MAPPING AND MONITORING THE IMPACTS OF CLIMATE VARIABILITIES ON RANGELANDS IN NORTH DARFUR, SUDAN

by

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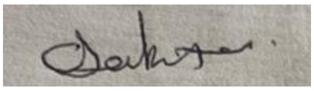
Declaration

I, Chido Jakata, declare that this research report is my own unaided work. It is being submitted for the Degree of Master of Science in Geographical Information Systems and Remote Sensing to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other university.

Signed ……  ………   Date…….20 October 2022……….

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Abstract

In North Darfur, rangelands are of great importance as they support economic activities such as pastoralism and help in environmental management by reducing desertification. However, alterations or shifts in rangelands may take place due to climate variabilities posing problems for resource and land managers as they seek to familiarise to variations in the environment and monitor and partially control effects of climate variability. Shifts in rangeland quality and quantity which may be experienced owing to climate variabilities pose problems for environmental managers as they are working on conserving and mitigate adverse impacts of climate variabilities on rangelands. The region has experienced various environmental and social impacts because of its ecological structure and geographical location. Massive alteration of the rangelands on farmlands have been experienced, leading to conflicts between farmers. Therefore, the monitoring of the rangelands for a longer season in North Darfur could lead to the increase in rangeland productivity. Conventionally, field-based surveys including focus groups, in-depth interviews, ethnography, questionnaires, and intercepts were implemented to monitor land use changes on bare land, rangelands, waterbodies, and farmlands. However, these methods have low spatial coverage making them unreliable in studying land uses and land cover change, especially over long periods of time. In this study, remote sensing (RS) Landsat 4,5,7 and 8 images and temperature and rainfall products were used for the period between 1985 and 2020 at five-year intervals. For each image, 29 scenes were downloaded to cover the whole study area. Using the climate data, rainfall and temperature anomalies were calculated to quantify climatic trends. Random forest classification was run in Aeronautical Reconnaissance Coverage Geographic Information System (ArcGIS). The land cover classes used in this study were bare land, farmlands, rangelands, and water bodies. Additionally, the Soil Adjusted Vegetation Index (SAVI) was used monitoring rangeland productivity in North Darfur. The findings of the study outlined and proved the early part of the period studied rangelands were dominant, covering up to 20% of the study area. Rangelands also covered most of the southern parts of the study area. However, by 2020, rangelands only covered 8% of the total area. Waterbodies concurrently decreased significantly, covering just 1% in 2020, where previously they had covered 18%. In contrast, farmlands became more dominant in the southern part of North Darfur by 2020, covering 33% of the total area while bare grounds increased to 58%. It is recommended that the government and the environmental managers in Sudan implement measures that help in safeguarding rangelands for sustainability.

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CHAPTER ONE

1. GENERAL INTRODUCTION

Kang et al., (2020) defined rangelands as areas unsuitable for land tillage and are a source of wood products, wildlife, and water. In addition to that, (Kang et al., 2020) also referred to rangelands as a source of forage for domestic and free-ranging native animals. Historically, summit vegetation was principally grass like plants, shrubs or forbs as projected by Butler et al., (2003). In the past decades, rangelands have accounted for at least 70% of all global land surface and 43% of the African land surface (Butler et al., 2003; Holechek, 2001). They support various types of vegetation which includes shrublands that are found in deserts and semi-desert areas (Butler et al., 2003). Rangelands may be naturally stable but however they can be temporarily directly disrupted by timber harvest as highlighted by Heady and Childs (1994) and Holechek (2001). Around 40 million pastoralists are found in the third world developing countries most of whom are subsistence herders who depend on natural grazing for their livelihoods (El-Dukheri, 2004). In North Darfur State (hereafter referred to as North Darfur), rangelands are of great importance as they support economic activities such as pastoralism and they help aid in environmental management (Mohamed et al., 2015). Rangelands provide services and ecosystem goods in North Darfur. Some conservation techniques applied on rangelands pose quite several social and economic effects both directly and indirectly. The conservation practices implemented on the rangelands produce quite several direct and indirect economic and social effects on them. Varying natural resource management and basic ecological linkages can directly influence quality and extent of goods and services produced.

North Darfur has experienced various environmental and social impacts because of its ecological structure and geographical location (Mohamed et al., 2015). Massive alteration of the rangelands on farmlands have been experienced, leading to conflicts between farmers and pastoralists. According to Mohamed et al., (2015), rangelands in North Darfur have been impacted on by climate variability which had led to changes in uses and cover of land. Concentration of precipitation is a significant factor in influencing desertification and land alteration in the Sahelian zone of Sudan. This concentration of precipitation takes place in two levels; on the one hand, rainfall is concentrated within the summerly wet season (high seasonality) and on the other, precipitation falls in a small number of short high intensity rainfalls at a time (Ibrahim, 1984 and Mohamed et al., 2015). A study by Ibrahim (1984) in eastern Sudan revealed that 84% of the annual precipitation falls between July and September.

According to Muneer (2008) high seasonality in climate, impacts on ecological processes differently in the various regions because the seasonal warming patterns and the modifications of precipitation are uniquely demonstrated in each region. According to Kevane and Gray (2008), high seasonality greatly impacts on rangelands as climate change or shifts exacerbate climate effects on animal and plant productivity and have impacts on the surface water reservoirs. According to Campos et al., (2013) severe climate seasonality may exacerbate the plant mortality in arid ecosystems as the present plants already withstanding limited accessibility of water.

Conventional tools, namely use of field-based surveys, were used in Darfur by Ibrahim (1984) and other areas by Sulieman and Elagib (2012) and Othow,et al., (2017) to study land use changes. These methods allow for the intervening of the moderator at any given point of the study and the moderator is capable of challenging and questioning of the participants. Ibrahim (1984) in his study of ecological imbalance proved conventional tools lack high spectral, spatial and temporal resolutions showing that conventional tools are not ideally suited for studying land use and cover change. With incorporation of remotely sensed data, the limitations of the conventional approach which include low spatial, temporal and spectral resolutions are addressed. Remote sensing (RS) technology and Geographical information systems (GIS) were incorporated by Sulieman and Elagib (2012) in their study in eastern Sudan on the implications for pastoralism and climate on the changes of the use and cover of land. Their main aim was to examine land use and landcover changes and changes in climate in El Gedaref livestock routes (Sulieman & Elagib, 2012). Their key findings were related to the main trends involving major shifts of natural vegetation in rangelands into large-scale cultivation land. The results of Sulieman and Elagib (2012) using high temporal and spatial resolution were significant in that they managed to cover a long period of time and contribute to resolving of complex land-management issues. Their findings revealed the major trends were drastic conversions of natural vegetation areas into large-scale mechanized agricultural land (Sulieman & Elagib, 2012).

1.1. Problem statement

North Darfur is in the marginal tropical region dominated by a desert in the north, the Jebel Marra Mountain at the very centre and also include the savannah in the south. Precipitation is concentrated into a short summer period with 30 ° C recording of the average temperature annually and average precipitation annually of just 54 mm (and both varying over space and time) (Othow et al., 2017). Range productivity varies from 0.8 t in the north to 25 t in the south. Owing to the climate variability, new agricultural approaches have been introduced through Western Savannah Development; these include permanent and seasonal ranching systems (AIACC, 2006). These new systems have led to excessive and uncontrolled farming which has accelerated desertification in North Darfur. Impacts of desertification have been noticed in the region which led to a shift of the region's boundary to the south between the semi-desert and the desert (An estimated distance of 50–200 km since 1930s when the recording of rainfall and vegetation began) (Vroman, 1999). Forward projections for Sudan suggested that from 1990 to 2005 projected, Sudan would have lost 12% of its forest cover due to the clearance of land to meet the energy needs (Vroman, 1999). With the escalation of desertification leading to shortage of land both for farmers and pastoralists, resource conflicts began, and continued to escalate. This led to the need for environmental management to find ways to quantify, monitor and protect rangelands. In eastern Sudan, changes in land uses/cover were determined by multi-temporal satellite imagery downloaded and investigated for 3 different sites along the eastern El Gedaref livestock routes (Sulieman & Elagib, 2012).

Sulieman and Elagib (2012) using remote sensing observed major changes and shifts of rangeland areas into large scale mechanized agricultural land, which leads to an increased rate of reduction of pasture in the whole region. During the 30 years of their study, time series of the data investigated revealed that 75% of the study period it was warmer that average and these changes rate of increase was 0.53 ˚C, 0.22 ˚C and 0.38 ˚C per decade for minimum, maximum and mean temperatures, respectively (Sulieman & Elagib, 2012). According to Flash Update Sudan (2021) in North Darfur, conflicts are ongoing. Thus, there is the need to map and monitor the effects of climate variabilities, and the changes in land uses/cover in rangelands. Availability of this data will contribute to proper safeguarding of rangelands and assist policymakers to prevent ongoing rangeland/environmental degradation. With remote sensing at high spatial and temporal resolution, longer study periods can be covered, and the spatial and temporal pattern and changes to rangelands can be monitored in North Darfur (Sulieman & Elagib, 2012).

1.2. Aim

The main aim of this research was to examine the effects of climate variabilities on rangeland dynamics in North Darfur using earth observation data.

1.3. Research objectives

The specific research objectives are to:

- Quantify the land use and land cover of North Darfur for 35 years at five-year intervals using Landsat images;
- Determine the spatial and temporal changes in temperature and rainfall patterns of North Darfur over 35 years; and
- Determine the productivity of Rangelands in relation to space and time of in North Darfur over 35 years.

1.4. Research questions

- How much has the land use and land cover of North Darfur changed in the past 35 years?
- What are the spatial and temporal changes experienced in temperature and rainfall patterns of North Darfur over the past 35 years?
- What are the spatial and temporal changes on rangelands that have taken place in North Darfur in the past 35 years?

1.5.Thesis Outline

The first chapter is an introduction that provides context for the research question, problem statement, and objectives. The second chapter highlights pertinent literature to situate the forthcoming research within existing theoretical paradigms and to highlight areas where additional research is required. The third chapter provides an explanation and justification for the employed research methodology, detailing the data collection methods with a focus on the scope and parameters. The fourth chapter presents descriptive statistics, the results of the statistical analysis, and images that illustrate the spatial and temporal results. Chapter 5 then provides a discussion of the research findings. In Chapter 6, there will be a conclusion, followed by a discussion of the study's limitations and recommendations for future research.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Overview of rangelands

Rangelands are areas of the world with low and erratic precipitation, poor drainage, and rough topology (Rhyma et al., 2020). Again, according to Rhyma et al., (2020) these are physical constraints that make the areas unsuited for farming and are mainly in the semi-arid regions and serve as forage pastures for the wild and domestic animals. This natural vegetation are also a source of water and wood products (Rhyma et al., 2020). Although estimates vary, of the earth's surface, 15% consists of ice, rock and desert, 3% in man-made constructions, 10% cropland, 25% dense forest and rangelands cover to about 47% of the total land surface (Ki-moon, 2022). Several vegetation types are supported by rangelands, and these also include temporary tree less areas in forests, deserts and steppes (Othow et al., 2017). Rangeland is also associated with soils which can be sandy, rocky, wet or saline (Frahaldour *et al*., 2008). Examples of rangelands include tall grass prairie and Pacific bunch grass in North America, and the South American rangelands consisting of the Patagonian Steppe, the Monte, the Pampas (Juma et al., 2020). In Africa, the rangelands include Darfur rangelands in the north of Sudan and the Kenyan rangelands dominated by the Masai people (Juma et al., 2020).

2.2. Characteristics and significance of, and threats to rangelands in North Darfur, Sudan

According to Frahaldour, et al., (2019), rangelands of Sudan cover about 110 million hectares (46%) of the country's total area. These vast rangelands grounds varying ecological zones reaching out from semi-deserts and deserts in North Darfur to low and high rainfall located in the southern parts. These differences in rangelands support mechanised agriculture forming part of the diverse production systems (Zaroug, 2000). The rangelands add to the revenue and subsistence of a huge proportion of the populace of Sudan (Hakim, 2011). Rangelands in Sudan also provide the animal herds with more than 80% of its total feed (Hakim, 2011). According to Sulieman & Elagib (2012), rangelands host wildlife and are important in the safeguarding of watershed, soil, ecological balancing and environmental sustainability and conservation. Rangelands in North Darfur constitute of grazing lands (grasslands, seasonal water courses), woodlands, mountain slopes and hills (Zaroug, 2000). From the north going to the south, the density and diversity of vegetation exacerbated from being semi-desert to being an area experiencing high savannah conditions (Zaroug, 2000). According to USAID (2016), pasture, water and forestry are the most crucial natural resources for pastoralism. Smith (2021) defines pastoralism as a form of land use system that depends mainly on livestock-raising using these interdependent natural resources. The sustainability of pastoralism and pastoral production systems therefore depends on the way these resources are managed (Smith, 2021). This also depends on how land managers and users interact with other components of the rangeland system (Campos et al., 2013).

According to Jail (2009), several environmental problems are encountered in North Darfur, and these include seasonal demand (including from pastoralists) increases for pasture, encroachment of the desert, extension of rainfed agriculture. This upsets the demand and supply of pasture for animals (Mohamed et al., 2015). Formally, a principal change that occurred was the legitimization of the illegal situation of the large-scale farmers (LSFs) (Sulieman, 2015). Simultaneously, LSFs were not obligated to follow the set laws issued by the state. According to Sulieman (2015) with their financial stability and capabilities, they accumulated vast amounts of land whilst they were also at a large extent involved in the rearing of livestock. Moreover, the introduction of agricultural technology in terms of machinery in the marginal regions caused inauspicious consequences to the environment including severe soil degradation prompting desertification (Sulieman, 2015).

Therefore, with the current production systems, negative environmental impacts are highly likely to continue. Rainfed agriculture at an excessive rate has been proven to be one of the main influences of desertification in the semi-arid region (Ibrahim, 1984). However, Lu et al., (2004) are of the view that two factors are involved with desertification, namely unsuitable land use methods and variability of rainfall. Consequently, Teluguntla et al., (2018) said the major cause for degradation is high rainfall variability. This is so because the rainfall and soil conditions mentioned are regarded as persistent factors of the ecosystem in the semi-arid and arid zones. Van-Lynden and Mantel (2001) point out that humans can use the present resources in an adapted manner and safeguard productivity for longer periods of time. However, they also stated that if people misuse these resources using inappropriate methods to acquire enormous profits in a limited period, they will destroy the regenerate ability of the natural ecosystems (UNDP, 2007 and UNDP, 2008). Regarding that, compromises must be made however, they must not be detrimental to sustainability.

