

Impacts of Land Use/Land Cover change on boundary layer climate over eastern South Africa

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The Google Earth Engine (GEE) platform was used to access and manipulate remote sensing Landsat imagery, while RStudio, Python, GrADS and QGIS 3.12 were also used to manipulate and visualise reanalyses, satellite imagery and climate observation data.



To my parents, Matome David and Mantsha Winnie Mohomi

“then I will send rain on your land in its season, both autumn and spring rain, so that you may gather in your grain, new wine and oil. I will provide grass in the fields for your cattle, and you will eat and be satisfied”.

Deuteronomy 11:14-16 (The Holy Bible, English Standard Version)

ABSTRACT

Land Use and Land Cover Change (LULCC) is a global phenomenon that has significant impacts on climate by regulating surface air temperatures and rainfall in a variety of ways. Examining the impacts of LULCC on surface moisture and heat fluxes, as well as hydro-meteorological variables has become critical to ensure that long-term climate variability and change are managed. The period (1990-2020) of rapid population growth and urbanisation necessitates the need for this study to determine the impacts of LULCC on climate variability and change over eastern South Africa in order to fully understand land-atmosphere interactions.

Multi-temporal Landsat imagery, ground-based observations and reanalysis datasets were analysed in the investigation of the impact of LULCC on boundary layer climate over eastern South Africa from 1990 to 2020. Landsat imagery classification into six classes Land Use Land Cover (LULC) was done using the Random Forest (RF) classifier in Google Earth Engine cloud platform. The Detecting Breakpoints and Estimation Segments in Trends (DBEST) algorithm was used to detect and analyse LULCC. The time series of LULC classes, Climate Hazards Group's Infrared Precipitation with Station (CHIRPS) rainfall, CRU minimum and maximum air temperature, Global Land Data Assimilation System (GLDAS) evapotranspiration (ET) and potential evapotranspiration (PET), and Famine Early Warning System Network (FEWS NET) Land Data Assimilation System (FLDAS) surface heat fluxes - latent heat flux (LHF) and sensible heat flux (SHF) were computed, whilst Mann-Kendall (MK) trend test was analysed in RStudio. The Pearson Correlation Coefficient was used to test the statistical significance of LULCC's impact on surface energy and moisture fluxes, as well as hydrometeorological variables. The most sensitive variable to change influencing boundary layer climate was identified using variables of importance. Furthermore, Multiple-Linear Regression and Pearson correlation analyses were used to determine land cover types that affect boundary layer climate.

LULCC is occurring more frequently and significantly primarily due to anthropogenic influence, with natural phenomena occasionally contributing to land surface modification. DBEST detected that LULCC is occurring annually and during periods of weather and climate extremes as significant abrupt change of natural land cover occurs. The MK trend test indicates that the Normalised Difference Vegetation Index (NDVI), and land surface temperature (LST) increased significantly, while Normalised Difference Infrared Index (NDII) indicates an insignificant decreasing trend. Furthermore, MK trends revealed that rainfall and LHF decreased insignificantly, while maximum temperature, evapotranspiration (ET), SHF and PET increased significantly from 1979 to 2020. The great escarpment over eastern South Africa influences climate conditions on the west side of the study, resulting in lower temperatures but higher rainfall due to orographic effects. Results indicated that LULCC have significant influence on rainfall and

temperature, and their impacts and significance vary across land cover and regions. The study revealed that PET is the most sensitive parameter affecting temperature variability over eastern South Africa, while LHF affects rainfall variability, influences rainfall over eastern region. The expansion of urban land and bare land in the study area have significantly altered rainfall and temperature patterns whilst water, cropland, grassland and forest influenced different study regions. ENSO and IOD were found to have a significant positive correlation with rainfall and temperature in this study. In eastern South Africa, the vulnerability of rainfall to IOD varied, with some regions exhibiting no correlation and others displaying significant positive and negative correlations.

Key words: LULCC; surface energy and moisture fluxes; ENSO; IOD; eastern South Africa.

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LIST OF ACRONYMS

CHIRPS	Climate Hazards Group's Infrared Precipitation with Station
CRU TS V4	Climate Research Unit Gridded Time Series Version 4
CHC	Climate Hazard Center
CA	Composite Analysis
DBEST	Detecting Breakpoints and Estimating Segments in Trends
DEM	Digital Elevation Model
DMI	Dipole Mode Index
KNMI	Royal Netherlands Meteorological Institute
KZN	KwaZulu Natal
GrADS	Grid Analysis and Display System
GLDAS	Global Land Data Assimilation System
GES DISC	Goddard Earth Science Data and Information Services Center
GEE	Google Earth Engine
GIS	Geographical Information System
ETM	Enhanced Thermal Mapper
ET	Evapotranspiration
ERSST	Extended Reconstructed Sea Surface Temperature
ENSO	El Niño-Southern Oscillation
FLDAS System	Famine Early Warning System Network (FEWS NET) Land Data Assimilation System
IOD	Indian Ocean Dipole
IPCC	Intergovernmental Panel on Climate Change

LandTrendr	LT
LHF	Latent Heat Flux
LT-GEE	LandTrendr-Google Earth Engine
LULC	Land Use/Land Cover
LULCC	Land Use/Land Cover Change
LST	Land Surface Temperature
LandTrendr	Landsat based Detection of Trends in Disturbance and Recovery
MLR	Multiple Linear Regression
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NOAH CPC	National Oceanic-Atmospheric Administration Climate Prediction Center
NDII	Normalized Difference Infrared Index
NIR	Near Infrared Reflectance
OMR	Observed Minus Reanalysis
OLI	Operation Lander Imager
OA	Overall Accuracy
PBL	Planimetry Boundary Layer
PET	Potential evapotranspiration
PA	Producer Accuracy
RS	Remote Sensing
RF	Random Forest
ROI	Region of Interest

TM	Thermal Mapper
Tmin	Minimum Temperature
Tmax	Maximum Temperature
SST	Sea Surface Temperature
SHF	Sensible Heat Flux
SA	South Africa
SWIR	Shortwave Infrared Reflectance
SRTM	Shuttle Radar Topography Mission
UHI	Urban Heat Island
UA	User Accuracy
WRF	Weather Research and Forecasting

CHAPTER 1 : INTRODUCTION

1.1 General Background

Arable land is one of the planet's most valuable and scarce natural resources (Atayi et al., 2016) which is a significant aspect in human population expansion. It enables man to have access to essential survival necessities such as housing, food (Musetsho et al., 2021), water, medications, and energy (Rounsevell et al., 2014). Environmental health is assured as a result of the ecosystem's good condition and long-term use. Different geographical components have varying effects on the ecosystem and climate of any given place (Lambin & Meyfroidt, 2011). They serve as a primary source of precipitation (Pielke et al., 2011), contribute to global carbon balance (Herrmann et al., 2020), cooling the environment through evapotranspiration, water, and nutrient cycling (Mahmood et al., 2014; Nyathi et al., 2020), prevent soil erosion, and promote water holding capacity (Borrelli et al., 2020).

Globally, rural communities rely on Land Use and Land Cover (LULC) to survive (Herrmann et al., 2020; Musetsho et al., 2021). Numerous studies from a variety of disciplines, including ecology, social science, applied biology, hydrology, climatology, health, and agriculture, have paid close attention to Land Use and Land Cover Change (LULCC) in different ways and at different spatial scales (Gillson et al., 2012). Human activity has resulted in an ongoing and rising exploitation of natural resources, exposing ecosystems to change (Dong et al., 2019; Herrmann et al., 2020). Rural communities rely on natural resources such as fertile soils, forests, plantations, grasslands, and water. Global demand for resources has increased pressure on LULC to be modified to meet the needs of the rising population (Garg et al., 2019; Herrmann et al., 2020) and provide them with a better life (Musetsho et al., 2021).

Surface modification such as clearing vegetation for agricultural crops, increased food production have alleviated food scarcity, while urbanisation provided safe housing and habitation for people (Gillson et al., 2012). Forest harvesting has resulted in the provision of wood for shelter, cooking fuel, and warming shelters (Nyathi et al., 2020; Musetsho et al., 2021). Despite these facts, it is critical to recognize that these changes have come at a cost, as they influence water quality and demand (Meer & Mishra, 2020), and the climate.

LULCC also has an effect on the climate and accelerates climate change (Dong et al., 2019; Herrmann et al., 2020). This makes LULCC a significant concern that needs to be prioritised, particularly during climate assessment and studies on the climate system. Although human activity is the primary cause of LULCC and the current climate change, natural processes also contribute to these changes (Herrmann et al., 2020; Musetsho et al., 2021). Several regions around the world have seen increased climate variability and extremes as a result of changes in

surface energy partitioning and surface water resources (Dong et al., 2019), influencing regional air circulation (Pontifes et al., 2018).

LULCC is often accompanied by a decline in infiltration, evapotranspiration, and groundwater recharge, as well as an increase in surface run-off. Land surface changes have considerable effects on the energy exchanges between the surface and the atmosphere (Li et al., 2020). LULCC influences how latent and sensible heat are partitioned, which influences the climate system (Ban-Weiss et al., 2011). For example, moisture in the soil and vegetation increases evapotranspiration flux, which cools the local environment by transferring more energy as latent heat. While an area that is densely vegetated receives twice the amount of precipitation as an area that is sparsely vegetated (Mahmood et al., 2014). Local cooling is driven by an increase in latent heat flux to the atmosphere during a warm local climate on a dry and unvegetated surface, according to (Ban-Weiss et al., 2011). Increased evapotranspiration fluxes in wet and vegetated surfaces contribute to the production of low clouds that reflect sunlight back into space, cooling both local and global temperatures and contributing significantly to precipitation increase (Mahmood et al., 2014).

Climate change has increased in frequency during the previous decade, and it has also been discovered to be more severe and catastrophic. On the other hand, rural areas in developing countries continue to be the most vulnerable due to the situation of the economy (Güneralp et al., 2018). LULCC is a primary contributor to both the frequency and extent of extreme climate variability and change (Hu et al., 2019). Additionally, it has been asserted that the Industrial Revolution and urban growth are major contributors to global warming, while sea level rise and frequent extreme weather events are associated with forest and grassland degradation (Li et al., 2018). The relationship between LULCC and climate has received widespread interest in a variety of ways from numerous studies (Li et al., 2011; Pielke et al., 2011; Oki & Blyth, 2012; Li et al., 2018; Ge et al., 2019; Idowu et al., 2019; Huang et al., 2020; Meer & Mishra, 2020). Additionally, some studies have revealed that LULCC also contributes to weather and climate extremes such as floods, heatwaves, tropical storms, and drought, all of which can pose significant challenges to ecosystem services, human society, and the economy (Hu et al., 2019).

Drought and high temperatures increase the probability of plants becoming flammable (Nolan et al., 2020), livestock becoming ill or dying, agricultural loss, and water and food deprivation. Floods and tropical cyclones can both damage infrastructure and inflict casualties (Mbokodo et al., 2020).

Extreme weather events have varied effects depending on the region (Pontifes et al., 2018) and season (Mahmood et al., 2014). Additionally, climates at high altitudes will respond differently to LULC modification than climates at low altitudes (Gogoi et al., 2019). Climate sensitivity to change

in these regions differs significantly between summer and winter. As a result, it is becoming increasingly crucial to investigate LULCC and its effect on climate from a variety of different spatial and temporal perspectives.

In southern Africa, particularly in South Africa, the degree and significance of LULCC have increased. Africa is one of the world's fastest-urbanising regions, a biodiverse and largely rural continent (Güneralp et al., 2018). The most pressing challenge in Africa is uncontrolled and unplanned urbanization (Güneralp et al., 2018), which according to Turok & Borel-Saladin (2014) degrades ecosystem quality and increases environmental risk and resource scarcity. These unplanned settlements face a stronger urban heat island than planned settlements (Ngie, 2020). South Africa, like the rest of the world, is undergoing natural land-scape change. Daily, the land surface is modified as a result of infrastructure development, which aims to improve living conditions and increase the region's economy (Odindi et al., 2012; Twisa & Buchroithner, 2019; Masroor et al., 2022). LULCC illustrates the earth's surface response to human-induced pressure and has become a substantial contributor to global climate change.

South Africa experiences a wide variety of climatic regimes with higher rainfall over the eastern, more vegetated side compared to the arid west (Landman et al., 2017). The eastern part, experiences a sub-humid climate partly due to the warm Agulhas ocean current, which provides moisture to onshore airflow to the region, whilst the western region is impacted by a cold Benguela ocean current (Landman et al., 2017). Most of South Africa's provinces experience warm temperatures which have increased in recent years and are projected to continue to do so (Engelbrecht et al., 2015). Extreme temperatures such as heatwaves occur regularly in South Africa, threatening surface moisture and increasing dryness, hence fuelling drought (Mbokodo et al., 2020). Orimoloye et al. (2019) reported a dramatic change in LULC (increasing build-up and sparse vegetation) between 2014 and 2018, whereas land surface temperature (LST) and surface dryness increased, likely contributing to the 2017 and 2018 droughts in Cape Town. According to Engelbrecht et al. (2015), soil moisture availability in some places of Africa will decline due to excessive evaporation, independent of the availability of high precipitation. Despite high vulnerability to high temperatures (Mbokodo et al., 2020) and drought, most South Africa's provinces continue to struggle with flooding (Chikoore et al., 2021), significantly affecting livelihoods of the rural poor.

Climate extremes are the result of several variables, including human-caused global warming and naturally occurring phenomena such as the El Niño/La Niña Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD), all of which influence weather and climate patterns (Chikoore et al., 2021; Landman et al., 2017; Ogwang et al., 2020; Puryajati et al., 2021). Also, interactions of energy, moisture and momentum at the sea surface are considered to play a significant effect in temperature variability and precipitation (Ndlovu & Demlie, 2020).

Prior research has concentrated mainly on the spatial distribution of LULCC (Odindi et al., 2012; Xulu, 2014; Tizora et al., 2016; Kamwi et al., 2018; Phan et al., 2021), its influence on LST and Urban Heat Island (UHI; Mbithi et al., 2006; Li et al., 2011; Ding & Shi, 2013; Idowu et al., 2019; Sanecharoen et al., 2019), precipitation (Meer & Mishra, 2020; Thapa, 2020) and temperature (Hu et al., 2017).

Thus, it is critical to examine the impacts of LULCC on surface heat flux, moisture flux, and hydrometeorological variables rather than focusing exclusively on one variable. This study was conducted to allow for a more detailed understanding of the land-atmosphere relationship. According to statistical records, South Africa's population has been increasing over the years, and as numerous studies have demonstrated, increased population results in increased urbanization (Odindi et al., 2012; Ngie 2020; Thapa, 2020) and increases demand for food (Rounsevell et al., 2014) through agricultural production, potentially leading to the LULCC.

1.2 Research Problem and Motivation

LULCC is a well-studied global phenomenon (e.g., Pielke et al, 2011; Liu et al., 2017; Idowu et al., 2019; Thapa, 2020; Herrmann et al., 2020; Musetsho et al., 2021), and is one of the primary drivers of environmental change that play a unique role in the climate system (Mahmood et al., 2014). Mahmood et al. (2014) recognize that the frequency of occurrence and magnitude of impacts may vary by geographical location and season.

The south-eastern region of South Africa has been undergoing land transformation for some time now as a result of increased agriculture, urbanisation, forest plantation, and cropland. These have modified surface physical properties such as albedo, soil moisture, and roughness length, affecting surface heat and moisture fluxes, atmospheric circulation, and the surface energy budget (Li et al., 2018). LULCC occurs as a natural vegetation and waterbodies are transformed through urbanisation, agriculture, forestation, and cropping (Herrmann et al., 2020; Musetsho et al., 2021). As a result, changes in vegetation cover and water bodies affect how energy is partitioned at the surface into either sensible heat, latent heat, or ground storage (Chikoore & Jury, 2010).

Additionally, land cover, along with irrigated agriculture and forests, contributes to climate cooling and increased precipitation through increased evapotranspiration and latent heat flux (Mahmood et al., 2014). Urbanisation is also a major contributor to global warming through the urban heat island and industrial emissions. Vegetation removal and a lack of moisture as a result of water body fragmentation or dry soil warm the local climate and alter precipitation patterns (Liu et al., 2017), because more energy is transferred as sensible heat (low evapotranspiration) and latent heat is decreased (Chikoore & Jury, 2010).

Climate change has a damaging effect on an area's functionality and habitability due to heat stress (Idowu et al., 2019). Additionally, it has the potential to affect agriculture, the economy, and human health (Mbokodo et al., 2020). Non-evaporative built-up surfaces have a high heat storage capacity (increasing LST), they obstruct air circulation, and alter hydrological cycling (Cao et al., 2020), resulting in an Urban Heat Island (UHI) and increased run-off, fuelling flooding during periods of heavy rain (Li et al., 2018). Floods have the potential to destroy structures, displacing, injuring, or killing residents (Mbokodo et al., 2020). LULCC is of primary concern.

It is critical to understand how land has been transformed on South Africa's eastern escarpment and the effect this has had on the local climate. This will assist in land use planning and future disaster preparedness, while also protecting the environment, increasing agricultural production, and sustaining human daily life.

1.3 Research Questions

Based on the research problem defined above, this study seeks to investigate the following questions:

- What are the most significant changes in land use and land cover types on the eastern escarpment of South Africa
- To what extent are surface energy and moisture fluxes, and the local boundary layer climate influenced by trends in LULCC?
- Which land cover classes are driving change in the boundary layer climate?

1.4 Aim

The aim of this study is to analyse the nature, extent and impacts of land use/land cover change on surface heat and moisture fluxes and hence the local climate of eastern South Africa from 1979 to 2020.

1.5 Research Objectives

The specific objectives of this study are: -

- To classify and quantify temporal changes in land use and land cover types in the study area via change detection
- To investigate the effect of land cover changes on trends in surface energy and moisture fluxes and hydrometeorological variables
- To determine the important land cover classes driving change in the boundary layer climate

- To explore the influence of external remote phenomena (i.e. ENSO and Indian Ocean Dipole) on variability in the boundary layer climate

1.6 Structure of the dissertation

This dissertation consists of 6 chapters which are defined as follows:

Chapter 1 has provided an overview of the entire research study and including background on changes in land use and land cover types and their impact on the climate. The chapter has detailed a problem statement, research questions, the study's primary aim, and research specific objectives.

Chapter 2 conducts a review of the available literature. This chapter includes a variety of analysis methods for determining the impact or role of LULCC. This chapter also discusses the factors affecting LULCC, as well as the impacts of climate variability and change.

Chapter 3 describes the datasets used in the study and provides their sources, whilst explaining why they were selected. Additionally, the chapter details the various methods of analysis employed to accomplish the study's objectives, and a description of the study area.

The dissertation consists of two results chapters. Chapter 4 presents LULC classification maps of different LULC classes, accuracy assessment of classification performed and LULCC detection. The trend of LULCC and Normalised Difference Vegetation Index (NDVI) are also presented in this chapter. Trends of surface heat and moisture fluxes and their impact on the local climate are presented in Chapter 5. The most sensitive climate variable to LULCC and the LULC that influences change are also presented in this chapter. The chapter also investigates the ENSO and IOD phenomenon and their influence on hydrometeorological parameters.

The conclusion, synthesis and recommendations of this work are summarised in Chapter 6.

CHAPTER 2 : LITERATURE REVIEW

2.1 Introduction

For years, LULC has been changing as a result of human activities, decisions, and natural processes that significantly alter the physical environmental landscape, inhibiting the earth system's functionality (Rounsevell et al., 2014). Changes in LULC can also influence and contribute significantly to climate change (Garg et al., 2019). As a result, there is a strong relationship between LULC and climate change. This can exacerbate climate and weather extremes, posing serious threats to ecosystem services, human health, and the economic viability of a region (Hu et al., 2019). Climate variability, according to the literature, will become more intense and prolonged as the population grows and the demand for resources increases (Garg et al., 2019; Yuvaraj, 2020; Herrmann et al., 2020; Musetsho et al., 2021). Monitoring the rate of change in LULC and fully comprehending its implications is critical for future land use planning and policy orientation, which is critical for combating climate change.

This chapter details the existing literature on the LULC transformation in South Africa and the factors influencing it. The chapter also discusses climate variability in South Africa, and provides understanding of LULCC and its overall effect on the local climate system. Additionally, it details the role of remote phenomena in the lower atmosphere. The final section of the chapter discusses the consequences of climate change.

2.2 Land Use/Land Cover (LULC) Change

LULC can be divided into land use and land cover, and while some researchers use them interchangeably, however there is a difference between the two. Land use refers to the purpose for which land is used, as well as the activities and inputs that humans perform on various land cover types, e.g. agricultural and grazing land, urban living, recreational areas, etc. (Briassoulis, 2009; Atayi et al., 2016) whilst land cover is earth surface characteristics such as water, vegetation, building or pavement and soil (Briassoulis, 2009; Tizora et al., 2016). Land cover plays a key role to human society as well as to the environment (Nyathi et al., 2020).

LULCC refers to the transformation of LULC or the earth's terrestrial surface by either human or natural activities (Pielke et al., 2011). Human activities are primarily motivated by the increased demand for resources as the population increases, and therefore play a significant role in the transformation process (Liu et al., 2017; Herrmann et al., 2020). Mining, urbanisation, deforestation, forest plantation, and agriculture are examples of human activities that alter the natural surface (Dong et al., 2019; Cao et al., 2020; Herrmann et al., 2020). However, natural phenomena which can result from climate change include drought, flooding, and earthquakes amongst others (Solanky et al., 2018; Yuvaraj, 2020).

