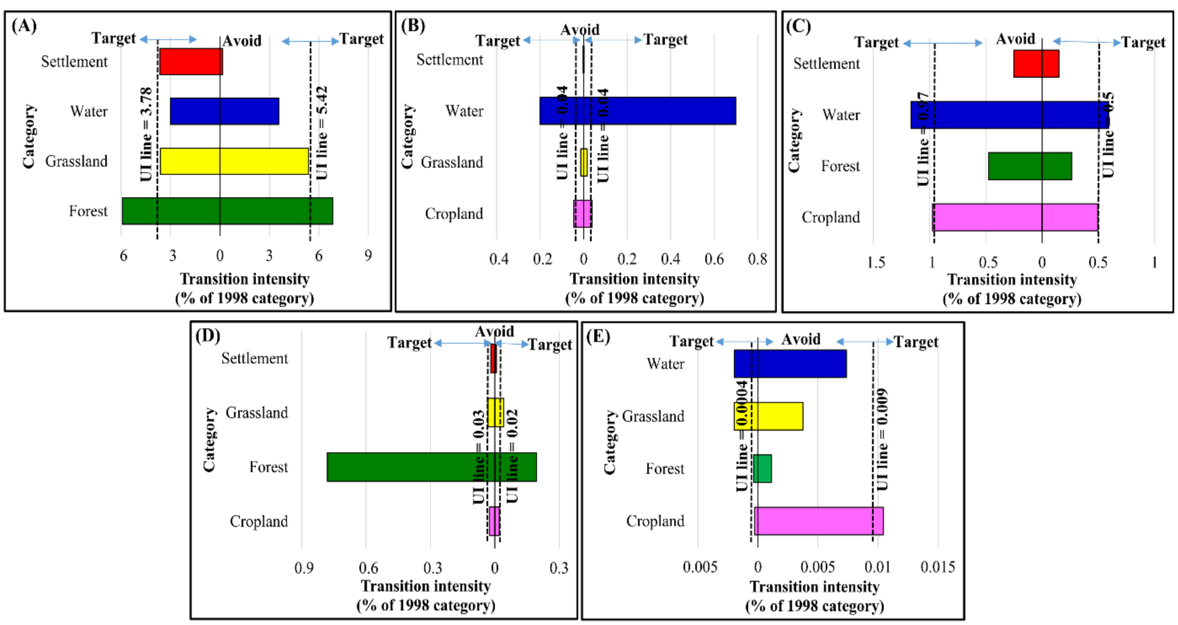

Figure 6.6: Transition level intensity of land use/ land cover (LULC) for the period 1998–2008. (A) cropland, (B) forest, (C) grassland, (D) water and (E) settlement (gains on the right and losses on the left.

The final ten years of the studied period (2008–2018), cropland had different transition intensity trends from the first and second periods and relatively similar transition intensity trends for the forest. In contrast, during this period, water experienced an expansion with transition intensity targeting forest and grassland (Figure 6.7). The intensity of water gained from grassland was more significant than for forest. Settlements expansion over this period targeted water and marginally cropland (Figure 6.7). Losses in settlement targeted water and grassland with marginal avoidance in cropland. In both cases of losing and gaining in the settlement, the highest transition intensity was from water and to water (Figure 6.7).

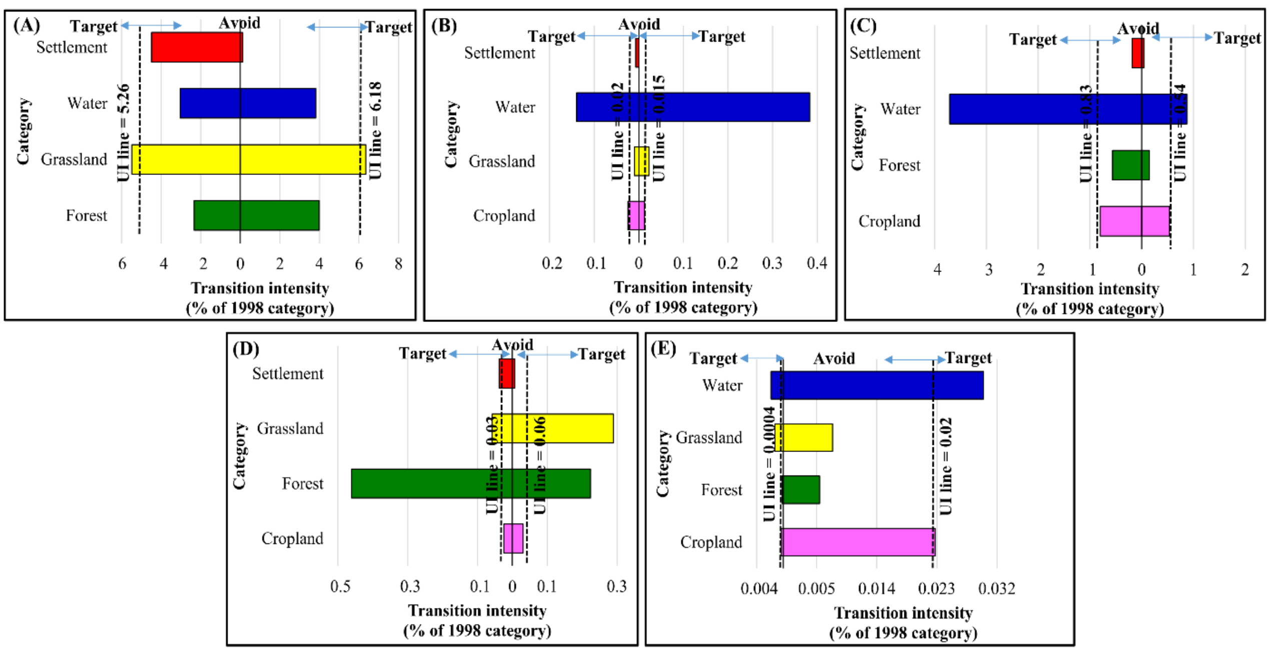

Figure 6.7: Transition level intensity of land use/ land cover (LULC) for the period 2008–2018. (A) cropland, (B) forest, (C) grassland, (D) water, and (E) settlement (gains on the right and losses on the left)

6.2.6 Future prediction of land use/ land cover (LULC)

The CA-ANN predicated future LULC for Gedaref state for the years 2028 and 2048 (Figure 6.8) based on the LULC maps of the years 2008 and 2018 that were generated from Landsat images

(Figure 6.8). The model predicted a slight increase in cropland area from 89.59% to 90.43% and a considerable decrease in forest area (0.47% to 0.41%) between 2018 and 2048 (Table 6.4). The model also predicted a marginal decrease in grassland (8.59 % to 7.78%) and an increase in settlement area from 0.44% to 0.50%. Whereas water area was predicted to be relatively consistent (0.89% to 0.88%) (Table 6.4) between 2018 and 2048.

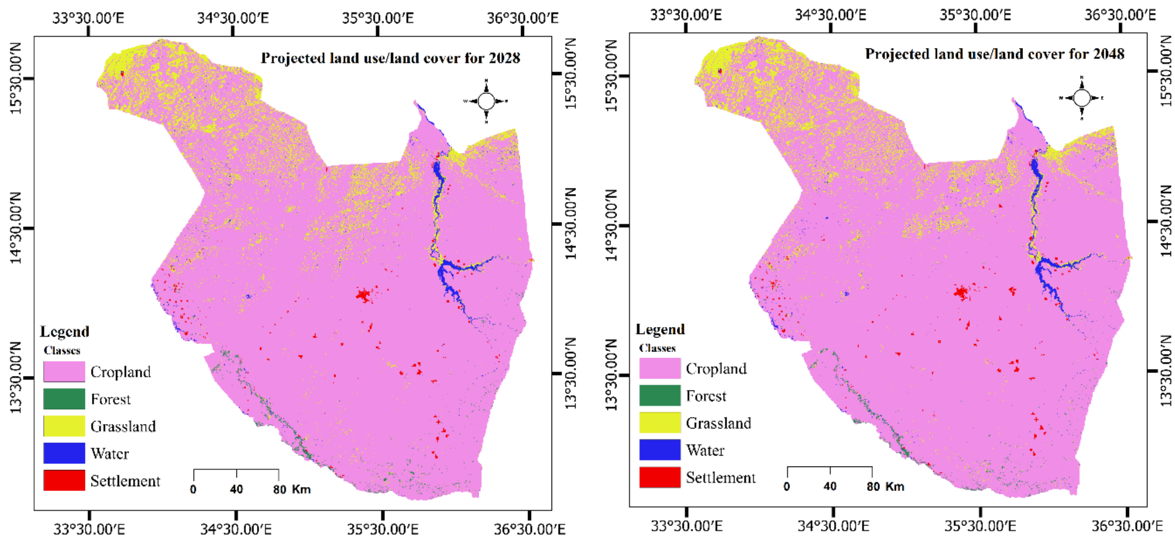

Figure 6.8: Predicted land use/ land cover (LULC) in Gadaref state for 2028 and 2048

Table 6.4: The proportion of predicted land use/ land cover (LULC) categories at Gedaref state

Year	**2018**		**2028**		**2048**	
	Area		**Area**		**Area**	
LULC	**ha**	**%**	**ha**	**%**	**ha**	**%**
Cropland	5723662.45	89.59	5731266.73	89.71	5777105.53	90.43
Forest	0030056.44	0.47	0029882.92	0.46	0025895.38	0.41
Grassland	0548998.87	8.59	0541367.59	8.48	0496928.83	7.78
Water	0057366.22	0.89	0057093.79	0.89	0056335.45	0.88
Settlement	0028278.13	0.44	0028751.08	0.45	0032096.92	0.50
Total	**6388362.09**	**100**	**6388362.09**	**100**	**6388362.09**	**100**

The validation results of the CA-ANN algorithm showed that the model adequately simulated the future LULC pattern in Gedaref state with an overall correctness of 87% and kappa coefficient of 0.86. This indicates that the simulated LULC map of the year 2018 was highly comparable to the actual 2018 map produced in this study, indicating an accurate model performance.

6.3 Discussion

In the present study, combined on-screen digitization of polygons and points from Google Earth Pro platform, RF classification algorithm and dense multi-date Landsat satellite images (1988–2018) were used to map LULC types in Gedaref state, Sudan. For the first time, LULC for 1988-2018 was mapped in the entire Gedaref state, and its future for the years 2028 and 2048 was predicted. In addition, this is the first attempt to evaluate LULC rate of change, intensity and transition in Gedaref for 30 years (1998 – 2018). The methodology for this study has several advantages as acquiring on-screen polygons and points from Google Earth can reliably be utilized to accurately characterize landscape structure, especially for satellite images that have a medium spatial resolution (Asante-Yeboah *et al.,* 2022; Hurskainen *et al.,* 2019; Taylor & Lovell, 2012). Also, for historical satellite image classification, real-time ground truthing observations might not be available. Hence freely accessible platforms like Google Earth can provide accurate reference data for classification experiments. To minimize the expected spatial autocorrelation, point observations with a distance not less than 100 m from the nearest training polygon were used to validate the classified LULC maps. Hence, this mapping approach provided accurate LULC patterns for Gedaref state, which has a dynamic landscape setup. The overall accuracies for the years 1988, 1998, 2008, and 2018 images ranged between 81.75% and 87.70%, which are greater than the recommended acceptable LULC classification accuracy of 70% (Akalu *et al.,* 2019;

Bhunia *et al.,* 2021). Nevertheless, the progressive increment in the LULC classification accuracy from the initial study year (1988) to the last year (2018) could indicate challenges associated with the availability of historical images of relatively better spatial resolution from Google Earth in the past decades.

The results showed that cropland was the most dominant LULC class covering between 78.64% and 89.59% of the total acreage of Gedaref state. This is due to the fact that Gedaref region is the main rainfed agricultural area of Sudan, where about 80% of the population in this state mainly depends on agricultural production for their livelihood (Osman *et al.,* 2021). In addition, clay soil and the high amount of rainfall (400–800mm) that characterize Gedaref state, offer the optimum conditions for the cultivation of many food and cash crops such as sorghum, millet, sunflower, sesame, and cotton. This also explains the domination of this area by agricultural land. The findings of this study also revealed accelerated LULC change between 1988 and 2018, with an expansion in cropland and settlement, and a decrease in forest and grassland areas. These land use dynamics could be due to human activity, such as the horizontal expansion of settlements and cultivated areas, not only by the local communities but also by the investors and other communities from the neighboring states and countries (Sulieman, 2013). Although there was a substantial increase in cropland, the change in water class was unsystematic over the study period, with a dramatic increase between 2008 –2018 (59.52%). This could be explained by the fluctuation in the amount of rainfall that was observed in the study area due to climate variability and change (Osman *et al.,* 2021).