The pastoralists in North Darfur also play a main part in the safeguarding of rangelands as they migrate in accordance with the annual variability of precipitation (Visa et al., 2011). This enables rangelands to regenerate before the arrival of the herds and possibly allows for new seeds to develop as well (Ibrahim, 1984). This has led to division of pastures into four categories, namely: 1) all-year-round pastures located in the central zone of rainfed cultivation associated with dense settlements; 2) dry-season pastures found in the south-western part of North Darfur where precipitation ranges between 400 and 800 mm annually; 3) rainy season pastures found in the semi-desert in the far northern part of Darfur situated between the 100 mm and the 200 mm isohyets; and 4) cool-season pastures found in Wadi Howar and the Jizu area to the north of the wadi (i.e., a valley, ravine, or channel that is dry except in the rainy season) (Ibrahim, 1984; Visa et al., 2011).

2.3. Monitoring the effects of temperature and rainfall variability

According to Sulieman, (2015) climate variability can be monitored in two ways, either by a conventional/traditional approach or by using recent RS methods. Conventional methods include data recorded by filed-based instruments (Zaroug, 2000). These instruments provide records of rainfall, temperature, etc. However, these datasets have major problems in that there is not enough scope of rain gauges (Schneider, et al 2013). For example, in a study by Zeng (2018), in quantifying the effect of rain gauge density and distribution on runoff simulation, the results show that imperfect precipitation inputs measured by a sparse and irregular rain gauge network led to substantial uncertainty in model parameter estimation and flood simulation. According to Gyasi-Agyei (2020) the optimum rain gauge network density varies from 14 km2 /gauge to 38 km2 /gauge, with an average of 25 km2 /gauge. Thus, it vital to incorporate RS precipitation estimates obtained from satellites.

2.3.1. Conventional approach for monitoring the effects of temperature and rainfall variability

Rooy (1965) derived an index for rainfall called Rainfall Anomaly Index (RAI) which classifies rainfall as either positive or negative anomalies and is considered as an index which is remarkably simple and requires precipitation and temperature data (Freitas, 2005). As postulated by Rooy (1965) RAI compares precipitation deviations and have been used the world over for analyzing the annual precipitation variability. For example, Koko et al., (2020) used the rainfall precipitation index to estimate rainfall anomalies and its impact on crop production using climatic raw data for a period of 40 years. According to Koko., (2020), the results show that the region under study lies within wet areas for 19 years but however 6 of the years there was normal wetness whilst 15 years dry conditions were experienced. This shows great climatic change leading to the deficit of rainfall thus eventually impacting negatively on crop growth. Also, Liebman et al., (2017) used RAI to monitor variability of the precipitation in Northeast Brazil. To achieve this, seven meteorological station data for daily precipitation were used for the period 1974 and 2015. Liebman et al., (2017) observed that the driest season of the year occurred from July to October whilst the rainy period at the basin occurred from January to April. RAIs major advantage is that it is easy to calculate as it needs one input (Rooy, 1965). This study therefore, adopted rainfall anomalies to determine the changes in temperature and rainfall patterns spatially and temporarily of North Darfur over 40 years.

In western Darfur, the traditional approach was successfully used for monitoring climate variabilities by Elagib and Elhag (2011). From the Sudan Meteorological Authority, Elagib and Elhag (2011). Acquired monthly temperature and rainfall data was acquired for El Gedaref for the period 1941 to 2009. From the data, Standardized Anomaly Indices (SAIs) was determined for minimum (night-time) and maximum (daytime). Average temperatures and rainfall data was also used to determine the trends of climate from the baseline (Elagib and Elhag (2011) for the period 1971 to 2000. The long-term evolutions of rainfall and temperature validity was estimated using Kendall Tau test (Jones & Hulme, 1996). Results by Elagib and Elhag (2011) revealed that the rate of increase of the maximum temperature anomalies of El Gedaref were at a largest for the whole country of Sudan. In addition, the study by Elagib and Elhag (2011) reported that anomalies of the temperature variables of the period 1971 to 2008 are negatively significantly, corelated and aligned to the rainfall anomalies. This study by Elagib and Elhag (2011) entrusts convincing proof of severe climate change and present the increasing rainfall and temperature variability in the eastern region of Sudan (Ibrahim, 1984). This makes traditional tools very significant to use for climate monitoring. However, because of time constraints to get raw data from the stations, this may make it difficult to produce results to use in a study at the right time (Campos, 2013). Also because of lack of reliable spatial, spectral, and temporal resolution, traditional method can be biased (Rhyma, 2020).

2.3.2. Remote sensing methods for monitoring the effects of temperature and rainfall variability

According to Campbell (2011) remote sensing is the process of deriving information about the Earth’s land and water surfaces using images acquired from an overhead perspective, using electro-magnetic radiation in one or more regions of the electromagnetic spectrum, reflected, or emitted from the earth's surface. According to Navalgund et al., (2007) spectral, spatial, temporal and polarization signatures are major characteristics of the sensor/target, which facilitate target discrimination. Earth surface data as seen by the sensors in different wavelengths (reflected, scattered and/or emitted) is radiometrically and geometrically corrected before extraction of spectral information. RS data, with its ability for a synoptic view, repetitive coverage with calibrated sensors to detect changes, observations at different resolutions, provides a better alternative for natural resources management as compared to traditional methods (Navalgund et al., 2007). There are several types of sensors which include for example multispectral and synthetic aperture radar. There are also different satellite platforms which include the unmanned aerial vehicles and satellites and the manned aerial vehicles and these have been used for mapping a diversity of forest variables including the productivity of rangelands (Lechner et al., 2020).

Several precipitation estimates are acquired from RS data products. These estimates include the African Rainfall Estimation (RFE), Tropical Rainfall Measurement Mission (TRMM) and Climate Prediction Centre (CPC) just to mention a few (Naumann, 2012). Naumann (2012) also mentioned that near-surface temperature estimate (Ta) is vital for agriculture, climate change and climate-related diseases studies. Land Surface Temperature (LST) a product of Moderate Resolution Imaging Spectroradiometer (MODIS) is suitable for estimating minimum and maximum air temperatures (Vancutsem et al., 2010). When analysing these data sets, indices are used to determine anomalies. Rainfall Anomaly Index (RAI), a conventional statistical method, can be used to calculate these indices both for rainfall and temperature. Rainfall Anomaly Index (RAI), developed by Rooy (1965), is used to classify the positive and negative severities in rainfall anomalies. It is considered an index of remarkable procedural simplicity because it requires only one set of data (Freitas, 2005; Fernandes et al., 2009). According to Rooy (1965), RAI aims to make the comparison between precipitation deviations in different regions feasible.

2.4. Impacts of climate variabilities on rangelands

The process of monitoring and mapping climate variabilities is very important as the impacts of these variabilities on rangelands can have significant environmental consequences at local, regional and global scales (Sulieman, 2018). These changes have strong implications for loss of biodiversity, distress in hydrological cycles, and increased soil erosion. Several methods were developed for monitoring these effects (Mohammed et al., 2018). There are two ways in which these can be monitored, namely via conventional/traditional and remote sensing methods.

2.4.1. Conventional methods on monitoring the impacts of climate variabilities on rangelands

Conventional research methods involve the use of field-based surveys that include qualitative focus groups, in-depth interviews, ethnography, questionnaires, and intercepts. According to Larsson et al., (1995), convectional research methods provide platforms for further questioning from the moderator and he or she is also allowed to challenge the participants during the study. This approach can be used to study changes in rangelands dynamics. For example, the study by Ibrahim (1984) on desertification in North Darfur followed the conventional approach. Data on the socio-economic conditions were obtained utilising a questionnaire which was passed out in 354 households in different regions of North Darfur. However, land use/cover and climate variability studies using the conventional approach have proved to be limiting in that they fail to accurately determine temporal and spatial changes in coverage (Kevane & Gray, 2008). The previously mentioned study by Ibrahim (1984) failed to determine some of the uses of land present in the study area as a questionnaire is guided; thus, some information regarding the land uses can be missed out (Othow et al., 2017).

2.4.2. Remote sensing approach on monitoring climate variabilities impacts on rangelands

Rangeland monitoring involves the analysis of the resources of the earths and benefits that comes from using remote sensing products that can collect large quantities of data at a cheap and at regular basis over much greater spatial resolution compared to field study (Mantel & Van Lynden, 2001). Advantages of remote sensing comprise the acquisition of data at a high spatial coverage; to characterization of natural and/or physical features on the earth's surface.; monitor land surface area changes over time; and the ability to merge data with other information that help to aid decision-making (Haugen et al., 2018).

Monitoring rangelands using remote sensing overall aims at comparing spatial representations of two points in time. Monitoring change in the use and cover of land involves methods and techniques expanded following institution of digital imagery encompassing digital orthophotography, airborne scanners and satellite imagery (Jensen, 1982; Martin, 1986; Jampoler & Haack, 1990). For example, Luo et al., (2017) used MODIS satellite imagery for 2000 to 2015 was used for the characterization of the vegetation browning trends and to differentiate between grazing and climate influenced trends. To do so, they first examined statistical trends in NDVI, and NDVI residuals after de-trending. According to Luo et al (2017) 24% of NDVI and 9% of NDVI residuals of landscape were the declining trends as the browning trends expanded. This remote sensing approach demonstrates inexpensive and constructive remote sensing methods for rangeland monitoring. Vogelmann (1988) for the years 1973 to 1984 compared their Multispectral Scanner (MSS) data for the Vermont Green Mountains and observed a decrease in the Near infrared (NIR) for severely damaged sites. Reduction in area, green leaf biomass accompanied by escalation of dead plant biomass explains the decreased reflectance. These studies showed that rangeland data obtained from remotely sensing significantly contributes to the knowledge of spatio-temporal variation of earth resources and their health. Tallying this with climate variability data acknowledge significant relationships to be observed and makes the testing of hypotheses for rangeland decline.

Generally, with the incorporation of remote sensing it has made it possible to generate changes in the environment at varying periods (Kumar, 2015). For example, Landsat images in Gog (Ethiopia) was used to assess the changes in land cover. (Othow et al., 2017). The study managed to visually present the changes in climate according to their different classes and with these images they also managed to work out the percentage change of the land cover. The Othow et al., (2017) study illustrated the applicability of GIS and RS in analysing forests in the Gog district using Landsat images.

In a study by Suleiman and Elagib (2012), multi-temporal satellite images provided an empirical means for monitoring and analysing LULC along livestock migration routes of East Darfur. According to Suleiman and Elagib (2012) the study also showed the drastic expansion of agriculture, a rapid decrease in rangelands and a significant area left denuded of vegetation. These general trends of LULC change in the study area confirm the results of other studies in El Gedaref region found by Suleiman and Elagib (2012) (e.g., Larsson, 1995; Sulieman, 2010).

Therefore, monitoring spatio-temporal LULC using remote sensing provides essential decision-making information required for appropriate planning, managing natural resources, and achieving sustainable development (Kumar, 2015). The use of RS data and GIS techniques was established several decades ago and observed as efficient tools for environmental resource management. The presence of RS data has allowed for a cheaper way of obtaining data as compared to ground surveys. Haugen et al., (2018) states that the LULC maps can also be generated using RS data and these maps assist in monitoring land use changes by differentiating multi-temporal land cover distributions. With the above explained, RS data allows for environmental planning and managed to have a basis that is baked by science for policy formation (Kumar, 2015). Various studies for example, Ezeomedo and Igbokwe (2019) conducted a study for mapping and analysis of LULC for sustainable development. They used low-resolution satellite images and GIS, remote sensing, multi-temporal data consisting of existing Topographical map, NigerianSat-1, and LANDSAT ETM+ images, and their results showed that vegetation experience a constant decline, from about 77% in 1964 to 65% in 2004. There was a further disturbing drop to a mere 20% in 2006.

2.4.3. Climate data products for monitoring climate variability on rangelands.

According to Kumar (2015) climate data are real-time historical climate observations coupled with direct model outputs that cover the historical, present and future periods. Climate products are a synthesis of climate data, that combines climate data with knowledge of climate to add value. Climate products include ones that deal with precipitation and temperature. This current study focuses on rainfall and temperature as climate products, and several types of such products are explained below. The TRMM is data collected in tropical and subtropical regions (Ceccato & Dinku, 2010). The mission uses five instruments that include Clouds & Earths Radiant Energy System (CERES), TRMM Microwave Imager (TMI), Visible Infrared Scanner (VIRS), Precipitation Radar (PR) and Lightning Imaging Sensor (LSI). According to the Climate data guide article by Schneider at al., (2013) 'TMI and PR are the main instruments used in an algorithm that forms the TRMM Combined Instrument (TCI) calibration data set (TRMM 2B31) for the TRMM Multi-satellite Precipitation Analysis (TMPA), whose TMPA 3B43 monthly precipitation averages and TMPA 3B42 daily and sub-daily (3 hr) averages are probably the most relevant TRMM-related products for climate research'' (Schneider at al., 2013). TRMM provided rainfall data and corresponding heat release that assists in powering the global atmospheric circulation that determines climate and weather. According to Koko et al., (2020) Global Precipitation Measurement (GPM) has supplied data since 2015 to date. GPM collects data between approximately 65˚ north and south latitude. According to Li et a.,l (2021), this allows the instruments of GPM to collect data in stormy conditions as they are progressing, and this makes GPM data to be able to contribute to the forecast of extreme weather events. Koko et al., (2020) also ascertained that temperature data can also be collected using Global Land Data Assimilation System (GDLAS).

2.5. Vegetation indices for monitoring rangeland productivity

Soil-Adjusted Vegetation Index (SAVI) and NDVI are remotely sensed derived indices which are commonly used in the monitoring of rangelands. SAVI can correct the influence of soil brightness hence it is capable to correct NDVI when applied in areas of low vegetation cover. A study by Isbell et al., (2017) investigated the application of NDVI and SAVI in studying productivity of Mangrove Forest vegetation covers. Remote sensing images were acquired from Satellite Pour l'Observation de la Terre (SPOT-6 and SPOT-7) as portrayed by Rhyma et al., (2020). Results of the analysis portrayed a relationship of the two indices (0.991) at a 99.99% significance level (Li et al., 2019, Haugen et al., 2018; Feddema et al., 2005). This shows that NDVI and SAVI are significant indices employed to measure vegetation productivity in the forests (Rhyma et al., 2020 and Costa and Rodrigues, 2017). To sum up, this chapter highlighted on the various publications of other studies that were conducted which focused on climate variabilities impacts to rangelands and how GIS and RS help in monitoring these. In particular, the chapter covered issues such as the productivity of rangelands, climate variability monitoring and the use of convectional and GIS and RS methods in monitoring rangelands and climate variabilities. The chapter also covered issues to do with SAVI in measuring productivity of rangelands. Gaps in the study area where also highlighted. This study will focus on examining the effects of climate variabilities on rangeland dynamics in North Darfur using earth observation data. Land use and land cover of North Darfur will be quantified using Landsat images, the spatial and temporal changes in temperature and rainfall patterns of North Darfur will also be determined using remote sensing methods. Lastly, rangeland productivity in relation to space and time will also be determined by use of vegetation indices.