Human action results in the transformation of soils, vegetation, and wetlands into non-evaporating materials like pavements, roads, and buildings (Yuan & Bauer, 2007; Ngie et al., 2017; Li et al., 2018; Idowu et al., 2019). Humans are regulating the climate system by the change of LULC (Oki & Blyth, 2012) and their alteration can have significant effects on the climate and weather systems (Mahmood et al., 2014). This changes the physical characteristics of the land surface and alters surface moisture, momentum and energy fluxes, and water movement between the surface and the atmosphere (Rounsevell et al., 2014; Idowu et al., 2019; Huang et al., 2020). According to Oki & Blyth (2012), for the atmosphere, the land surface serves as an interactive lower boundary condition. Furthermore, under any given condition, it receives rainfall and radiation and returns sensible heat, latent heat, and moisture to the atmosphere.

2.3 Causes of change in LULC

Governments, communities, and individual landowners exercise control over and decide how their land is used (Tizora et al., 2016). They control certain land uses, which presents a challenge because legislation varies by region. Socioeconomic and biophysical factors have been identified as the drivers of land use change because they affect and influence how land managers make decisions (Mishra et al., 2020). However, the primary drivers of change are human activities and decisions (Dong et al., 2019; Herrmann et al., 2020) such as construction and agricultural land expansion, while the fundamental aspect is the result of complicated relationships between political, social, biophysical, and demographic variables (Tizora et al., 2016). In South Africa, the issue of land claims is also a factor influencing change (Akinyemi, 2021).

2.3.1 Biophysical Factors

Biophysical factors influence the change in LULC caused by human activities. Environmental conditions favour land change; for example, the availability of fertile soil and the slope of the land either cause or influence the decision to use such land for agricultural expansion (Duraismy et al., 2018). Rocky ground, and a lack of underground water can result in land being fallow and unused, as no farmer wants to risk planting on such land when fertile and suitable land is available elsewhere (Duraismy et al., 2018). Climate variability may be a factor in LULCC. Vegetation grows in areas with sufficient moisture in the soil, but without rainfall or with high temperatures, the moisture in the soil is altered, preventing plant growth (Ban-Weiss et al., 2011), and the area becomes dry and totally lacking in plant cover. Climate dictates the locations of certain activities, such as agricultural land (Rounsevell et al., 2014). This could be due to changes in temperature, rainfall, wind speed, or vulnerability to fire. High temperatures can initiate drought and heatwaves (Hu et al., 2019), increasing the flammability of vegetation (Nolan et al., 2020) and altering the LULC. Additionally, it makes the area more susceptible to pests and disease attack, which can negatively impact plant growth (Sun et al., 2019). Heavy rains can cause flooding, transforming

the area's landscape by uprooting vegetation or forested land, as well as infrastructures, eroding roads and agricultural land (Chikoore et al., 2021).

2.3.2 Urbanisation, Population Growth, Economy and Technological factors

Population growth is a critical factor in most urban areas' growth, as it exerts pressure on land use. Population changes and growth rates influence the structure and shape of urbanisation. Population growth is the primary driver of resource consumption (Garg et al., 2019), for necessities and settlement construction (Gillson et al., 2012; Herrmann et al., 2020). The economy and technology are also the driving force behind change in every part of the world and in every possible way (Herrmann et al., 2020). An economic expansion and technological advancement facilitate access to information and creates opportunities for export and import (Duraismy et al., 2018). It further makes it easily possible for the growing population to modify land to make it more conducive to their way of life, meet their needs and provide comfort in their lives. Hence, we see industrial development, construction of shopping malls, development of manufacturing industries, nuclear power plants, and increased agricultural production. It results in the construction of a network of smooth roads and bridges to access these remote areas for resources. Furthermore, it enables farmers to gain access to machinery that enables them to expand into new areas and areas with difficult terrain (Briassoulis, 2009; Duraismy et al., 2018). Overall, it aids in the development of crops that are resistant to extreme weather and disease, as well as chemicals that protect vegetation and plants from pest infestation (Akbari et al., 2009).

These developments have significantly altered the landscape at the expense of the most sensitive land and resources that contribute significantly to the environment and climate. All the developments also attract people from diverse backgrounds due to comfort, diversity of opportunities, and services (Odindi et al., 2017; Ngie, 2020; Yuvaraj, 2020). At times, this results in the birth or establishment of densely populated informal and formal settlements, as people lack the financial means to afford adequate housing (Mudau et al., 2014). Rustenburg, South Africa saw a significant urban expansion due to employment opportunities emanating from mining (Mudau et al., 2014). Furthermore, some parts of the City of Johannesburg are overcrowded as a result of educational, recreational, and employment opportunities that attract people from all South Africa's provinces (Nkosi et al., 2019). The city's overcrowding has resulted in an extensive expansion of formal and informal settlements on the outskirts (Ngie, 2020). This also results in increased land use, degradation, and deforestation, because informal settlements are largely lacking in basic services, as residents cut down trees for fuel and to sell for subsistence. Musetsho et al. (2021) observed the clear-cutting of thicket and dense bush for commercial purposes, resulting in the loss of valuable land cover. Globally, vegetation and forests are cleared every day to make way for housing, roads, and fuel (Herrmann et al., 2020).

2.3.3 Political Factors

Politics affect or dictate how things are done throughout the world, as their decisions affect almost everything (Nkosi et al., 2019). Most importantly, when political leadership changes, many leaders implement new policies that alter the entire framework of government and, at times, international relations (Gang, 2006; Helms, 2020). Typically, this is done to attract international investment rather than for the benefit of the local population. The investment is for development and basic services such as roads, housing, and modes of transportation (Briassoulis, 2009), which all have an effect on how LULCCs in one way or another. South Africa is an excellent example; its policies addressing the colonial past in order to alleviate poverty have been both beneficial and detrimental in terms of LULCC, including the land reform, land claims, and tenure program (Lidzhegu & Palamuleni, 2012; Mudau et al., 2014). The South African land reform program has altered agricultural production with 90% transferred land largely unproductive (Chitonge, 2013). For example, arable land used for agricultural productivity are converted to game farms, settlements, estates and golf courses in some rural provinces after land redistribution (Akinyemi & Mushunje, 2019). A politician's decision has a significant impact on how government policies are changed and how things are done in such a way that donors and agencies can be influenced to release funds to invest in specific economic activities (Duraisamy et al., 2018). This means that LULCC will be dependent upon such a decision. A perfect example as mentioned by Duraisamy et al. (2018) is what occurred in the 1990s when an irrigation project was invested in Pravara, Nilwande, and Mandohol as a result of policy certainty, increasing access to water and resulting in rapid expansion of cultivated areas.

2.4 LULCC in South Africa

LULCC has been occurring in South Africa for decades now and is one of the most vital and simply noticed indicators of changes in living support systems and ecosystem service (Musetsho et al., 2021). Municipalities around the country have accelerated the transformation to LULC by focusing on the past planning inefficiencies created by prior regime policies (Lidzhegu & Palamuleni, 2012). This resulted in a huge increase of ineffective urban areas and informal settlements that are unmanaged and unplanned. According to Ngie (2020), South Africa's biggest city (Johannesburg) and second largest city (Cape Town) have seen growing populations associated with significant increases in informal settlements. Most of the surfaces or materials used according to Ahmed et al. (2013) are characterised as impermeable materials with high heat conductivity. Additionally, the land reform, claim, and tenure program has also halted of agricultural activity, with some farmland converted to cattle grazing and others abandoned (Lidzhegu & Palamuleni, 2012).

A study by Odindi et al. (2012) found that LULCC in some parts of South Africa is due to population increase which transformed the landscape particularly due to restrictive Prevention of Illegal

Squatters Act of 1951 which is no longer in effect. This land surface change in South Africa is happening differently to other parts of the world as a result of that. In other parts of the world changes are mainly due to road construction, and big cities unlike in South Africa where there is more of an informal setting and great demand for housing and land. Tizora et al. (2016) also conducted a LULCC study in the Western Cape between 1990 and 2014 which observed a significant decrease in natural surfaces. Furthermore, mines and pits in the area showed a dominant increase (52.82%) as a result of the need for the construction industry sand. In Rustenburg, South Africa Mudau et al. (2014) monitored urban growth between 2007 and 2012 and found population growth of 25.5% which is higher than that experienced by other cities in the country. Odindi et al. (2017) found a significant change in LULC which was dominated by urban growth across three coastal areas of South Africa which is eThekweni, Buffalo and Nelson Mandela Bay Municipality. Furthermore, Orimoloye et al. (2019), also established a drastic LULCC between 2014 and 2018 with only build-up and sparse vegetation increasing in the city of Cape Town. A recent study by Musetsho et al. (2021) analysed the LULCC in South Africa's essential biodiversity and discovered woodland as the most significant change, increasing by 46.94 %. While deforestation was the primary cause of forest (thicket and dense forest) change, it was also the second most significant factor, decreasing by 38.79 % over a 28-year period (1990 to 2018). Additionally, the study noted a 1.09% increase in built-up area and a 0.04% decrease in wetland area due to residential development.

The above demonstrate the magnitude of LULCC and how it occurs across the country, at differing rates and across a range of LULC types. Due to a lack of knowledge and understanding about the critical nature of LULC, it risk destroying even the most vital biodiversity that contributes significantly to human survival (Musetsho et al., 2021). Implying that without appropriate policies and strategies to manage change, this will be a disaster in the future.

2.5 Climate variability in South Africa

Global temperature has been shown to have increased substantially over the past decade and this change is attributed to human activities (Jia et al., 2019). According to Engelbrecht et al. (2015), Africa's temperature has been rising over the last decade, faster than the global temperature rate. Southern Africa is most vulnerable to climate change as a result of multiple influencers and due to low adaptive capacity (Dennis & Dennis, 2012). South Africa's climate is undergoing significant change, as the country has been experiencing widespread warming, which is expected to continue. Extreme temperatures and natural disasters are just a few indicators that the current state of our climate is changing (Gries et al., 2019). This warming would be accompanied by many types of extreme events, including heatwaves, which are projected to increase in intensity, frequency and duration in the coming years. Mbokodo et al. (2020), in South Africa found that the number of cold events has decreased, while the number of hot extreme

events has increased. Additionally, daily maximum temperatures will continue to rise, increasing by 6 degrees between 2070 and 2099 (Mbokodo et al., 2020). This is consistent with the latest Intergovernmental Panel on Climate Change 6th Assessment Report (IPCC AR6) report, which demonstrated that human-induced climate change is already affecting a variety of weather and climate extremes and projects that it will continue to do so over the next several decades (Jia et al., 2019).

Rainfall in South Africa has decreased, and disruption of rainfall patterns is expected in the future (Dennis & Dennis, 2012). However, changes vary across the country; some areas have experienced low mean temperatures and abundant rainfall. This is largely due to the country's complex topography and ocean (Landman et al., 2017). Rainfall is a critical variable in climate change, its changing patterns and trends require critical study within the context of climate change (Botai et al., 2018). Extreme climate events such as flooding and drought will become more frequent and intense while increased rainfall will fuel floods (Dennis & Dennis, 2012; Ogwang et al., 2020). For example, in 2019 the north-eastern South Africa received intense rainfall, resulting in floods that caused disruption of socio-economic activities (Chikoore et al., 2021). According to Botai et al. (2018), changes in rainfall patterns have exacerbated drought in several South African provinces, five of which were officially designated as drought disaster regions. Chikoore & Jury (2021) found that recent droughts in the country have been more intense and severe than in previous decades due to the effect of global warming. Climate change and climate extremes have occurred in the past and will continue to do so if the IPCC report's mitigation measures are not followed and implemented.

2.6 Topography and Climate

Topography is critical in determining the earth's atmospheric circulation because it acts as a barrier to air flow which may result in lifting of moisture (Ogwang et al., 2014). Topography influences the climate which is due to orographic effect (Singleton & Reason, 2006; Chikoore et al., 2021). Orographic precipitation results from clouds formed along the great escarpment serving as source of rainfall (Landman et al., 2017). Tahir et al. (2015) noted significant increases in monsoon rainfall events in South Asia region attributable to topography. According to Landman et al. (2017), the complex topography over the South African domain can result in severe convective storms. Temperatures on the other hand are relatively low in high altitude/mountain tops (Mahmood et al., 2014), hence Ngie (2020) found lower land surface temperatures above the mountains. In South Africa, lower temperature is experienced across the southern and eastern escarpment due to altitude (Landman et al., 2017). According to Ogwang et al. (2014), low topography areas tend to experience high mean air temperature and reduced maximum rainfall. While Sevruk & Miegilitz (2002), also established that daily precipitation changes correlate more with altitude, whereas rainfall decreased with altitude. In an extreme rainfall event in the north,

strong winds interacted with the Soutpansberg Mountain Range enhancing low-level convergence and lifting, resulting in 300 mm of sub-daily rainfall, causing flooding in Thohoyandou, northeastern South Africa (Chikoore et al., 2021). Topography has also been found to be a significant factor in extreme rainfall events including those associated with cut-off low pressure systems (Singleton & Reason, 2006).

2.7 Role of LULCC in the boundary climate layer

Climate impacts result from modification of the atmosphere's lower boundary (Pielke et al., 2011). At the surface, altered energy partitioning into sensible heat, latent heat, and ground storage occurs as a result of altered physical properties of the surface (Chikoore & Jury, 2010). This results in the formation of a new structured Planetary Boundary Layer (PBL), cloud cover regime, local wind and weather pattern (Mahmood et al., 2014). Vegetation is a critical land cover type that has the potential to influence the climate. Furthermore, according to Pielke et al. (2011) pasture experience soil moisture deficit compared to forests hence the area experiences warm and dry conditions. Surface soil moisture also plays an important role in the boundary layer climate, because it enhances rainfall and keeps the environment cooler due to evapotranspiration and latent heat flux. The interaction between the surface and the atmosphere is influenced by biogeophysical variables such as soil moisture, surface heat flux, surface roughness, evapotranspiration, and albedo (López-Espinoza et al., 2020). The impacts or influence of LULCC can never be underestimated and different surface cover and property have a serious influence on the lower atmosphere (Masroor et al., 2022).

2.7.1 Surface albedo and roughness length

According to Li et al. (2018), the albedo/reflective capacity of the land surface is the fraction of solar energy reflected back to the atmosphere. Changes in surface cover influence both surface albedo and evapotranspiration. Converting forest to grassland or bare surface cover increases albedo and decreases evapotranspiration. Removal of vegetation also alters surface roughness, which refers to the effect of obstacles on the wind (Jiang & Weng, 2017). For example, a terrain covered in bushes and dense forest has a longer roughness length than grassland, and thus wind speed is slowed more by forests and mountains (resulting in wind convergence) compared to grassland. Vegetation cover and health are critical because they act as a critical land cover with the potential to influence the climate (Masroor et al., 2022).

The climate is extremely sensitive to changes in vegetation and its composition (Shen et al., 2018). Vegetation regulates surface temperatures (Jury, 2013), through absorbing and reflecting solar energy, as well as by regulating heat fluxes and their response to rainfall (Chikoore & Jury, 2010; Pablos et al., 2016; Yuvaraj, 2020). In the absence of vegetation, surface roughness increases warming the atmosphere and decreasing rainfall. A study by Ngie (2020) established

that the hottest temperatures are located in areas of less vegetation and more urban settings. Vegetation increases transpiration as a result increases and decreases latent and sensible heat respectively which then lowers the surface temperature (Mahmood et al., 2014). Vegetation removal increases albedo and sensible heat flux, while decreasing evapotranspiration and latent heat. Furthermore, the boundary layer height increases with rainfall and deepens even more during maximum vegetation, so removing vegetation reduces its height. Land-atmospheric interaction is strongest at the atmospheric boundary layer (Chikoore, 2005; Mahmood et al., 2014). Vegetation has been found to be strongly correlated with temperature and rainfall (Chikoore & Jury, 2010).

2.7.2 Soil Moisture

Soil moisture is water that is retained in the soil's pore spaces (Jiang & Weng, 2017) and changes to the land surface influence soil moisture. It can be impacted by transitioning from natural cover to impervious surfaces or by clearing vegetation to bare land thereby exposing soils to sunlight (Zipper et al., 2019). Soil moisture is a type of water that is critical to the climate system. When moisture levels are altered, whether through urbanisation or agriculture, the distribution of surface energy and rainfall patterns can be altered (Chikoore, 2005; Mahmood et al., 2014; Li et al., 2018).

Soil moisture provides moisture for evaporation control, which in turn controls how available energy at the ground is partitioned into sensible and latent heat exchange (Chikoore & Jury, 2010). Temperature and rainfall patterns are influenced by soil moisture. Substituting forest or agricultural land for bare land or grassland reduces sensible heat flux and stabilizes the lower atmosphere (Mahmood et al., 2014). Wet soil results in a decrease in sensible heat flux and an decrease in stability in the lower atmosphere, resulting in increased precipitation and a cooling effect on the environment due to high evapotranspiration and latent heat flux (Ban-Weiss et al., 2011). Drought, flooding, temperature, and precipitation are all regulated by surface soil moisture conditions (Chikoore, 2005).

On the other hand, low rainfall conditions limit soil moisture availability resulting in a decrease in latent heat flux due to decreased evapotranspiration and an increase in sensible heat (Lyon, 2009). Furthermore, low rainfall impacts vegetation health via soil moisture to grow and increase transpiration, which favours latent heat flux. However, according to Engelbrecht et al. (2015), soil moisture availability will decrease in some regions of Africa due to high evaporation regardless of the availability of high rainfall. Understanding and forecasting the climate system requires an understanding of the relationship between soil moisture and evapotranspiration.

2.7.3 Evapotranspiration

Evapotranspiration (ET) is a key element in the surface water budget and surface energy balance system (Wu et al., 2020), that helps determine the humidity of the lower atmosphere. ET is given by the sum of the process of evaporation and transpiration (Jiang & Weng, 2017). Liou & Kar (2014) refers to evaporation as the primary process by which water is removed from a watershed. Transpiration is defined as the process by which water is absorbed by the roots of plants and transported to the pores on the underside of leaves, where it is converted to vapor and released into the atmosphere (Jiang & Weng, 2017). As a result, ET is the transfer of moisture from the surface to the atmosphere, which provides vapor to the atmosphere. While according to Wu et al. (2020), ET is the process by which water is transferred from land surfaces to the atmosphere, primarily via turbulence, which is determined by the aerodynamics of the surface as determined by the land surface cover and climate conditions. It is responsible for 15% of the atmosphere's water vapor hence, when altered there is a rainfall deficit due to reduced cloud formation. Global warming is expected to result in more atmospheric water vapor, even though a warmer atmosphere has a higher dew point temperature (Neelin et al., 2022). It is critical information for agriculture, water resource management and research on climate change impacts (Wu et al., 2020).

Deforestation decreases the surface ET which leads to an increase in surface air temperature (Mahmood et al., 2014). ET is influenced by a variety of factors (Jovanovic et al., 2015), but it decreases as temperature rises (Jury, 2013), resulting in a decrease in latent heat flux and an increase in sensible heat flux (Mahmood et al., 2014; Li et al., 2018). It entails energy transfer because the latent heat generated during evaporation is transferred to the atmosphere via water vapor. The atmospheric boundary layer's height, temperature, humidity, and pressure are critical and sensitive meteorological variables for ET (Wu et al., 2020). ET influences the surface energy budget by supplying humidity at the local boundary, which in turn influences the local climate (Legates et al., 2011; Mahmood et al., 2014). As a result, clouds, and rainfall form, acting as a cooling agent at the surface. Climate and ET are closely connected to the material on the surface. The transformation of the surface alters the surface moisture, either in the air or on land, which influences the ET process, limiting/increasing the amount of water reaching the atmosphere and thus affecting the climate (Legates et al., 2011; Meer & Mishra, 2020). As a result, this can either favour rainfall formation (Harper et al., 2014) and lower atmosphere cooling, or it can limit/reduce rainfall formation and warm the atmosphere (Teuling et al., 2017).

2.7.4 Latent and Sensible heat flux

Latent heat flux (LHF) refers to energy exchanges between land surface and the atmosphere, which is used for water phase changes through ET and subsequent condensation (Li et al, 2018). While the sensible heat flux (LHF) is the rate at which heat is lost to the air due to a temperature

difference via convection and conduction (Liou & Kar, 2014). LHF and SHF plays a significant role in the atmosphere. SHF at the bottom means energy available immediately to the atmosphere and contributes to heating or deepening the PBL (Mahmood et al., 2014).

A study by Zhang et al., (2020), found LHF and SHF to be sensitive to land conversion, while changes in other fluxes seemed to be weaker. LHF and SHF are influenced by spatial and temporal variations in soil moisture, which affect the near-surface air temperature and humidity (Legates et al., 2011; Cao et al., 2020). This, in turn, has the potential to alter rainfall. LULCC significantly transforms soil moisture which alters surface energy budget hence the portioning of energy at the surface to either LHF, SHF or ground storage is also affected. Once the energy budget is altered, fluxes of heat, moisture, and momentum within the PBL are directly altered (Mahmood et al., 2014).

The partitioning of energy available at the surface into LHF and SHF depends crucially on the soil moisture. However, surface moisture does not directly heat the atmosphere but increases LHF which raises moisture/vapor water content to the boundary layer which increases cloudiness and contributes to the formation of rainfall. While an increase in SHF warms the boundary layer. Vegetation surface cover can draw water from the depth of 1 m using the roots (Folwell et al., 2022). While for bare land, water available is only the one which is a few cm of the soil that contributes for evaporation (Harper et al., 2014). As a result, the change in surface cover affects that capability to draw water for evaporation. The difficulty for water access can be determined using the Bowen Ratio (BR), which is the ratio of LHF and SHF, and is used as a proxy to estimate evaporation. Surface materials such as pavements resulting from urbanisation have high value (BR) due to the difficulty of accessing water and this is mainly because they are non-evaporative surfaces and do not store any water within (Chikoore, 2005). On the other hand, vegetated area and water bodies will have lower BR values due to the transpiration process and evaporation process due to water readily available while bare land is limited to a few cm hence its values will be between (Mahmood et al., 2014).