Specifically, cropland has increased from 78.64% to 89.59% during the study period between 1988 and 2018, while the forest area declined from 1.08% to 0.47% of the total area in Gedaref state. These findings agreed with the results of Gadallah et al. (2020), who has reported a decrease of forest area in Wad Albashir forest in Al Rahad locality, Gedaref state, from 72.2% in 2001 to 58% in 2017, whereas cropland increased from 25.9% to 38.3% over the same period. This has been confirmed by our transition mapping, which showed a huge transformation of forested area to agricultural land, particularly along Al Rahad River where Wad Albashir forest is located, and in other forested areas in the southern Gedaref state. Generally, the decline in the forest area could be linked to agricultural expansion, firewood, charcoal production, timber, construction, flooding, soil erosion and desertification. The decline in grassland (-56.23%) from 1988 to 2018 in Gedaref region confirms the results of other studies that were conducted in some parts of the state (Sulieman & Elagib, 2012; Sulieman, 2010). This decrease can also be explained by the fact that agricultural areas usually expanded at the expense of grassland. Also, the transition analysis showed substantial transformation of agricultural area at expense of grassland mainly in the northern and northern-eastern parts of Gedaref state. The regulations and policies of land use in Gedaref are biased toward cropland, compared to the grassland that was used by the pastoralist for grazing. A study by Sulieman & Elagib (2012) reported that this bias was adopted in the solution of disputes during the British colonial period when the Soil Conservation Committee recommended in 1944 that "where nomadic pastoralists were in direct competition for land with settled cultivators, the rights of the cultivator should be considered as paramount because his crops yield a higher return per unit area". Although new laws and regulations were put in place in Gedaref state, the 1944 recommendation was still implemented in some areas. The results also showed that the settlement areas drastically expanded more than three times (319.61%) between 1988 and 2018. This expansion was mainly taking place in central Gedaref where the capital city is located and along Atbara, Al Rahad, Saiteet, and Basalam Rivers. Likewise, the southern and western parts of the state, where the major agricultural schemes are exist, experienced the same transformation from cropland to settlement. This expansion in settlement is primarily to meet the demand for shelter for the rapid population growth and the increase of industrial areas in the region. This is coupled with the increase in cropland, which can be explained by the rising demand for food to meet the growing population. Biratu et al. (2022) reported an increase in cropland and settlement areas in Ethiopia between 1986 and 2021 because of the growing population's demand to ensure food and nutrition security in the country.

The unsystematic change in water class in this study could be explained by many seasonal waterways and rivers, such as Atbara, Al Rahad, Saiteet, and Basalam, flowing northward from the Ethiopian highlands in the rainy season, which differs from one year to another. However, the high increase in water class between 2008 and 2018 is associated with the construction of the Upper Atbara and Setit Dam complex, which is a twin dam consisting of two dams: Rumela Dam on the Upper Atbarah River and Burdana Dam on the Setit River (Zarroug *et al.,* 2019). Construction of the dam began in 2011 and was completed in 2016, intending to provide irrigation water for agriculture, potable supply water for the eastern states of Sudan, and power generation.

The interval level intensity revealed an intensive change of LULC in the first 10 years (1988 – 1998) compared to the second (1998 – 2008) and third (2008 – 2018) intervals. However, change in 2008–2018 was slower than in 1998–2008. This indicates that the impacts of socio-economic and physical driving factors during the three decades were different. This also implies a rapid change in Gedaref landscape in the first decade of the study period. The rapid LULC changes correspond to the areal extent of mechanized rainfed farming in the area since the late 1970s, which has attracted some migrants from different parts of Sudan, leading to rapid change in LULC over the first interval. A study by Miller (2005), reported that the development of mechanized agricultural and grain trade in Gedaref during the 1970s enhanced immigration to the state from different parts of Sudan, which increased socio-economic activities in the region.

The categorical intensity analysis main findings showed that forest, grassland and water were active losers and gainers. This explains that gains and losses of these categories happen at intensities greater than the average intensity of all LULC categories. The intensity of active losses and gains in grassland and water could be explained by the associated seasonality of these two categories with the rainy season in Gedaref state. In contrast, the active gaining and losing in forest can be explained by the attempts of controlling the invasive Mesquite trees (*Prosopis juliflora*). This plant rapidly invades and colonizes the uncultivated land and farmers mostly cut down Mesquite trees to clear the land for cultivation, which might result in a fluctuation in forest cover. Secondly, the settlement was active gaining and losing between 1988 and 1998, active gaining and a dormant loser in the 1998–2008 and 2008–2018 periods. This could be linked to lack of visual clarity of settlement pixels when reference data were gathered from Google Earth platform. In addition, the nature of the hut houses (locally called *quttiyya*), which are made of wood, grass and reeds might have been mixed up with the forest class in the classification process. Thirdly, cropland continued as a dormant loser and dormant gainer throughout the studied three intervals. This is because cropland accounts for the biggest percentage of the landscape compared to other LULC categories.

Analysis of intensity at the transition level revealed that cropland gains from forest were higher between 1988 and 1998 compared to the gain in cropland from the similar LULC category over the second study period (1998 – 2008). However, cropland avoided gains and losses of forest in the third interval (2008 – 2018). This suggests that the expansion in cropland resulted in a decline in the forest area. Nevertheless, the loss of agricultural area to the forest is associated with the spreading of Mesquite in cropland as we mentioned earlier. This study also showed the transition of forest to water in the three change periods. This might be linked to misclassification between the two classes as most of the forests in Gedaref state are Nilotic trees such as *Acacia nilotica* and *Acacia seyal*, which lie mainly around the seasonal rivers and watercourses. Similarly, the gains in grassland from the settlement in the first period (1988–1998) could be a likely result of the slight misclassification of wood, grass and hut houses as grassland. The second explanation is that the low resolution of the satellite image for 1988–1998 might have contributed to the misclassification of settlements as grassland, as the result of other periods did not show such intensity. The intensity analysis also showed the gain of grassland from water in the second and third periods (1998–2008 and 2008–2018). This is explained by the fact that grassland overlaps with water due to the seasonality of water bodies in Gedaref state. Another interesting key finding was observed in grassland losses to water, which was higher in the period between 2008 and 2018, compared to the losses in grassland to the similar LULC category over the first and second periods. This is perhaps as a result of the construction of the Upper Atbara and Setit Dam complex and the increase of water storage ponds for drinking water, domestic use and irrigation of agricultural land during this period. The settlement loss targets water and grassland in the three study periods, with the addition of the forest in the second period (1998–2008). This could be linked to pastoralism movements through seasonal migration routes and settling where there are grass and water. Whereas gaining in settlement target cropland and water in the second and third periods, respectively, with no gain from any LULC class in the first period. Settlement is usually located in flat areas, where cropland can also be found in these areas. Hence, the expansion in settlement areas is likely to target cropland and water gathering sites.

The predicted results revealed that by 2028 and 2048, cropland is expected to increase by 0.12% and 0.72%, respectively as compared to 2018. This is partly attributed to the expansion of mechanized farming in the study area. Similarly, the settlement might be increased from 0.44 to 0.50% between 2018 and 2048. This could be attributed to the rapid population growth and refugee influx in the study area (Gadallah *et al.*, 2019). Whereas the forest acreage is anticipated to decrease from 0.47% in 2018 to 0.41% in 2048. This could be linked to illegal cutting, overgrazing and mechanized agriculture since the population in Gedaref state depend mainly on farming activities for livelihoods (Abdalla, 2018; Idreas, 2015). The model prediction showed that the trend of grassland will continuously decrease by 7.78% in 2048 from 8.59% in 2018. Water will be relatively consistent in the region in 2018, 2028 and 2048 by 0.89%, 0.89% and 0.88%, respectively.

The findings presented in this study could guide policymakers and different stakeholders to effectively plan and manage the landscape in Gedaref state, Sudan. For example, to ensure that human settlement does not completely eliminate crop farming in Gedaref State, the government should consider the following strategies: implement land use planning and zoning regulations, promote sustainable agricultural practices, strengthen legal frameworks and enforcement, develop rural infrastructure and services, promote agroforestry and reforestation, community involvement and education, and support research and development. Also, the study provides some insights on the main drivers that could play a vital role in changing the current and future landscape structure in most important rainfed farming areas in Sudan. Knowing the areal extent, change rate, intensity and transition of important LULC categories like cropland and grassland over 30 years could enable informed crop and grassland production monitoring. Specifically, the results of the present study could complement the findings of chapter four, which predicted the relationship between climate factors and crop yield in Gedaref state under climate warming. Hence, total crop production in Gedaref could be predicted and forecasted using both study findings. In general, different land use and environmental policy and planning initiatives in Gedaref state or even in Sudan could make use of the findings presented in this study.

Despite the fact that this study used a robust and efficient machine learning RF algorithm in LULC classification experiment, the method has some limitations. For instance, when a large number of decision trees are used, the algorithm can be too slow to make the classification predictions as it requires more computational power. Another disadvantage of RF is that the method is a black or grey box approach with very little control over what the algorithm does (Feng *et al.,* 2020). On the other hand, the simulated the future (2028 and 2048) LULC predictions using the current natural and anthropogenic factors that might considerably change in the future. In addition, other factors that could play a significant role in the future LULC shift like fire, flood, conflict, and other geopolitical and socio-economic variables were not considered in our study.

6.4 Conclusions

In conclusion, this study is the first attempt to map and predict future LULC changes and their intensities and underline the processes that cause the change in the landscape of Gedaref state. The results showed that LULC in Gedaref has undergone a distinct change in 30 years period (1988 – 2018), with a considerable decline in forest and grassland areas and an expansion in settlement areas. The classified LULC maps and model validation for future LULC prediction provided high accuracy (overall correctness = 87%). This demonstrates the possibility of mapping and predicting LULC classes using on-screen reference data from Google Earth images, dense multi-date Landsat images, RF classifier and CA-ANN model. The findings of this study provide information on LULC patterns in Gedaref region that could be useful for designing management plans and developing policies for assessing and monitoring crop and grassland production, other natural resources produce, landscape fragmentation and degradation, and ecosystem functions. This information is, therefore, critical in managing one of the most important rainfed agricultural landscapes in Sudan.

6.5 Summary

Mapping of LULC dynamics has gained significant attention in the past decades. This is due to the role played by LULC change in assessing climate, various ecosystem functions, natural resource activities and livelihoods in general. In Gedaref landscape of Eastern Sudan, there is limited or no knowledge of LULC structure and size, degree of change, transition, intensity and future outlook. Therefore, the aims of the current study were to (1) evaluate LULC changes in the Gedaref state, Sudan, for the past thirty years (1988–2018) using Landsat imageries and the random forest classifier, (2) determine the underlying dynamics that caused the changes in the landscape structure using intensity analysis, and (3) predict future LULC outlook for the years 2028 and 2048 using cellular automata-artificial neural network (CA-ANN). The results exhibited drastic LULC dynamics driven mainly by cropland and settlement expansions, which increased by 13.92% and 319.61%, respectively, between 1988 and 2018. In contrast, forest and grassland declined by 56.47% and 56.23%, respectively. Moreover, the study shows that the gains in cropland coverage in Gedaref state over the studied period was at the expense of grassland and forest acreage, whereas the gains in settlements partially targeted cropland. Future LULC predictions showed a slight increase in cropland area from 89.59% to 90.43% and a considerable decrease in forest area (0.47% to 0.41%) between 2018 and 2048. These findings provide reliable information on LULC patterns in Gedaref region that could be used for designing land use and environmental conservation frameworks for monitoring crop produce and grassland condition. In addition, the result could help in managing other natural resources and mitigating landscape fragmentation and degradation. The next chapter will present results on the integration of satellite remote sensing data and small-scale farmers' perceptions to determine land use/ land cover changes and their driving factors in Gedaref State, Sudan.