CHAPTER THREE

3. MATERIALS AND METHODS

3.1. Study area

North Darfur, is a state of Sudan, covering an area of 296,420 km², (and has an estimated population of approximately 1583000, and has Al-Fashir as the capital city of the state (Mohmmed et al., 2018). It is dominated by desert in the north, the Jebel Marra Mountains in the centre and rich grassland savannah in the south. Range productivity varies from 0.8 hectares per year in the north to 25 hectares per year in the south. The major land cover classes found in the state include natural vegetation, bare land, agricultural lands, water resources and built-up areas (Ibrahim, 1984). The natural vegetation includes grazing lands that are made up of perennial and seasonal pastures (Ibrahim, 1984).

North Darfur is in the margins of the tropical zone these zones experience heavy rainfall during their short summer period. The annual average temperature reaches to 30 °C and the annual average rainfall totals to54 mm. Among the pastoral groups, many households combine animal-rearing with cultivation, while others have taken up urban-based occupations, without cutting their links to their rural home areas (UNDP, 2007 & UNDP, 2008). There are two types of nomadic activities in North Darfur, namely 1) semi-nomadic (transhumance) migration of livestock between pastures in the mountains during in summer hot seasons and migration to the low laying areas till year end. and 2) nomadic, that is a year-round movement of herders, the herds and their families as they follow pastures. Owing to climate variability and LULC changes, Assessment of Impacts and Adaptations to Climate Change in Multiple Regions and Sectors (AIACC) (2006) noted that new patterns of land use have been introduced through the Western Savannah Development; these include permanent and seasonal ranching systems.

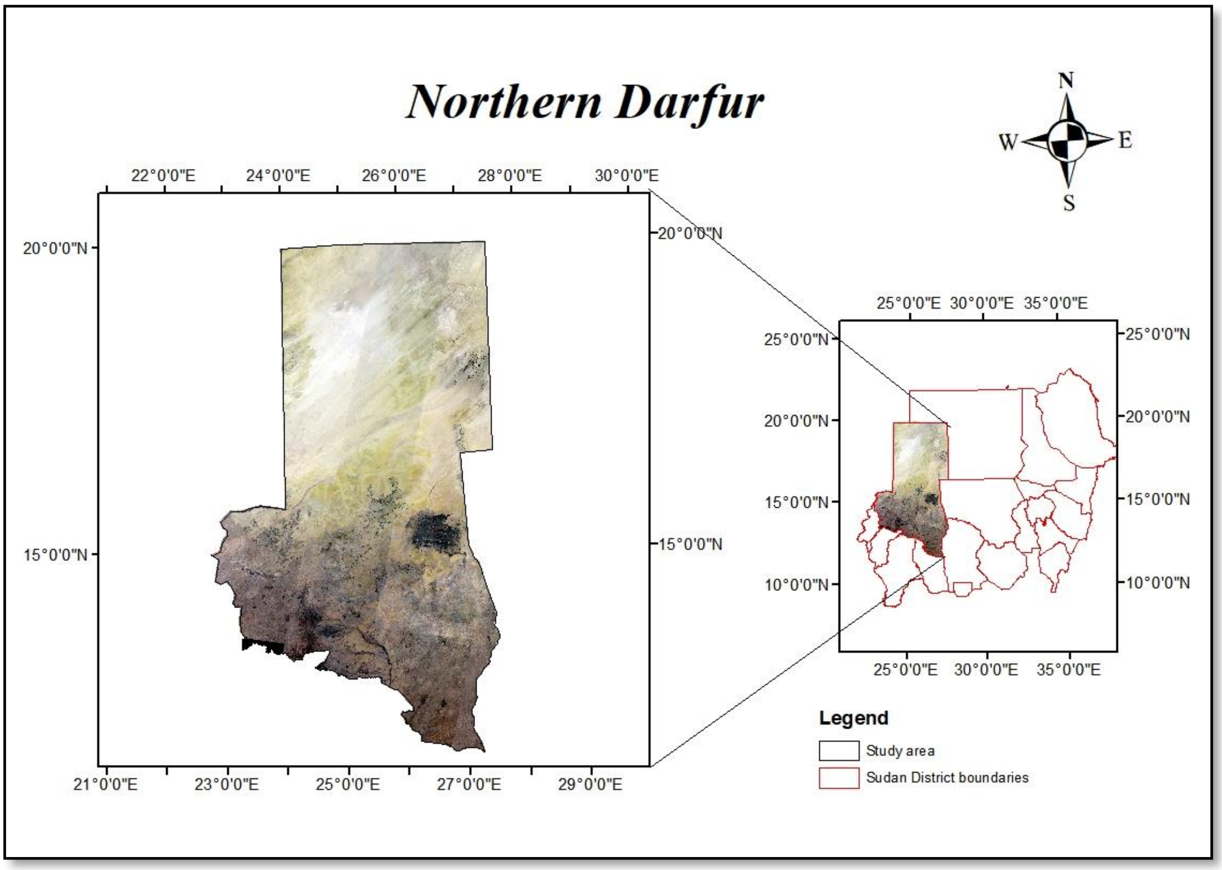

Figure 1: *Map of the area of the North Darfur region (main map) and its location in North Sudan (inset). The overlaid image is a mosaic of Landsat images (Source: www.glovis.usgs.gov/) and shows some of the main vegetation types that include bare areas in the north and grasslands in the south.*

3.2. Data acquisitions

Cloud free Landsat satellite imageries for North Darfur, spatial resolution of 30 m were acquired from the United States Geological Survey (USGS) website (www.glovis.usgs.gov). The images spanned a period of 35 years (1985–2020). A total of 29 tiles of Landsat imagery were downloaded to cover the study area, path 176 row 48 to 52, path 177 row 176 to 152, path 178 row 46 to 52, path 179 row 46 to 52 and path 180 row 50 to 52. A summary of the details of the downloaded images is given in Table 1. The data obtained were for March and April and this was done to minimise deviations in seasons and reduce cloud cover.

Table 1: *A summary of the downloaded satellite images used in this study.*

Year	Date of Acquisition Range	Sensor Identifier	Satellite
1985	1985/04/23	MSS	Landsat 4
1990	1990/04/15	MSS	Landsat 4
1995	1995/04/12	MSS	Landsat 5
2000	2000/04/07	MSS	Landsat 5
2005	2005/04/04	ETM+	Landsat 7
2010	2010/04/02	ETM+	Landsat 7
2015	2015/04/01	OLI/TIRS	Landsat 8
2020	2020/03/15	OLI/TIRS	Landsat 8

Table 2: *Spectral characteristics of the downloaded Landsat images.*

Landsat 4 and 5 (MSS)			
Bands	Nominal Spectral Location	Spectral Sensitivity (µm)	Ground Resolution (m)
Band 1	Green	0.5–0.6	30 × 30
Band 2	Red	0.6–0.7	30 × 30
Band 3	Near Infrared (NIR)	0.7–0.8	30 × 30
Band 4	NIR	0.8–1.1	30 × 30
Landsat 7 (ETM+)			
Band 1	Blue	0.45-0.52	30 × 30
Band 2	Green	0.52-0.6	30 × 30
Band 3	Red	0.63-0.69	30 × 30
Band 4	NIR	0.77-0.9	30 × 30
Band 5	Short wave Infrared (SWIR)	1.55-1.75	30 × 30
Band 6	Thermal Infrared	10.4-12.5	100 × 100
Band 7	SWIR	2.09-2.55	30 × 30
Landsat 8 (OLI/TIRS)			
Band 1	Coastal Aerosol	0.43-0.45	30 × 30
Band 2	Blue	0.45-0.51	30 × 30
Band 3	Green	0.53-0.59	30 × 30
Band 4	Red	0.64-0.67	30 × 30
Band 5	NIR	0.85-0.88	30 × 30
Band 6	SWIR 1	1.57-1.65	30 × 30
Band 7	SWIR 2	2.11-2.29	30 × 30

3.3. Image pre-processing

Before image classification, an atmospheric correction was performed on the images to take care of the effects of the atmosphere. According to Chavez (1996), atmospheric correction is a technique for conversion of data from spectral radiance to spectral reflectance performed to lessen the effects of molecular scatter and absorption of radiation caused by dust and water molecules. Atmospheric correction is a procedure of fundamental importance prior to the classification of satellite imagery data as it eliminates scatter and absorption effects from the atmosphere and provides surface reflectance characteristics (Liang et al., 2001). This theoretically improves the accuracy of determining different land covers using remote sensing. In this current study, atmospheric correction was done using the Dark Object Subtraction (DOS) method in Quantum GIS (QGIS) to atmospherically correct all the satellite images prior to classification (Belgium & Drăguţ 2016). The DOS method surmise reflectance from dark objects obtains a high component of atmospheric scattering. The contribution of this scattering was corrected by subtracting the non-value pixels from every band of the image composited to make a workable image

Mosaicking is the process of composing two or more merged raster datasets (Li, 2019) and this technique produces a raster of large area coverage, from various input raster tiles with a common coordinate system. Mosaicking of raster tiles also includes compositing data sets for the same area by averaging the reflectance values within overlap areas (Knöpfle et al., 1998). For each year, the 29 tiles were composited and mosaicked into a single map for each year covering the study area. Thereafter, a GIS shapefile for the North Darfur study area was used to clip the new raster so that it covered only the extent of the study area. The satellite images were georeferenced from source, thereby eliminating the need for geometric correction.

3.4. Image classification

Random forest (RF) classification method was selected for use in this study. It was selected because of its relatively high classification accuracy, fast processing speed and high stability (Chan & Paelinckx, 2008). Breiman (2001) defines the RF classifier as a classifier that employs regression trees to make a prediction. According to Belgium and Drăguţ (2016), regression trees are generated by obtaining a subset of samples which will be called the training samples by use of the bagging approach. About two-thirds of the sample are obtained for this purpose, while the remaining of the samples are used for validation, thus checking how well the model has performed in classifying. Resources such as topographic maps and Google Earth were used for ground truthing.

Before running the algorithm, sample points were generated by ArcGIS software using the classification tool to create signature files based on spectral characteristics. The 200 points that were not used in the classification were used in coming up with a confusion matrix (Visa et al., 2011). The kappa coefficient was used to assess classification accuracy (Foody., 2020).

The user directs RF algorithm to designate land cover classes and defines the training samples. To ensure development of an efficient classifier, representative training and validation samples for each LULC were obtained from the Landsat 5 images for the period 1985 to 2005 and Landsat 8 image for the years 2010 to 2020. The LULC classes for which the samples were collected were bare land, farmlands, rangelands, and water bodies. A total of 1000 polygons were used for training samples of the images. In all, 250 polygon samples for each class were created.

1000 training samples were then used for classifying satellite images into different land cover classes. The samples were extracted from the Landsat images by individually picking samples using the classification tool. Each land cover class had a total of 250 training samples. For each land cover class, 200 sampling points were used during the process of image classification, while 50 were retained for accuracy. This followed a classification: accuracy assessment ratio of 30:70 for validation and training respectively (Liebman and Polley, 2017). Table 3 below shows the land cover types that were used in this study.

Table 3: *Explanation for the land use and land cover classes (LULC) that were used for image classification.*

LULC	Characteristics
Bare land	These are exposed rocks and non-vegetated ground. The land has little potential of supporting life and there is a vegetation cover of less than one-third of the area
Rangelands	Extensive areas of land occupied by native shrub like vegetation that is grazed by domestic or free-ranging animals. These may include tallgrass prairies, steppes desert shrublands, woodlands
Water bodies	Streams, rivers, ponds and reservoirs
Agricultural	The land is used primarily to produce fibre and food and includes parcels with commercial and horticultural production

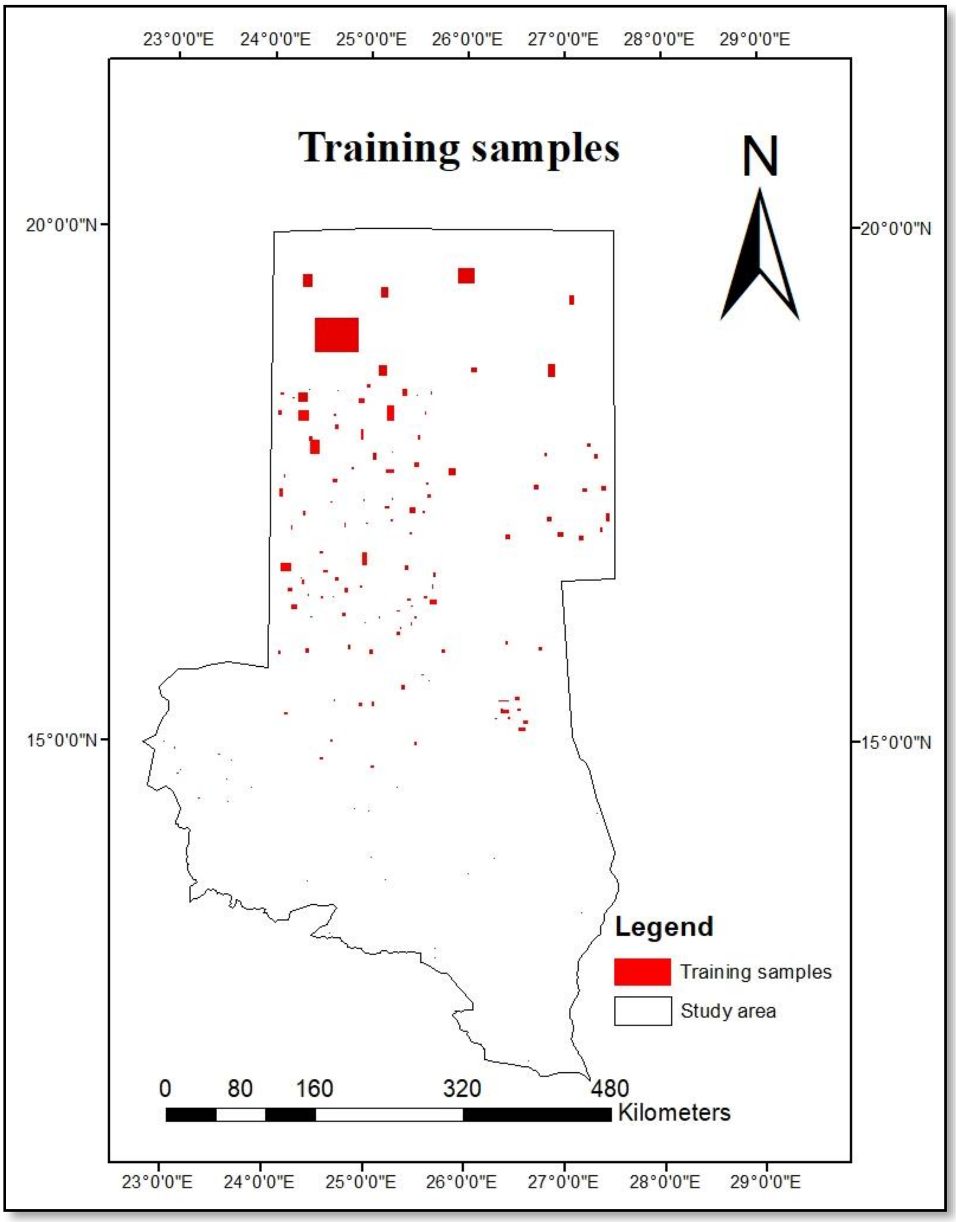

Figure 2: *Distribution of the training samples used in classifying the satellite images.*