2.7.5 Land Surface Temperature and Urban Heat Island

Land Surface Temperature (LST) is critical for environmental studies and resource management on the Earth because it is used to calculate the effective radiative temperature at the earth's surface (Sun et al., 2017). According to Voogt & Oke (2003), surface air temperature is a critical variable in urban climate research. It is also a significant factor in determining how available energy is partitioned into SHF and LHF. The rate of change of LST is highly dependent on the land surface characteristics, including soil moisture, land use, and vegetation (Mbithi et al., 2006). As a result, different land surface materials exhibit distinct properties that influence LST, resulting in the formation of distinct microclimates (Voogt & Oke, 2003; Ngie et al., 2014). LST is highly

correlated with temperature and rainfall (Thapa, 2020) and can be used as a drought indicator as well as a proxy for soil moisture, ET, and vegetation (Chikoore, 2016).

Removal of a high evaporative surface (Kumari et al., 2020), such as waterbodies/soil moisture and vegetation by pedestrian footpaths, garden paths, highway roads (Ngie et al., 2014; Mohajerani et al., 2017), tall buildings, and pavement, all of which increase thermal mass (Hu et al., 2017) increasing LST. Hence, study by Sadeghinia & Alijani (2015) observed high LST in areas covered with dark materials such as asphalt and concrete. The relationship between vegetation and LST has been established, and vegetation cover determines LST using LHF from the surface to the atmosphere via ET (Yuan & Bauer, 2007). At low elevations, where vegetation growth is limited by a lack of water and high temperatures, the relationship is inverse (Akbari et al., 2009; Yuvaraj, 2020). Aik et al. (2020), found rising LST in Cameron Highlands due to LULCC driven largely by urbanisation. Urbanisation is a major cause of the thermal climate that is warmer than the surrounding non-urban (Ngie et al., 2014; Sadeghinia & Alijani, 2015). Furthermore, it increases the surface roughness and enhances convergence (Lin et al., 2011) and therefore, cloud development and rainfall. Urban areas become dominated by SHF, resulting in the development of Urban Heat Island (Mahmood et al., 2014). The term "Urban Heat Island" (UHI) refers to a phenomenon in which urban areas experience significantly higher atmospheric and surface temperatures than surrounding areas (Ngie, 2020). According to Yuan & Bauer (2007), increased temperature in this area may alter rainfall patterns, which is why the magnitude and pattern of UHI have been a major focus of numerous urban climatology studies.

Previous studies have demonstrated that LST retrieved from thermal infrared sensors can be used to monitor the UHI effect (e.g., Mbithi et al., 2006; Sadeghinia & Alijani, 2015). Mbithi et al. (2006) discovered that the LULCC in Addis Ababa city, Ethiopia was accompanied by change in LST leading to intensive UHI effect in the urban areas. Furthermore, the study shown that change from forest and agricultural land to shopping, residential and industrial facilities contributed significantly to the increase in LSTs. UHI intensify with the increase in LST. Urban geometry (the size, shape, height, and arrangement of buildings) also influences the formation of UHI (Ahmed et al., 2013; Ngie et al., 2014; Idowu et al., 2019). Air circulation and wind flow are easily obstructed by the narrow street and tall buildings (Idowu et al., 2019). Unrestricted air movement and wind flow aid in near-surface cooling by reducing the formation of UHI (Ngie et al., 2014; Idowu et al., 2019). On the other hand, coastal areas, and areas adjacent to forests may experience a different condition as a result of sea and forest breezes, which can help cool areas subject to UHI. UHI can have a significant impact on how a community functions and how its residents live (Ngie et al., 2014; Odindi et al., 2015; Ngie, 2020). Ngie (2020) determined that the UHI effect is stronger in unplanned areas than in planned settlements. This is because it is not limited to a particular type of ground surface, but also to the activities that occur. UHI causes

heatwaves to be more severe in urban areas than in rural areas (Basara et al., 2010). Sundborg (1950) found a negative relationship between wind speed, relative humidity, cloud cover, and UHI in the first study to correlate UHI and meteorological variables. As a result, UHI occurrence intensifies in conditions of reduced wind speed, relative humidity, and cloud cover. This finding is consistent with recent study conducted by Anibaba et al. (2019) in Ibadan, south-western Nigeria. Odindi et al. (2015) has also noted that UHI promotes cloud and fog formation.

2.8 Attributing LULCC to Climate

Interactions between the surface and the atmosphere are very complex (Zhao & Li, 2015). However, models can assess these interactions and it has been used to attribute LULCC to the climate (e.g., Li et al., 2020; López-Espinoza et al., 2020). There are different models that are used to link the LULC with the atmosphere. The performance of this model during simulation solely depends on the classification accuracy (López-Espinoza et al., 2020), hence it is significant to ensure that the land surface information is accurate (D. Li et al., 2020).

The most used model is the Weather Research and Forecasting (WRF) model which has been used to assess the impact of LULCC on climate (Cao et al., 2020; Li et al., 2018). According to Li et al. (2020), the WRF can be used for spatiotemporal simulation of meteorological variables and LULCC influence on SHF. Furthermore, the model has the capabilities to also detect the meteorological variable change as a result of topographical change. The study by Li et al (2020), was able to attribute elevation change to the spatial distribution of temperature conducted in the Lhasa River basin, Tibetan Plateau. Other models include the Noah Land Surface Model (Noah LSM) which is employed to evaluate the heat transport and moisture dynamics as it links the atmospheric characteristics and LULC (Li et al., 2018) at the micro and mesoscale (Zhao & Li, 2015).

Studies such as that of Meer & Mishra (2020), used GIS and statistical analysis in attributing LULCC to ET and rainfall variability. Another method used is the Observation minus the Reanalysis (OMR). This method has produced good results in studies used in different areas, though it is not widely used or popular (Yang et al., 2009). Yang et al. (2009), used it in eastern China and discovered LULCC due to human activities to have contributed to OMR warming trend/increase in surface air temperature for decades. Urban land was identified as the main cause of the increasing temperature in the study. The method was also successful as it was used by Gogoi et al. (2019), in eastern India to link LULCCs and NDVI to surface temperature. The study was able to attribute temperature changes to vegetation changes brought about by urbanisation, with cities/urban settings exhibiting elevated temperatures. Additionally, the study examined SHF and LST in relation to the variety of LULCCs. Several methods are available and can be applied in

any region or area; as a result, more LULC-climate sensitivity research should be conducted globally to aid in addressing future climate variability as well as land planning and management.

2.9 Influence of remote phenomena on climate

Remote phenomena are linkages between weather variations that occur in widely distant parts of the world, such as those induced by natural phenomena such as the El-Niño/La Niña Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD). In addition to land surface alteration, these well-known natural phenomena over southern Africa has been linked to extreme weather and climate (Chikoore et al., 2021; Chikoore & Jury, 2021; Landman et al., 2017). ENSO is a tropical Pacific phenomenon characterised by a reversal of surface air pressure at opposite ends of the Pacific Ocean, resulting in westerly winds, a strengthening of the equatorial counter current, and extensive ocean warming (Puryajati et al., 2021).

ENSO is a sea surface temperature (SST) anomaly that occurs in the tropical Pacific Ocean and is composed of three distinct phenomena: normal conditions, La Niña, and El-Niño (Puryajati et al., 2021). El-Niño is a large ocean warming in the eastern equatorial Pacific that increases the chance of drought in southern Africa. Whereas La Niña is a state in which the central and eastern tropical Pacific Ocean cools more than usual, which relates to severe rainfall and flooding, lowering the chance of drought.

ENSO might endanger vegetation development and distribution due to decreasing rainfall and warm/hot temperatures that reduce surface moisture, favouring SHF over LHF. According to Landman et al. (2017), it is linked to summer rainfall and temperature variations in South Africa via circulation anomalies. Furthermore, it has a global impact on weather and climate patterns by generating prolonged warming or cooling of the east-central Pacific Ocean SST (Landman et al., 2017). This has the potential to have a significant impact on regions that rely largely on rainfed agriculture, potentially resulting in drought. It is used in southern Africa to anticipate seasonal rains (Chikoore, 2016) and droughts when the SST of the central and eastern equatorial Pacific Ocean is higher than normal (Ndlovu & Demlie, 2020; Ogwang et al., 2020; Chikoore & Jury, 2021).

Since not all anomalous events happened during El-Niño or La Niña, ENSO alone cannot explain all climate extremes; thus, IOD is one of the most important phenomena that might impact climate extremes. According to Heng et al. (2019), IOD occurrences have a significant impact on global climate, notably rainfall variability. IOD was found to have a considerable influence on regional rainfall patterns and malaria incidence in eastern South Africa (Behera et al., 2018). The SST anomalies that occur in the tropical Indian Ocean are referred to as IOD (Puryajati et al., 2021).

Positive IOD, negative IOD, and normal state are the three types of IOD phenomena. The eastern Indian ocean near Java and Sumatra experiences cooler-than-normal SST during a positive IOD, while the western tropical Indian ocean experiences warmer-than-normal conditions (Saji & Yamagata, 2003; Heng et al., 2019). Negative IOD reverses the region's warm or cool pattern, as well as the resulting impact. Negative IOD reverses the region's warm or cool pattern, as well as the resulting impact. The difference in ocean conditions between east and west influences wind, rainfall, and temperature patterns in a region (Puryajati et al., 2021). However, the effects of various IOD events on regional temperature and rainfall vary. The impact of extreme IOD on the increase in heavy short rains across East Africa was also demonstrated by Black et al. (2003). IOD have significantly influenced the climate in southern Africa, but their emergence and expansion are dependent on the collaboration of the atmosphere and ocean (Behera et al., 2018). Ogwang et al. (2020), found a negative correlation between Dipole Mode Index (DMI) and point OND rainfall over South Africa.

2.10 Impacts of climate variability

Climate impacts have become more prevalent in most areas. Thus, it is critical, as the severity and intensity of climate change increases, its impact on the environment and people becomes extremely significant. Climate change is expected to result in an increase in the frequency and severity of natural disasters such as drought, flooding, and heat waves (Mpandeli & Maponya, 2013). The implications for water quality, human health, agriculture, and the economy can be significant (Pereira, 2017). Water and food insecurity, infrastructure damage due to flooding, fatalities due to heat stress, and power outages all contribute to the economy deteriorating and an increase in disease due to climate variability. Paying close attention to changes in land surface is critical for mitigating the impact and changing climate (Meer & Mishra, 2020). The following section examines the climate's impact on agriculture, and the economy.

2.10.1 Agriculture

Southern African countries rely heavily on climate-sensitive agriculture for survival and economic development (Pereira, 2017). Agriculture also has a significant impact on the climate system because it increases ET and LHF (Mahmood et al., 2014). However, climate change has a significant positive impact on agriculture .

When growing crops or any other type of food, climate becomes critical, as different plants require unique growing conditions, including temperature and rainfall (Cook et al., 2015). As a result, agricultural production is dictated by climatic conditions. Heat stress slows the growth of some crops and depletes the water supply of the plant due to soil moisture deficits which affect crop particularly in the reproduction phase (Sun et al., 2019). Maize, for example, requires 60% soil

moisture and a temperature range of 20-30°C in South Africa (Mbokodo et al., 2020). Climate change will exacerbate extreme weather events like floods and storms, having a negative effect on crops.

As temperatures rise and weather patterns shift, other undesirable species, such as pests and weeds, will expand their ranges. Globally, extreme heat is one of the most serious threats to agricultural production (Sun et al., 2019). By 2090, high temperatures during the growing season are expected to pose a serious threat to food security (Khan et al., 2013). Excessive heat can exacerbate drought by impairing the plant's ability to cool itself via transpiration (Khan et al., 2013). Livestock farming and animal health are also threatened by rising temperatures and flooding as a result of heavy rain. Drought also degrades grassland, which these animals rely on for food (Chikoore & Jury, 2021). In 2015/2016, five provinces in South Africa, including Limpopo, Mpumalanga, Free State, North West, and KwaZulu Natal, were declared disaster areas due to climate variability (Maponya & Mpandeli, 2016). Furthermore, this reduced grazing, water for livestock, and irrigation, all of which had a negative impact on the agricultural sector (Maponya & Mpandeli, 2016).

2.10.2 Economy

According to Mohajerani et al. (2017), climate change can have a significant impact on an area's liveability and contribute to environmental problems. Rainfall and temperature variability can have an effect on the economy by reducing agricultural output (Ndlovu & Demlie, 2020). Climate change, regardless of season, influences the urban environment by increasing the demand for energy in buildings to provide thermal comfort for urban dwellers (Mohajerani et al., 2017; Idowu et al., 2019; Sanecharoen et al., 2019; Kumari et al., 2020). As the population continues to increase this level of comfort is achieved by upgrading the air conditioners and refrigerators. However, the more energy-intensive the equipment, the more likely there will be an outage.

South Africa is the ideal illustration of a country suffering from a power shortage or power outage, and rising temperatures will exacerbate the problem (Pegels, 2010). The economy will be crippled as a result of most of the country's critical economic sectors being unable to operate at full capacity due to the power outage. SA is a country that is highly dependent on coal as a primary source for power generation (Beidari et al., 2017). When energy is generated in this manner, an increase in energy demand will significantly contribute to air pollution or the increase of greenhouse gases in the atmosphere (Yuan & Bauer, 2007; Kumari et al., 2020). This greenhouse gas may contribute to local and global climate change, compromising human health (Idowu et al., 2019; Kumari et al., 2020), and deteriorating air quality (Yuan & Bauer, 2007; Sanecharoen et al., 2019).

2.11 Summary

The chapter outlined LULC and discussed LULCC and the different factors that influence change. Furthermore, it demonstrated how LULCCs interact with the atmosphere and, as a result, how climate change is influenced. It provides a general background on the impact of LULCC and topography on the climate system. It also provided a general background on the relationships between remote phenomena such as the ENSO and IOD and the climate. Lastly, it discussed how climate extremes such as drought, flooding, and heatwaves are associated with the impact on health, agriculture, and the economy. This chapter has aided in the development of a more complete understanding of LULCC and its relationship to the atmosphere as well as its impact.

This chapter concluded with the following: -

- a) For years, LULC has been undergoing tremendous transition and has grown to become a global issue that is not limited to South Africa.
- b) LULCC is a significant phenomenon that is mostly driven by human behaviour and decision-making, owing to population growth and rising demand for resources. While natural events surely contribute to the alteration of the LULC, it is human behaviour that propels this shift (Herrmann et al., 2020).
- c) Numerous studies in South Africa have indicated that significant LULCC is occurring across the country's provinces, and that this change is occurring across a variety of land cover types, including critical biodiversity areas.
- d) Although the country has a complex climate, temperatures have been steadily increasing for years as a result of human activity (Jia et al., 2019). The warming has been accompanied by heatwaves, droughts, flooding and changes in rainfall patterns.
- e) The link between LULCC and the climate system is substantial.
- f) The topography is critical to the earth's atmospheric circulation.
- g) Climate extremes such as drought, flooding, and heatwaves in Southern Africa are strongly correlated with the ENSO and the Indian IOD.
- h) Climate variability can have a detrimental effect on agricultural production, resulting in severe food insecurity, which endangers human health and contributes to economic instability.

The next chapter describes each dataset that was used in this research. Additionally, it discusses the methodological approaches used to analyse the dataset to accomplish the overall aim and objectives as described in Chapter 1.

CHAPTER 3 : DATA AND METHODOLOGY

3.1 Introduction

Researchers can now access and study climate and land surface change using a range of methods and datasets due to the recent availability of satellite data through remote sensing technologies. There are also methods to fill in gaps and eliminate biases generated by station data and traditional approaches (Lillesand et al., 2004; Mather & Koch, 2011). The use of an in-situ sensor mounted on a stationary meteorological station, or the traverse of a car were previously utilised methods of measurement (Idowu et al., 2019; Zhou et al., 2019).

Remote sensing technology is used because it provides access to free, long-term time series, high-quality data, and increased sensors with a high spatial-temporal resolution, as well as a verification technique (Tomlinson et al., 2011; Zhou et al., 2019). Remote sensing is popular and effective, because of data availability, consistency, recurrence of recording, and a high degree of earth measurement (Husna et al., 2018). According to Khandelwal et al. (2018), high resolution satellite data allows for monitoring and study of the relationship and influence of LULCC on climate change and meteorology that was previously unattainable using traditional approaches. Google Earth Engine (GEE) is one of the platforms that has gained popularity in remote sensing and has been used in different studies successfully hence this study has adopted the same approach (Xulu et al., 2021; Masroor et al., 2022). GEE is preferred because of access to open-source big data (Landsat and climate data).

The purpose of this chapter is to describe the data used in this study, as well as the sources from which it was acquired. The study area is also defined. The chapter also examines the methodologies used to analyse the data to accomplish the study's specific objectives, as outlined in chapter one. The sections that follow describe the datasets utilized in this study and the methods used to analyse the data.

3.2 Study Area

The study area is located in the southeast of South Africa (Figure 3.1). It lies along the Great Escarpment with topography that varies between 1040 and 2290 meters above mean sea level with lower altitude in the east. It receives an annual average temperature between 14°C and 17°C, and the annual average rainfall between 700 mm and 900 mm (Ezemvelo KZN wildlife, 2014; Amajuba District Municipality, 2021).

The issue of LULCC is noticeable throughout the study area. Therefore, in order to provide a precise and clear assessment of the issue, in the study there are four regions, being identified as regions A, B, C, and D. Region A is Memel in Free state which is agriculturally dominant alongside

a variety of other land cover types, including grass and shrub, and change is as result of cropland growth and expansion which cause change on the other cover types. In region B, a developed area in the city of Newcastle, KwaZulu-Natal (KZN) surrounded by crops and shrubs. Population growth frequently results in an increase in settlement and agriculture/crop growth (Amajuba District Municipality, 2021). As a result, this area has experienced expansion of township which have affected other land cover, particularly crops. In region C, is Normandien, KZN which is distinguished by Ntshingwayo Dan (previously Chelmsford). It consists of a mixture of water bodies surrounded by crops and grass, and water bodies have changed over time and the effect of surrounding land use on the change was due to crop growth which necessitates water withdrawal (Amajuba District Municipality, 2021). Region D in Paul Pietersburg, KZN contains a variety of vegetation types, including crops, grass, and shrubs, but it is primarily a forest, which experiences changes in forest harvesting/planting affecting the crops and other land covers (Ezemvelo KZN wildlife, 2014).

The magnitude of this change must be determined, and due to the diversity of LULC, it is an ideal location for this research, which will examine landscape change and compare the significance of LULC. It enables the assessment of changes in a broad range of significant LULCs and their consequences for a changing climate.

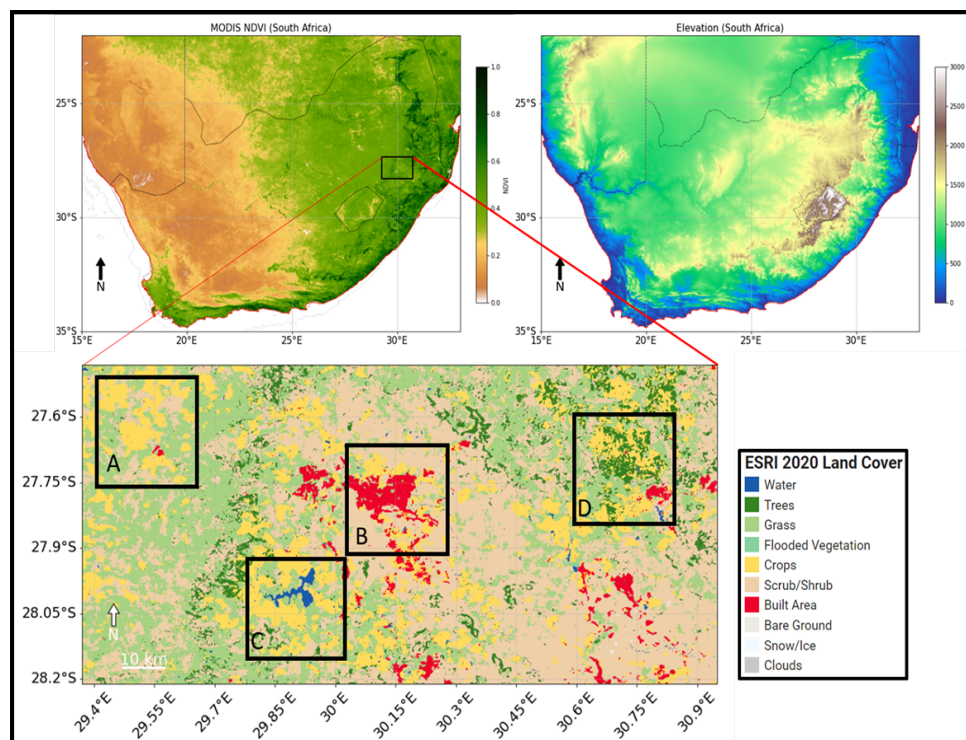


Figure 3-1: Location of the study area over the eastern South Africa. The study focuses on 4 regions shown in an inset as A, B, C and D.