CHAPTER SEVEN

INTEGRATING SATELLITE REMOTE SENSING DATA AND SMALL-SCALE FARMERS' PERCEPTIONS TO DETERMINE LAND USE/ LAND COVER CHANGES AND THEIR DRIVING FACTORS IN GEDAREF STATE, SUDAN

7.1. Introduction

This chapter presents results on assessment of the perception of local land users of LULC change trends and determined the approximate and undelaying drivers that caused LULC dynamics in Gedaref state, Sudan. The LULC trends obtained in chapter six were compared with the perceptions of the local land users and the cultural crop cultivation area in Gedaref state. In addition, the effect of the rapid population growth in Gedaref state and climate variables (temperature and rainfall) on the dynamics of the main three LULC categories (cropland, forest and settlements) was evaluated. Furthermore, this chapter examined whether expansion of cropland in Gedaref state has led to an increase in crop yield.

7.2 Results

7.2.1 Land use/ land (LULC) maps and trends

The LULC maps (Figure 6.1) in chapter six, section 6.2.1 were used for this study to compare the LULC trends generated from the maps with the perception of the local land users. Figure 7.1 shows the proportionate coverage area (Figure 7.1A) and change rate (Figure 7.1B) of each LULC class in Gedaref state for the same period. In the initial year of the study, i.e., 1988, cropland was the most predominant LULC class, occupying 78.64% of the total area of Gedaref state, followed by grassland (19.64%), while forest, water and settlement covered less than 2% of the study area (Figures 7.1). In the other studied years (1998, 2008 and 2018), the LULC class followed the same trend of coverage. During the entire study period (1988-2018), settlement areas increased nearly fourfold (i.e., 319.61%), whereas cropland increased from 78.64% to 89.59%. Conversely, forest, and grassland, drastically decreased in the same period (Figures 7.1). However, water classes increased throughout the study period, except for 2008. The highest net loss between 1988 and 2018 was detected in the forest area, followed by grassland (Figure 7.2). Although the losses were relatively higher in forest and grassland, the rate of change did not occur equally (Figure 7.2).

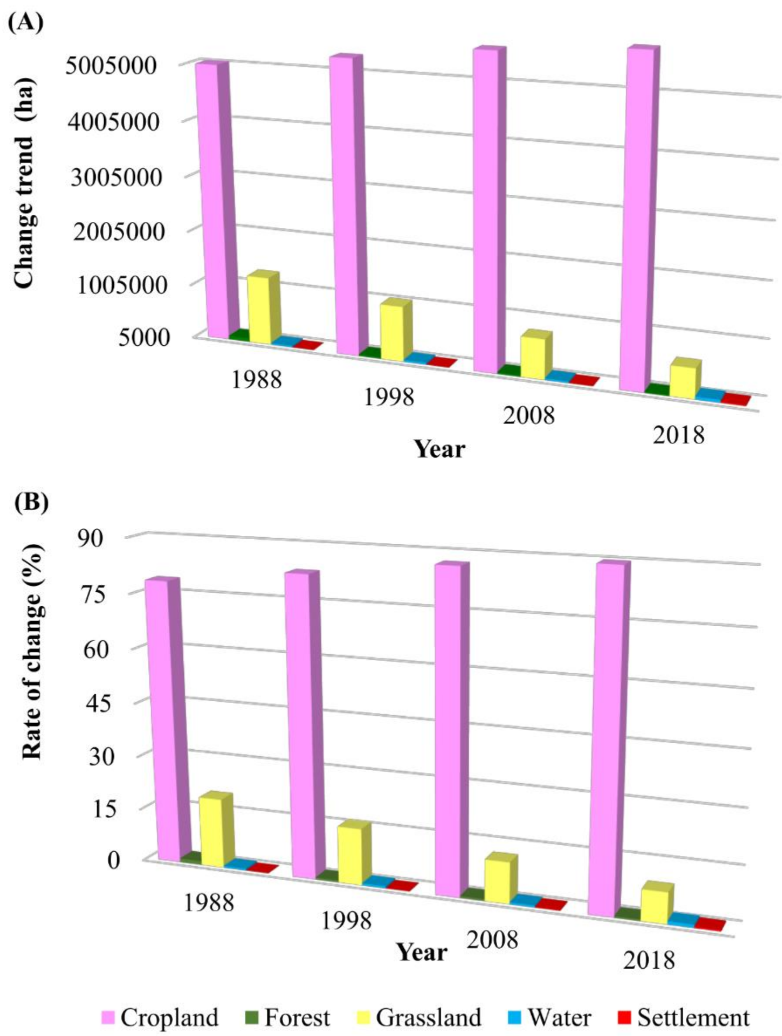

Figure 7.1: Land use/ land cover (LULC) change trend **(A)** and rate **(B)** of Gedaref state, Sudan

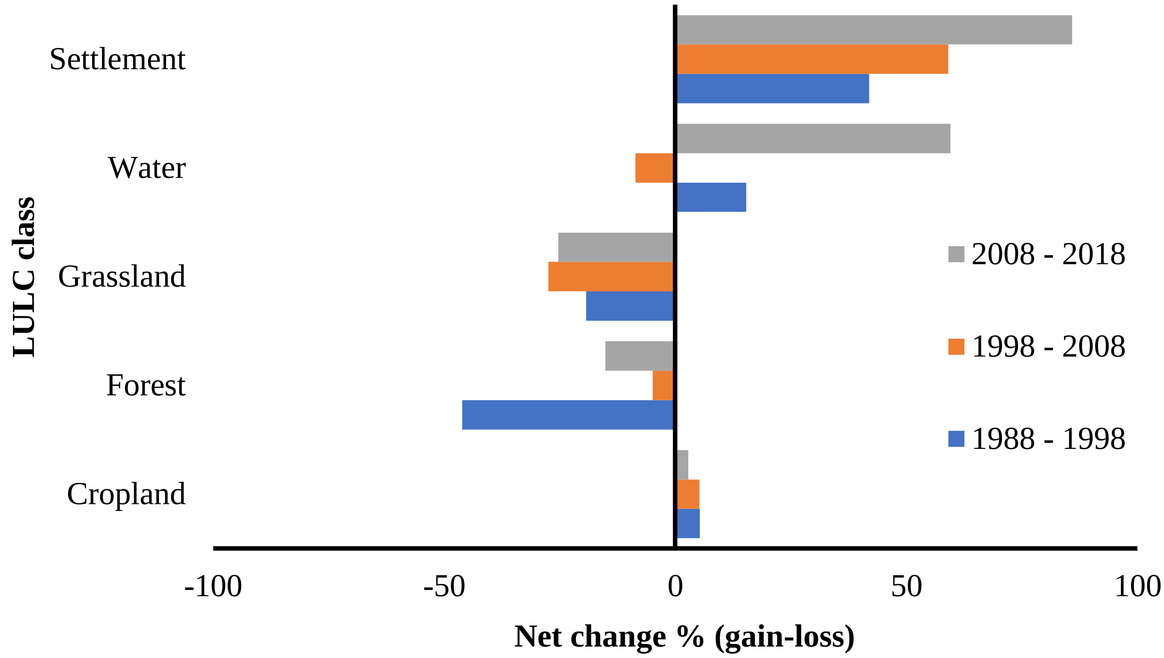

Figure 7.2: Net change in land use/ land cover (LULC) classes of Gedaref state, Sudan between 1988 and 2018.

7.2.2 Socio-economic and demographic characteristics of sampled households

Table 7.1 represents the socio-economic and demographic characteristics of the respondent. The majority (79.8%) of the respondents were male, while 20.3% were female (Table 7.1). Thus, about 58.3% of households were male-headed. The average age of the sampled respondents was 43.3 years old, ranging between 20 and 82 years. Regarding the education status, 27% of the respondents were illiterate, 34.8% and 20.8% had primary and secondary level school qualifications, respectively. Forty-three percent (43%) of the respondents lived in Gedaref state for more than 41 years, while 7.3% lived for less than 15 years (Table 7.1). The size of the household ranged from 1 to 17 individuals, with an average of 6 individuals per household. The proportion of respondents who owned land was 74.5%, while land size varied between 0.42 and 21 ha, with an average of 4.85 ha. Approximately 61% of the respondents were involved in agricultural activities with 68.0% of the farmers having more than 41 years of experience in farming. Furthermore, 2.3% of the farmers were involved in selling forest products and 36.8% were engaged in on-farm activities, such as construction and government employees and businesses.

Table 7.1: Summary of household characteristics for small holders farming communities in Gedaref state, Sudan (N = 400)

Household characteristics	Category	Frequency	Percent (%)
Sex	Male	319	79.8
	Female	81	20.3
Head of the household	Male	233	58.3
	Female	167	41.8
Number of years living in the village	< 15	29	7.3
	16 - 30	109	27.3
	31 - 40	90	22.5
	> 41	172	43.0
Age	< 21	13	3.3
	22- 40	180	45.0
	41 - 64	163	40.8
	> 65	44	11.0
Main sources of income	Farming	244	61.0
	Salaried employment	74	18.5
	Self-employment	73	18.3
	Selling forest products	9	2.3
Farming experience	< 10	35	8.8
	11 - 20	59	14.8

Table 7.1 (cont.)

Household characteristics	**Category**	**Frequency**	**Percent (%)**
Farming experience	21 - 40	34	8.5
	>41	272	68.0
Land tenure	Owned	298	74.5
	Rent in	82	20.5
	Share in	12	3.0
	Share out	8	2.0
	0.40 - 2.99	169	42.3
	3 - 5.99	93	23.3
	6 - 8.99	91	22.8
	> 9	47	11.8
Family size (individuals)	< 5	55	13.8
	6 - 10	133	33.3
	11 - 14	138	34.5
	>15	74	18.5
Education level	Illiterate	108	27.0
	Primary	139	34.8
	Secondary	83	20.8
	University graduate	70	17.5

7.2.3 Perception of small-holder farmers of the drivers of land use / land cover (LULC) change in Gedaref state, Sudan

The local land users (respondents) identified 12 drivers of LULC changes in Gedaref state (7 proximate drivers and 5 underlying drivers) during the study period (Tables 7.2 and 7.3). The local land users ranked firewood collection, agricultural expansion, and charcoal production as the top proximate drivers that influenced LULC changes in the studied landscape, with firewood collection being the main driver, followed by agricultural expansion (Table 7.2). Similar findings were revealed by key informant interviews and FGDs, which ranked firewood collection, agricultural expansion, settlements, and charcoal production as the primary causes of LULC dynamics in Gedaref state.

Table 7.2: Perceived proximate drivers of land use/ land cover (LULC) changes by local land users in Gedaref state, Sudan

LULC proximate drives	Number of respondents per rank							Weight	Ranking index	Rank
	1	2	3	4	5	6	7			
Firewood collection	221	101	62	13	2	1	0	2523	0.225	1
Agriculture expansion	133	83	140	29	14	1	0	2289	0.204	2
Charcoal production	38	155	95	94	14	4	0	2097	0.187	3
Settlements	9	44	49	157	30	83	28	1484	0.132	4
Construction	0	12	35	72	253	28	0	1350	0.120	5
Timber	2	3	20	26	75	256	18	991	0.088	6
Bush fires	0	1	5	8	8	24	354	489	0.044	7

Poverty and rapid population growth were ranked as the most vital underlying factors that drive LULC change in Gedaref state, with a ranking index of 0.280 and 0.216, respectively (Table 7.3). This was followed by a lack of law enforcement and financial resources, ranked third and fourth, respectively (Table 7.3). Similarly, the rapid population growth, poverty, rainfall fluctuation, lack of law enforcement and high cost of agricultural inputs were reported by key informant interviews and FGDs to be the key underlying drivers of LULC changes in Gedaref state.

Table 7.3: Perceived underlying drivers of land use/ land cover (LULC) changes in Gedaref state, Sudan

LULC underlying drives	Number of respondents per rank					Weight	Rankong index	Rank
	1	2	3	4	5			
Poverty	237	60	55	44	4	1682	0.280	1
Population growth	42	156	76	111	15	1299	0.216	2
Lack of law enforcement	73	85	106	131	5	1290	0.215	3
Lack of financial resources	49	89	150	99	13	1262	0.210	4
Demand for timber	0	10	14	16	360	474	0.079	5

7.2.4 Multinomial logistic regression results of perceived drivers of land use/ land cover (LULC) changes

The sex of the household head had a significant ($p \leq 0.05$) effect on the perception of the respondents on the collection of firewood, charcoal production, timber, agricultural expansion, poverty, population growth, lack of financial resources and law enforcement as LULC drivers in Gedaref region (Table 7.4). Poverty was significantly ($p \leq 0.05$) affected by the sex of respondents, sex of the household head, age, and education level. Whereas family size had no significant influence on the perception of the small-holder farmers of LULC change.