3.5. Accuracy assessment

Accuracy assessment using Kappa coefficient was performed on each image of the years under consideration. The remaining 200 points from each of the land cover types were used for accuracy assessment. Accuracy assessment is significant in image classification because according to Liebman and Polley, (2017), spectral confusion, noise and weaknesses of classification algorithms result in classification errors on classified images. Therefore, a quality check of the product of classification is essential (Lu et al., 2004). Accuracy assessment was used to determine the accuracy of the categorization of pixels. This study made use of a confusion matrix to carry out an accuracy assessment. According to Iiames et al., (2008), a confusion matrix is created by employing ground truth points of interest to calculate the kappa statistic (equation 4), user accuracy (equation 3), overall accuracy (equation 1), and producer accuracy equation 2). Overall accuracy is seen by the proportion that is left representing the probability of a correct classification for a randomly selected point (Lu et al., 2004). The formulae used for computing accuracy are:

Equation 1

$$Overall\ accuracy = \frac{\sum(Correctly\ \ classified\ classes\ along\ diagonal)}{\sum(Row\ total\ or\ Column\ total)}$$

The probability of the labelled image pixel being classified correctly is referred to as producer's accuracy (Kraemer, 2014).

Equation 2

$$Producer's\ accuracy = \frac{Number\ of\ the\ correctly\ classified\ classes\ in\ a\ column}{Total\ number\ of\ verified\ items\ \ in\ that\ column}$$

According to Kraemer (2014) the user's accuracy is computed by dividing the number of correctly classified samples for a class by the total number of verified samples belonging to the class.

Equation 3

$$User's\ accuracy\ = \frac{Correctly\ classified\ number\ of\ items\ in\ a\ row}{Total\ number\ of\ verified\ items\ in\ that\ row}$$

The kappa coefficient (equation 4) is defined by Adam et al., (2014) as the score of relative difference between real or factual agreement and the agreement expected by chance. It runs on a scale of 0 to 1 with 1 indicating perfect agreement of the classification and the ground truth points, and 0 indicating a lack of an agreement (Adam et al., (2014). The kappa coefficient is computed by the formulae given in equation below:

Equation 4

$$K = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i\, C_i)}{N^2 - \sum_{i=1}^{n}(G_i\, C_i)}$$

To determine arial coverage after image classification, statistical tools in ArcMap were used and to determine the area cover of each land use land cover in percentage of the study area. The following formula (equation 5) was used (Othow et al., 2017):

Equation 5

$$\text{Area in \%} = \frac{\text{Observed pixel value}}{\text{total number of pixels}} \times 100 \qquad \text{(Othow et al., 2017)}$$

3.5.1. Mapping spatio-temporal variations in rangelands

The SAVI (equation 6) was used to map the spatial and temporal variations in rangelands. According to Huete (1988), equation 6 attempts to minimize the background influences by using a soil brightness correction factor. The index (equation 6) is best used in arid regions where vegetative cover is low (Huete, 1988**)**.

Equation 6

SAVI = ((NIR − Red) / (NIR + Red + L)) × (1 + L) (Huete, 1988)

Where:

NIR = pixel values from the near-infrared band

Red = pixel values from the near red band

L = amount of green vegetation cover

The L value varies depending on the amount of green vegetative cover. Generally, in areas with no green vegetation cover, L = 1; in areas of moderate green vegetative cover, L = 0.5; and in areas with very high vegetation cover, L = 0 (which is equivalent to the NDVI method). This index outputs values between −1.0 and 1.0 (proarcgis.com).

Images were obtained for the summer seasons of study, so that the productivity stages of vegetation would not differ, and this season allowed for the year-by-year differences in the vegetation to be determined. The period from 1985 to 2020 was chosen because of the availability of data and also because during that period desertification was more prevalent (Kang, 2020). In this study, SAVI was used to measure productivity at a threshold of 0.156 (i.e., pixle value of 0.156 and above are rangelands). The threshold was determined by calculating the mean SAVI of each year and then the total means of the 8 years divided by 8 to get the general mean applicable to the 8 years (Appendix 1). That is, all the areas reflecting 0.156 and above were regarded as rangelands and the rest were not.

3.5.2. Meteorological data

Meteorological data were collected from multiple stations, which are Al Fashir, Kutum, Mellit, Kabkabiya, EL Malha, Umm, Kadadda, ELTawiesha, AL Liait, Saraf Omra, Kuma, and Dar el-Salaam. There was sufficient coverage of North Darfur by the meteorological stations and it was deemed by the researcher that interpolated data from these stations would cover the whole study area with a fair degree of accuracy. The meteorological data covered a study period of 35 years from 1985 to 2020. Before analysis, the data were checked for completeness as well as removing meteorological parameters that were not relevant in this study (that is, all data other than temperature and rainfall average data). The retained data included the daily temperature and rainfall totals which were then calculated into averages for the year to incorporate anomaly indices.

3.6. Climate variability analysis

The average temperature and rainfall data were used for calculating the SAIs. The rainfall and temperature SAIs measure anomalies in the parameters by considering the positive and negative anomalies. A positive index shows that the temperature observed or recorded is warmer than the set baseline and a negative anomaly index show that the recorded or observed temperature is cooler than the set baseline (Rooy, 1965). The formula for rainfall and temperature anomalies respectively were adopted from Rooy, (1965) as:

Equation 7

$$Positive\ anomaly \quad = 3\left(\frac{N-\overline{N}}{\overline{M}-\overline{N}}\right)$$

$$Negative\ anomaly \quad = -3\left(\frac{N-\overline{N}}{\overline{X}-\overline{N}}\right)$$

Where:

N = Current yearly rainfall in mm

$\overline{N}$ = Yearly average rainfall of the historical scenes in mm

$\overline{M}$ = Average of the ten highest yearly precipitations of the historical scenes in mm

$\overline{X}$ = average of the ten lowest yearly precipitations of the historical scenes in mm

Equation 7 was also used as the formula for temperature anomaly Rooy (1965):

Where:

N = Current yearly temperature in degrees Celsius

$\overline{N}$ = Yearly average temperature in degrees Celsius

$\overline{M}$ = Average of the ten highest yearly temperatures in degrees Celsius

$\overline{X}$ = average of the ten lowest yearly temperatures in degrees Celsius

The long-term trends and their significance level were evaluated by the non-parametric Spearman rank correlation test. A value of a 0.05 is set to define the statistical significance (Kevane & Gray, 2008) both for rainfall and temperature.

3.7. Mapping the spatial and temporal variation of rainfall

Global precipitation measurement (GPM) data (https://giovanni.gsfc.nasa.gov) were downloaded to map the spatial variation of rainfall over time. The data were downloaded from 1985 to 2020 at five-year intervals. Monthly spatial and temporal data at a spatial resolution of 30 m were downloaded for the whole of the study area. Tropical Rainfall Measuring Mission

(TRMM) that was applied uses five instruments, namely: PR, TMI, VIRS, CERES and Lightning Imaging Sensor (LSI). Global Land Data Assimilation System (GLDAS) temperature data were also downloaded from Giovanni (https://giovanni.gsfc.nasa.gov) to monitor and map spatial variation of temperature in North Darfur. To be able to cover the whole study period, GLDAS, TRMM and GPM data were downloaded and combined. GLDAS Launched in 1979 covered the years 1985, 1990 and 1995 of the study periods; TRMM launched in 1997 covered the years 2000, 2005 and 2010 of the study periods; GPM launched in 2014 covered the years 2015 and 2020 of the study period. This was done to be able to access accurate and up to date data of all time periods. The GLDAS and TRMM data are coarse since they are the latest data, but GPM is finer since it is the improved and more accurate data (Figure 7). The GLDAS data were downloaded at five-yearly intervals for the years 1985–1995 covering the study area at a 50 m spatial resolution.

CHAPTER FOUR

4. RESULTS

This chapter's purpose is to explain and `present the findings of the research. These findings are based on the data acquired through remote sensing as indicated in the previous chapter. Data are presented using different techniques and the emerging patterns, trends and outlooks are interpreted. The chapter answers the objectives and research questions that were set in chapter one.

4.1. Temporal variations in land cover in North Darfur

Figures 4a and figure 4b indicated the spatial variations in land cover in North Darfur between 1985 and 2020. The data indicated that from 1985 (figure 4a) to 2020 (figure 4b), the dominant land cover in the study area was desert or bare ground. Over the period covered by the study, there was a trend of increasing bare grounds, farmlands and a decrease in waterbodies and rangelands as depicted in tables 4 and 5. In 1985, rangelands had the lowest cover of 142.1 hectares (5%) compared to 1990 which was 643.7 hectares (20%), with waterbodies and farmlands also having a low rate of cover for that year of 544.4 hectares (17%) and 704.1 hectares (22%) respectively. In 1990, water bodies were the land cover type that covered the least area of 202.8 hectares (6%) with the more northerly parts being dominated by desert. Rangelands significantly increased over the period 1985 to 1990 from 142.1 hectares (5%) to 643.7 hectares (20%), and farmlands experienced a slight increase compared to the previous years from 704.1 hectares (22%) to 724.7 hectares (23%). The 1995 data shows there was a slight drop in rangelands from 643.7 hectares (20%) to 367.9 hectares (12%) and slight increase in waterbodies from 202.8 hectares (6%) to 393.7 hectares (12%) from the preceding years. The data for 2000 then shows presence of significant reduction in the area covered by waterbodies to 23 (1%) hectares and a slight increase in rangelands to 593.5 hectares (19%) compared to 1995, while the farmlands slightly decreased to 585.1 hectares (18%). In 2005, while the north-lying parts of the study area were still dominated by desert, there was a substantial rise in water bodies to 349.5 hectares (11%) and a slight reduction in both rangelands and farmlands to 416.1 hectares (13%) and 436.5 hectares (14%) respectively. In 2010, there was a substantial rise in cover by farmlands (738.6 hectares (23%) with rangelands slightly decreasing to 400.8 hectares (13%); however, there was a noticeable decrease in the abundance of waterbodies to 208.5 hectares (7%).

In 2015, bare ground area covered about three quarters of the northerly parts of North Darfur covering 1823.2 hectares (58%) in total area and farmlands were more prevalent in the southern parts of the state covering 812.1 hectares of land. As for the rangelands, while they had previously been dominant in the south-eastern side, they then diminished in extent in that area to 335.9 hectares (10%). In 2020, rangelands decreased to 246.8 hectares (8%) but were now somewhat dominant in the south-western areas. Farmlands were more dominant not only in the south-east but had also increased over time to completely cover the southern areas covering a total area of 1022.1 hectares (33%). Waterbodies also highlighted a significant decline to 17.3 hectares (1%) in abundance over this period due to reduced rainfall totals and a rise in temperatures. Bare grounds had the most coverage of 58% which is 1803.2 hectares.

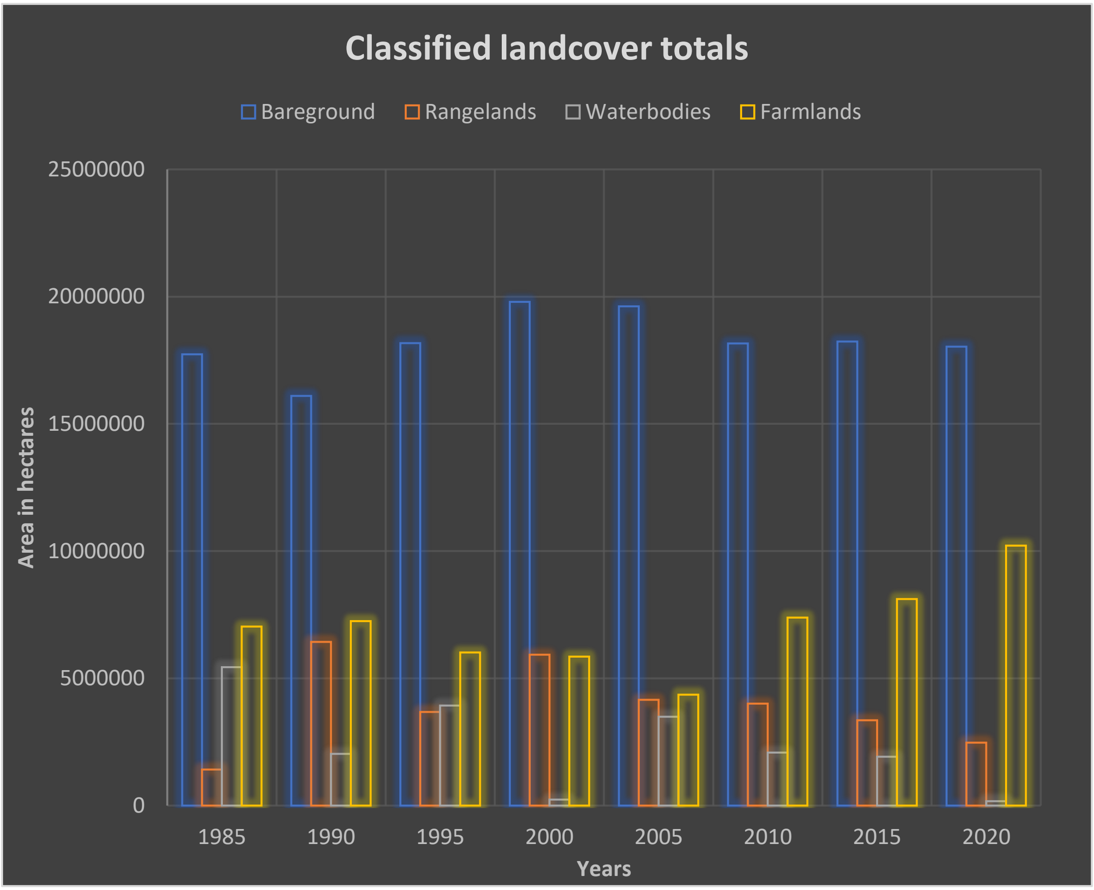

Figure 3: Graphical representation of the total areas in hectares of each of the eight classified images from 1985 to 2020 at a 5-year interval