3.3 Dataset Description and Sources of Data

3.3.1 Landsat imagery

When identifying and evaluating LULCC for the study, it's crucial to use imagery with a cloud cover of 0%. This is because cloud cover contaminates data and prevents efficient detection and extraction of required information from the image. However, due to having little or no satellite images with zero cloud cover, 10% cloud cover was considered as it were images that can be used for analysis with no contamination (Mohajane et al., 2018). Landsat is well-known for its long-term earth observation records from orbit, and it has carried five generations of satellites since 1975. Landsat 5 (Thematic Mapper - TM), Landsat 7 (Enhanced Thematic Mapper Plus - ETM+), and Landsat 8 (Operational Land Imager - OLI) are used as secondary data sources (1990-2020), and were launched in 1984, 1999, and 2013, respectively. Study sourced data from 1990 to 2020 for LULCC analysis. The information or data is accessed freely through the Google Earth Cloud platform. Landsat 5, 7, and 8 images were accessed according to the period of operation and the 1T (first level) radiometric, geometric, and terrain-corrected images were used for image classification. Landsat images were chosen because of its high spatial resolution of 30m x 30m, which makes it ideal for LULC analysis (Ding & Shi, 2013; Li et al., 2011), and they are widely used, accessible (Ngie et al., 2014), 16-days revisit and can be used for long time series of land monitoring.

3.3.2 Digital Elevation Model

A Digital Elevation Model (DEM) is a representation of the terrain of the ground surface in a digital raster format (Abrams et al., 2020). It is used to extract topographic information for environmental analysis purposes (Abrams et al., 2020). Shuttle Radar Topography Mission Digital Elevation model (SRTM DEM) is used in the study, which is accessed from the CGIAR-CSI Geoportal here <https://srtm.csi.cgiar.org/>. The data is available at a spatial resolution of 3 arc seconds (90 m) and in a 5° x 5° tile format. A single image covers an area of 60 x 60 kilometres (Khandelwal et al., 2018). As a result of filling data gaps, this is high-quality elevation data hence it was preferred in this study.

3.3.3 Land Surface Temperature

LST is the temperature that is stored in the earth's materials and characteristics, such as soil, water, buildings, and flora (Khandelwal et al., 2018). It is a critical component of understanding urban climate and has a direct impact on urban heat islands, as they play a critical role in urban energy balance (Peña, 2009). The temperature of various surface features on the ground is expressed using this dataset. The LST data is available from 1984 and the data from 1990 to 2020 was accessed from the Climate Engine website: <https://climate-engine.appspot.com/climateEngine>. The data were derived from Landsat imagery using a mono-

window algorithm for the Landsat 5 and 7 periods, and a split-window algorithm for the Landsat 8 period. Sekertekin & Bonafoni (2020) have exhaustively described the algorithm. Landsat LST based was preferred because of long period from 1984 and spatial resolution of 30m x 30m, which is capable of assessing/measuring LST of relative smaller objects. LST has acquired prominence as a drought indicator and a proxy for soil moisture, evapotranspiration, and vegetation (Chikoore, 2016).

3.3.4 Normalised Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is used to assess the state of a region's vegetation. NDVI gauges spongy mesophyll (Gu et al., 2007) and is sensitive to chlorophyll levels (Burapapol & Nagasawa, 2016). It has been used significantly globally for the past few years and it is still used for determining how the environment is changing. It is commonly used for the monitoring of agriculture and drought (Jayawardhana & Chathurange, 2020). This is popular because monitoring from space allows real-time spatial information, and it also has long-term spatial data covering the entire world (Jayawardhana & Chathurange, 2020). It has a strong correlation with precipitation and evapotranspiration and can be used to estimate photosynthetic activity. This study maps the extent of vegetation using the Landsat Top of Atmosphere derived NDVI data with the dataset that was acquired from 1990 to 2020 from the Climate Engine website: <https://clim-engine.appspot.com/climateEngine>.

NDVI is a remote sensing index that utilises spectral data to extract information about a specific aspect of the earth's surface. It is a technique for mapping and quantifying the amount of vegetation on the earth's surface that utilizes near-infrared and red band images (Das & Angadi, 2020). It is calculated using the following equation (Mohajane et al., 2018): It is calculated as the ratio of the difference and sum of the refracted radiation in the near infrared and red wavelengths.

$$NDVI = \frac{(NIR\ Band - Red\ Band)}{(NIR\ Band + Red\ Band)}$$

where R and Near Infrared (NIR) are red (600–700 nm) and near-infrared (700–1300 nm) spectral bands, respectively. NIR is sensitive to vegetation type, density, water content, and plant health, and because high NIR reflectance indicates healthy, green vegetation, healthy vegetation has a high digital number in NIR. NDVI values range from -1 to +1, with + values indicating vegetation and – values indicating water. Typically, values range from -0.1 to 0.7, with values less than 0.3 indicating bare vegetation, 0.3 indicating sparse vegetation and water stress, and values greater than 0.5 indicating dense and vibrant vegetation (Jury et al., 1997; Mulugisi, 2015; Chikoore, 2005, 2016; Mbokodo et al., 2020).

3.3.5 Rainfall

Rainfall is critical for monitoring hydrological processes, access to and availability of water, and water disasters (Shen et al., 2020), and as such, it is critical to measure it using the most accurate and reliable datasets available. The Climate Hazards Group's Infrared Precipitation with Stations (CHIRPS) dataset provides a global data at daily, five-day, and monthly temporal and a high spatial resolution of $0.05^\circ \times 0.05^\circ$ (Funk et al., 2015). The CHIRPS data are available from 1979 to present, allowing for improved time series trend analysis for several environmental monitoring systems. The monthly CHIRPS dataset, which is used in this study was accessed from ClimateSERV website; [ClimateSERV - Map \(servirglobal.net\)](https://climate.servirglobal.net/), from 1979 to 2020. This dataset provides dependable precipitation statistics, particularly in mountainous locations (Gebremicael et al., 2017; Shen et al., 2020). According to Funk et al. (2015) data was primarily produced for agricultural drought monitoring. This is the most recent dataset that combines satellite (Meteosat) and station observation estimates which provide the best reliable estimate of rainfall over the areas with complex terrains (Funk et al., 2015). It does this due to the eliminated biasness of satellite data which underestimate the severity of extreme rainfall events due to the complexity of the terrain, and that of station data, which suffer from lack of rain gauge stations in most rural settings (Funk et al., 2015; Gebremicael et al., 2017).

3.3.6 Evapotranspiration and Potential evapotranspiration

ET is the water that evaporates from plants and soil, as well as the water that transpires from underground plant components (Szewczak et al., 2020) has a significant role in the surface water and energy balances. ET varies according to geography, climate, landscape, soil type, and vegetation (Jovanovic et al., 2015). The Global Land Data Assimilation System (GLDAS) version 1 data is a NOAH model which is available from 1948 to 2000, and version 2 data is available from 2000 to present, with the monthly temporal and spatial resolution of $0.25^\circ \times 0.25^\circ$. GLDAS can generate quality controlled, spatially and temporally consistent data (Mbatha & Xulu, 2018).

Potential evapotranspiration (PET) is the amount of water that would evaporate and transpire if water sources had unlimited water storage. It is directly influenced by temperature increases (Szewczak et al., 2020). It can be estimated using either the Thornthwaite or Penman method equations, however for the sake of this study, the Penman-Monteith technique was used. Penman-Monteith technique is an equation that is used for estimating PET, combining fixed bulk surface and vapor aerodynamics (Tukimat et al., 2012). This is because it is a good index of climate change since it is computed utilising daily mean temperature, wind velocity, humidity and solar radiation or sunshine hours (Zhang et al., 2020). Different studies have found that the radiation-based method performs better than the temperature-based method (Thornthwaite equation). These datasets (ET & PET) were downloaded from 1979 to 2020 from the Giovanni Earth Data website (<https://giovanni.gsfc.nasa.gov/giovanni/>).

3.3.7 Surface Soil Moisture

The term "surface soil moisture" refers to the amount of water available in the soil's top ten centimetres (Wang & Qu, 2009). Because the Normalized Difference Infrared Index (NDII) is a proxy for soil moisture storage (Sriwongsitanon et al., 2015), it was used to obtain monthly data about soil moisture. It is a critical variable in hydrological processes (Wang & Qu, 2009), as it affects the water and energy balance by regulating LST and evapotranspiration (Pablos et al., 2016). It has a significant impact on the water and energy balances, regulating LST and ET, aiding in drought monitoring, and regulating floods. The index is denoted by the algorithm below and is calculated as the ratio between the difference and sum of refracted near infrared and shortwave infrared radiation.

$$NDII = \frac{(NIR - SWIR)}{(NIR + SWIR)}$$

NDII is calculated using bands or reflectance data in the near-infrared (700–1300 nm) and shortwave infrared (1550–1750 nm) regions. NDII values range between -1 and +1, with positive (+) values indicating a wet season or soil and negative (–) values indicating a dry season or soil. NIR wavelengths remain constant as water level rises, whereas Shortwave Infrared (SWIR) is sensitive to soil moisture due to electromagnetic energy absorption at this wavelength (reflectance decreases as water content increases in surface) (Ji et al., 2011). Because the index readily demonstrates the interaction between rain, soil moisture, and water content, it is useful for drought monitoring and hydrological modelling as an indicator. This was chosen because it has been shown to be a reliable indicator for monitoring root-zone moisture content based on the observed state of vegetation (Sriwongsitanon et al., 2015; Mbatha & Xulu, 2018).

3.3.8 Surface heat fluxes

Sensible and latent heat fluxes constitute the transfer of heat between the atmosphere and land surface as a result of differences in temperature and change in phase of water vapour (Ge et al., 2019). Sensible heat flux is the energy used during land surface temperature changes (Ban-Weiss et al., 2011; Li & Duan, 2017), while latent energy exchanges between land surface and the atmosphere, which is used for water phase changes through ET and subsequent condensation (Li et al., 2018). The unit of measurement for latent and sensible heat fluxes is watt per square metres (W/m²). The dataset was obtained from Famine Early Warning System Network (FEW NET) Land Data Assimilation System (FLDAS) model which was accessed from Giovanni Earth Data website; <https://giovanni.gsfc.nasa.gov/giovanni/>. The FLDAS model is a reanalysis dataset that has been in operation from 1982 until present and this study used data that runs from 1980 to 2020 with monthly temporal and spatial resolution of 0.1°x 0.1°..

3.3.9 Minimum and Maximum Temperature

These two are important datasets because minimum temperature alone is almost certainly not good parameter to detect heat accumulation in the atmosphere (Mahmood et al., 2010). It is also much more sensitive to LULCC than maximum temperature (Hale et al., 2008). In this study the monthly temporal resolution of 1979 to 2020 and spatial resolution of $0.05^\circ \times 0.05^\circ$ Climate Research Unit gridded Time Series Version 4 (CRU TS v4) weather station observation at 2-m dataset was used and it was available through the KNMI climate explorer website: (<http://climexp.knmi.nl/start.cgi>). The data is used because it has a long record of data from 1901, and high spatial resolution of $0.05^\circ \times 0.05^\circ$. This monthly grid of land-based observation has no missing value and has been used for biases correction of the model and reanalyses and data is well described by Harris et al. (2020).

3.3.10 Climate Indices

To monitor and assess how the remote phenomena influence climate, the ENSO and IOD indices were also analyzed. The Extended Reconstructed Sea Surface Temperature (ERSST) version 5 Niño 3.4 and ERSST Dipole Mode Index (DMI) from the National Oceanic-Atmospheric Administration (NOAA) – Climate Prediction Centre (CPC) with a spatial resolution of 2° was obtained from the KNMI climate Explorer website; (<http://climexp.knmi.nl/start.cgi>). Due to the improved bias correction applied on ship observations, ERSST according to Huang et al (2018) represent better analysis and perform better than the previous version (4,3b).

Variability in equatorial SSTs can be obtained from the ENSO index focusing on the Niño3.4 region while the strength of IOD is monitored with the Dipole Mode Index (DMI), which is a measure of surface temperature difference between the western and eastern tropical Indian Ocean (Puryajati et al, 2021). ENSO is computed taking the area-averaged sea-surface temperature (SST) within the Niño3.4 region, which is at 5°N – 5°S longitude and 120° – 170°W latitude in the Pacific Ocean (Anyamba et al., 2018). While DMI is calculated by taking the difference between the SST anomalies in the western equatorial Indian Ocean (60° – 80°E ; 10°S – 10°N) and southeastern equatorial (90° – 110°E , 10°S – 0°) Indian Ocean (Anyamba et al., 2018; Saji & Yamagata, 2003).

3.4 Analysis Methods

3.4.1 Data Pre-Processing

This is the most critical step in the processing and analysis of satellite imagery, as it directly affects the quality of the results (Mulugisi, 2015). Pre-processing is the process of correcting remote sensing data, which includes geometric correction, radiometric correction, topographic correction, and image registration (Ngie et al., 2014). By removing distortions introduced during data

collection, this process aims to improve dataset quality. Geometric correction eliminates geometric distortions of the raw data due to the motion of the sensor, perspective of the optical scheme, terrain and other factors (Mather & Koch, 2011). Radiometric correction is used to normalize data obtained at different times and locations to ensure spectral values of the same pixels would be the same (Lillesand et al., 2004). Whilst image registration is matching images from different orbits and sensors, topographic correction is to ensure identical coordinate systems (Mather & Koch, 2011). Landsat 5, 7, and 8 images with Level 1T or Level 1G processing levels will be used in the study because they are readily geometric, radiometric, and topographically corrected (Ngie et al., 2014).

In this study, before any further processing is done, the different Spectral bands of imagery were stacked, and a virtual band was created on GEE. The Landsat scene had a larger extent than all the regions, therefore sub-setting of original scenes was done using geometry defined as Region of Interest (ROI) on GEE covering the study area. Image sub-setting refers to the operation of cutting out the area of interest on a Landsat scene. It is used to reduce the spatial extent of an image, cropping the image to cover only a specific area (Lillesand et al., 2004). This eliminates any possible errors that may occur during classification, which may affect the quality of result. For proper interpretation and analysis of remotely sensed images, distortions or flaws must be removed or minimized and pre-processing techniques are pivotal to increasing the quality of satellite images (Babu et al., 2020).

Data was downloaded on a daily and monthly temporal resolution and therefore to be able to efficiently correlate to LULC class time series data, the hydrometeorological dataset was resampled on python to annual temporal resolution. It is also important that all the hydrometeorological datasets used in the study for analysis are complete and have no gaps between. Therefore, the dataset which contains no data in between was interpolated using RStudio software, so that the gaps can be filled to allow a complete and comprehensive analysis of the time series.

3.4.2 Random Forest classifier

Supervised classification is a technique that is entirely dependent on the researcher's knowledge of the area of study, which can be obtained by site visits, aerial images (Tarawally et al., 2018), or the historical imaging function of Google Earth. Classification is the process of assigning spectral properties to individual pixels in an image to classify images as LULC classes (Lillesand et al., 2004; Mather & Koch, 2011). The classes are defined, together with the pixel value to which classes should be assigned (Tarawally et al., 2018). The image is classified based on its spectral signature, and the training classes include the lowest and maximum features associated with each class's spectral signature. To determine whether any changes in LULC occurred between

1990 and 2020, it is necessary to employ this technique, which has been successfully applied in remote sensing image processing for LULC mapping and other environmental applications.

Random Forest (RF) was used to classify the Landsat images into different land cover classes from 1990 to 2020, spanning a 31-year period of land usage. This assists to determine what type of land surface is available in the study and to what extent are the surface distributed. RF is a machine learning algorithm used for identification and classification and is well discussed by Sheykhmousa et al. (2020). Machine learning algorithms, namely the random forest (RF) classifier, were chosen as the best fit classification technique because it has been shown to be successful in several studies and to produce highly accurate results. Masroor et al. (2020) determined that RF was the best technique for distinguishing between urban and barren land, and hence was used in this investigation. QGIS and ArcGIS was used for further to create final spatial map from classified GeoTif file from GEE. The sample set was trained using the random forest technique based on GEE, with the number of decision trees set to 300. According to Zhao's study (2021), the most critical parameters of a RF classifier based on GEE are the classification tree, the variable associated with each classification tree, the minimum sample size of leaves, and the decision tree input variables. When the decision tree's accuracy is increased, the overall classification accuracy increases (Breiman, 2001). The outcome of supervised classification is highly dependent on the training sample of inputs (Kulkarni & Lowe, 2016). To accurately discriminate between ground objects in a variety of environments and conditions, a large sample set is required to train the classifier in complex domains (Breiman, 2001). To ensure accuracy, a sufficient sample size is necessary. The initial categorisation counts in this investigation began with 80 samples and subsequently rose. After each iteration, the classification results were compared to the corresponding satellite image, and if the classification results were not good, further training samples were added until a satisfactory classification result with an accuracy greater than 85 % was attained. Xulu et al. (2021) effectively used RF to distinguish vegetation from non-vegetation areas in a South African mine area using Google Earth Engine (GEE) and reached a 78% accuracy. The classifier was also used in South Africa by Dlamini & Xulu (2019), during the classification of the Richards Bay mineral and it achieved an accuracy of 99%. Sheykhmousa et al. (2020), indicated that RF has been frequently used by researchers due to its decreased computational complexity and greater interpretability capacity. Furthermore, it is easy to use, and one can simply learn both simple and sophisticated classification functions.

A RF supervised classification technique was used to determine the spectral difference between distinct classes. Six distinct classes have been found across the four regions of eastern South Africa: water, urban, bare land, forest, cropland, and grassland (Table 3-1).

Table 3-1: Land Use Land cover class scheme over the eastern escarpment.

LULC classes	Description
Water	This Includes natural lakes, rivers, open water, ponds, reservoirs, and estuaries
Bare Land	It is comprised of unvegetated land, visible erosion and rocks, exposed soil, and human induced barren area.
Urban	These are built-up areas where people live on a formal and informal settlement, might have been and industrial areas. It also includes pavement and tarred roads.
Forest	Natural and plantation forest planted trees which are maintained by human activities, and Mangrove.
Cropland	This is area which cultivated and is covered with crops
Grassland	Dominated by grass-like, non-woody, plants associated with grassland and savanna biome

3.4.3 Accuracy Assessment

All maps generated through remote sensing analysis must be validated against a comprehensive independent dataset (Xulu et al., 2021). Classification accuracy assessment is crucial (Mulugisi, 2015) since without it, the classification is invalid (Odindi et al., 2017; Tarawally et al., 2018; Thapa, 2020). It is vital to collect precise data and determine if an image has been classified successfully or unsuccessfully (Das & Angadi, 2020). Ground truthing will be performed using Google Earth Engine to interpret land use. The study makes use of the historical imagery function to classify high-resolution Google Earth images to validate the classified images. Two frequently used methods for assessing classification accuracy are the confusion/error matrix and kappa statistics. It is a component of standard descriptive and discrete multivariate statistics that is used to compare classification results to previously analyse the data obtained (Mulugisi, 2015).

Confusion matrix is a technique used to summarise the performance of the classification algorithm (Lillesand et al., 2004). It is carried out by picking a representative sample of reference locations and comparing their classification to the classifications on the land cover map (Stehman, 1997). Stehman (1997), stated that the reference sample should be chosen independently of the data used to train and/or create the classification algorithm. A confusion matrix was generated to show the producer's accuracy (PA), the user's accuracy (UA), and the overall accuracy (OA). According to Odindi et al. (2017) the PA value indicates the likelihood that the classification was correctly associated with the image pixel. The UA value indicates the probability that a randomly selected point is correctly classified on the map, whereas the OA value indicates the probability of a

randomly selected point being correctly classified on the map. The kappa values are classified into three categories: values less than 40% indicate poor agreement, values between 40% and 80% indicate moderate agreement, and values greater than 80% indicate strong agreement.

3.4.4 Change Detection

Identifying LULCC in the study area over a 31-year period is one of the research objectives. Change detection is a fundamental component of environmental change that is still employed successfully. Andualem et al. (2018) describe change detection as the "process of identifying differences in the state of a feature phenomenon through several observations". It is used to determine how a surface characteristic changes over time (Andualem et al., 2018). Post-classification change detection is employed in most remote sensing applications; it is accomplished by comparing two classified images captured before and after a change occurred (Mulugisi, 2015; Mohajane et al., 2018). However, this method's accuracy is dependent on the overall accuracy of the two images being compared, which implies that if the classification accuracy is low, the outcome would be influenced as well. When using this method, it was demonstrated that obtaining robust and accurate land cover maps takes time and is prone to error propagation (Mugiraneza et al., 2020). This technique was not employed to determine and quantify change over time in this study; instead, the Detecting Breakpoints and Estimating Segments in Trends (DBEST) algorithm using RStudio was used to analyse LULCC progress or change (Jamali et al., 2015).

3.4.4.1 Detecting Breakpoints and Estimating Segments in Trends

DBEST is an automatic detection algorithm that is effective for both short- and long-term LULCC analysis (de Jong et al., 2021). It operates pixel by pixel and treats each pixel's time series data as a separate object during the change detection procedure, regardless of spatial and temporal resolution (Jamali et al., 2015). Due to its flexibility, it accommodates for seasonal variations and decomposes time series into trend, seasonality, and residual (Shen et al., 2018). The algorithm generates a time series and identifies the trend, the location and time period of the change, the size, the direction of the change (negative or positive), the type of change (abrupt or gradual), and the significance of the change (Shen et al., 2018). Xulu et al. (2021) successfully applied the method to the Tronox Hillendale Mine in South Africa, where the study analyses the pattern of disturbance and reclamation that initiated the closure process of the mine. The study established the time period during which vegetation began to decline/disappear, when it reached its lowest point, and the time period during which the mine rehabilitation process began, as shown by a burst of plant regeneration.

According to Jamali et al. (2015), DBEST is the fastest and most robust algorithm for detecting both abrupt and non-abrupt changes, as well as estimating the time and magnitude of changes.