Table 7.4: Significant ($p \leq 0.05$) socio-economic factors influencing respondents' perceptions on the drivers of land use/ land (LULC) cover changes in Gedaref state, Sudan

Perceived driver of LULC change	Independent variable	Estimate	Standard error	Wald	*p*-Value	95% Confidence Interval	
						Lower bound	Upper bound
Firewood	Head of the household	2.148	0.927	5.372	**0.020**	0.33146	3.963761
	Land size	-0.243	0.124	3.848	**0.050**	-0.48451	0
Charcoal production	Head of the household	-1.120	0.385	8.461	**0.004**	-1.87732	-0.36528
	Age	0.031	0.011	7.659	**0.006**	0.00896	0.052592
	Land tenure	-0.566	0.237	5.698	**0.017**	-1.03002	-0.10093
	Farming experience	-0.040	0.012	11.183	**0.001**	-0.06401	-0.01715
Timber	Head of the household	-1.722	0.740	5.408	**0.020**	-3.17009	-0.2705
Construction	Age	-0.044	0.015	9.251	**0.002**	-0.07257	-0.01613
	Farming experience	0.031	0.015	4.213	**0.040**	0.001	0.060154
Agriculture expansion	Head of the household	1.171	0.524	4.993	**0.025**	0.1441	2.198002
	Age	0.037	0.015	6.091	**0.014**	0.007968	0.065788
Poverty	Sex	1.856	0.442	17.593	**0.000**	0.988797	2.723202
	Head of the household	-2.261	0.603	14.047	**0.000**	-3.44202	-1.07881
	Age	0.043	0.017	6.586	**0.010**	0.00995	0.076961

Table 7.4 (cont.):

Perceived driver of LULC change	Independent variable	Estimate	Standard error	Wald	*p*-Value	95% Confidence Interval	
						Lower bound	Upper bound
Poverty	Education	0.796	0.197	16.262	**0.000**	0.408793	1.182953
Population growth	Sex	0.872	0.290	9.055	**0.003**	0.303801	1.439361
	Head of the household	-1.206	0.364	10.955	**0.001**	-1.91732	-0.49102
Lack of financial resources	Sex	-0.967	0.342	8.010	**0.005**	-1.63476	-0.29706
	Head of the household	0.812	0.389	4.352	**0.037**	0.04879	1.574018
Lack of law enforcement	Sex	-1.098	0.339	10.522	**0.001**	-1.76026	-0.43541
	Head of the household	1.712	0.376	20.780	**0.000**	0.976068	2.44807
	Education	-0.233	0.118	3.895	**0.048**	-0.46522	-0.002
Demand for timber	Education	-0.678	0.245	7.639	**0.006**	-1.15836	-0.19723

7.2.5 Comparison between small-holder farmers' perception and land use / land cover (LULC) classification

The results of farmers' perceptions of LULC trends are presented in Figure 4. About 55.5% of the respondents indicated that the cropland area had increased in the study area, while 39.5% claimed that there was no change in the cropland coverage (Figure 7.3A). Additionally, the majority of the respondents (90.8%) also claimed that forest area had decreased over the study period (1988–2018) in Gedaref state (Figure 7.3B). Whereas 96.5 % of the interviewed farmers perceived an increment in settlement area during the study period (Figure 7.3C). Although the respondents have indicated an increase in cropland area, the majority of 90.8% claimed that crop production has decreased in Gedaref state in the period between 1988 and 2018 (Figure 7.3D). The results of Mann–Kendall trend analysis of the satellite imagery showed a significant ($p \leq 0.05$) increase in cropland area in Gedaref state by about 249,421 ha each 10 years between the years 1984 and 2018, which confirmed the community's perception (Figure 7.4A; Table 7.5). Similarly, farmers' perception agreed with the trend of classified forest area, which showed a significant ($p \leq 0.05$) decrease by -9,175 ha each 10 years, with a confidence interval ranging between -28082.75 and -2252.72 ha (Figure 7.4B; Table 7.5). The settlement area had significantly ($p = 0.05$) increased by 6,414 ha each 10 years, with a confidence interval between 3,179.44 and 12,136.97 ha for the study period (Figure 7.4C; Table 7.5), which also agreed with the farmers' perception.

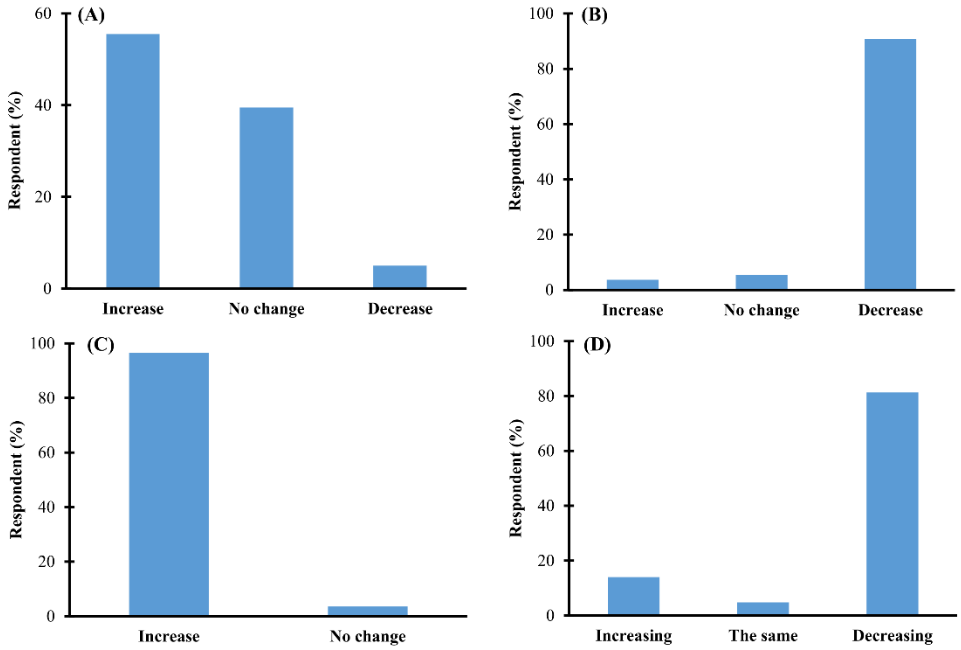

Figure 7.3: Farmers' perception towards changes in (A) cropland area; (B) forest area; (C) settlement area; and (D) crop production in Gedaref state, Sudan

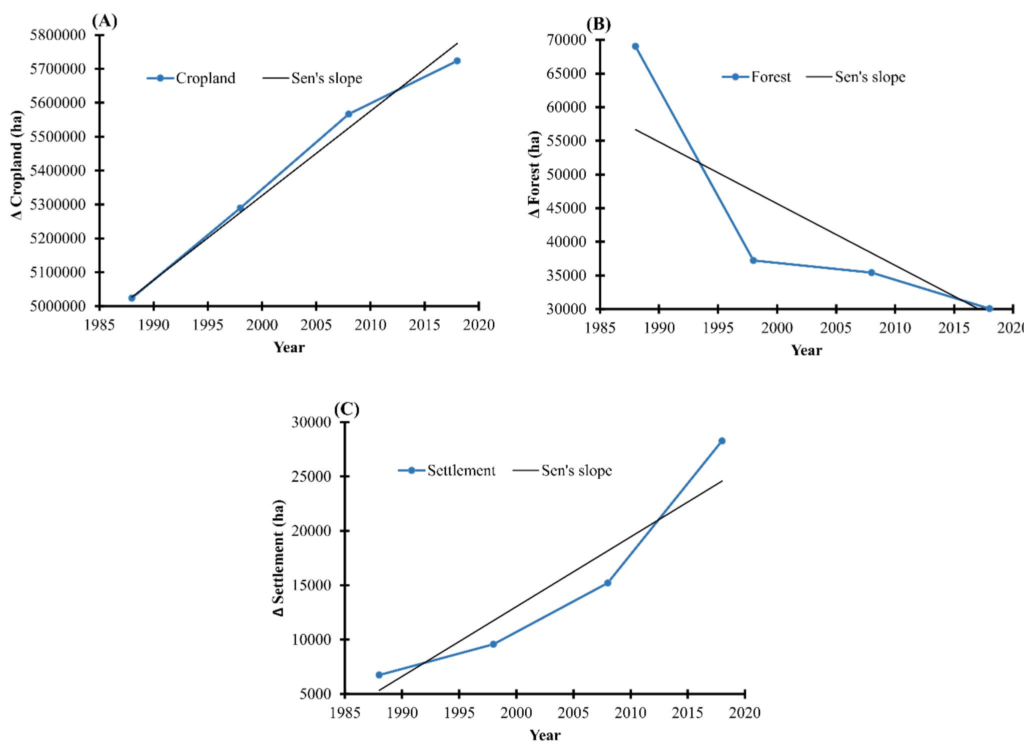

Figure 7.4: Satellite-based land use/ land cover (LULC) change trends in Gedaref state, Sudan between 1988 and 2018. (A) cropland; (B) forest; and (C) settlement.

Table 7.5: Estimated Sen's slope values for cropland, forest, and settlement (ha) trends in Gedaref State, Sudan between 1988 and 2018.

Class area	**Range**		**Sen's slope**	**95% Confidence Interval**	***p*-Value**
	Minimum	**Maximum**			
Cropland	5023958.04	5723662.45	249421	171830.53 – 275872.05	0.006
Forest	30056.44	69053.13	-9175	-28082.75 – -2252.72	0.041
Settlement	6739.02	28278.13	6414	3179.44 – 12136.97	0.051

7.2.6 The actual trend of cultivated area, crop yield and production

The data obtained from the ministry of agriculture showed that the cultivated areas for the five major crops significantly ($p \leq 0.05$) increased between 1988 and 2018 (Figure 7.5; Table 7.6). This further confirmed the increase in cropland area of the satellite-based LULC maps as well as farmers' perceptions. The trend analysis showed that the actual cultivated area for sorghum, millet and sunflower significantly ($p \leq 0.05$) increased by 3732, 4200, and 840 ha per year, respectively, between 1988 and 2018 (Figure 7.5; Table 7.6). As an increase in the total cultivated area, the crop production increased by 11249.17, 3539.39, 1543.19, 517.71, and 159.67 tons for sorghum, sesame, millet, sunflower, and cotton, respectively (Figure 7.6; Table 7.7). The farmers' perceptions of crop production over the study period disagreed with the actual trend of crop production, which increased over time (Figure 7.6). The majority of the farmers (81%) indicated that crop production in the study area has decreased, while 14% and 4.8% of the farmers indicated increased and no change in crop production, respectively. Although the actual trend showed an increase in crop production over time, the crop yield per unit (kg ha^{-1}) remained constant, with a weak correlation detected between cultivated area and crop yield (Figure 7.7).