Table 4: Total areas in hectares for each class of the eight classified images from 1985 to 2020 at a 5-year

Area (Ha)	1985	1990	1995	2000	2005	2010	2015	2020
Bare ground	1773.0	1609.8	1817.4	1979.3	1961.5	1815.6	1823.2	1803.2
Rangelands	142.1	643.7	367.9	593.5	416.1	400.8	335.9	246.8
Waterbodies	544.4	202.8	393.7	23.0	349.5	208.5	192.3	17.3
Farmlands	704.1	724.7	602.0	585.1	436.5	738.6	812.1	1022.1

Table 5: Total areas in percentage for each class of the eight classified images from 1985 to 2020 at a 5-year interval

Area in % of the total area.	1985	1990	1995	2000	2005	2010	2015	2020
Bare ground	56	51	57	62	62	57	58	58
Rangelands	5	20	12	19	13	13	10	8
Waterbodies	17	6	12	1	11	7	6	1
Farmlands	22	23	19	18	14	23	26	33

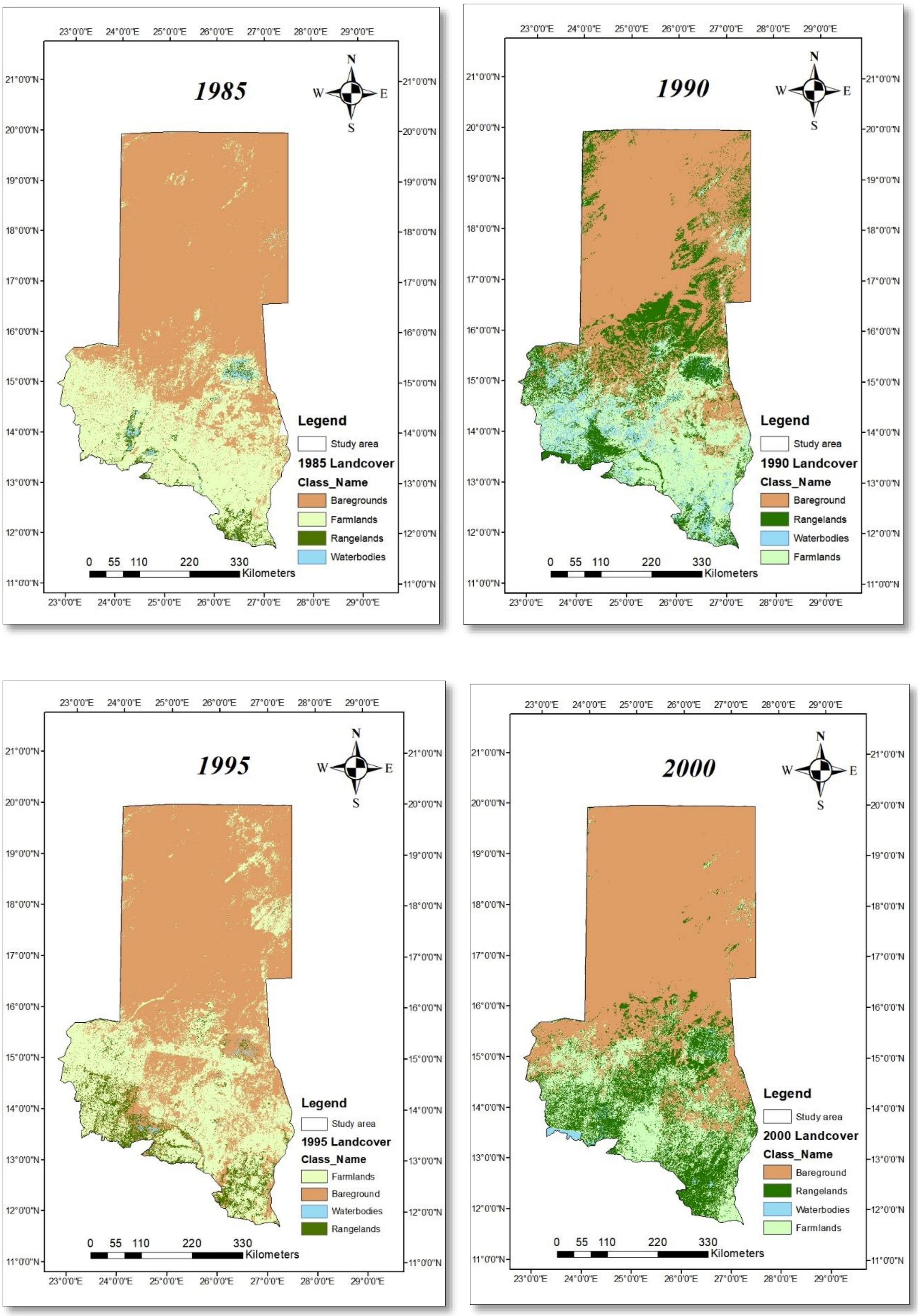

Figure 4a: The land use/land cover (LULC) changes from 1985 to 2000 at a five-year interval.

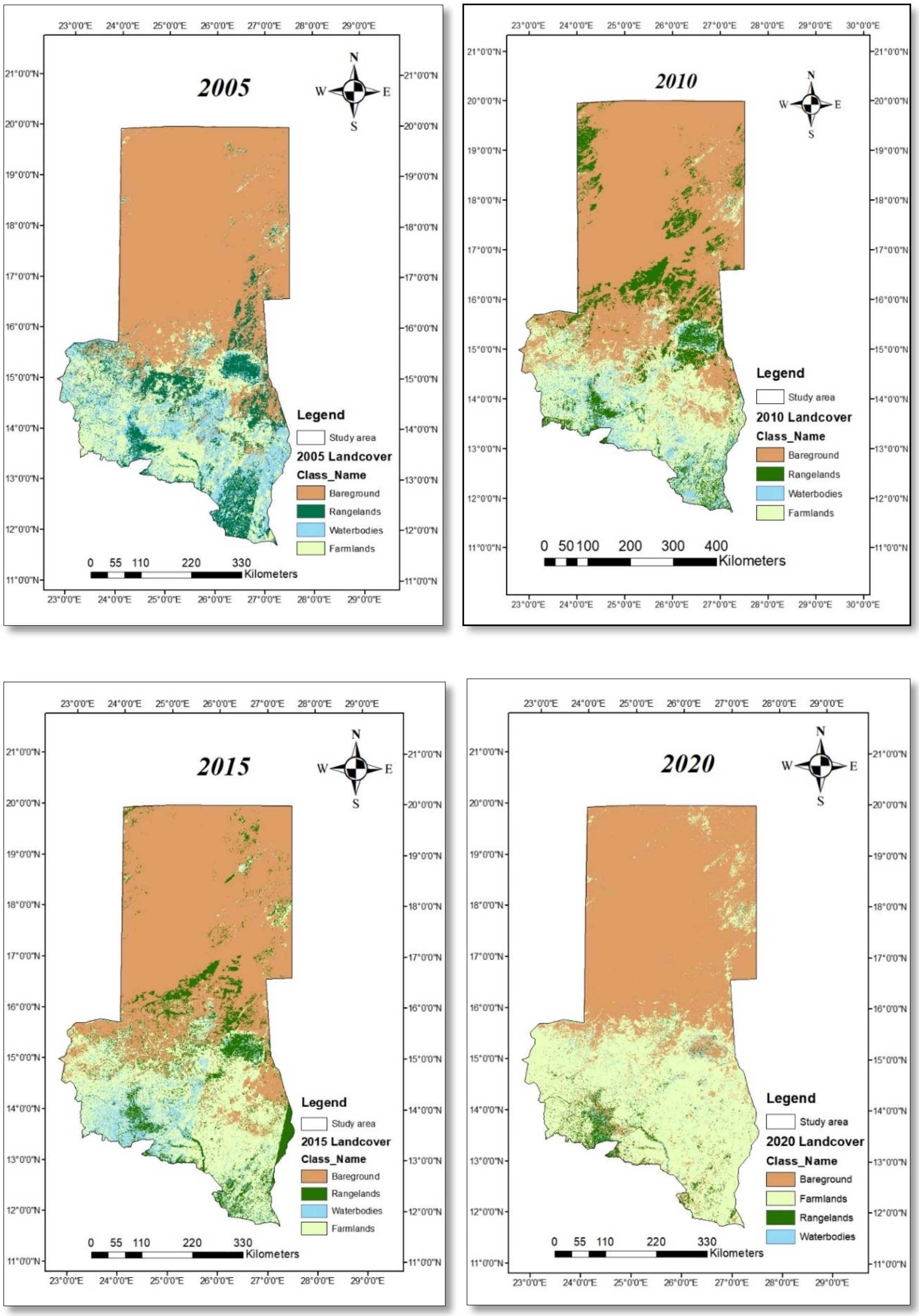

Figure 4b: The land use/land cover (LULC) changes from 2005 to 2020 at a five-year interval.

4.2. Spatial and temporal variations in rainfall and temperature

4.2.1. Rainfall anomaly index

Figure 5 indicated that rainfall for North Darfur from the period 1985 to 2020 dropped significantly. Considering the *p-value* of 0.22 (Appendix 1), it also indicated that there was no significant relationship between time and rainfall; thus, there was no clear trend in average rainfall levels over the period studied. In 1985 precipitation was very low with a sharp increase in 1990. A significant decrease was then experienced in 1992, followed by low total rainfall in 1995. In 2000, precipitation was also relatively low, followed by a rise in total precipitation in 2004; this was then followed again by a drop in 2006. In 2009, a slight increase in total precipitation was experienced followed by constant decrease until 2020.

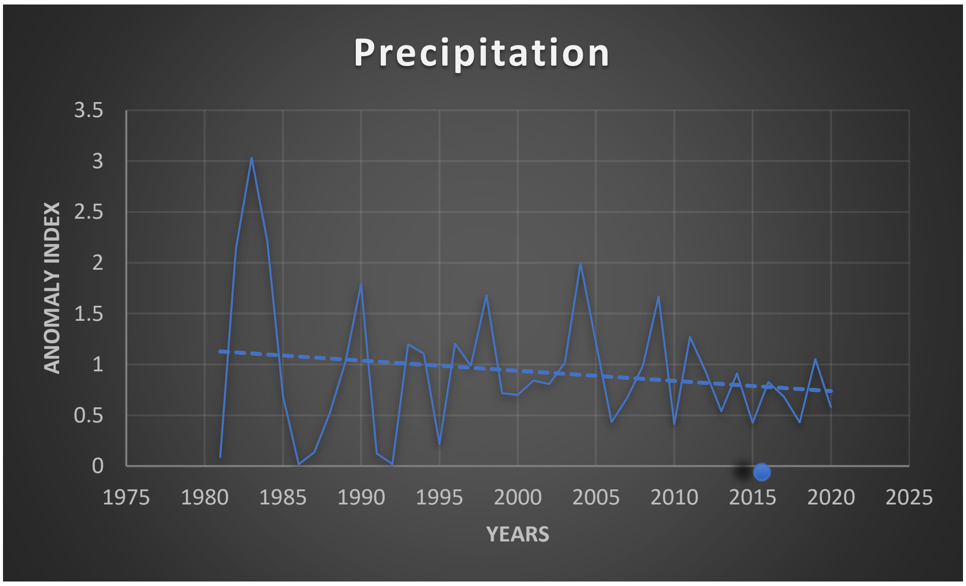

Figure 5: Rainfall anomaly index for the 35 years of study

4.2.2. Temperature anomaly index

Figure 6 indicated statistical results for the years 1985 to 2020, the average temperatures of North Darfur were relatively constant. The anomaly index for that period fluctuated between 0.03 and 0.12. However, as shown in Figure 6, in the early part of the period studied, the temperature in North Darfur was low followed by a sharp increase then eventually moderately low in recent years. The *p-value* of 0.02 also indicated that there was a significant negative relationship between temperature and time which means that over the years there was a significant decrease in temperature. In 1985, temperatures were relatively low followed by a rise in 1986 to 1989. 1990 experienced a drop in temperatures. In 2000 to 2010 temperatures where low. However, 2015 to 2020 temperatures were particularly high.

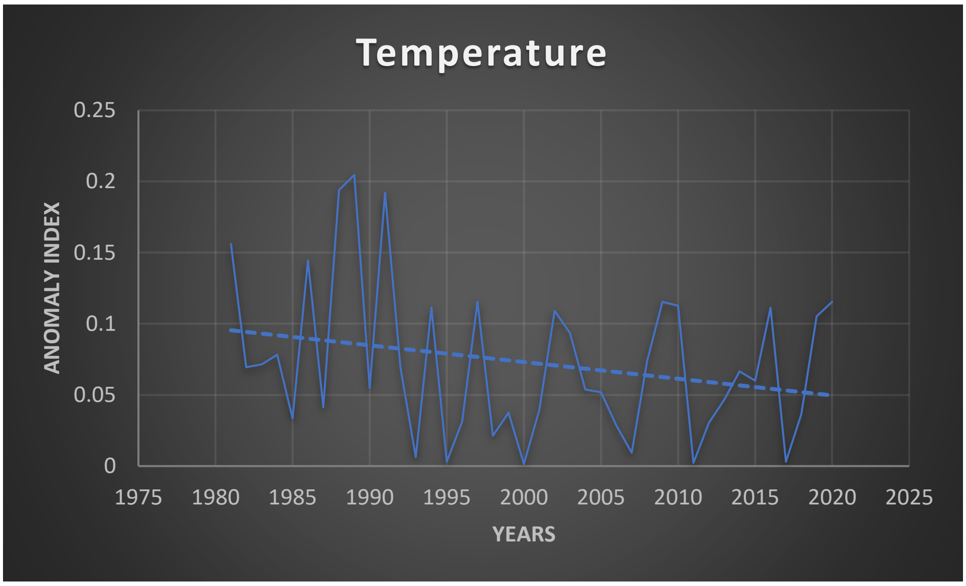

Figure 6: Temperature anomaly index

4.2.3. Spatial variation in rainfall patterns

Spatially, TRMM data indicated that there was a deviation in total rainfall. As indicated in Figure 8a and Figure 7b, within North Darfur, overall rainfall is very low. Further, for the period studied, the northern parts of the study area on average received less rainfall than the southern areas; this pattern was particularly clear in 1990 (figure 7a) and 2000 (figure 7a). In 2005 (figure 7b), in the south-western region of North Darfur higher than average total rainfall was experienced. However, from 2010 (figure 7b) to 2020 (figure 7b) a slightly different pattern emerged with higher-than-average rainfall in the north. This is indicated by some yellow patches present in the northern region for this period (see Figure 7a and Figure 7b).