This was discovered while validating and evaluating the algorithm's results for detecting significant changes in NDVI trends over Iraq between 1982 and 2006. The algorithm is applicable to a wide range of disciplines, including hydrology and climatology (Jamali et al., 2015), ecology and other human-induced factors that influence changes (Shen et al., 2018), and hence was used in this study to analyse LULCC. Jamali et al. (2015) concluded that the DBEST has simplified the process of detecting trends and changes in LULC without sacrificing accuracy or speed, even over broad areas, and hence may be used in global studies.

3.4.5 Time series analysis

3.4.5.1 Trend analysis

Trend analysis is a statistical technique applied in this study using Python to produce a temporal pattern of surface energy, moisture fluxes and the hydrometeorological parameters. Furthermore, trend analysis is applied on Niño3.4 and DMI as indicators of ENSO and IOD phenomena. The trend analysis was also applied on the monthly mean of the data from 1979 to 2020. For testing the trend of time series data, both parametric and nonparametric tests are routinely utilized in climate, environmental, or hydrological data. A parametric test, according to Ahmad et al. (2015), requires normally distributed and independent data. Nonparametric tests, on the other hand, data must be independent, however, it is resistant to outliers (Ahmad et al., 2015; Mbatha & Xulu, 2018; Liu et al., 2021). When using a nonparametric test, results are not influenced by these outliers (Ahmad et al., 2014) or the missing values (Liu et al., 2021). As a result, the nonparametric Mann-Kendall (MK) test will be used to detect statistically significant time series in this study. The test uses the null hypothesis (H_0) which argues that no trend exists, while the alternative hypothesis (H_1) rejects the null and states the existence of a trend in parameters that could be positive or negative (Ahmad et al., 2015). The trends were tested for statistical significance at the 95% level of confidence if p-values are less than 0.05.

3.4.5.2 Correlation analysis

Correlation analysis is a widely used technique for identifying interesting relationships between variables or datasets, which enables the realization of predicted attributes with respect to the target class (Kumar & Chong, 2018). Correlation analysis using Pearson Correlation Coefficient in RStudio was done between LULC class and moisture fluxes, surface energy fluxes, and hydrometeorological variables in the study from 1990 to 2020. Furthermore, graphical Pearson Correlation Coefficient analysis was performed on variable importance results to ascertain the significance of the correlation between rainfall, temperature, and other variables. This aid in determining the effect of LULCC on this variable, allowing for a better understanding of the factors that contribute to the change in the local boundary climate. Since a small correlation must be tested, the correlation was tested to quantify the strength and direction of the relationship between

the variables and LULC and remote phenomenon. Correlation coefficient values range from -1 to +1; when no correlation exists, the value is 0, when a negative relationship exists, the value is -1, and when there is a positive correlation, the value is +1 (Mulugisi, 2015). According to Tanni et al. (2020), the relationship strength is commonly interpreted as weak when $R < \pm 0.4$, moderate when R is ranging from ± 0.4 to ± 0.7 , and strong when r is ± 0.7 . However, a high correlation does not necessarily imply causation and therefore the statistical significance of correlation was tested using Pearson.

3.4.6 Variable of importance

Variable importance is used to rate or rank the importance of variables in a regression or classification (Debeer & Strobl, 2020; Strobl et al., 2007). Variables are presented in descending importance depicted by Increase Mean Square Error (%IncMSE) which measure how much accuracy the model loses when a variable is altered, and the Increased Impurity Index (IncNodePurity) which measures how much each variable contributes to the homogeneity of the data in the resulting random forest (Echeverry-Galvis et al., 2014). The higher the value of %IncMSE or IncNodePurity, the more the importance of the variable in the model. Therefore, to determine the important hydro-meteorological variable that influences climate variability, RF was employed using the 'randomForest' library in R. An ensemble of classification trees is created in RF by drawing several bootstrap samples or subsamples from the original raining data and fitting a single classification tree to each sample (Strobl et al., 2008). As a result of random variation in the samples and the instability of the single classification trees, the ensemble in RF consists of a diverse set of trees (Strobl et al., 2008; Debeer & Strobl, 2020; Mathivha & Mbatha, 2022). As with Mathivha & Mbatha (2022), factors such as parameter tuning to optimize RF performance, the number of features, and the use of the classical method of splitting the input data into training and testing were used to improve the RF model's accuracy and avoid overfitting in this study. 70% of the data was used for training, while 30% was used to validate a portion of the model during data segmentation. This is a model commonly used as a predictor function and the model has been proven useful in a variety of applications (Debeer & Strobl, 2020). Non-parametric regression in RF is a popular and widely used technique in scientific studies (Strobl et al., 2008; Debeer & Strobl, 2020). Their popularity is due to high prediction accuracy and ability to model high dimensional complex data. It was used by Mathivha & Mbatha (2022) to determine the important climate indices that influence drought in the Luvuvhu River Catchment in Limpopo, South Africa. According to Strobl et al. (2008) in comparison to other univariable screening methods, RF can cover the impact of each predictor variable individually as well as in multivariate interaction with other predictor variables. It was used in this study to rank the variables according to their importance, allowing for the identification of the most important or sensitive variable to change in LULC.

3.4.7 Multiple-Linear Regression

Multiple Linear Regression (MLR) is a statistical technique for predicting the value of a single dependent variable using the values of two or more independent variables (Alexopoulos, 2010; Grant et al., 2019). Because one of the study's objectives is to quantify the impact of different land uses/covers on critical variables that are sensitive to change, hence local boundary layer climate, and therefore a model was used in this study. The model estimates the amount by which a dependent variable changes in response to changes in the independent variables (Grant et al., 2019). It aids in determining the relative importance of one variable to another by examining how one variable behaves when the others change. It was used in this study to determine which land cover classes have the greatest influence on the important variable, allowing for the identification of the land cover class most likely to influence the local boundary climate. The MLR model can be represented as follows (Alexopoulos, 2010; Mbatha & Xulu, 2018):

$$y_i = \beta_0 + \beta_1 x_{i2} + \dots \beta_p x_{ip} + \varepsilon_i$$

where $i = 1, 2, 3, \dots, n$, y_i is the response variable which is the important variable as per random forest result, x_{ip} is the predictors variables which are all classified LULC classes, β_0 is the intercept, and $\beta_1, \beta_2, \dots, \beta_p$ are the regression coefficient of the x terms. The term ε_i is the model's error terms, which it is always attempting to minimize (Mbatha & Xulu, 2018).

3.5 Summary

This chapter described the study area, the datasets employed and their sources, as well as the analysis methods that was employed to meet the study's research objectives. The study is located eastern South Africa and purposefully segmented and has four regions due to LULC variation and topography which is distinguished by high topography towards the west and low towards the east. Landsat data is vital for estimating the change in LULC over time, as well as for computing the critical indices that enable the assessment of vegetation distribution, health, and growth via NDVI. Additionally, NDII is computed using this dataset to determine the surface soil moisture content. Surface energy and moisture fluxes, as well as hydrometeorological variables, are all significant data sets that have been analysed to determine how changes in LULC affect all these variables. ENSO and IOD were explored to ascertain their role in climate variability. To meet the study's objective, GEE, QGIS, ArcGIS, RStudio and Python were used to analyse the data.

CHAPTER 4 : CLASSIFICATION AND CHANGE DETECTION OF LAND USE/LAND COVER IN EASTERN SOUTH AFRICA

4.1 Introduction

LULCC is the result of both anthropogenic and climate forcings over time (Mahmood et al., 2010, 2014; Dong et al., 2019). As a result, future planning and mitigation of significant LULCC and its associated impacts becomes critical to human lives, as it plays an important role in their survival (Mishra et al., 2020). In the period of significant population increase and urban development, assessing this phenomenon is important. It contributes to understanding the land-atmosphere relationships, since various studies have shown that LULCC have a significant role in climate variability and change (Jia et al., 2019).

The aim of this chapter is to analyse the extent and patterns of LULCC over the study area from 1990 to 2020. The data were analysed with a confusion matrix which assessed the accuracy and validity of the classification. In addition, the temporal and spatial distribution and change of vegetation, surface soil moisture and LST over the four regions were examined. The DBEST algorithm was then employed to perform change detection over the area and the outcome of these techniques were also presented in this chapter.

4.2 Mapping Land use/Land cover

Mapping land use and land cover is critical for managing natural resources and ecosystem services, much more so in an era of continued population growth and economic development. To conduct a meaningful study of LULC classification and change, it is necessary to construct accurate land cover maps. Land cover mapping needs the separation and delimitation of specific or typical land cover classes from remotely sensed data in order to fully appreciate the earth's surface and its change.

The Google Earth Engine was utilised to do the classification process in its entirety, and QGIS was used to construct the final spatial map from the GeoTif file generated by GEE. Figures 4-2, 4-4, 4-6, and 4-8 depict the spatial distribution of the LULC classes within each Region. The area covered by each class and the proportion of the area covered by each class are visible in Figure 4-1, 4-3, 4-5, and 4-7. Urban land, as a human-induced class, reflects land usage and intensity, which may result in changes in land cover. Over the past 30 years, the region has grown fast, owing to strong economic expansion and population growth, which have increased demand for dwelling space.

It may be difficult to comprehend land cover dynamics without measuring individual land cover categories during a given time period. Graphs and surface area computations provide a

comprehensive data set describing the general state of the landscape, including the nature and quantity of changes. Land cover statistics were calculated in this study using Google Earth and then exported to Excel and provided as area extent, as shown in Section 4.3, see Figure 4-1, 4-3, 4-5, and 4-7.

4.3 Quantification of Land Use/Land cover areal extent and distribution analysis

4.3.1 Overview of LULC for regions A-D

4.3.1.1 Region A: Memel, FS

Figure 4-1 summarises the trends in LULCC from 1990 to 2020 using six classes derived from region A and each having a proportional coverage area. Total areal coverage of all land cover class within the research area is around 49854 m². In 1990, grassland dominated the LULC pattern as a proportion of the total area studied, accounting for 87.5% of the total area studied, followed by bare land (11.2%), cropland and forest equally (0.5%), water (0.3%), and urban (0.03%). Additionally, the trend was found for all LULC throughout a 31-year period. In 2020, the observed LULC pattern remained dominated by grassland (89.6%), followed by bare land (9.4%), urban area (0.46%), and forest (0.3%), with cropland and water both accounting for 0.1%. In 1990, grassland covered more than 85% of the area, but by 2020, it had expanded by 2.1% of total coverage. A 0.2% decrease in water availability is another cause for concern, since it puts pressure on water supply and increases vulnerability. The 0.43% growth in urban regions is critical and notable. Below is a spatial perspective that provides information on LULC in this region (see Figure 4-1).

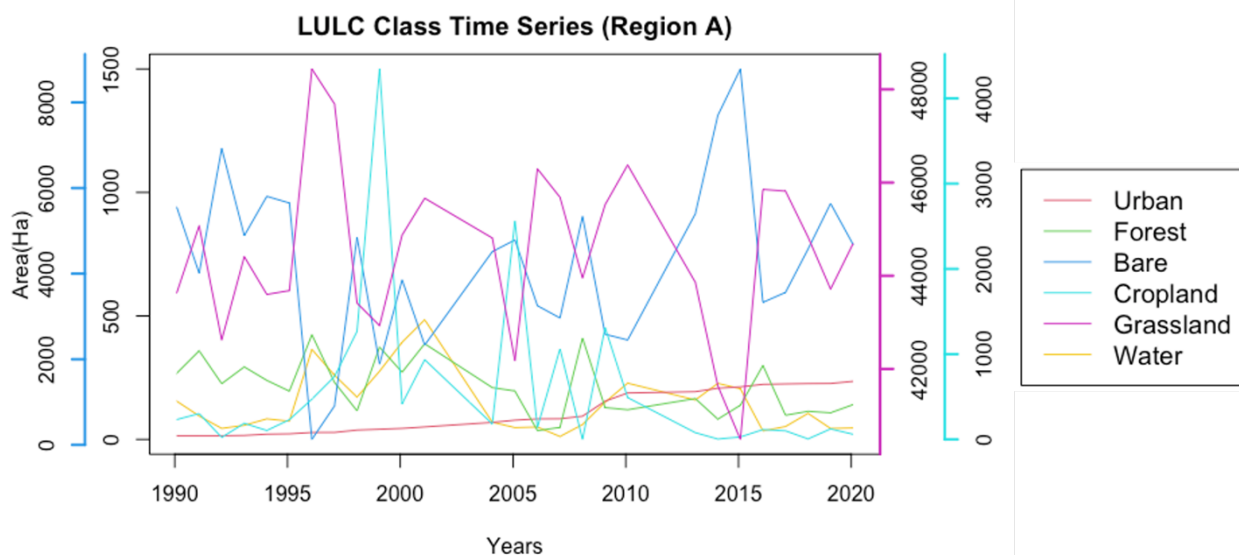


Figure 4-1: Land Use Land Cover time series over Region A from 1990 to 2020.

The spatial map in Figure 4-2 depicts the distribution of LULC throughout region A, which had a predominance of grassland throughout the study. There were small patches of cropland at the beginning of the study, but it expanded and demonstrated dominance distribution across the entire area by 1999, while bare land also demonstrated an even distribution for 31 years. While forest distribution changes over time, patches of visible forest and water patches were observed in 1990 but deforested and evaporated, respectively, after 1990 and became visible in 1996 (Figure 4-2). Notably, urban land has expanded significantly over time and is concentrated in the region's south, where high distribution and expansion were observed in 2001.

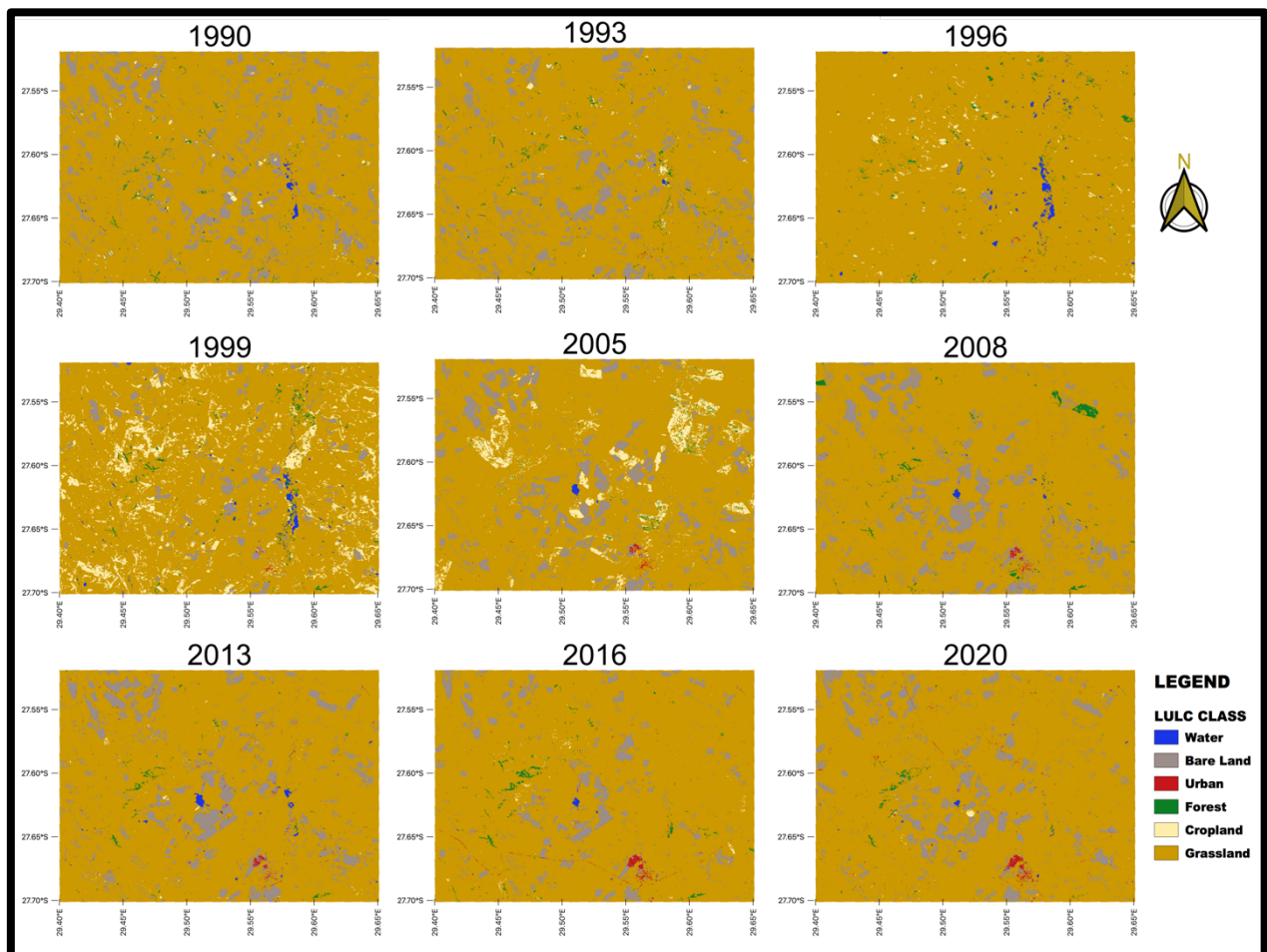


Figure 4-2: Spatial distribution of LULC over Region A from 1990 to 2020.

4.3.1.2 Region B: Newcastle, KZN

The trend is based on six classes taken from region B (Figure 4-3), each with a proportional coverage area. Total areal coverage of all land cover class within the research area is around 54226m². As indicated in Figure 4-3 and Figure 4-4, the LULC analysis revealed an increase in urban land over the last three decades.

In 1990, grasslands dominated the pattern of LULC as a proportion of the total area analysed, accounting for 52.9% of the total area studied, followed by bare land (37%), urban (7.3%), cropland (1.8%), water (0.9%), and forest (0.1%). Additionally, the trend was observed for all LULC over a 31-year period. In 2020, grassland continued to dominate the LULC pattern (51%), followed by urban areas (22.8%), bare land (19.2%), cropland (4.7%), water (1.7%), and forest (4.7%). In 1990, grassland covered more than 50% of the area, but by 2020, it had reduced to just 1.9% of total coverage. The 15% increase in urban land is a cause for concern because they represent highly irreversible coverage types that annihilate the original natural landscape and are unlikely to be restored to its natural state.

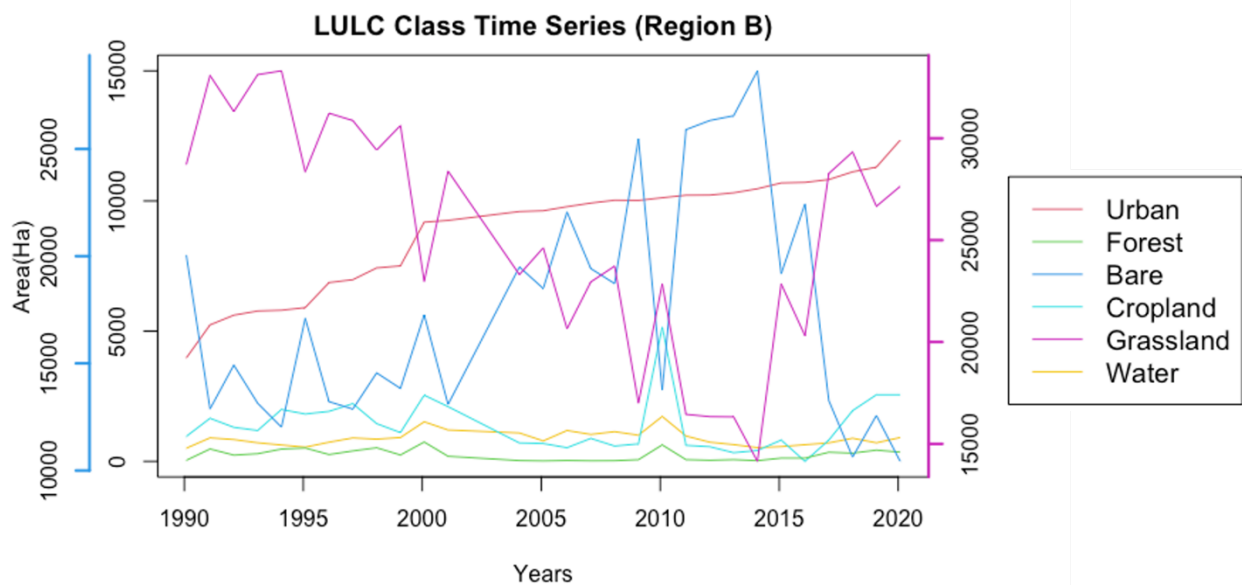


Figure 4-3: Land Use Land Cover time series over Region B from 1990 to 2020.

From 1990 to 2020, grasslands demonstrated dominance across the region while bare land is primarily concentrated around urban areas and extends to the region's east. Small bodies of water are isolated and scattered throughout the study, with the river running from the north to the east (Figure 4-4). The distribution of urban built-up regions from west to centre began in 1990 and has expanded to the south and east over the years but remains relatively dominant in the centre. Cropland and forest looked to be scattered across the study's area, however it predominate above the urban area. The predominance of urban areas and their fragmentation have had a significant role in the manifestation of grassland fragmentation.