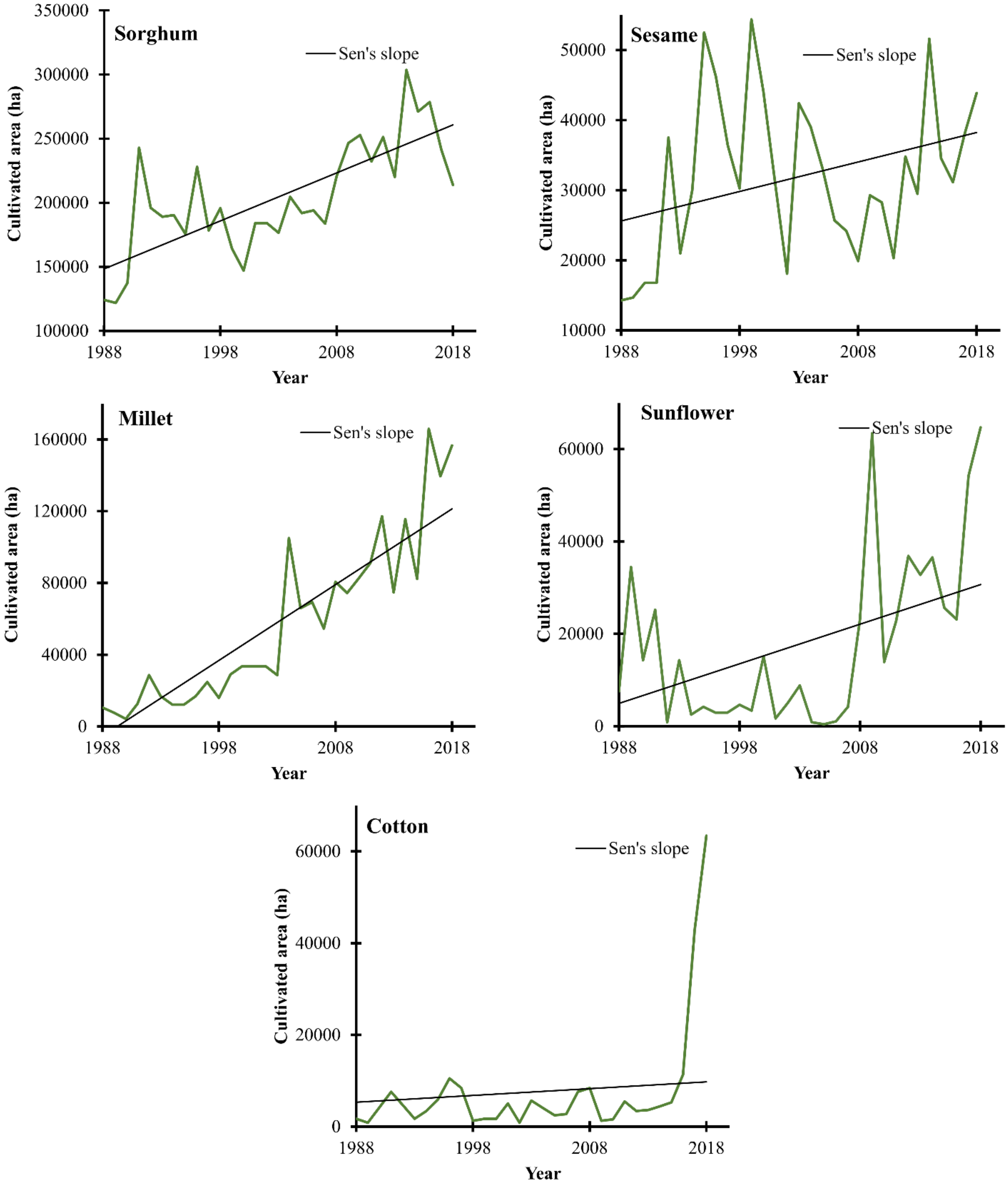

Figure 7.5: Annual actual cultivated area trends for sorghum, sesame, millet, sunflower and cotton in Gedaref state, Sudan between 1988 and 2018.

Table 7.6: Estimated Sen's slope values for culitvated area of sorghum, sesame, millet, sunflower and cotton (ha) trends in Gedaref State, Sudan between 1988 and 2018

Cultivated area (ha)	**Range**		**Sen's slope**	**95% Confidence interval**	***p*-Value**
	Minimum	**Maximum**			
Sorghum	121800	303576	3732	-12222 – 17200.8	0.000
Sesame	14280	54390	411.2	-4767.0000 – 5871	0.146
Millet	4200	165900	4200	-3108.0000 – 13480	0.000
Sunflower	420	64680	840	-4956 – 6935	0.000
Cotton	840	63420	142.8	-1219.68 – 4676.86	0.018

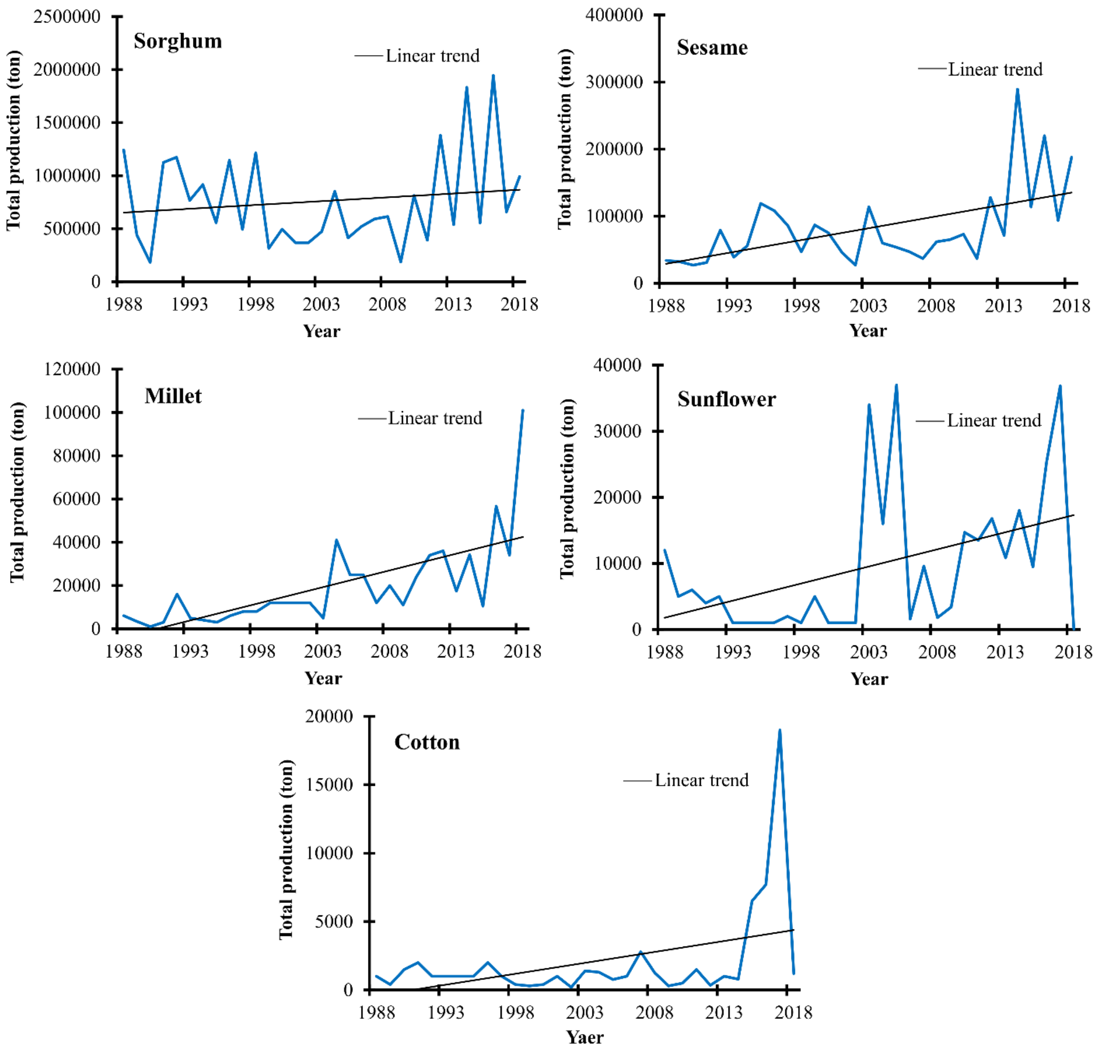

Figure 7.6: Annual crop production trends for sorghum, sesame, millet, sunflower and cotton in Gedaref State, Sudan from 1988–2018

Table 7.7: Estimated slope of linear regression for the annual crop production trends for five crops (sesame, sorghum, cotton, millet, and sunflower) grown in Gedaref state, Sudan from 1988–2018.

Crop	**production range (ton)**		**Slope**	**95% Confidence Interval**	***p*-Value**
	Minimum	**Maximum**			
Sorghum	183000.00	1946000.00	11249.17	-7715.37 – 30213.69	0.234
Sesame	27000.00	289500.00	3539.39	1455.61 – 5623.18	0.001
Millet	1000.00	101000.00	1543.19	930.19 – 2156.19	0.001
Sunflower	66.50	37000.00	517.71	107.24 – 928.18	0.152
Cotton	200.00	19000.00	159.67	0.06 – 0.76	0. 224

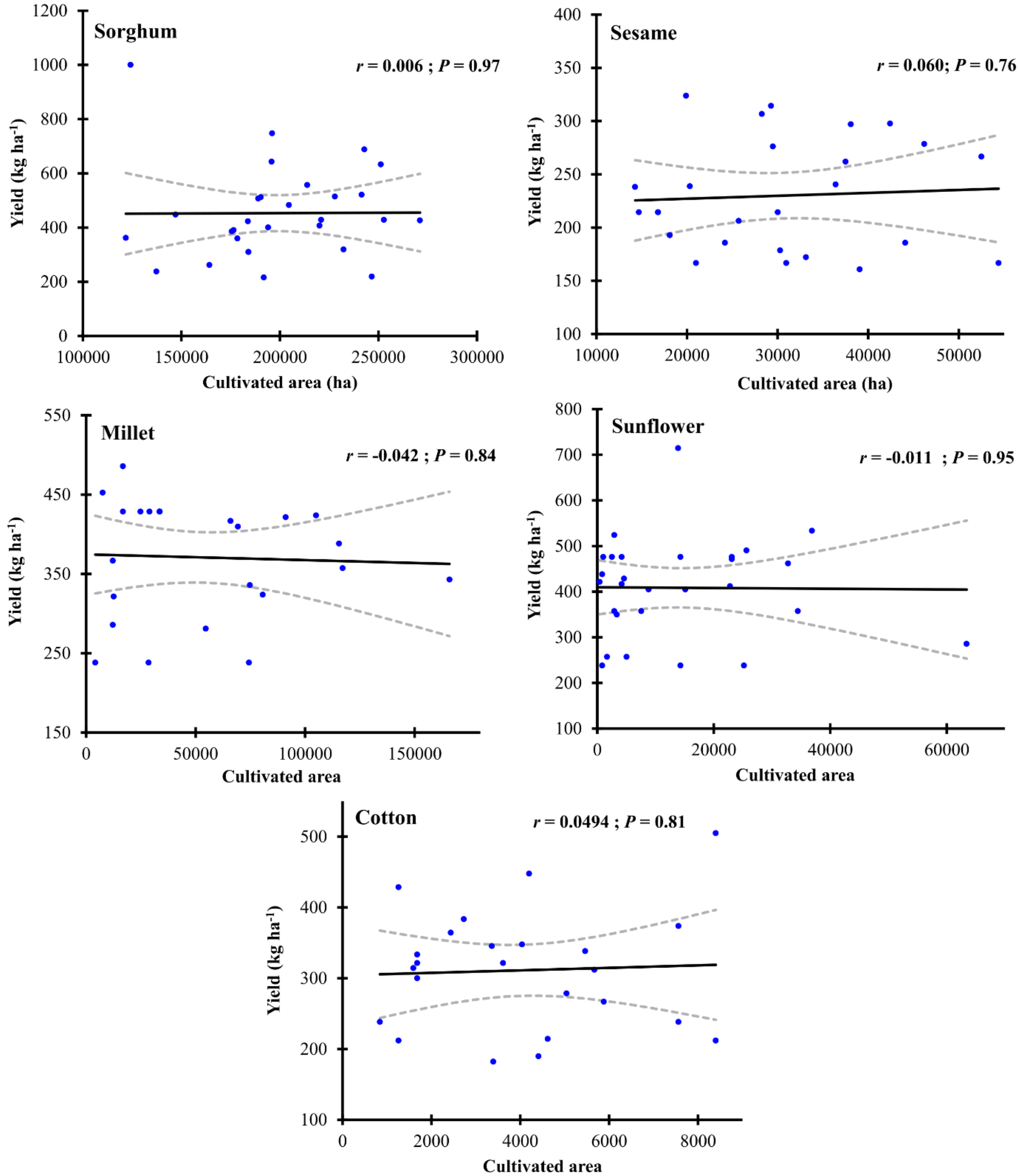

Figure 7.7: The relationship between cultivated area (ha) and yield of sorghum, sesame, millet, sunflower and cotton in Gedaref state, Sudan using Pearson's correlation test. The dashed lines above and below the trend lines are the confidence intervals.