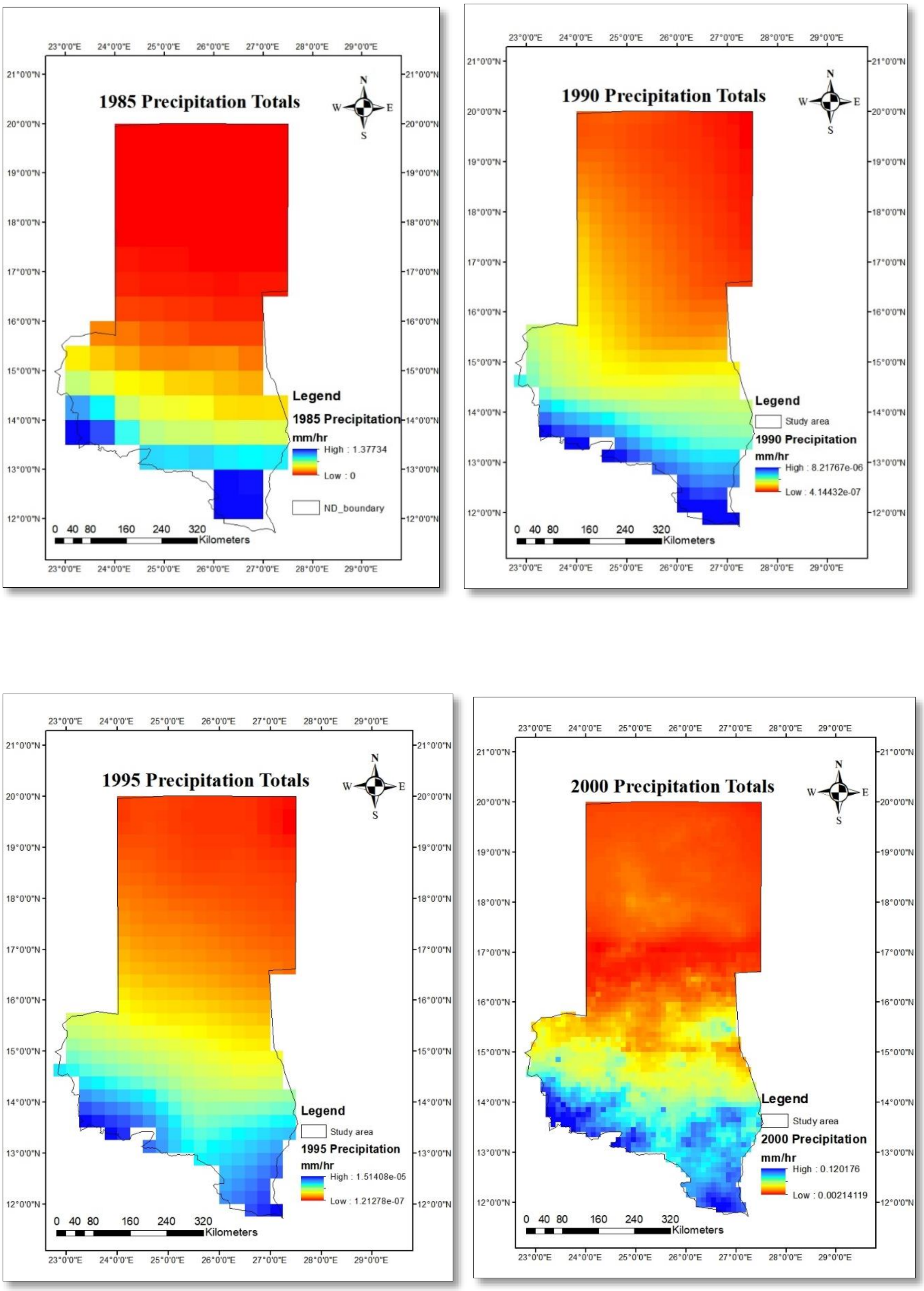

Figure 7a: Spatial and temporal variation in precipitation totals from 1985 to 2000.

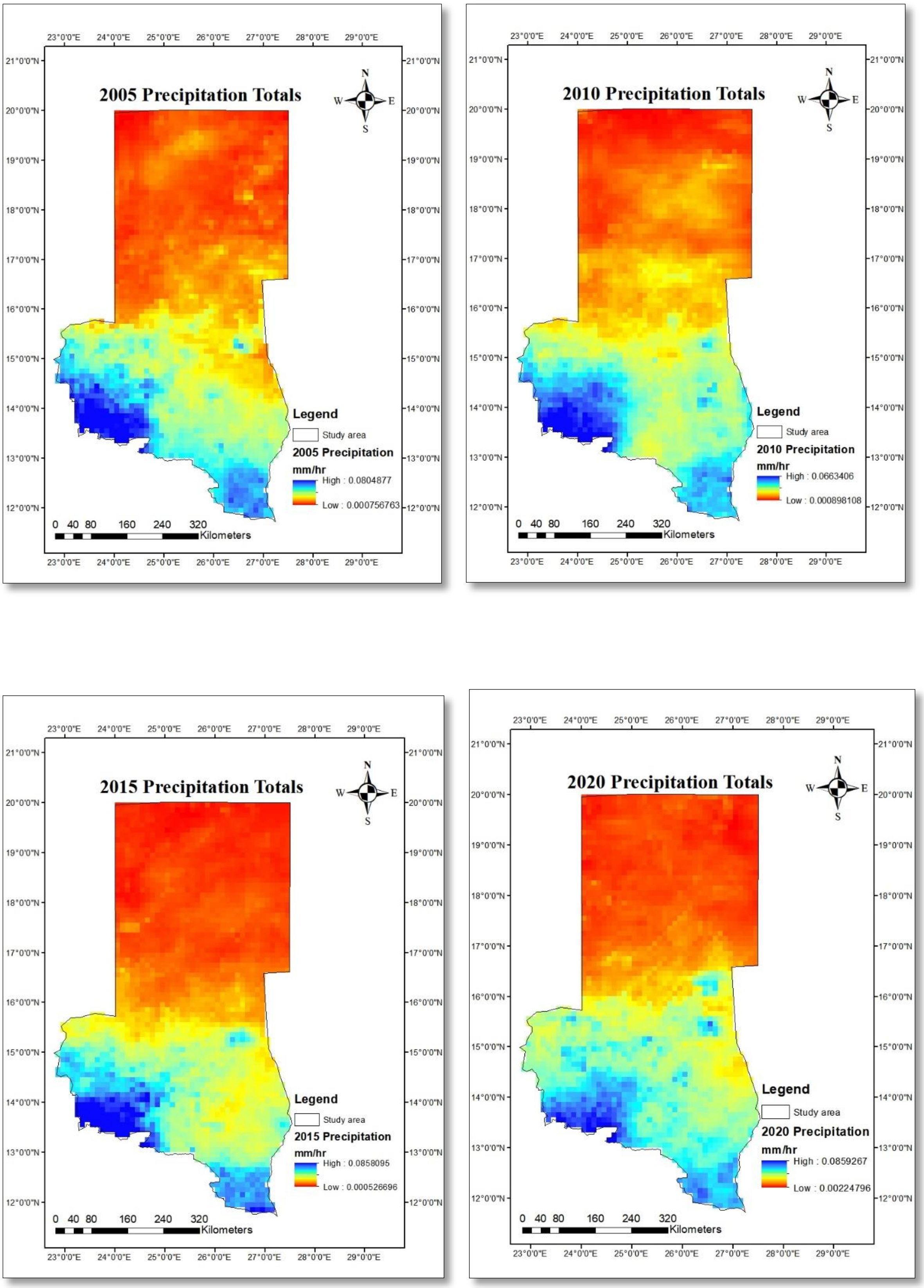

Figure 7b: Spatial and temporal variation in precipitation totals from 2005 to 2020.

4.2.4. Spatial changes in temperature patterns

Figures 8a and 8b indicated the spatial and temporal changes in temperature from 1985 to 2020. North Darfur has consistently experienced high average temperatures, based on the 35-year period investigated in the study. From a spatial variation perspective, from 1985 (Figure 8a) to 2020 (Figure 8b), the highest temperatures in North Darfur were as high as 43 ^{o}C in the north and north-western side of the region. In the east of the region, temperatures throughout the study period were moderately high. In the south, from 1985 (figure 8a) up until 2020 (figure 8b) comparatively low temperatures were recorded. In 1990 and 2000, relatively low temperatures were experienced, compared to 2020 during which temperatures were particularly high.

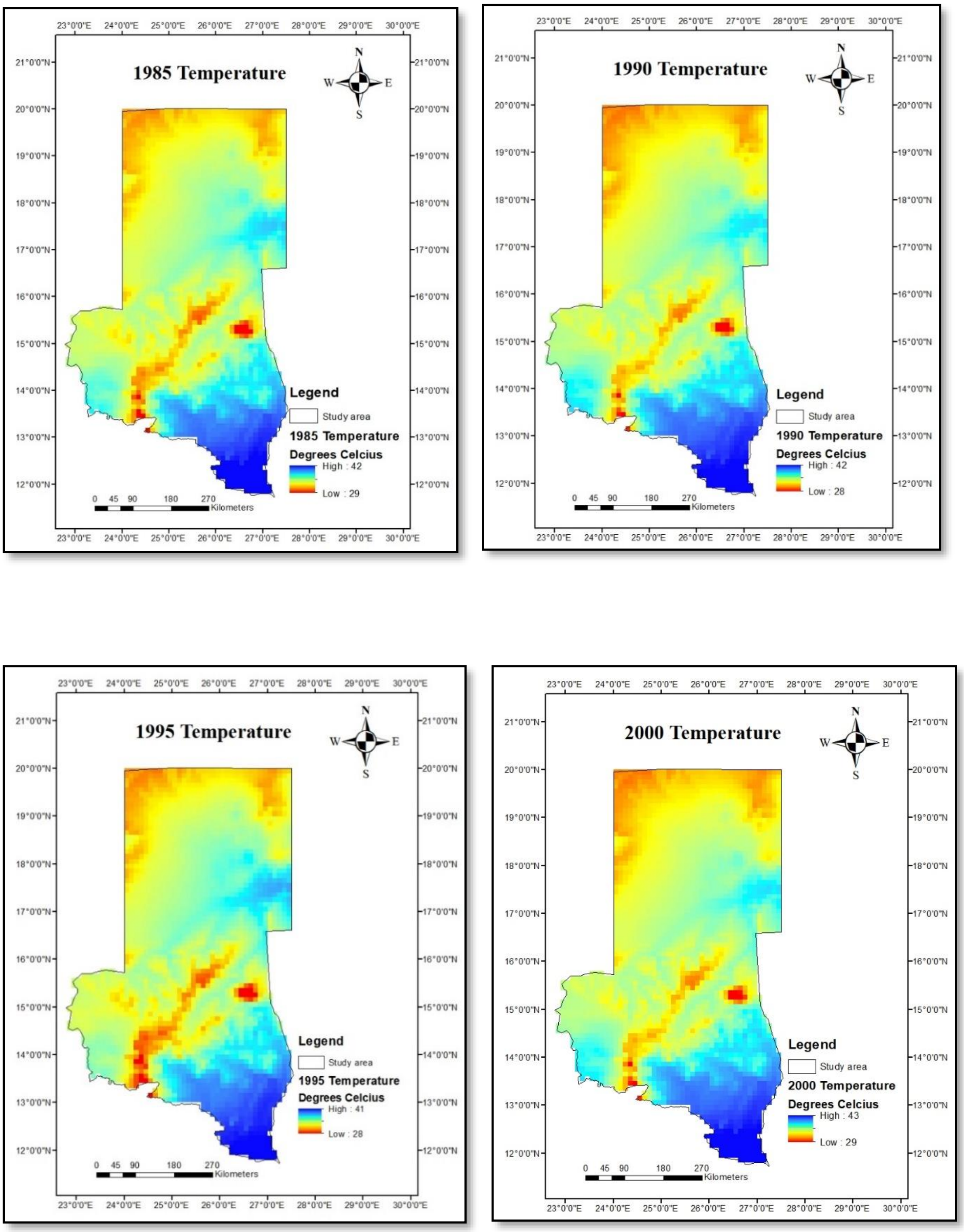

Figure 8a: Spatial and temporal changes in temperature from 1985 to 2000.