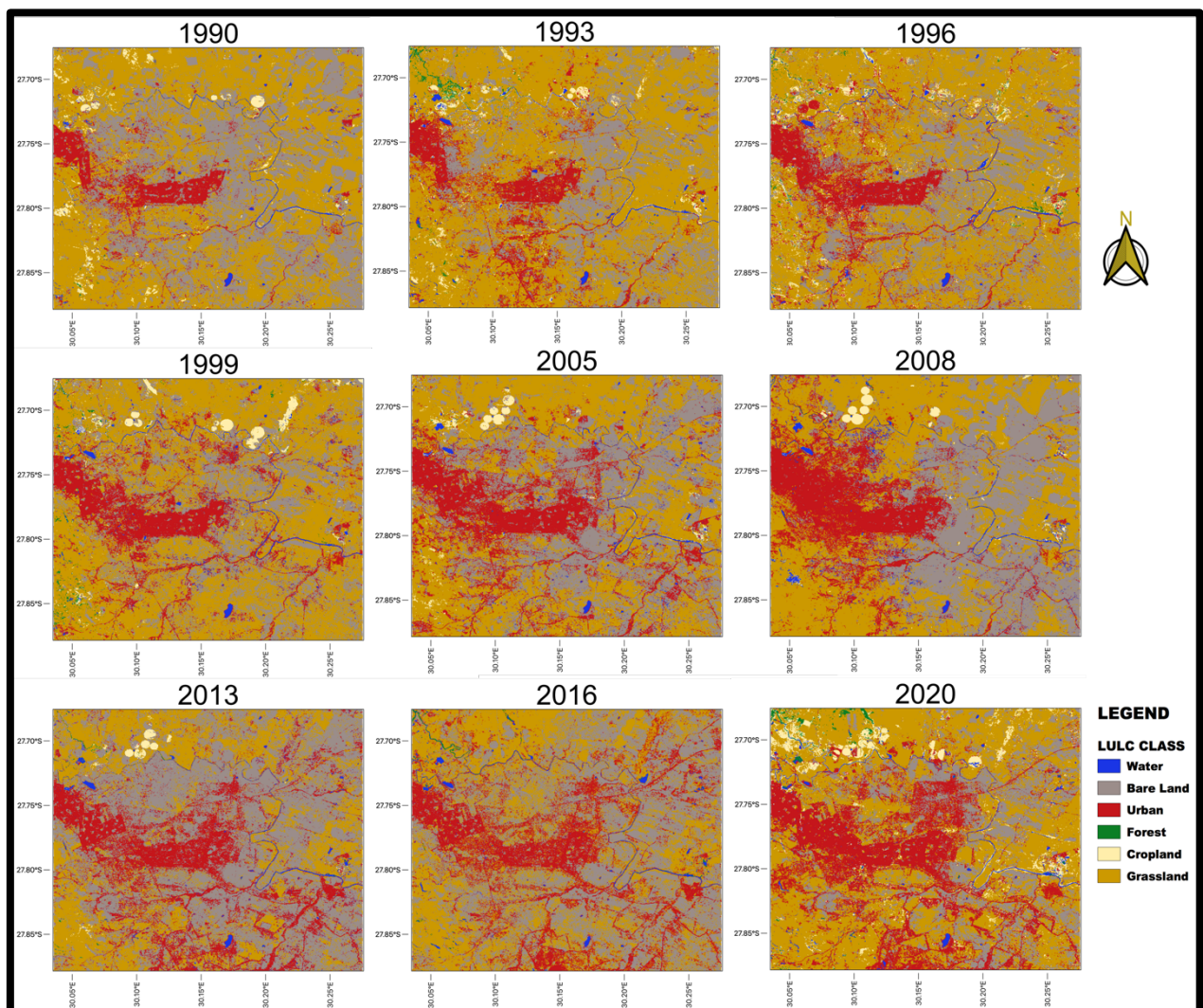


Figure 4-4: Spatial distribution of LULC over Region B from 1990 to 2020.

4.3.1.3 Region C: Normandien, KZN

The trend in LULCC from 1990 to 2020 is summarised in Figure 4-5. The trend is based on six classes collected from region C, each with a varying coverage area. Additionally, Figure 4-5 depicts the regional distribution of LULC types from 1990 to 2020. Total area coverage of all land cover class within the research area is about 57872 m².

In 1990, grassland dominated the pattern of LULC as a proportion of the total area analysed, accounting for 76.6% of the total area studied, followed by bare land (13.7%), water (6.2%), forest (2.8%), cropland (0.7%), and urban (0.1%). Additionally, the trend was found for all LULC throughout a 31-year period. In 2020, grassland still dominated the observed LULC pattern (73.9%), followed by bare land (14.3%), water (5.4%), forest (3.8%), cropland (2.3%), and urban area (0.2%). In 1990, grassland covered more than 75% of land, but by 2020, it had reduced by 2.7 % of total coverage.

The increases of 1.0% and 1.6% in forest and agriculture areas, respectively, are critical and notable. This is because it plays a critical role in climate regulation and serves as a good source of moisture for the atmosphere, which can contribute significantly to climate change. It is also necessary to note the growth in urban and bare land, which indicates a loss of vegetation, and may contribute to climate change.

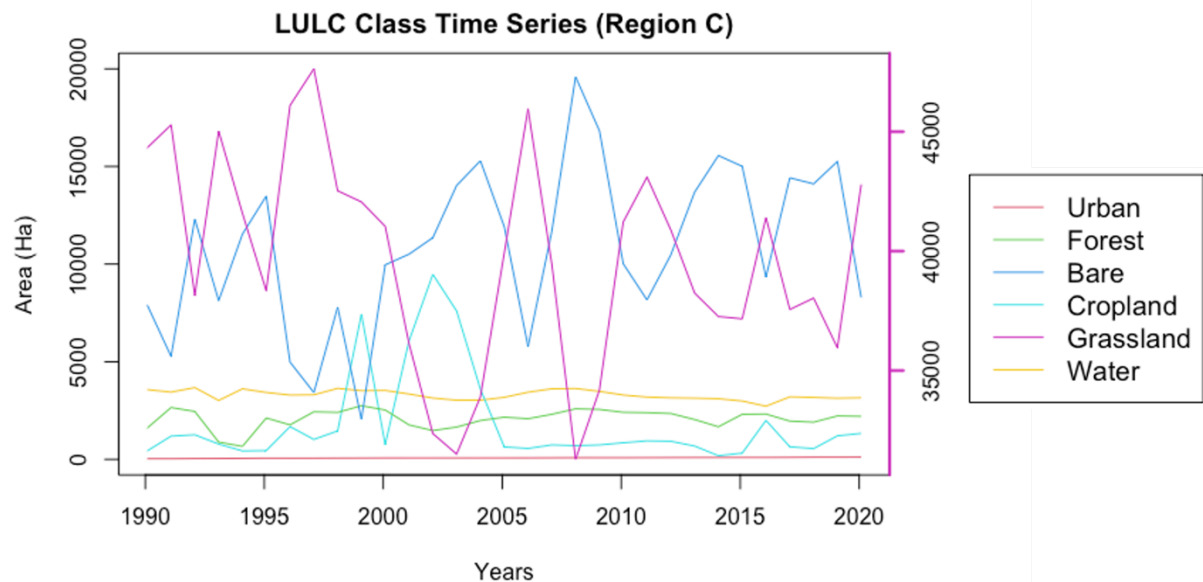


Figure 4-5: Land Use Land Cover time series over Region C from 1990 to 2020.

Grasslands was the most prevalent and extensive feature; however bare ground is also found across the studied locations (Figure 4-5). A larger body of water is plainly visible in the centre of the study, with little patches of water isolated and spread around the region C, as illustrated in Figure 4-6. The urban built-up areas exhibited a distribution that is noticeable in the study's south-east and a small patch in the north-east. Cropland and forest appeared to be dispersed primarily on the western side, but forest predominates primarily on the north-west side. The land cover distribution has been generally stable over the last three decades, with forest and agriculture expanding in size and visibility (Figure 4-6). The predominance of urban areas and their fragmentation have had a significant role in the fragmentation of grassland.

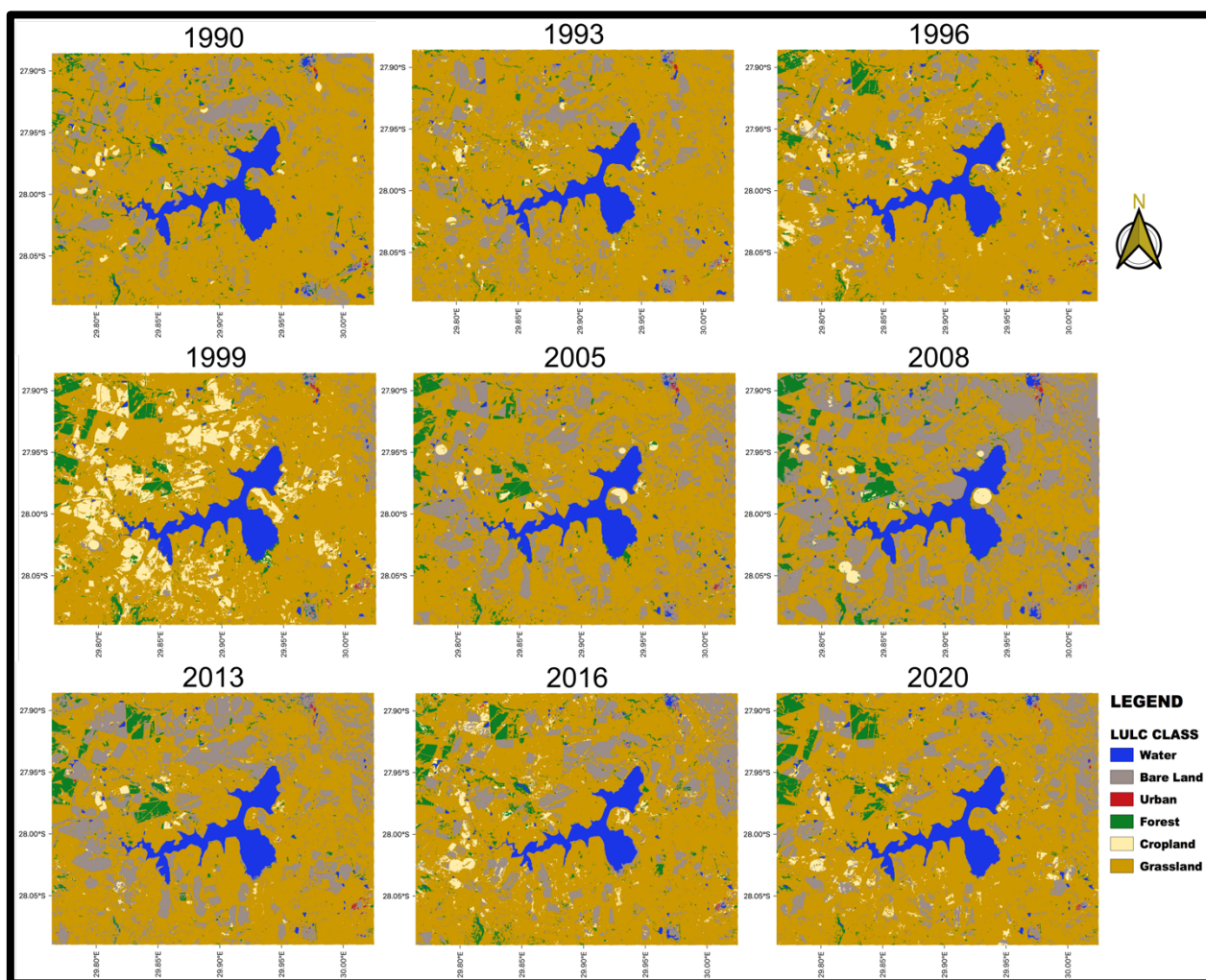


Figure 4-6: Spatial distribution of LULC over Region C from 1990 to 2020.

4.3.1.4 Region D: Paul Pietersburg, KZN

The trend in LULCC from 1990 to 2020 is summarised in Figure 4-7. The trend is based on six classes collected from region D, each with a proportional coverage area. Additionally, Figure 4-8 depicts the regional distribution of LULC types from 1990 to 2020. The total area covered of all land cover class within the area is about 58054m².

In 1990, grassland dominated the pattern of LULCC as a proportion of the total area analysed, accounting for 61.1% of the total area studied, followed by forest (27.0%), bare land (10.8%), cropland (0.8%), water (0.3%), and urban (0.1%). Additionally, the trend was found for all LULC throughout a 31-year period. By 2020, grassland still dominated the reported LULC pattern (48.6%), followed by forest (35.2%), bare land (14.9%), urban areas (0.7%), and cropland and water all accounting for 0.3%. In 1990, grassland covered more than 60% of the area, but by 2020, it had reduced by 12.5% of total coverage. The increases of 0.6% and 4.1% in urban areas and bare land, respectively, are cause for concern. The development in urban land raises

concerns about the loss of habitat for essential species and the alteration of their role in ecosystem service provision. It is worth noting that over a 31-year period, the forest has increased by 8.2%, more than any other class.

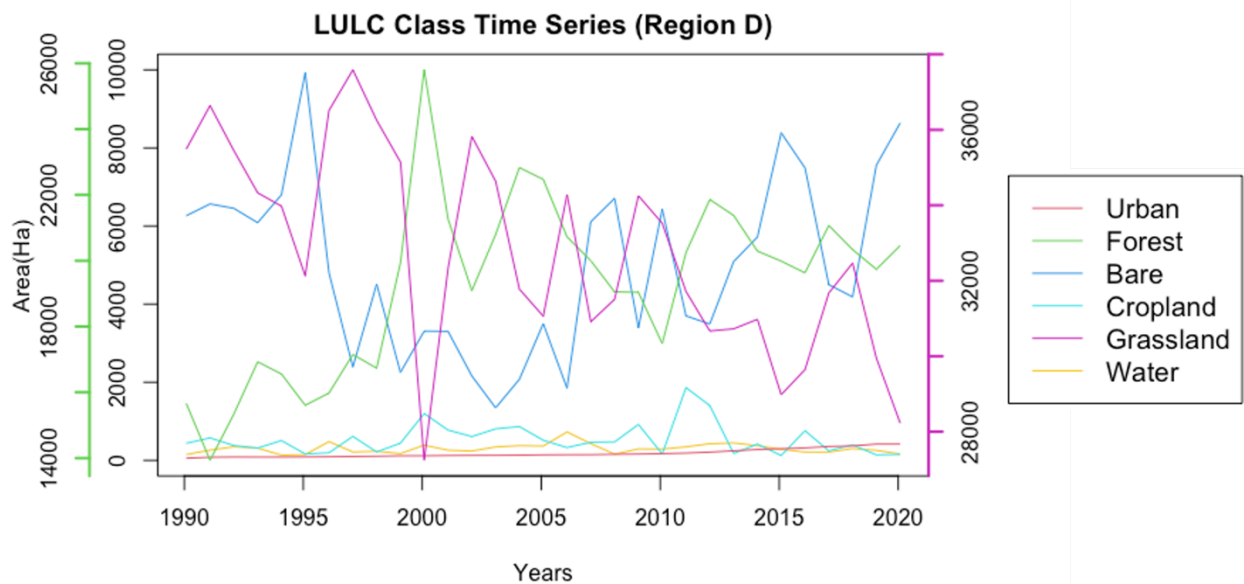


Figure 4-7: Land Use Land Cover time series over Region D from 1990 to 2020.

Grassland is the most noticeable and ubiquitous feature while forests are dispersed across the area and are also richer and healthier (Figure 4-8). There are isolated and dispersed bare land patches throughout region D, especially in areas of deforestation or forest harvesting, and minor water patches are likewise isolated and scattered. The urban areas were distributed east of the study region, as well as north and west of the study area, but were rather prominent in the east. Cropland appears to be modest and concentrated on the north-western part of region D in most years, although they are dispersed across the area in others. Land cover distribution remains generally stable over a 31-year period compared to 1990 but varies as classes grow in size and cover a larger area over time.

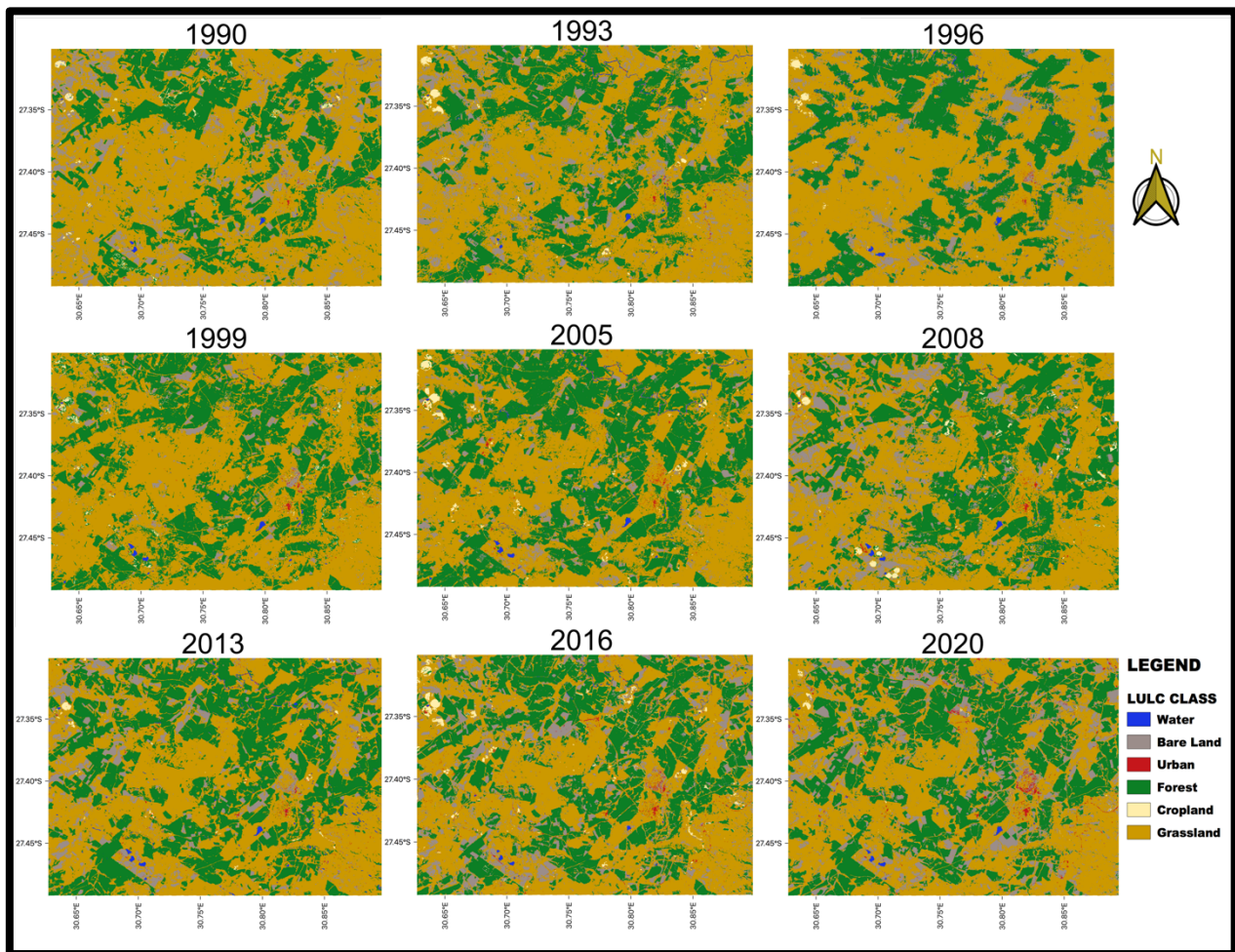


Figure 4-8: Spatial distribution of LULC over Region D from 1990 to 2020.

4.4 Classification Accuracy assessment

Numerous elements, such as the satellite data's property, the research area's scale, and the level of information in the LULC classes, can all affect the accuracy value. Evaluating the accuracy of classification results is a critical step in the remote sensing satellite image classification process. It is proposed that when identifying LULC using remote sensing, the total accuracy should be at least 85% and the classes should be at least 70%. Because an error or confusion matrix is generally employed in remote sensing research, the accuracy of thematic maps constructed from multispectral imagery was determined in this study using an error or confusion matrix and basic descriptive statistics.

GEE assessed the classification results for each remote sensing imagery and sample point for the accuracy of the confusion matrix and calculated the accuracy to confirm the random forest algorithm's classification effect. The results indicate that the average overall classification accuracy for regions A and C is 99%, while regions B and D are 98%. Additionally, the kappa coefficient for regions A, B, and D is 98%, while region C is 99%, showing that classification

accuracy is high. This suggests that, based on validation data, the classification maps generated in this study were around 98% correctly classified. Additionally, the User Accuracy (UA) and Producer Accuracy (PA) of each land cover class are extraordinarily high, ranging between 80% and 100%. As can be seen from the findings above, the accuracy was consistent and steady across the three research areas, with maximum values across the region and classes. The results clearly indicate that overall classification accuracy is satisfactory and correct, as the values are above the 80% threshold for strong agreement, indicating that classification and actual ground class concur. This is an appropriate level of accuracy for subsequent analysis and change detection. With the growing use of remote sensing and matrix error, it appears as though researchers have not yet achieved the requisite level of accuracy. However, the employment of GEE and an RF classifier made it feasible, and it has demonstrated its dependability on a continuing basis.

Accuracy assessment is critical in change detection data analysis because it affects the outcomes of any change detection approach utilised. The classification data can only be considered relevant and accurate if the classified datasets have high accuracy as per the recommended accuracy. The high accuracy results provide a high level of confidence in the outcomes of the change detection.

4.5 LULCC trends and synthesis of trends

The GEE platform's RF machine learning algorithm was used to classify six LULC classes across four regions, resulting in a 31-year annual time series.