7.2.7 Relationship between climatic variables, population and land use/ land cover (LULC) classes

The result of the relationship between each LULC class area (cropland, forest and settlement) and climatic variables (rainfall and temperature) on the one hand, and population on other hand are represented in Figure 7.8. The climatic variables and population were positively correlated with the change in cropland area (Figure 7.8 A-C), with correlation coefficient (*r*) ranging between 0.80 and 0.98. However, these variables negatively influenced the change in forest area with a correlation coefficient (*r*) ranging between 0.47 and 0.88 (Figure 7.8 D-F). The correlation between population growth in Gedaref state and the settlement area was significant ($p < 0.05$), and positive with (*r*) = 0.97 (Figure 7.8G).

Table 7.8 shows the results of a multiple linear regression that estimated changes in three LULC areas (cropland, forest, and settlement) as a function of rainfall, temperature, and population growth. The combination of the three independent variables in the model revealed that 98%, 83% and 97% variabilities of the change in cropland, forest, and settlement areas, respectively explained by these factors (Table 5). Nevertheless, only temperature and population significantly ($p \leq 0.05$) influenced the increase of cropland area. In addition, the coefficient of population growth was significantly ($p \leq 0.05$) influencing the expansion of the settlement area (Table 5). Although the relationship between the three variables and the change in forest area was insignificant ($p \geq 0.05$), temperature and population growth natively influenced the change in the forest area.

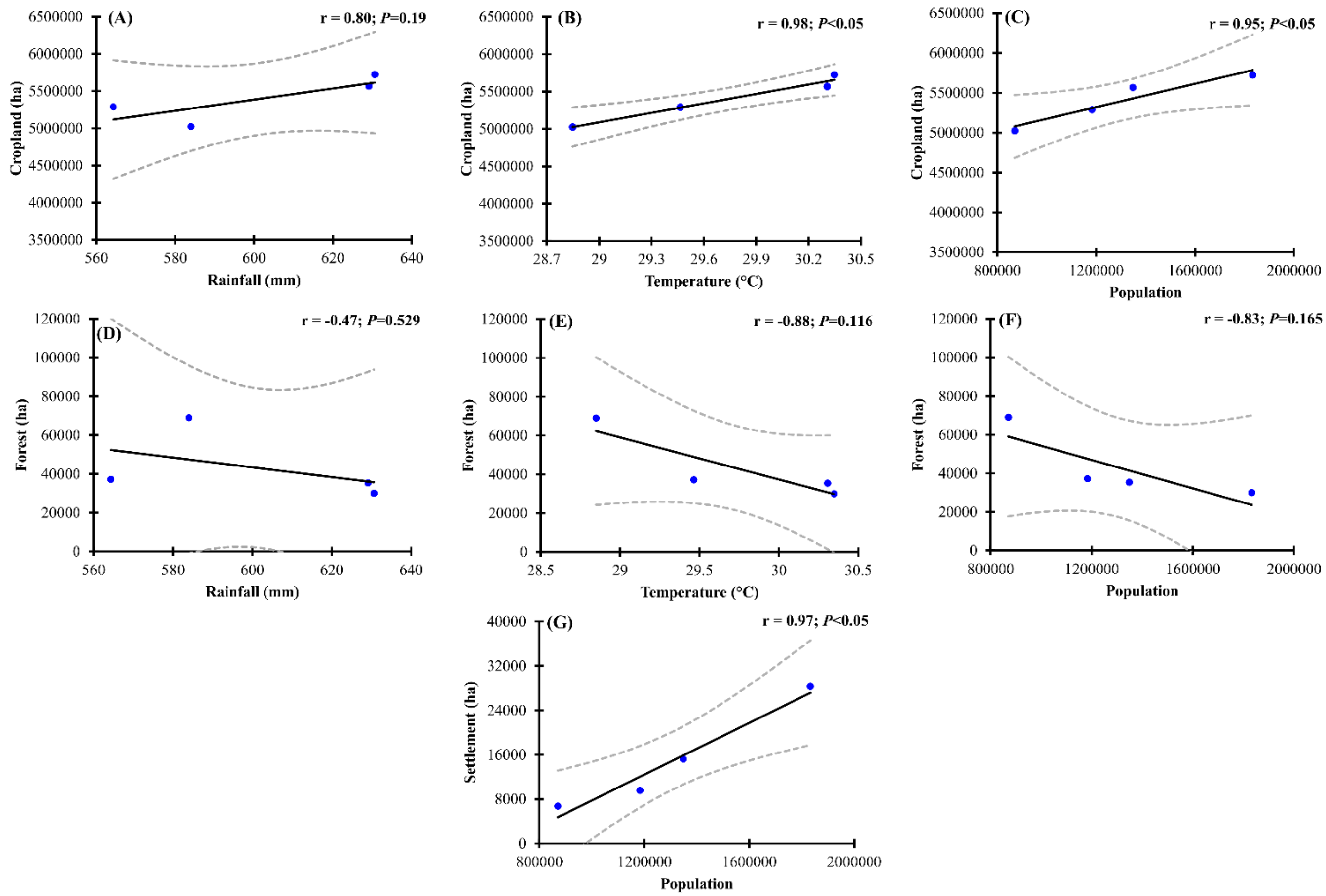

Figure 7.8: The relationship between: **(A)** cropland area and rainfall; **(B)** cropland area and temperature; **(C)** cropland area and population; **(D)** forest area and rainfall; **(E)** forest area and temperature; **(F)** forest area and population; **(G)** settlement area and population using Pearson's correlation test. The shaded lines above and below the trend lines are the confidence intervals

Table 7.8: The multiple linear regression terms and coefficients of determination (R^2) estimating the change land use/ land cover (LULC) areas as a function of rainfall, temperature, and population in Gedaref state, Sudan

LULC class		**Intercept**	**Tmean (°C)**	**Rainfall (mm)**	**Population**	**R^2**
Cropland	Coefficient	7.000e+05	1.089e+05	-1.998e+02	6.047e-01	0.98
	p-value	0.505	**0.027**	0.207	**0.001**	
Forest	Coefficient	3.199e+05	-6.758e+03	1.631e+01	-2.814e-02	0.83
	p-value	0.216	0.338	0.594	0.117	

Settlement	Coefficient	1.652e+04	-9.541e+02	2.614e+00	2.455e-02	0.97
	p-value	0.742	0.525	0.700	**0.003**	

7.3 Discussion

Between 1988 and 2018, Gedaref state in Sudan experienced significant and increased rates of LULC changes. Cropland is the major LULC class in both 1988 and 2018, accounting for 78.64% and 89.59% of the total Gedaref landscape. This is because Gedaref state is the Sudan's main rainfed agricultural area, with approximately 80% of the population in the state relying on agricultural production as the primary source of income (Osman *et al.,* 2021). Furthermore, Gedaref area is characterized by multi-cultivation of various food and cash crops and this is due to the fact that Gedaref area has rich clay soil and receives, on average, about 600 mm of rainfall (Sulieman & Elagib, 2012). The expansion of cropland area, which was calculated from the satellite-based data and a machine learning classifier, agreed with the actual cultivated area that was obtained from the ministry of agriculture of Gedaref state. Similarly, farmers' perception showed an increase in cropland area, which was in line with the satellite-based cropland area. The increase in crop production trend of the five major crops in Gedaref state can be explained by the increasing trend in the total cultivated area. The farmers' perceptions of crop production over the study period disagreed with the actual trend of crop production. This is mainly attributed to the fact that the present study focused on small-scale farmers who experience limited access to farming technology and production inputs. This can result in low crop yield and production coupled with a small farm size. Also, the crop production trend of the data acquired from the ministry of agriculture was for the whole Gedaref state, which could be affected by large-scale mechanized farming in the region. Although cultivated area has increased during the study period, the crop yield per unit for the five major crops remained the same with a slight fluctuation. This fluctuation in crop yield might be attributed to the amount of rainfall that varies for one year to other in Gedaref state (Osman *et al.,* 2021). Therefore, the expansion of cropland is probably due to the high demand for food to meet the need of the rapid population growth in Gedaref and Sudan at large.

In the present study, the forest area has dramatically decreased, which is in agreement with the farmers' perception. The increase of cropland area at the cost of forest and grassland areas between 1988 and 2018 could be attributed to the expansion of mechanized farming in Gedaref state (Issa, 2018). Additionally, the interviewed respondent (local land users) correctly perceived an increment in the settlement in recent years, confirming the findings of satellite-based LULC changes in the period of 1988–2018. The results of this study also concur with the findings of Abdelmalik et al. (2021), who recorded that forest area declined by 38.3%, while cropland and settlement areas increased by 61.1% and 225%, between 1990 and 2017, respectively in Gedaref state. The rapid population growth rate, the flow of refugees from the neighboring countries, high rates of natural increase and internal migration from other states to the study area accelerated the rate of LULC dynamics, especially the expansion of the settlement area (Mohammed, 2016).

The findings of the household surveys, FGDs as well as the key informant interviews, revealed that local land users perceived firewood collection, agriculture expansion, charcoal production, and settlements as the main proximate factors that drive LULC dynamic in Gedaref state. These factors were driven by the rapid population growth rate, high poverty level, rainfall fluctuation, high cost of inputs such as fertilizer and pesticides and lack of law enforcement by the government. Many studies emphasized the significance of studying socio-economic group variances in respondents' perceptions of LULC changes (López-Santiago *et al.,* 2014; Zoderer *et al.*, 2016). Accordingly, the results of this study showed a connection between the perception of LULC change drivers and socio-economic factors. The results of the multinomial logistic regression model showed that the perception of an individual of LULC change drivers differs from one person to another depending on certain socio-economic factors: their sex, sex of the head of the household, age, educational level, land tenure, land size, family size and farming experience. The results showed that sex of the respondents, sex of the head of the household, age, educational level, and farming experience are the most significant factors affecting the farmers' perception of LULC change drivers. The age of the respondents has significantly influenced their perception on charcoal production, construction, agricultural expansion, and poverty as the major drivers of LULC change. This confirmed the results of Ariti et al. (2015), who reported that age of the respondents significantly influenced farmers’ perception of LULC changes drivers in Ethiopia. Also, farming experience has significantly influenced farmers’ perception of charcoal production and construction as LULC change drivers. Moreover, educational level has significantly influenced farmers’ perception of poverty, lack of law enforcement and the demand for timber. According to Kouassi et al. (2021) and Ketema et al. (2021), experienced and educated land users are expected to have more information and knowledge about the drivers of LULC changes.

Overall, the perceived LULC change trends observed by the local land users and quantitatively by remote sensing approach were relatively similar. This revealed the advantage of earth observation tools in detecting and estimating the changes in LULC at a landscape scale and beyond. However, earth observation methods can encounter some sources of errors and cannot provide vital information on why the changes in LULC took place (Ewunetu *et al.,* 2021; Kleemann *et al.,* 2017). In contrast, local land users explained in detail the reasons for LULC changes and the underlining factors that drive such changes. For instance, local land users elaborated on why the area of forest in Gedaref state dropped while the amount of urbanization increased. Local land users elaborated on why forest coverage decreased and why settlement area increased in Gedaref state. This implies that the quantitative limitation of the earth observations can be improved by some information generated from the knowledge of local land users. Nevertheless, earth observations have advantages over the respondent's perception due to its capability to numerically quantify the rate, extent, and spatial-temporal dynamics of LULC patterns. However, the local viewpoint approach allowed for a more thorough explanation of the reasons these processes occurred during the study period. Consequently, the knowledge of local communities on LULC dynamics enables the identification of the important LULC drivers in a particular area. The LULC drivers cannot be easily determined through earth observation tools and this limitation could be complemented by the knowledge of local land users, a better understanding of LULC dynamics and consequently, better resource management.

The expansion in cropland area is positively correlated with climatic variables (temperature and rainfall) and population. Being a rainfed agricultural area, the fluctuation in the amount of rainfall in the past thirty years in Gedaref (Osman *et al.*, 2021) might have attracted more investors and small-scale farmers, leading to an expansion in cropland. On the other hand, the high demand for food to meet the high population growth rate in the state could have led to an increase in cropland, as earlier mentioned. This could also explain the strong positive correlation between population growth and the change in cropland area. A study by van Vliet et al. (2013) reported that the expansion in cropland prompted in the Sahel region is attributed to the population growth and the amount of rainfall, which is in accordance with the findings of this study. The results of this study also showed that climatic variables (temperature and rainfall) and population were negatively correlated with changes in the forest area. It has been demonstrated that a rapid increase in rural population growth resulted in a decreased forest area (Misra *et al.*, 2014). In the case of Gedaref state, the negative relationship between the population growth and the change in forest area might be due to the need for land and timber for house construction to meet the increased population. This could also explain the strong positive correlation between the population and the change in the settlement area. Indeed, the clearance of forests in rural areas is highly affected by agricultural expansion, woodcutting for timber and charcoal production (Misra *et al.*, 2014).