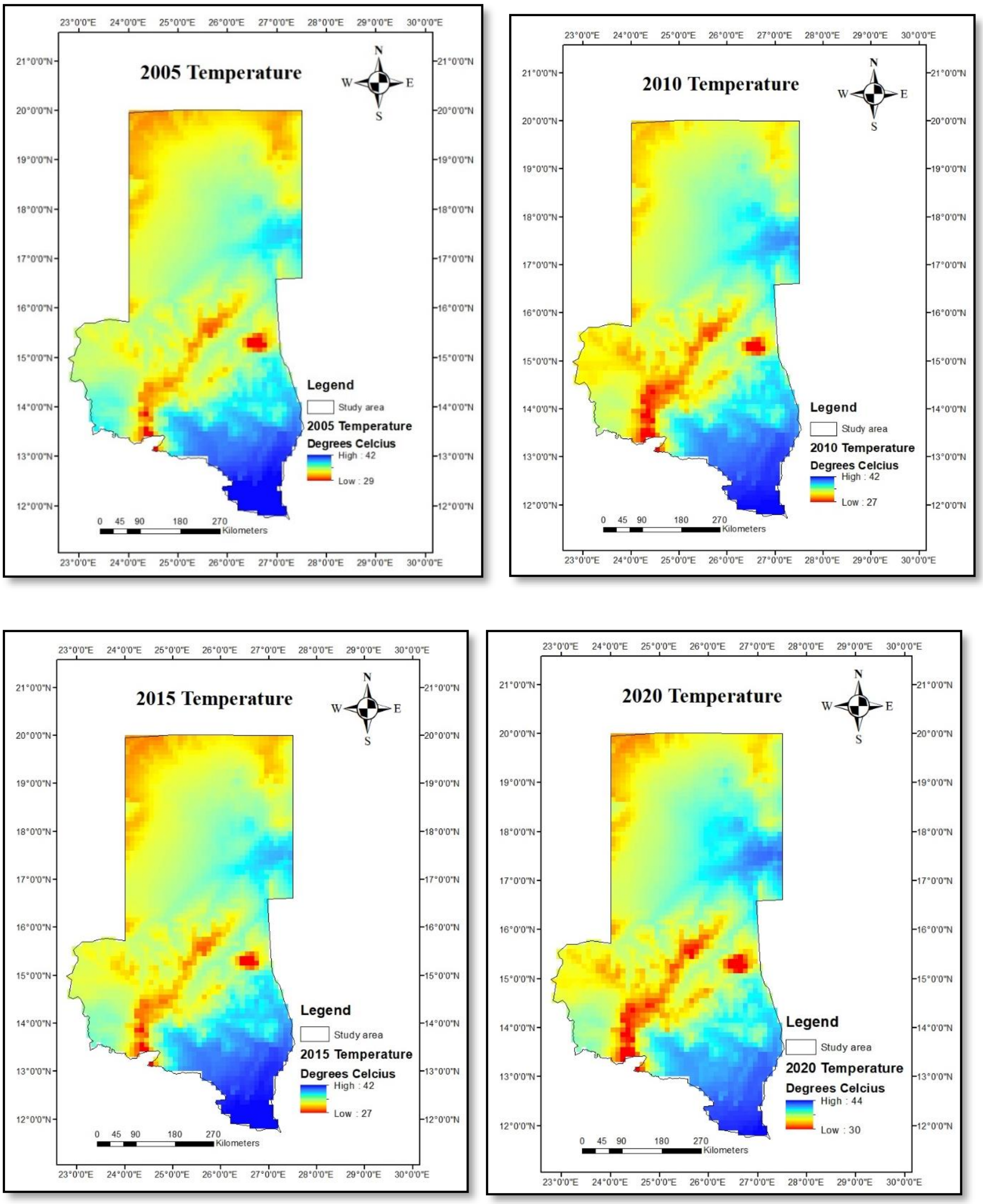

Figure 8b: Spatial and temporal changes in temperature from 2005 to 2020.

4.3. Productivity of rangelands in relation to space and time

SAVI was calculated for the eight years and figures 9a and 9b show the eight images that were generated from the SAVI calculations. The images indicated that in 1985 (figure 9a), there was more rangeland associated with comparatively high productivity reaching 1.5 over the whole study area, including the northern parts. By the year 2000 (figure 9a), the far northern parts were dominated by the desert while the southern parts retained their greenness indicated by high productivity (1.5). The year 2015 (figure 9b) showed comparatively high productivity in the southern parts, which may be because of the farmlands present in the area. However, in the far northern areas, the desert seemed to spread south. By 2020 (figure 9b), most of the rangelands had become depleted and there was only a tiny coverage in the south region that indicated the presence of productive rangelands. Further, in 2020 (figure 9b) the derived threshold indicated that rangelands experienced the lowest productivity level for the whole study period, ranging between -0.8 and -0.7.

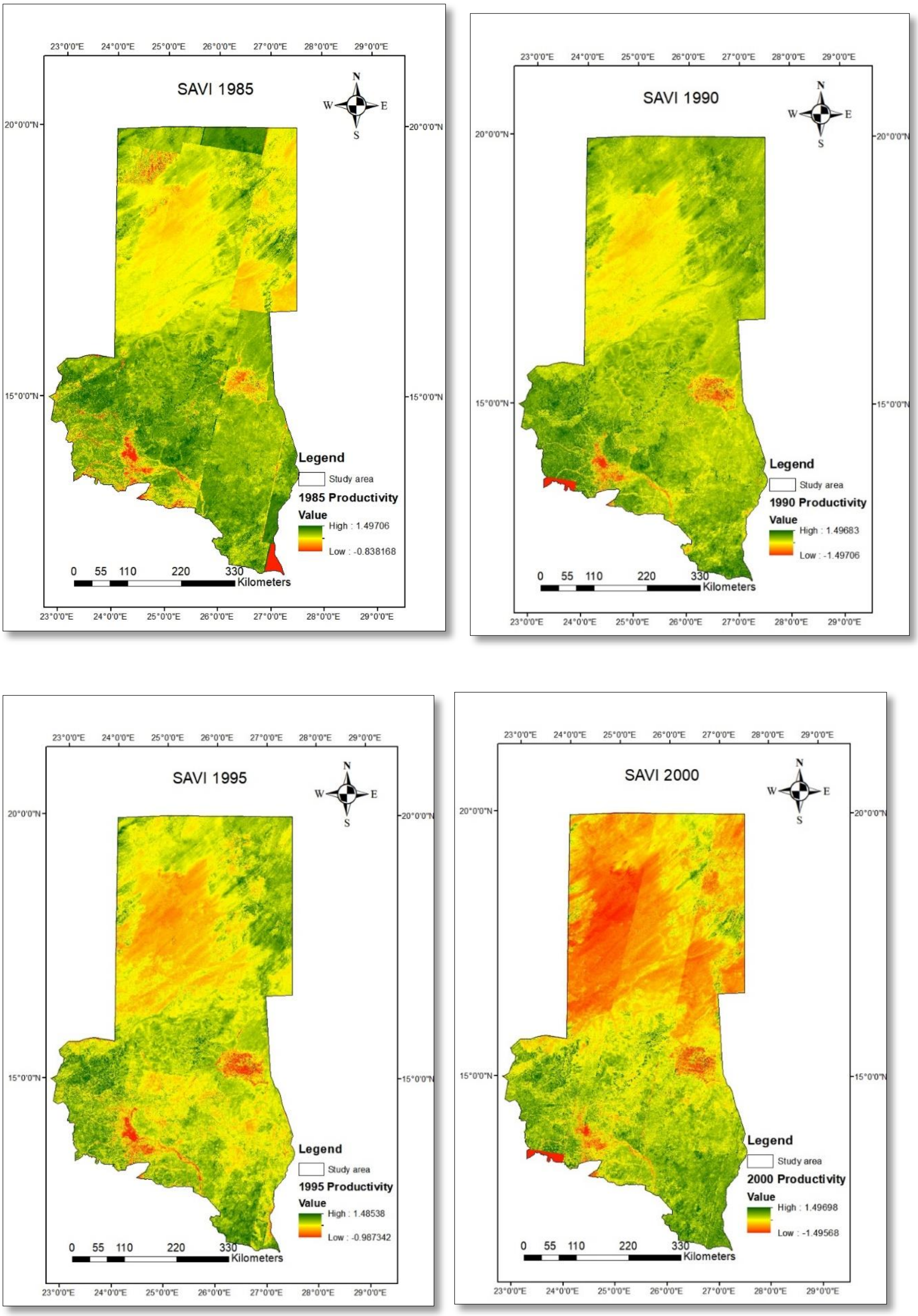

Figure 9a: Soil-Adjusted Vegetation Index for the years 1985 to 2000 showing rangeland productivity.

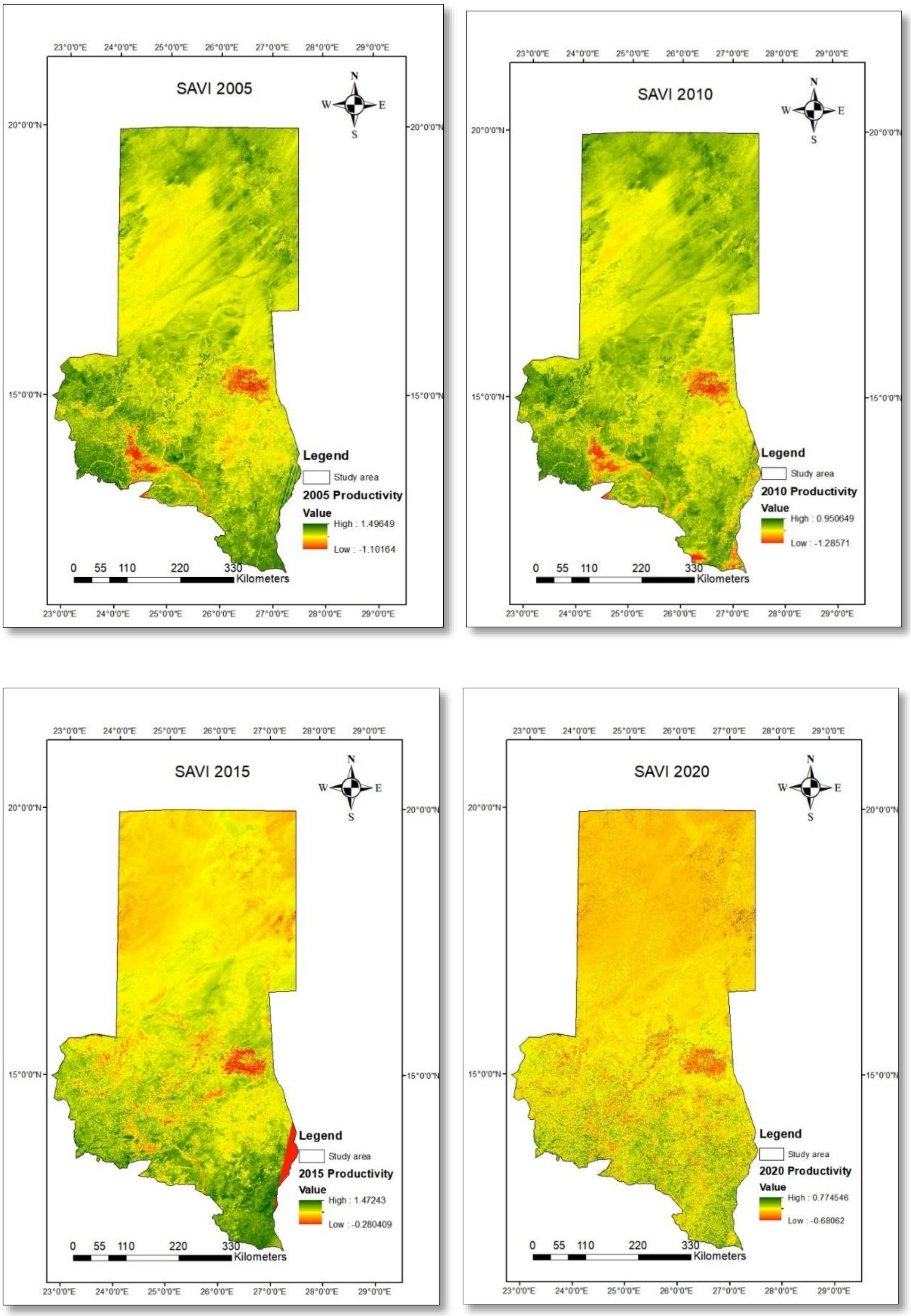

Figure 9b: Soil-Adjusted Vegetation Index for the years 2005 to 2020 showing rangeland productivity.

CHAPTER FIVE

5. DISCUSSION

5.1. The spatial and temporal variations in land cover

Results of this study indicated an increase in rangelands from 142 hectares to 246 hectares from 1985 to 2020 but however between the years there where instances where rangelands decreased and increased significantly. Farmlands decreased from 704 hectares to 1022 hectares, and bare ground increased from 1773 hectares to 1803 hectares, respectively. A reduction in the extent of waterbodies from 544 hectares to 17 hectares from 1985 to 2020. The decrease in waterbodies can be explained by the recent increase in temperatures and the reduction in rainfall experienced; these changes are attributed to climate change. This result mirrored those of other studies done in semi-arid regions. For example, Ibrahim (1984) observed a decline in rangelands in Sudan over 15 years from 1960 to 1975. The location of North Darfur in the marginal tropical zone meant that climate variations and climate change have intensified the process of desertification. Climatic patterns also caused variations in the land cover of the El Gedaref region. The decline in vegetation cover was also explained by Mohmmed et al., (2018) where they observed that elevated temperature levels have increased the frequency of droughts while decreasing rainfall. Furthermore, the Government of Sudan (2007) identified that climate change poses significant challenges to Sudan's land cover by causing desertification and hence enlarging the desert area. Climate change also represents a serious sustainable development problem that affects in the population of Sudan, particularly those in rural communities. These communities are particularly dependent on the natural environment, and hence they are especially vulnerable.

The decrease in rangelands can at least partially be explained by the evident decrease in rainfall and increase in temperature. The reduction in rangelands is also a resulted of the shifts from nomadic farming to other farming activities which include crop cultivation that require clearing of natural vegetation for the creation of farming lands. Similar findings were obtained by Sulieman (2018) who was exploring the causes of forest degradation Sudan. The previous study by Sulieman (2018) showed that the favours that are posed to agricultural practises by the government of Sudan have adverse impacts on rangelands of Sudan. In their study using Landsat satellite images, they observed that large-scale mechanized agriculture in Butana communal rangeland in eastern Sudan increased incrementally from 2.5% in 2000 to 17.6%

(Sulieman, 2018) in 2014. This caused a significant decline in rangelands. Furthermore, as stated by Sulieman (2018) the increase in rangelands can be explained by climatic changes which may include increased CO_2, shifts of the patterns of precipitation just to mention a few.

5.2. Spatial and temporal variations in temperature and rainfall in the study area

5.2.1. Rainfall

Results of this study demonstrated that there were decreases in rainfall in 1986 and 1991, respectively, while there also been years of relatively high rainfall (in 1990, 2004 and 2009, respectively). The pattern of declining rainfall in this region can be explained by climate change, the reduction of rangelands and increasing desertification in the region increasing surface albedo hence reduction in precipitation. This result were like other studies done in comparable environments. For example, the east Africa regional mission of Juma et al., (2020) that serves South Sudan and Sudan observed that at the global scale, the region is particularly sensitive to variations in climate and climate change. Increased variability of rainfall coupled with high frequency of droughts in the past decades has greatly contributed to the negative impacts of the rainfed cultivation and pastoralism activities in the region (Juma et al., 2020). The years that experienced high rainfall can be explained by the presence of high temperature which led to the presence of high amounts of warm air which can hold more moisture since it is key ingredient to heavy rainfall (USAID 2016).