4.5.1 Water

Water is a vital natural resource for all forms of life on the earth's surface (Heinke et al., 2020). Water is critical for plant growth and agricultural production, livestock farming, energy generation, and domestic use (Heinke et al., 2020). Additionally, it serves as a habitat for animal and plant species and supports marine life. Water's annual variation over 31 years is depicted in Figure 4-9. The result indicates that region C is the most water-capable region, followed by B, D, and finally region A. The MK trend test revealed an insignificant decreasing trend in region A (z score = -1.1897 and p-value = 0.2341) and B (z score = -0.06798 and p-value = 0.9458), while there is a significant decreasing trend in region C (z score = -2.9234 and p-value = 0.003462), indicating that the area is becoming drier. Thapa (2020) and Duraisamy et al. (2018) also discovered a significant decline in waterbodies. Water scarcity is a serious issue that cannot be ignored because it is necessary for the provision of goods and services (Jury & Vaux, 2005). Additionally, the MK trend indicates that region D is becoming wetter, characterised by an insignificant increasing trend (z score = 0.61187 and p-value = 0.5406). This is consistent with the findings of

Masroor et al. (2022), Musetsho et al. (2021), and Phan et al. (2021), who discovered that water levels have increased over time. Considering that South Africa is currently experiencing a water crisis, such a reduction in water in regions A, B, and C further depletes already scarce water resources. Water scarcity affects not only humans and the climate, but also aquatic species that play a critical role in the ecosystem (Jury & Vaux, 2005). Water resources need to be conserved for the livelihood, wealth, and wellbeing of the South African people (Orimoloye et al., 2019).

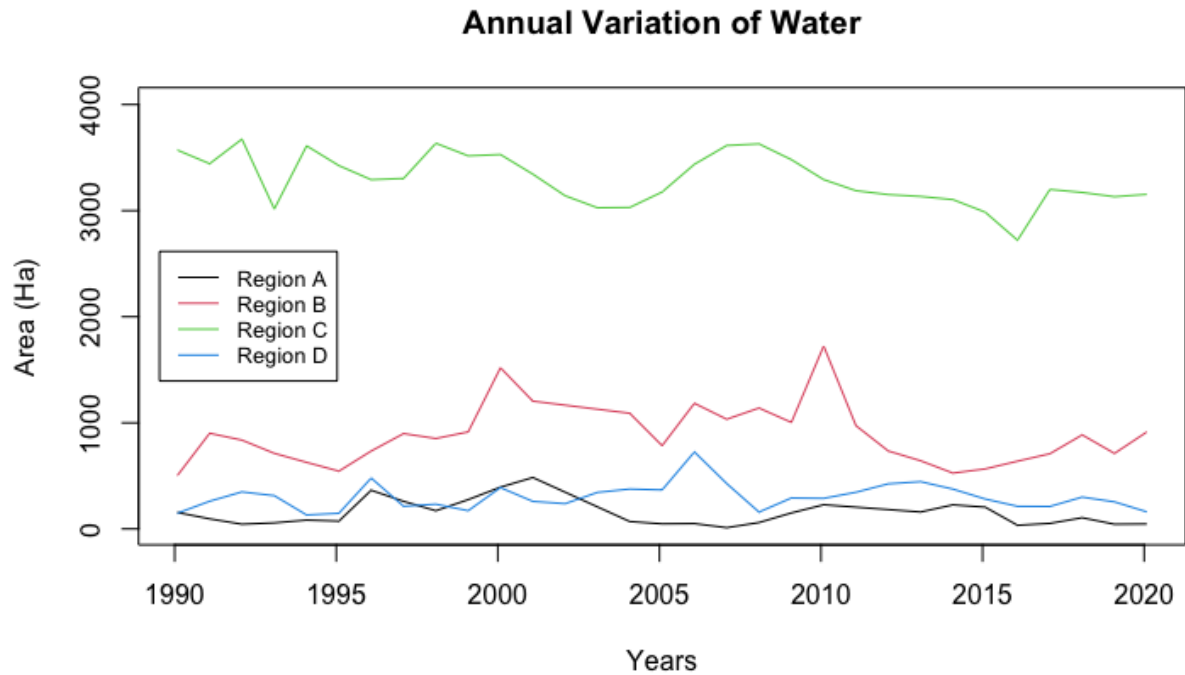


Figure 4-9: Annual variation of water over eastern South Africa from 1990 to 2020.

4.5.2 Bare Land

Figure 4-10 illustrates the annual variation in bare land across four regions. Over a 31-year period, bare soil dominates region B, followed by C, and D and A alternately dominate each other. The MK trend test, on the other hand, indicates that regions A (z scores = 0.4759 and p-value = 0.6341), and D (z scores = 0.64586 and p-value = 0.5184) have increased insignificantly, whereas region B (z scores = 1.6996 and p-value = 0.0892) and C (z scores = 2.4815 and p-value = 0.01308) have increased significantly. This demonstrates that bare land in region C is increasing and can become drier in the future, as well as the rate at which vegetation is being removed at the surface, which is cause for concern as it will contribute to increased climate variability and ecosystem vulnerability. This is supported by Meer & Mishra (2020), Musetsho et al. (2021), and Phan et al. (2021), who discovered that barren land has increased significantly. In comparison, bare land was found to have decreased significantly over Sikkim Himalaya India due to agriculture, vegetation, and built-up (Mishra et al., 2020). Bare ground should be vegetated because it is prone to erosion during rainfall, which can result in degradation and ultimately render the land useless due to the lack of plant life (Jury & Vaux, 2005). This is because soil organic carbon and

nitrogen levels are depleted as a result of degradation, affecting soil quality and fertility. When the soil quality and fertility are affected, this as a result prevents agricultural production that can occur on that piece of land.

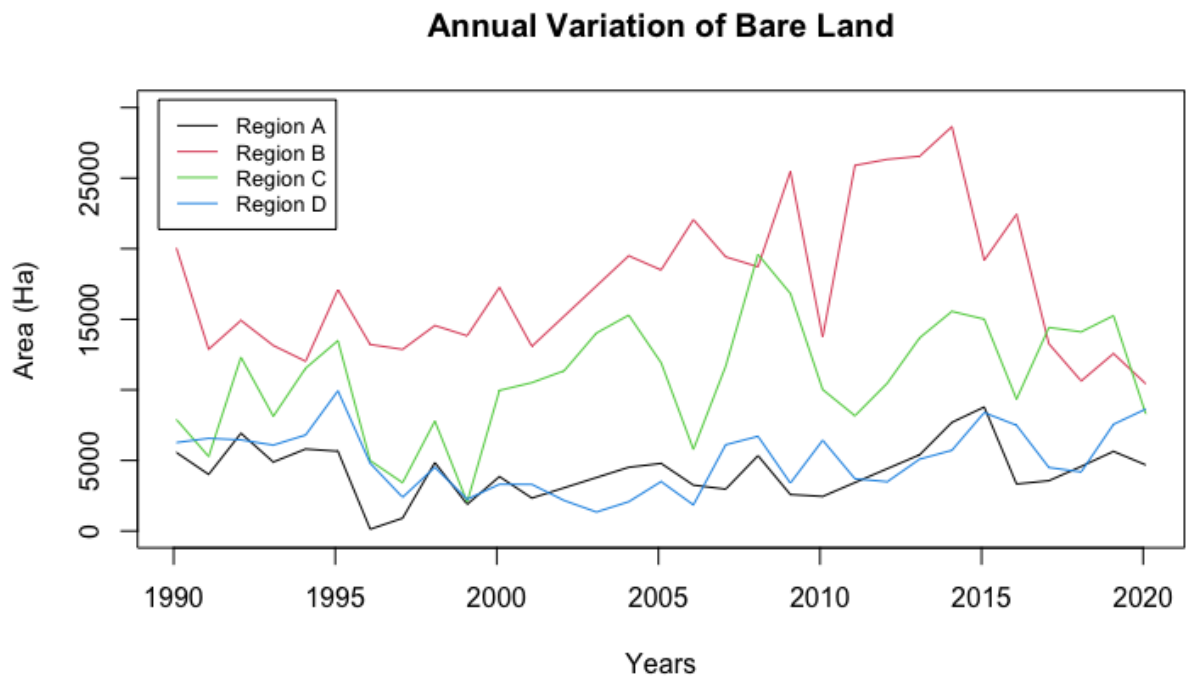


Figure 4-10: Annual variation of bare land over eastern South Africa from 1990 to 2020.

4.5.3 Urban Land

Urbanisation or settlements remain one of the most intensive LULCC influences, accounting for irreversible land fragmentation. Region B, as indicated by its high area coverage in Figure 4-11, is the area with the most urban settlement and population. From 1990 to 2009, region D dominated, while region A was dominant in 2010 (Figure 4-11). However, from 2011 to 2020, region A outperformed the other regions. A is the third most populous region with urban settlements, having been less populous than C from 1990 to 2005 but assuming dominance from 2005 to 2020. Overall, the MK trend test revealed that urbanisation has increased significantly in region A (z score = 7.8863 and p-value = 3.112×10^{-15}), B (z score = 7.8523 and p-value = 4.083×10^{-15}), C (z score = 7.7844 and p-value = 7.007×10^{-15}), and D (z score = 7.7844 and p-value = 7.007×10^{-15}), indicating a high demand for living space as the population grows and the economy of the country grows.

This is cause for paramount concern, as this change is irreversible and will have a long-term impact on the environment and climate, in contrast to vegetation fragmentation, which can be restored to its natural state. In Europe, Huang et al. (2020) discovered that urban sprawl increased primarily on agricultural land, resulting in densely populated areas as a result of population and economic growth. Dong et al. (2019) also discovered that urbanisation has expanded at a rapid

rate in response to rapid population growth and GDP development, at the expense of cropland. Between 1984 and 2010, developed land increased significantly over Benji, increasing by 27% (Hu et al., 2017). Mudau et al. (2014) observed a 25.5% increase in urban spatial area at the expense of non-urban area over a five-year period in Rustenburg, South Africa. Other studies across a variety of regions found a similar result to this one (Al-Saady et al., 2015; Twisa & Buchroithner, 2019; Meer & Mishra, 2020; Thapa, 2020). This demonstrates that human activities have continuously altered the LULC pattern throughout the world, as population growth and economic development subsequently result in LULCC, putting a strain on available resources; consequently, special attention is required to manage and control this global expansion. Despite its small area coverage throughout the world, it has been shown to have a significant impact on ecosystem services and climate, making it critical to ensure that when it does occur, it expands into areas with little to no vegetation (Zhou et al., 2016).

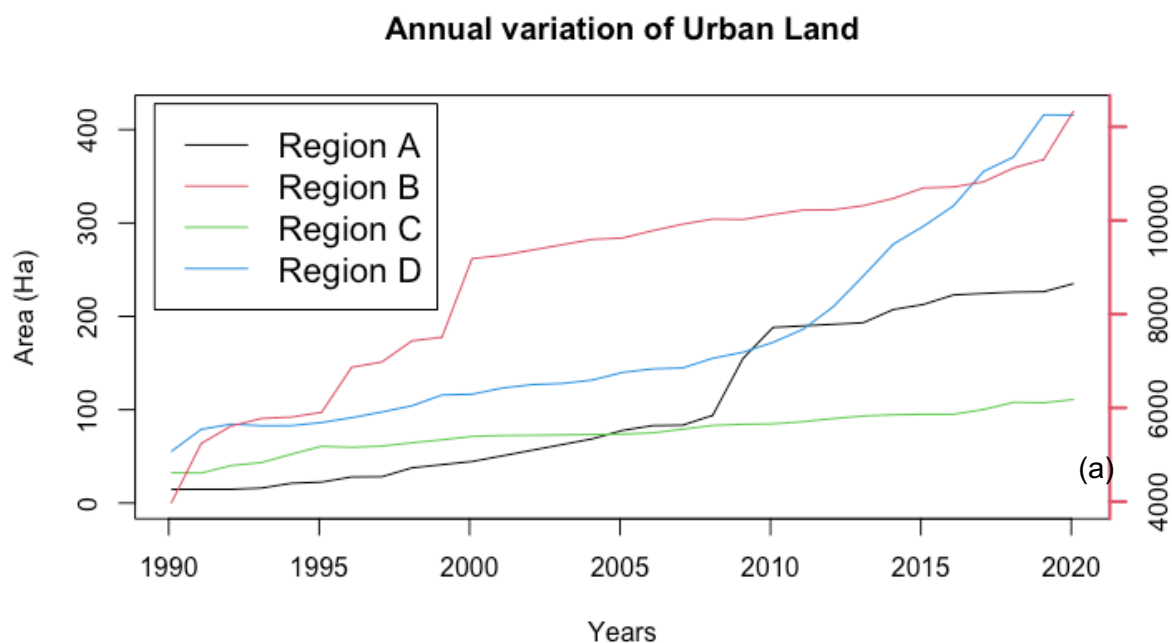


Figure 4-11: Annual variation of urban land over eastern South Africa from 1990 to 2020.

4.5.4 Forest

The result indicates that region D (Figure 4-12) has forest dominance, followed by region C, while regions A and B have alternated in the dominance over a 30-year period (Figure 4-12). The MK trend test revealed that region A (z score = -2.8894 and p -value = 0.00386) experienced a significant decrease in forest cover, whereas region B (z score = -0.9518 and p -value = 0.3412) experienced an insignificant decrease. The findings corroborate numerous studies conducted in various countries that discovered a significant decline in forest cover (e.g., Herrmann et al. 2020; Meer & Mishra 2020; Phan et al., 2021; Thapa 2020). Additionally, forest cover decreased marginally in Region C (z score = 0.067986 and p -value = 0.9458), while it increased significantly

in Region D (z score = 2.9914 and p-value = 0.002777). Mishra et al. (2020) discovered an increase in dense forest in Sikkim Himalaya India due to human influence. Duraisamy et al. (2018), also discovered no change in forested areas when identifying LULCC hotspots in India.

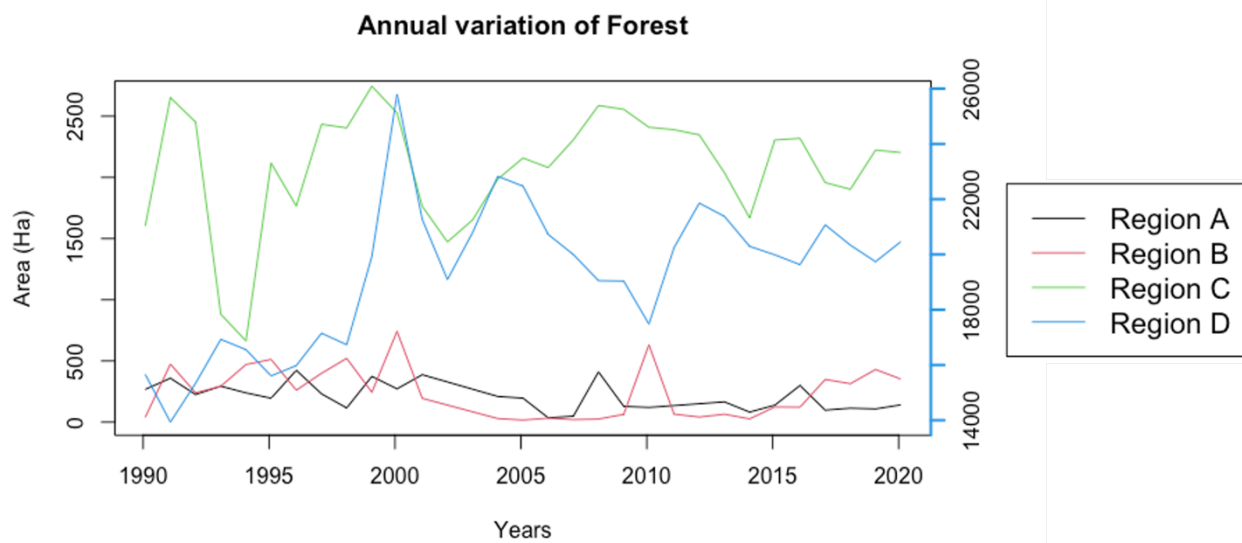


Figure 4-12: Annual variation of forest over eastern South Africa from 1990 to 2020.

4.5.5 Cropland

The annual variation in cropland cover across four regions is depicted in Figure 4-13. The result indicates that region C had a significant amount of cropland in 1999, 2002, and 2016, whereas region B had a significant amount of cropland from 1990 to 1999, 2010, and 2017 to 2020. Additionally, region A demonstrated dominance in 2005. However, the MK trend test revealed that cropland in regions A (z score = -1.9376 and p-value = 0.05267), B (z score = -1.7336 and p-value = 0.08298) has decreased significantly, while C (z score = -0.61187 and p-value = 0.5406) and D (z score = -0.71385 and p-value = 0.4753) exhibited an insignificant decreasing trend. Numerous studies conducted throughout the world have discovered a decline in cropland as a result of LULC. Other studies have discovered that cropland has decreased significantly as a result of urbanisation and built-up areas (Li et al., 2018; Masroor et al., 2022). In comparison, Phan et al. (2021) and Al-Saady et al. (2015) discovered that cropland is increasing. Croplands are critical for improving food security and also for sustaining a strong economy and providing livelihoods (Sazib et al., 2020). This decrease in cropland across the region is cause for concern, as it exposes communities to vulnerability and increases food insecurity, necessitating attention to prevent this from happening and increase cropland.

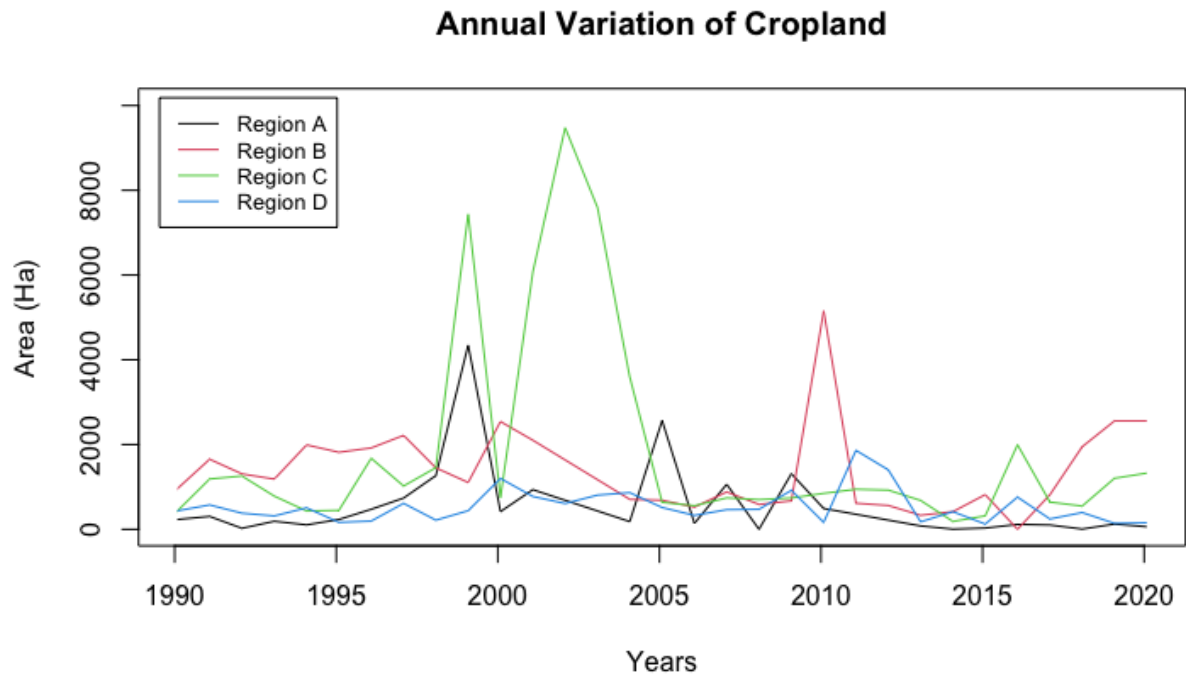


Figure 4-13: Annual variation of cropland over eastern South Africa from 1990 to 2020.

4.5.6 Grassland

Annual variation in grassland cover is depicted in Figure 4-14 for four regions. Grassland remained the dominant land cover type across the entire study area and was determined to be the most prevalent vegetation type in eastern South Africa. The result indicates that region A has a high proportion of grassland, whereas region B has a low proportion. However, the MK trend test indicates that grassland in region A has increased insignificantly, with a z score of 0.23795 and a p-value of 0.8119. This is consistent with Twisa & Buchroithner, (2019), who found an increase in grassland. While in region B (z score = -4.0791 and p-value = 4.52×10^{-05}), C (z score = -1.9716 and p-value = 0.04866) and D (z score = -4.3511 and p-value = 1.355×10^{-05}), the z score has decreased significantly, correlating with findings from various studies (e.g., Li et al., 2018; Musetsho et al., 2021; Phan et al, 2021). Due to the magnitude of change and transformation occurring throughout regions B, C, and D, it must be prioritized and preserved. It risk experiencing severe destruction in the future, jeopardizing vital ecological services (Sun et al., 2020). This is because it play a critical role in soil stabilisation, water and nutrient cycling, energy production, sustenance provision through modern agricultural activities, and grazing production for livestock (Andrade et al, 2015).