Although few significant relationships between climate, population, and LULC class coverage were detected in this study using the linear regression models, the coefficients of the models can be utilized to quantify the impact of these variables on LULC dynamics (Osman *et al.*, 2021; Poudel & Shaw, 2016). For instance, a unit increase in the population could lead to an increase in cropland and settlements areas by 0.6 and 0.02 ha, respectively, and a reduction in forest area by -0.03 ha. In addition, the positive or negative sign of the linear regression coefficients indicates a positive and negative change in the LULC class versus the change in climate variables and population growth (Nicholls, 1997). Furthermore, this study showed that the linear regression model captured 98%, 83% and 97% of the variability in the change of cropland, forest and settlements areas, respectively as a function of temperature, rainfall and population growth. This indicates that the change in cropland, forest and settlement areas were well explained by these three factors and the rest of the variations could be explained by the other confounding variables that were not included in the model.

7.4 Conclusions

In conclusion, this study examined LULC changes in Gedaref state, Sudan for the period between 1988 and 2018 using satellite-based data and a machine learning classification algorithm. The satellite-based LULC maps were compared with the farmers' perception and with actual ground truth data obtained from the Gedaref ministry of agriculture. The results showed an increase in cropland and settlement areas and a substantial decrease in forested areas during the study period (1988–2018). Also, the expansion in cropland was in line with the actual cultivated area during the study period. Firewood collection, agriculture expansion, and charcoal production were ranked by the local communities as the most important proximate drivers for LULC changes in Gedaref state. On the other hand, farmers identified poverty, population growth and the lack of law enforcement as the most important underlying drivers of LULC changes in the study area. Therefore, sustainable resource management in Gedaref state that allows for successful coexistence between local users and conditions for environmental, social, and economic well-being remains a significant challenge. Even though the current study was conducted at a landscape scale to assess how rapid human modifications and climate become a critical driving force for LULC changes, it implies the implication of these drivers on the global LULC change trends. Moreover, the findings of this study could be used in formulating environmental planning strategies, natural resources management, guidelines for the maintenance of ecosystem services, and conservation and utilization of natural resources in Gedaref region or other regions with similar settings.

7.5 Summary

Understanding land use/ land cover (LULC) dynamics and the factors that drive these changes is critical for future prediction of landscape structure and development of sustainable and robust land-management strategies and policies. However, little is known about the proximate and underlying factors driving LULC dynamics and perceptions of land users of these dynamics. This study aimed to i) assess the local farmers' perception of LULC changes in Gedaref state; and (ii) determine the drivers of LULC changes in Gedaref state. Initially, satellite-based LULC maps for the period 1988 – 2018 that were generated using a robust approach were utilized in this study. Subsequently,

Mann–Kendall trend analysis was used for the satellite-based LULC changes (area in ha) and the actual crop cultivated area (ha), which were compared with local farmers' perceptions. A multinomial logistic regression was also employed to determine the major drivers that influence LULC changes in Gedaref state. This was based on a semi-structured questionnaire with 400 respondents. Furthermore, Pearson correlation test and multiple linear regression were employed to assess the effect of change drivers on the area (ha) of the main landscape classes in Gedaref state (i.e., cropland, forest and settlement). Cropland and settlement areas increased (from 78.64% to 89.59%) and (from 0.11% to 0.44%), respectively, during the study period. In contrast, forest area decreased (from 1.08% to 0.47%). The results of the semi-structured questionnaire revealed that the satellite-based LULC change trends (area) agreed with respondents' perceptions. Specifically, 55.5% of the respondents observed an expansion in the cropland area and 96.5% reported an increment in the settlement. Whereas 96.5% of the respondents observed a decline in the forest area. Furthermore, the study shows that the main drivers for LULC changes in Gedaref state were firewood collection, agricultural expansion, charcoal production, settlements, poverty and population growth. The sex of the household head, age, sex of the respondent, education level and farming experience significantly ($p \leq 0.05$) influenced the respondents' perceptions of LULC changes in Gedaref state. Moreover, temperature, amount of rainfall and population growth were positively correlated with the change in cropland and settlement areas (a correlation coefficient (r) ranged between 0.80 and 0.98). While the same variables negatively influenced change in forest areas, with r ranging between 0.47 and 0.88. The findings of this study could be useful for planners and decision-makers for developing coherent land use policies and management strategies. The next chapter will present an overall conclusions and recommendations on mitigating the impacts of climate change, and land use-land cover dynamics on small-scale farmers in Gedaref State of Sudan.

CHAPTER EIGHT

SYNTHESIS, GENERAL CONCLUSIONS AND RECOMMENDATIONS

8.1 Introduction

This chapter provides general conclusions and recommendations and highlights potential future research areas on climate change and land use/ land cover (LULC) in Gedaref State and other similar settings.

8.2 Synthesis

The preceding chapters of this thesis investigated the impacts of climate trends and LULC changes on crop production of small-holder farmers in Gedaref state, Sudan. Despite the importance of climate change in the agricultural sector, little is known about climate variability and change in Sudan and there is no study that had assessed the relationship between climate trends and crop yield in Gedaref state, which is the Sudan's hub of rainfed agriculture area. This might be due to the fact that assessing climate impacts on crop yield is a challenging endeavor, because crop yield is associated with many factors, such as soil fertility and agricultural inputs, rather than climatic variables (Nicholls, 1997). In addition, mapping LULC trends, and their intensities and the driving factors triggered changes in landscape structure for the entire Gedaref state. This has not been investigated before. Furthermore, small-scale farmers' perception of climate trends and LULC changes has not been assessed. Therefore, further work is required to comprehend LULC dynamics and climatic changes in Gedaref state. This thesis has contributed to knowledge generation that helps to bridge these information gaps.

Chapter four looked at climate and crop yield trends in Gadaref state between 1984-2018 using Man-Kendall trend analysis (Kendall, 1948), daily climatic observations (rainfall and temperature) and annual crop yield data for five major crops that are commonly cultivated in Gedaref state under rainfed conditions; namely, sorghum, sesame, millet, cotton and sunflower. An in-depth analysis of temperature and rainfall variability indices between the years, rainfall patterns such as the amount of rainfall, onset and cessation dates, length of the rainy season, and the number of rainy days in each year were carried out. In addition, the relationship between the length of the rainy season and crop yields was established for a better understanding of the effect of rainfall patterns on crop yields. Furthermore, the relationship between climatic variables and crop yields was determined. Although assessing the impact of climate change on crop yield is difficult as mentioned earlier, the present study overcame the challenge of separating non-climatic variables using the so-called 'first difference approach'. This method was initially introduced by Nicholls (1997) and thereafter adopted by studies that evaluated the effect of climate change on crop yield (El-Maayar & Lange, 2013; Peltonen-Sainio *et al.,* 2010; Zhang *et al.,* 2014).

Since chapter four looked at climate and crop yield relationships, it is important to understand the perceptions of the affected community, especially small-scale farmers who are more vulnerable to climate change. Thus, chapter five analysed the perceptions of small-holder farmers of climate variability and change and identified the adaptation measures that they use to cope with its negative impacts on their farming activities. This was done using a semi-structured questionnaire, key informant interview and FGD. The farmers' perception of climate variability and change was compared with the actual trend of meteorological records. This enabled the understanding of whether the small-holder farmers are aware of climate change in Gedaref state. Understanding climate trends, climate and crop relationship, and farmers' perception are very important in awareness creation amongst different stakeholders and policymakers. In addition, it highlights the need for resource allocation to support the uptake of adaptation practices that ensure resilience amongst agricultural communities within the state. This can be useful in implementing and monitoring adaptation measures through the integration of farmers' perceptions with scientific knowledge to improve crop yield in Gedaref state and other rainfed agricultural areas in Sudan.

Land use land cove change (LULC) and climate change are related to each other (Dale, 1997). For example, in Sudan, the reduction in rainfall has turned millions of hectares of marginal semi-desert grazing land into a desert (UNEP, 2007). On the other hand, large-scale deforestation might lead to warmer climatic conditions and change the rainfall pattern. Therefore, the emerging challenge of climate and LULC changes should not be considered independently but to evaluate the combined effects of these changes. Hence, chapter six mapped the spatio-temporal changes in LULC over time in Gedaref state for the years 1988 to 2018 using remote sensing techniques, Google Earth Engine and the machine learning random forest classifier. For the first time, this study determined the underlying dynamics that cause the changes in the landscape structure using intensity analysis. In addition, the study predicted the future LULC trends for the years 2028 and 2048 using cellular automata-artificial neural network (CA-ANN). This helped in providing information on LULC patterns in Gedaref region that could be useful for designing management plans and developing policies for assessing and monitoring crop and grassland production, other natural resources produce, landscape fragmentation and degradation, and ecosystem functions.

Overall, the earth observation tools (remote sensing) have an advantage of detecting and estimating the changes in LULC at a landscape scale and beyond. However, earth observation methods can encounter some sources of errors and cannot provide vital information on why the changes in LULC took place (Ewunetu *et al.*, 2021; Kleemann *et al.*, 2017). Therefore, it is important to integrate the results generated from remotely sensed data with the perception of local land users for better understanding the approximate and underlying drivers that cause the change in landscape structure. In this regard, chapter seven assessed the perception of local land users on LULC change trends and determined the approximate and underlining drivers that caused LULC dynamics in Gedaref state. The local land users explained in detail the reasons for LULC changes and the underlining factors that drive such changes. For example, the local farmers provided a detailed explanation on why forest area in Gedaref state declined while the cropland and settlements areas increased in the last decades. Such information cannot be generated from remote sensing imagery and that is the advantage of engaging the local land users in such studies. In fact, the perceived LULC change trends observed by the local land users and that quantified by the remote sensing approach were relatively similar, which indicated the reliability of the classified LULC maps in chapter six. In addition, the expansion in cropland area generated from LULC maps was also similar to the trends of the cultivated areas that were obtained from the ministry of agriculture in Gedaref state. Furthermore, the relationship between the expansion in cropland area and crop yields was also determined in chapter seven.

8.3 Conclusions

The average annual temperature in Gedaref state has increased by 0.04°C per year for the period between 1980 and 2018, with fluctuation in the amount of rainfall and frequent occurrence of droughts, confirming the earlier report of climate variability and change in Sudan. Between 1984 and 2000, the anomalies of annual temperature were below the long-term average, indicating a cold period in the study area. However, after the year 2000, temperature anomalies were above the long-term average, indicating a warm period. The increase in maximum and minimum temperatures by 0.03 and 0.05 per year, respectively, has negatively affected crop yields of five major crops that are cultivated in Gedaref state under rainfed conditions, namely; sorghum, sesame, millet, cotton and sunflower. On the other hand, the trend and standardized anomalies of rainfall in Gedaref states showed that the amount of rainfall fluctuated over time with frequent occurrence of droughts in the years 1984, 1987, 1990, 1991, 2011, and 2013. The amount of rain and the length of the rainy season were the most important climate factors that positively influenced the yield of sesame, sorghum, sunflower, and cotton in Gedarfe state.

Climate change has taken place in Gedaref state, and it has a negative impact on crop yields. Fortunately, small-scale farmers in this state are aware of climate variability and change and they have developed some adaptation measures to cope with this negative climate change impact. These adaptation measures include crop rotation, early cultivation, and cultivation of short-maturing crop varieties, mixing farming, use of appropriate agricultural inputs such as fertilizers and introduction of drought tolerant varieties. However, the uptake of these adaptation measures depends on the socio-economic characteristics of the farmer. For example, the uptake of mixed farming considerably depends on sex of the head of the household, land tenure, and family size. Therefore, government policies that promote climate adaptation strategies in Gedaref state should consider the socio-economic indicators of the farmers to enhance their likelihood and adoption rate of such climate-smart technologies.