Results from models of time series models signifies mean rainfall will decrease by about 6 mm per month (Sulieman and Elagib 2012). These shifts in temperature and rainfall will adversely affect the agricultural, water resources sector and health sectors of Sudan. Furthermore, Intergovernmental Panel on Climate Change (IPCC) (2007) state that the decline in rainfall can be partially explained by the accelerated modification of land cover (transitions from natural vegetation to transformed landscapes from clearing of land for farmlands, and livestock rearing). Ibrahim (1984) observed that the 62 years of land transformation in Sudan by human land use (including the rational exploitation of natural resources) had left barren lands which however cause ecological imbalance; this, in turn, affects rainfall totals.

5.2.2. Temperature

Results of this study indicated that there was a relative increase in average temperature in the years 1986, 1988, 1991, 1997, 2014 and 2020. In contrast, there were decreases in average temperature for 1995, 2000, 2002, 2011 and 2017. The increases in temperature in this region can at least partially be explained by the lack of rainfall which leads to reduction of waterbodies, hence increasing albedo; thus, high temperatures are experienced (Sulieman & Elagib, 2012). This can also be explained by climate change and the associated increase in desertification in the region; this contributes to the ongoing decline in rangelands and significant increase in bare ground. These results were similar to other studies carried out in comparable environments. For example, climate scenarios analysis conducted by Muneer (2008) in Greater Kordofan region shows that the average temperature was expected to rise significantly (from 1.5 ºC to 3.1 ºC) relative to baseline expectations (www.wri.org). Khartoum was expected to be one of the five cities with the greatest temperature increases in the world. Other predictions also were made regarding these increases; for example, Jos Lelieveld (2016) is a climate scientist from the Max Planck Institute for Chemistry, who told CNN that North Africa although already hot, is particularly at risk of strongly increasing temperature of which North Darfur is part of North Africa. According to Muneer (2008) at some point in this century, part of the region will become uninhabitable. Another study by Sulieman and Elagib (2012) also observed that during the 68 years (from 1941 to 2009) of their study, 75% of the years were warmer than normal and the rate of increase was 0.53 ° C per decade as portrayed by Sulieman and Elagib (2012). This factor contributes to rapid shifts from rangelands to farmlands.

CHAPTER SIX

6. CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

In this study, Landsat satellite images were used to monitor the impact of climate variabilities and land use and land cover change in North Darfur, Sudan. The use of Landsat earth observation data with GIS and remote sensing techniques was found to be useful in quantifying the changes on rangelands from the year 1985 to 2020 in North Darfur. Analysis was carried out using GIS and statistical techniques to detect spatio-temporal LULC dynamics. These techniques were used to identify the impact of climate variabilities and LULC in North Darfur. The analysis of Landsat observations focused on change patterns and transitions over 35 years at five-year intervals. Random forest classification and RAI coupled with SAVI were used to monitor the changes.

Using Landsat images, the first objective was to quantify the land use and land cover of North Darfur for 35 years at five-year intervals. The application of random forest classification revealed a significant decrease in rangelands and a massive increase in farmlands.

The second objective was to determine the spatial and temporal changes in temperature and precipitation patterns in North Darfur over a period of 35 years. These changes were calculated statistically using RAI, and the results indicated a significant decrease in precipitation totals and an increase in temperature. The obtained GLDAS, TRMM, and GPM images were spatially analyzed. The third objective, to determine Rangeland productivity in relation to space and time, was attained by executing a SAVI, which spatially demonstrated a reduction in rangelands.

This study shows that changes or shifts in rangelands were also influenced by the increase in time coupled with the changes in temperature and rainfall causes increase in rangelands as shown by this study. Rangelands were shown to be dominant in the earlier years of the study; at that stage (i.e 1985 to 2000), they covered much of the study area. However, climate variabilities coupled with increases in farming activities, caused the rangelands to decrease in the northern parts and become more dominant in the southern parts. Farmlands also expanded owing to the marked transition from pastoralism to crop farming in North Darfur. Government initiatives were established in support of crop farming for example ‘The Rationale for a Possible Market Support Program in Darfur, Sudan.’ This was commissioned by the USAID and implemented by Cooperative for Assistance and Relief Everywhere Cooperative for Assistance and Relief Everywhere (CARE).

6.2.Limitations of the study

Although the study yielded favourable findings, there were factors limiting the process. The limitations include:

- The unavailability of a single scene to cover the whole study area led to more processes that include compositing bands and mosaicking needing to be carried out. This may have led to loss of essential information.
- In the current study, only rainfall and temperature were considered to explain changes in rangelands and this left a relatively large variance score that was unexplained. Other factors like pastoralism, climate change itself, soil type and water table level can be used in future studies to produce better results and reduce unexplained variance.
- There were no field measurements made to allow the RS sensor to derive an error matrix on its own. This could have been used to validate RF classification. Ground truthing would also have helped with atmospheric correction to reduce error. Since satellite images pass through the atmosphere, they encounter absorption.

6.3. Recommendations

There is a need for:

- Carrying out fieldwork to validate the results obtained.
- Further assessment of other anthropogenic activities that hinder rangeland regrowth and expansion.
- Future studies to cater for the most recent years (2015 to 2021) to see if there is still a direct relationship between time and rangelands.

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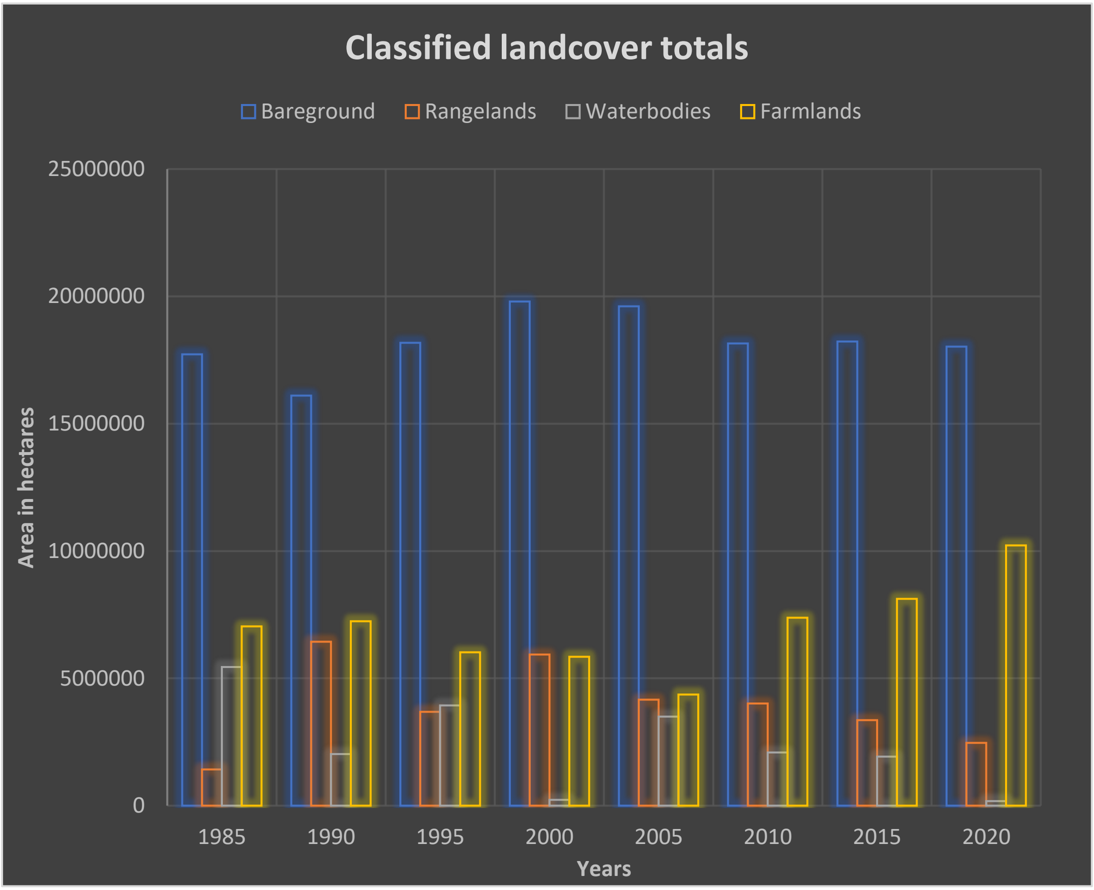
APPENDIX 1

1. Image classification



2. Accuracy assessment tables

Table 1: Accuracy assessment

	1985	1990	1995	2000	2005	2010	2015	2020
OA	54.25	48	38.11	80.83	57.28	66.75	64.52	63.52
UA								
Bare ground	95	100	95.24	97.92	90.91	95	95.24	95.24
Rangelands	75	50	15.79	27.78	41.18	70	61.11	72.2
Waterbodies	45	40	20	100	59.09	75	71.43	57.14
Farmlands	45	40	42.86	42.86	70	75	71.43	71.43
PA								
Bare ground	47.5	76.92	47.62	97.92	47.62	67.86	58.82	58.82
Rangelands	88.24	71.43	75	27.78	87.5	87.5	73.33	86.67
Waterbodies	90	72.73	80	100	92.86	93.75	88.24	70.59
Farmlands	69.23	88.89	47.37	42.86	82.35	75	100	100
Kappa	53.33	47.69	68.26	67.78	54.94	71.67	66.97	69.78

Overall accuracy average for the eight images = 58.53%

The seven images overall accuracy in 58.53% which means that overall, the images were correctly classified at 58.53%.

User Accuracy Average for the eight images

Bare ground = 95.61%

Rangelands = 48.69%

Waterbodies =58.65%

Farmlands = 55.31%

Producers Accuracy Average for eight images

Bare ground =63.47%

Rangelands =72.97%

Waterbodies =88.22%

Farmlands =72.24%

Kappa Coefficient Average for the eight images = 61.52%

Accuracy for the eight images fell at 61% which is a good score so this means that we can accept the results of the RF classification which was performed. This indicates that 61% of the classes were correctly classified according to the kappa coefficient.

1985

	Bareground	Rangelands	Waterbodies	Farmlands	Total (User)
Bare ground	19	0	0	1	20
Rangelands	3	15	0	2	20
Waterbodies	9	1	9	1	20
Farmlands	9	1	1	9	20
Total (Producer)	40	17	10	13	80

1990

	Bare ground	Rangelands	Waterbodies	Farmlands	Total (User)
Bare ground	20	0	0	0	20
Rangelands	6	10	3	1	20
Waterbodies	10	2	8	0	20
Farmlands	10	2	0	8	20
Total (Producer)	46	14	11	9	80

1995

	Bare ground	Rangelands	Waterbodies	Farmlands	Total (User)
Bare ground	20	1	0	0	21
Rangelands	12	3	0	4	19
Waterbodies	10	0	4	6	20
Farmlands	10	1	1	9	21
Total (Producer)	42	4	5	19	81

2000

	Bare ground	Rangelands	Waterbodies	Farmlands	Total (User)
Bare ground	47	0	1	0	48
Rangelands	6	5	2	5	18
Waterbodies	0	0	23	0	23
Farmlands	2	4	2	6	14
Total (Producer)	55	9	27	11	103

2005

	Bare ground	Rangelands	Waterbodies	Farmlands	Total (User)
Bare ground	20	1	0	1	22
Rangelands	10	7	0	0	17
Waterbodies	7	0	13	2	22
Farmlands	5	0	1	14	20
Total (Producer)	42	8	14	17	81

2010

	Bare ground	Rangelands	Waterbodies	Farmlands	Total (User)
Bare ground	19	1	0	0	20
Rangelands	3	14	0	3	20
Waterbodies	3	0	15	2	20
Farmlands	3	1	1	15	20
Total (Producer)	28	16	16	20	80

2015

	Bare ground	Rangelands	Waterbodies	Farmlands	Total (User)
Bare ground	20	0	1	0	21
Rangelands	6	11	1	0	18
Waterbodies	2	4	15	0	21
Farmlands	6	0	0	15	21
Total (Producer)	34	15	17	15	81

2020

	Bare ground	Rangelands	Waterbodies	Farmlands	Total (User)
Bare ground	20	0	2	0	21
Rangelands	8	13	2	0	18
Waterbodies	3	2	12	0	21
Farmlands	5	0	0	15	21
Total (Producer)	34	15	17	15	81

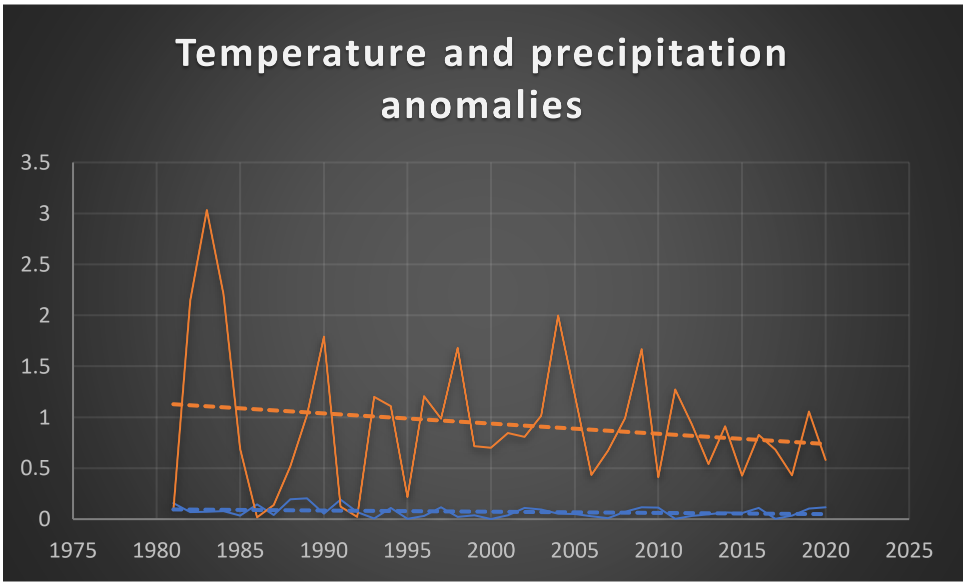
3. Spearman rank correlation

Temperature Spearman rank

Coeffient®	-0.25196
N:	35
T statistic:	-1.49566
DF:	33
p value:	0.072122

Rainfall Spearman rank

Coeffient®	-0.17783
N:	35
T statistic:	-1.03813
DF:	33
p value:	0.153379



Trends of rainfall and temperature anomalies.

4. **SAVI threshold**

YEARS	1985	1990	1995	2000	2005	2010	2015	2020
Total of high and low mean	0.66	0	0.5	0	0.4	-0.34	1.19	0.1
Yearly Average of the means	0.33	0	0.25	0	0.2	-0.17	0.595	0.05
Total means for 8 maps	1.255							
8 maps average	**0.15688**							