There was a drastic change in LULC in the period between 1988 and 2018. Cropland was the most dominant LULC class in Gedaref state. Forest and grassland areas were considerably decreased by 56.47% and 56.23%, respectively, between 1988 and 2018. However, cropland and settlement areas dramatically increased by 13.92% and 319.61%, respectively, during the study period. This clearly demonstrates that the expansion of cropland and settlements areas was at the expense of forest and grassland areas. The future prediction showed a slight increase in cropland area from

89.59% to 90.43% and a considerable decrease in forest area (0.47% to 0.41%) between 2018 and 2048. Therefore, the study concludes that the total cultivated area and settlements are increasing in Gedaref state at the expense of forest and grassland due to cumulative anthropogenic activities.

The increase in cropland and settlements areas and decrease in the forest area in Gedaref state were validated using the perceptions of the local land users. The small-holder farmers identified 12 approximate and underlining drivers of LULC changes in Gedaref state. The approximate drivers that caused LULC dynamics were firewood collection, agricultural expansion, charcoal production, settlements, construction, timber, bush fires. While the underlining drivers were poverty, population growth, lack of law enforcement, lack of financial resources and demand for timber.

8.4 Recommendations

Based on the aforementioned concluding remarks, this study recommends the following for new insights, policy strategies and future research:

1. There is a need for awareness creation amongst different stakeholders and policymakers in Gedaref state on the impacts of climate variability and change on crop production and the need for resource allocation to support the uptake of adaptation practices that ensure resilience amongst agricultural communities within the state,

2. Government should emphasize and put more effort into enhancing the adaptive capacity of small-scale farmers to climate change in Gedaref state through extension services, agricultural inputs, education of the farmers and diversification of the source of income to improve food and nutrition security,

3. Government policies that promote climate adaptation strategies in Gedaref state should consider the socio-economic factors that influence the uptake of adaptation measures to improve the likelihood of small-holder farmers. This enables an enhanced adoption of climate-smart strategies to cope with negative impact of climate change,

4. Farmers should be well trained in adopting climate-smart adaptation measures to improve crop yields and income under a changing climate,

5. The protection of the natural resources in Gedaref state, such as forest, requires strong policy enforcement framework to minimize the risk of deforestation and land degradation,

6. This study used only climatic variables (temperature and rainfall) to assess crop yields under climate change and it did not incorporate other factors that influence yields such as soil properties and other farming practices. Future studies should include all factors that influencing crop yield in a holistic modelling framework such as DSSAT, and

7. The study recommends that the models developed for estimating crop yields should be tested and assessed using an independent test dataset collected at different points in time.

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Appendices

Appendix 1: Questionnaire

General Information

Enumerator's Name: ___________________________________

Date of Interview: ______________________________________

Village: ______________________________ Locality: _________________________________

Geographic coordinates: ____

Respondent's Name: __________________________________Phone No: __________________

Number of years the respondent is living in the village: _________________

A. General Questions

1. Demographic and Socioeconomic Characteristics

Sex of the respondent **Codes A**	Head of the household **Codes B**	Marital status **Code C**	Age **(years)**	Education **Code D**	Experience in agriculture **(years)**	Main sources of income **Code E**	Land tenure **Code F**	Land size **(ha)**	Family size	Estimated annual income

Codes A
0=Male
1=Female

Codes B
0=Male
1=Female

Codes C
1 Single
2 Married
3 Separated
4 Divorced
5 Widowed
6 Refused to answer

Code D
1 Illiterate
2 Primary
3 Secondary
4 Graduate

Codes E
1 Farming (crop + livestock)
2 Salaried employment
3 Self-employed (business, trade, handicraft)
4 Selling of forest produce (e.g. charcoal, firewood, timber, poles)
5 Other, specify………

Code F
1Owned
2 Rent in
3 Share in
4 Share out

B. Climate Change Perception

1. Do you observe any changes in the rainfall pattern in last 20 years?

   Yes ( ) No ( )

2. If yes, what are the changes you observed? (Multiple choices are possible)

   a. Decrease of rainfall amount ( ) b. Increase of rainfall amount ( )

   c. Late onset of rainy season ( ) d. False onset of rainy season ( )

e. Early end of rainy season ( ) f. Rainfall fluctuations/erratic ( )

g. Frequency of droughts ( ) h. Frequency of floods ( )

i. Increased length of the dry spells ( ) j. Other (specify):______________________

3. Have you faced drought over the last 20 years?

   Yes ( ) No ( ) Don‘t know ( )

4. If yes, how do you describe the frequency of occurrence of drought for the last 5-10 years as compared to the past 30 years?

   Increased ( ) Decreased ( ) Followed a similar trend ( )

5. Have you faced a flooding problem over the last 20 years?

   Yes ( ) No ( ) Don‘t know ( )

6. If yes, how do you describe the frequency of occurrence of flood in last 5-10 years as compared to the past 30 years?

   Increased ( ) Decreased ( ) Followed a similar trend ( )

7. Do you observe any changes of temperature during summer season?

   Yes ( ) No ( ) Don‘t know ( )

8. If yes, what are the changes you observed?

   a. Increase of daytime temperature ( ) b. Decrease of daytime temperature ( )

   c. Increase of nighttime temperature ( ) d. Decrease of nighttime temperature ( )

   e. No change ( )

9. Do you observed any changes of temperature during winter season?

   Yes ( ) No ( ) Don‘t know ( )

10. If yes, what are the changes you observed?

    a. Increase of daytime temperature ( ) b. Decrease of daytime temperature ( )

    c. Increase of nighttime temperature ( ) d. Decrease of nighttime temperature ( )

    e. No change ( )

C. Adaptation Options

1. Do you think climate change has already happened?

   Yes (   )   No (   )   Don‘t know (   )

2. If the answer to Q.1 is yes, how did you feel that on your farming activities?

   a. Positively affected (   )   How? ____

   b. Negatively affected (   )   How? ____

3. How do you evaluate the trend of crop production for the last 30 years?

   a. Increasing (   )   b. Decreasing (   )   c. The same (   )   d. I do not now (   )

4. What alternative measures do you take when enough rain is not available for your farm?

____

____

5. According to your view, are those measures effective enough to save crops? Explain?

____

____

____

6. Does the local government provide any support in facing challenges related to climate change?

   Yes (   )   No (   )

7. What are the agricultural adaptation measures you have taken to cope with climate change?

No	**Adaptation options**	**Mark**
a	Early cultivation	
b	Delayed cultivation	
c	Cultivation of short maturing varieties	
d	Intercropping	
e	Crop rotation	
f	Soil conservation	

g	Practice supplementary irrigation	
h	Use of technologies as fertilizers and pesticides	
j	Introduce water stress tolerant varieties (specify) _____________	
k	Rainwater harvesting	
l	Cover the soil around the plant with straw, stone, plastic and/or crop residues to facilitate water infiltration and decreased water evaporation	
m	Mixing farming	
n	Use of underground water	
o	Others (specify) ____________________________________	

8. Are you interested in using adaptation measures? Yes ( ) No ( )
9. Why? ____

____

____

10. Do you have access to climate information? Yes ( ) No ( )
11. If your answer for Q 10 is yes through which channel do you receive the climate information?
    a. Government extension officers ( ) b. Radio ( ) c. Mobile phone ( ) d. Personal contact or social group ( ) e. Research institutions/NGOs f. Development agents ( ) g. another channel, specify ____
12. Have you got advice in agricultural activities from extension service? Yes ( ) No ( )
13. If the answer to Q 12 is yes on which area the advice was given?
    a. Crop husbandry ( ) b. Crop diversification ( ) c. Animal husbandry ( )
    d. Marketing ( ) f. Post-harvest ( ) g. Climatic information ( )
    h. Others, specify____

D. Land use/ land cover Perception

1. Did you observe changes in cropped areas? No ( ) Yes ( )
2. If your answer for Q 1 is yes, has crop production area declined or increased over the past 20 years in your community?

   a. Declined ( ) b. Increased ( )
3. Has crop production declined or increased over the past 20 years in your community?

   a. Declined ( ) b. Increased ( ) c. No change ( )
4. If you indicated that crop production has declined, which, in your opinion, are the main reasons for this decline in crop production? (**Check the one that applies**)

Soil infertility		Lack of agricultural inputs		Pests and diseases		Inadequate labour	
Unreliable rainfall		Fluctuating markets/prices		Lack of knowledge and skills		Limited land	
Lack of improved seed		Lack of money for inputs		Other			

5. Do you know of any forests in your area?

   No ( ) Yes ( ) Name them: ____
6. If yes, how do you think these forests came into existence?

   a. Natural ( ) b. Man-made ( ) c. Both ( )
7. What is the current status of the forests in your area?

   a. Declining ( ) b. Constant ( ) c. Increasing ( )
8. If the answer is declining is it due to?

   a. Settlements ( ) b. Population growth ( ) c. Agricultural expansion ( )

   d. Cutting ( ) e. Forest fires ( ) f. Grazing ( )

   g. Lack of law enforcement ( ) h. others, specify_____________________

9. Do you think the population of your community has increased over the past 20 years?

No ( ) Yes ( )

10. If yes, what do you think have caused the population increase?

a. High fertility ( ) b. Immigration ( ) c. Both high fertility and immigration ( )

b. Other, specify ____

11. Do you think that more land will be needed as your family grows?

No ( ) Yes ( )

12. If yes, how much extra land do you think you will need when you have a new family member?

a. 0.5 acres ( ) b. 1 acre ( ) c. 2 acres ( ) d. > 2 acres ( )

e. Don't know ( )

13. What kind of land would you clear when your family size increases?

a. Forest ( ) b. Fallow land ( ) c. Grazing land ( )

c. Other (specify) __________________

14. What do you think are the causes of land-use and land-cover changes in your area (rank on a scale of 1 to 5; 1 = least important and 5 = most important).

Proximate cause	**Rank**					
	1	**2**	**3**	**4**	**5**	
Firewood						
Charcoal production						
Timber						
Construction						
Agriculture expansion						
Bush fires						
Settlements						

Others (Specify)						
Rank						
Underlying Causes	**1**	**2**	**3**	**4**	**5**	
Poverty						
Population growth						
Lack of financial resources						
Lack of law enforcement						
Demand for timber						
Others (Specify)						

Appendix 2: Key informant interviews

A. General Information

Respondent's name: ____

Respondent's email: ____

Respondent's organization: ____

Respondent's sex: ____

Village: ____

B. background Information

1. Respondent's Role (e.g. farmer, village leader, extension officer)

   ____

2. Main livelihood(s) in village

   ____

3. How many years have you lived in this area?

   ____

4. What is your age?

   ____

C. Changes in Climate

1. What are some of the biggest changes you have observed over the last few years?

____

____

____

____

2. Please place a check mark next to the changes in weather, climate and extreme events that took place. Check all that apply

Increased rainfall	
Decreased rainfall	
Changes in timing of seasons	
Drought	
Loss of water source	
Flooding	
Heat waves/hotter days	
Cold spells	
Wildfires	
Changes in wind	
Erosion/landslides	
Other (please specify)	
None	

D. Impacts and Responses

1. How have the changes in weather you mentioned above impacted your main livelihood?

____

____

____

2. How have people in the area responded to these impacts?

____

____

____

____

3. Which of these responses is working well and which isn't?

____

____

____

____

____

4. How have the changes in climate you mentioned affected natural resources used by the community?

____

____

____

____

____

5. Please place a check mark next to the change in activities in response to changes in weather and climate that have mentioned above?

Crop practices	
Livestock practices	
Livelihood type	
Livelihood location	
Water management	
Disease/Pest management	
Natural resource use	
Natural habitat encroachment	
Land conversion	
Migration	
Other (please specify)	
None	

Appendix 3: Checklist for focus group discussions

Background information of respondent:

- Income level
- Household size
- Head of the household
- Farm size
- Rainfall and temperature variability
- Timelines and trend lines

Current exposure sensitivities Climatic risks:

- Temperature changes
- Rainfall changes
- Droughts
- Perception(s) towards major climatic hazards
- Biophysical/Social/Economic
- Water and climate
- Historical data (when and how exposed)

Current adaptive/response strategies Present adaptive practices/ responses:

- Formal and Local response mechanisms
- How exposures are managed
- What constrains adaptive strategies

Land use and land cover change:

- Changes in cropped areas
- Crop production declined or increased over the past 20 years in the community
- If crop production has declined, what are the main reasons for this decline in crop production
- Forests in the area and from where these forests came into existence
- The current status of the forests in the area
- If the answer is the forests declining, what is it due to
- The status of the population in the community
- The causes of land-use and land-cover changes in the area