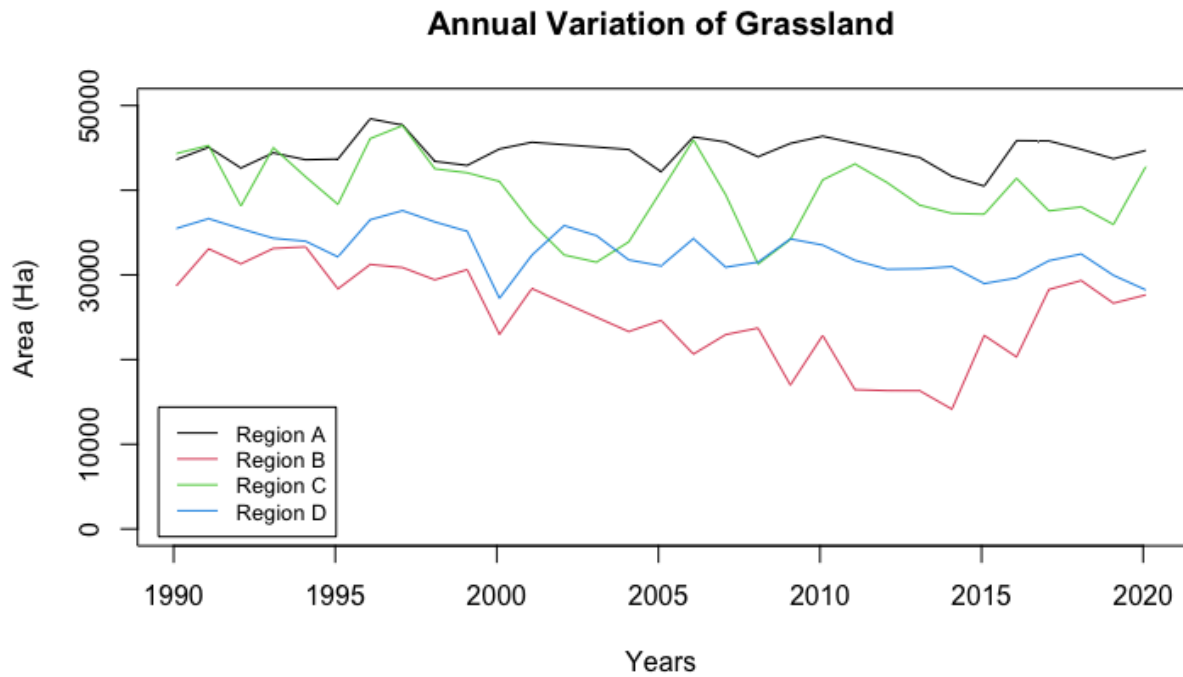


Figure 4-14: Annual variation of grassland over eastern South Africa from 1990 to 2020.

4.6 Trend and change of Vegetation, surface soil moisture and temperature

The temporal trend analysis of Normalized Difference Vegetation Index (NDVI), Normalized Difference Infrared Index (NDII) and Land Surface Temperature (LST) over a 31-year span for region A, B, C and D was calculated and the results as shown in Table 4-1. The result in Table 4-1 shows a mean annual variation of NDVI, which is a proxy for vegetation health across the four regions, including grassland, forest, and cropland. The results revealed a significant increasing trend in the annual NDVI ($p < 0.05$ and positive z value) in all regions. This indicates that vegetation has been increasing over time, with region D increasing at a faster rate than the rest of the area as indicated by the slope of 0.0029/year. On the other hand, NDII is characterised by insignificant decreasing trend ($p > 0.05$ and negative z value) in the in region A and C. Whereas, region B and D demonstrated insignificant increasing trend ($p > 0.05$ and positive z value). This means that region B and D is becoming wetter while the rest of the region is gradually becoming drier. However, region B is urban dominated and have experienced significant urban expansion. Furthermore, Region D's forest cover had a great impact on soil moisture than proximity to a large water bodies (such as the dam in region C). Surface moisture assessment over a long period is critical for understanding the trend of climate variability, as it can indicate both wet and dry spells in a region. LST revealed a significant increasing trend for all regions, despite the increase in vegetation and surface soil moisture in region B and D.

Table 4-1: Monthly and annual trend analysis of NDVI, NDII and LST

Variable	Period	Region A			Region B			Region C			Region D		
		ZMK	p-value	Slope	ZMK	p-value	Slope	ZMK	p-value	Slope	ZMK	p-value	Slope
NDVI	Monthly	1.799	0.0719 .	0.5	2.432	0.0150 *	0.57	2.180	0.0292 *	0.55	3.606	0.00031 ***	0.63
	Annual	2.583	0.0097 **	0.0013	2.855	0.0042 **	0.0012	2.685	0.00724 **	0.002	4.640	3.472 x 10 ⁻⁰⁶ ***	0.0029
NDII	Monthly	-0.738	0.461	-0.09	-0.732	0.465	-0.41	-0.683	0.495	-2.02	0.0768	0.938	0.4
	Annual	-0.101	0.9188	-0.0002	0.849	0.3954	0.0002	-0.169	0.865	-0.00036	1.240	0.2146	0.0003
LST	Monthly	3.78	0.0001 6 ***	0.71	4.07	4.781 x 10 ⁻⁰⁵ ***	0.64	3.47	0.000514 ***	0.57	5.54	3.099 x 10 ⁻⁰⁸ ***	0.76
	Annual	3.0254	0.0024 **	0.139	2.957	0.0031 **	0.139	2.685	0.00724 **	0.0806	4.487	7.221e-06 ***	0.1938

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

4.6.1 Normalized Difference Vegetation Index

4.6.1.1 Temporal analysis of NDVI

The NDVI over the eastern escarpment has a strong seasonal component. Additionally, there is a significant decrease in the NDVI values across the study areas, as seen in region C (Figure 4-15C) and region D (Figure 4-15D). For example, October 1990 (-0.22) was the month with lowest value in Region C, followed by November 1995 (-0.02), June 1997 (0.02), October 2010 (0.06), August 2018 (0.09), and September 2020 (0.1). While September 1990 (0.02) and September 1994 saw a significant decrease in region D (0.02). All of this significant decline occurred across multiple seasons, even during times when vegetation is expected to be abundant; however, some abrupt changes can be attributed to the 1994/95 and 1997/1998, 2015/2016 El Niño events (Mbatha & Xulu, 2018). During spring in an El Niño event, vegetation withers and sheds leaves, reaching a minimum just before summer season arrives as a result of a lack of precipitation and also drought influence (Sazib et al., 2020).

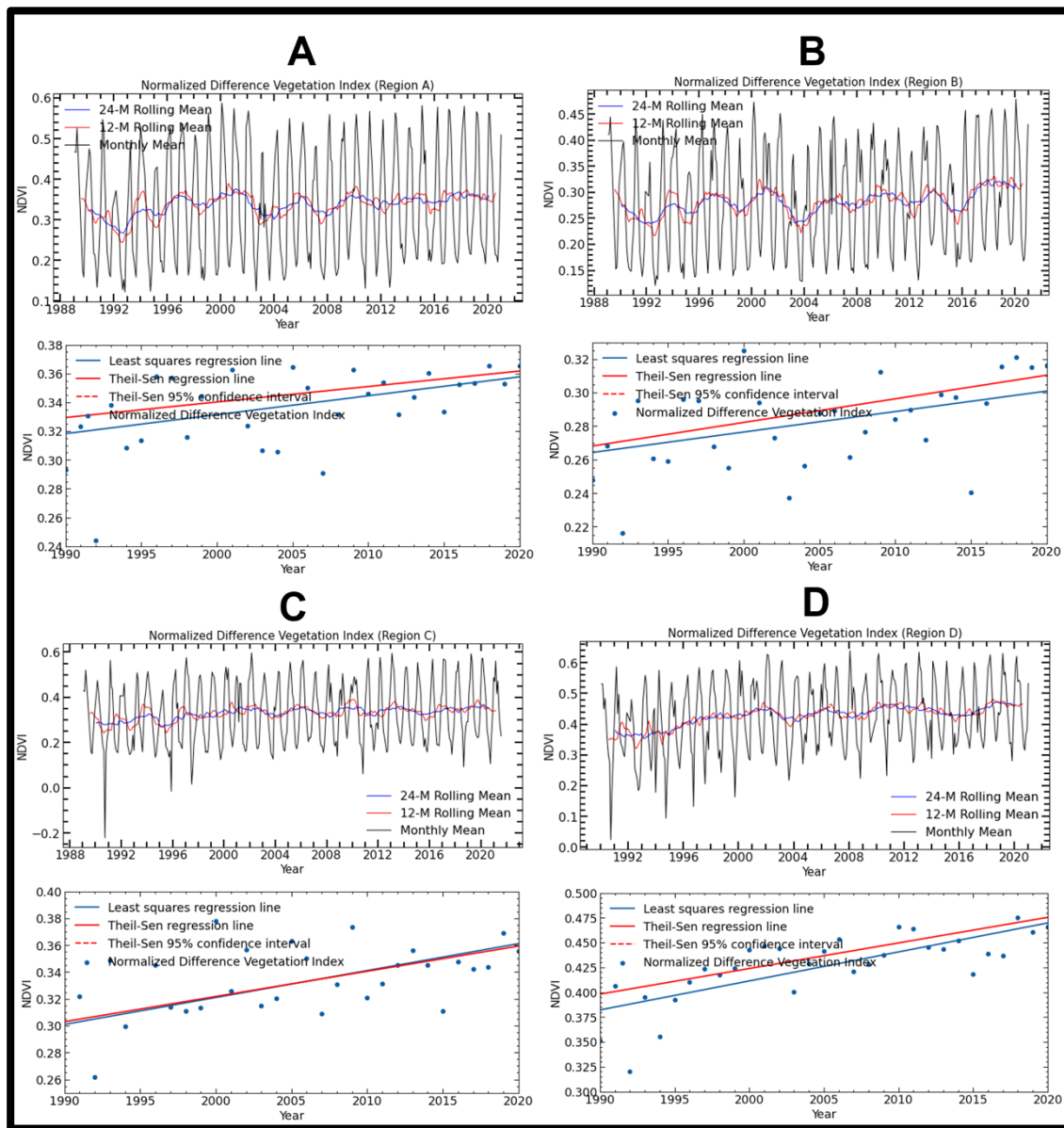


Figure 4-15: Temporal mean monthly, 12 month (annual) and 24 month running trends of NDVI over (A) Region A (B) Region B (C) Region C and (D) Region D of Eastern South Africa from 1990 to 2020.

4.6.1.2 Spatial distribution of NDVI

Figure 4-16 summarise the spatial annual variation of NDVI. Over a 30-year period, significant high-healthy vegetation with values > 0.6 has been observed primarily in the western part of region A, indicating a high-vegetation distribution with a strip which was clearly visible in 1992/94. However, it experienced significant increases in vegetation cover in 1999, 2001, 2004, 2010, and 2011 (see Figure 4-16). Additionally, the eastern portion of the study area appears to be vulnerable, as it was found to be devoid of vegetation in 1992 and in 2016.

As illustrated in Figure 4-16B, region B has an increasing vegetation cover, which is consistent with the MK trend test. Despite its increasing trend, this region has had relatively little vegetation

cover in the past few years. Between 1995 and 2008, the region's vegetation was removed, leaving nothing but bare ground and unhealthy vegetation cover, with 2008 being particularly hard hit. This was due to extreme dryness that was observed over the area (Ndlovu & Demlie, 2020). However, following this period of non-vegetation cover, vegetation regeneration occurred, and the highest vegetation distribution was recorded between 2009 and 2014 (Figure 4-16B). It was during this period that the region saw vegetation increase until 2020. The vegetation appears to be evenly distributed across region C, covering the entire area. In 2008, there was little and unhealthy vegetation, whereas in 1994, 1999, and 2009/10/11, vegetation was noticeably high, healthy, and well-distributed (see Figure 4-16C). Furthermore, similarly to region B the area depicted an increasing trend as from 2009. Region D is a forested area that makes up the study, and the spatial map indicates that this is the only area with vegetation that is significantly healthy (Figure 4-16D). In other sections of the study, bare land was visible; however, in 1999, 2005, 2010, and 2011, there was a significant vegetation distribution with relatively little patch of bare land. In comparison to the other period, 1994 and 1998 was the most unvegetated and highly bare land year.

All of these periods of significant high vegetation and unvegetated coincide with drought and flooding events in southern Africa, such as the 1991/92 and 2015/16 droughts (Mahlalela et al., 2020), as illustrated in Figure 4-15. The summer of 2010/11 was characterised by a significant La Niña event. Most regions (B, C and D) all experienced above average rainfall. The growth could be as a result of high surface moisture that allowed vegetation to thrive even during drought period.

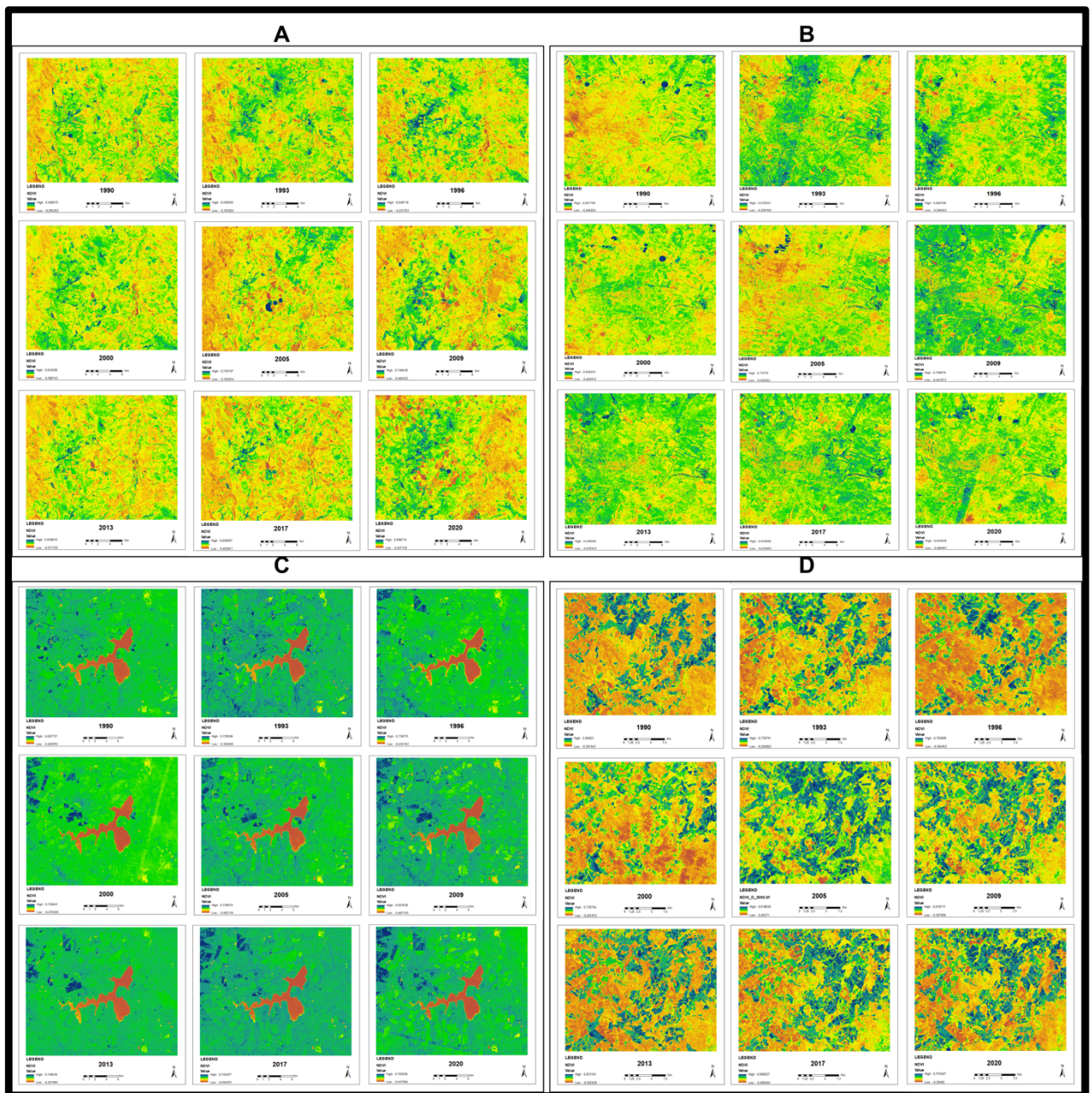


Figure 4-16: Spatial mean Annual distribution of NDVI over (A) Region A, (B) Region B, (C) Region C and (D) Region D from 1990 to 2020.

4.6.2 Surface Soil Moisture

The moisture content affects the BR, rainfall to infiltration, runoff, and evaporation ratios (Chikoore, 2016). Additionally, soil moisture is a critical state variable in the Earth's climate system, assisting in the regulation of water, energy, and carbon exchanges between the Earth's surface and the atmosphere (Ban-Weiss et al., 2011). Soil moisture is a key factor that affects the spatial and temporal vegetation distribution (Huang et al., 2021). Insufficient rainfall and excessive evaporation create moisture deficits, which reduce surface runoff. It has the potential to influence the atmosphere's variability. rainfall and temperature, according to (Sazib et al., 2020), can increase water availability and favour soil moisture, resulting in increased plant activity.

4.6.2.1 Temporal Analysis NDII

The peaks in Figure 4-17 represent significant phenomena such as periods of excessive moisture/wetness. Region C exhibits a significant moisture peak in September 1990 (0.46), which correlates with or can be associated with the La Niña. Both regions, however, experienced significant drought in 1992, coinciding with the most severe drought that occurred in conjunction with El Niño and a positive IOD in 1991/1992 (Chikoore, 2016). This drought had the greatest impact on regions A and B, which experienced a loss of recording < -0.12 of soil moisture, as illustrated in Figures 4-17. Additionally, region D reached a peak in December 1993, with an NDII value of 0.39. It's interesting to note that the majority of droughts appear to have been more severe in region B than in other regions, including the 1991/92, 1995/96, 2004/05, and 2015/16 droughts (Chikoore & Jury, 2021), which can be attributed to urban dominance. Regions B and C also reached a peak in February 1996 and November 1995, with NDII values of 0.17 and 0.37, respectively, as illustrated in Figure 4-17B and 4-17C. However, region C appears to have received more moisture than region B, which can be attributed to increase in irrigation to supply the increased cropland. Additionally, region B saw a peak in March 2018 with NDII values of 0.13. This means that NDII has been shown to accurately reflect vegetation water content because it was able to reflect both water deficit and wet spells during heavy rainfall.

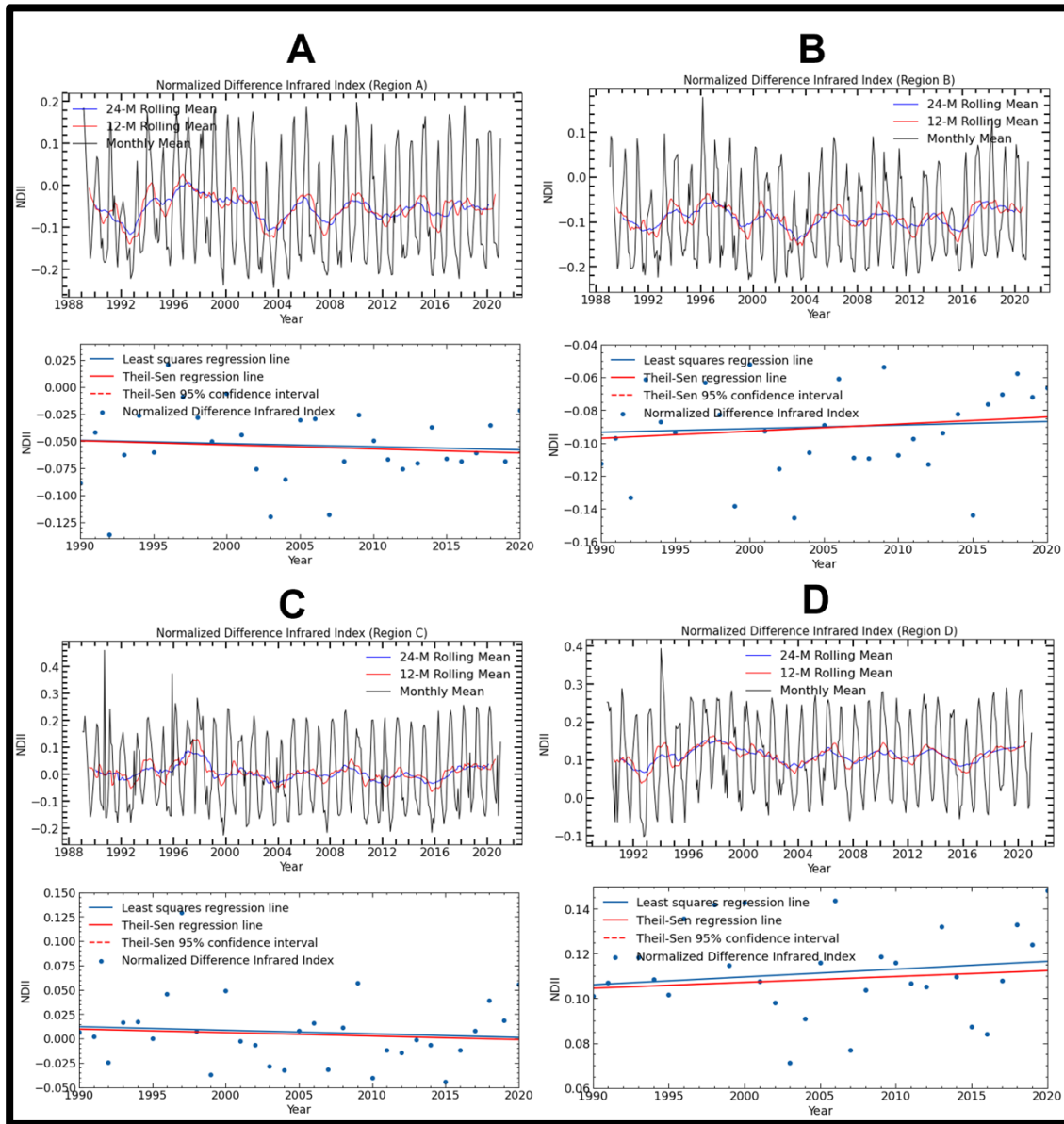


Figure 4-17: Temporal mean monthly, 12 month (annual) and 24 month running trends of NDII over (A) Region A (B) Region B (C) Region C and (D) Region D of Eastern South Africa from 1990 to 2020.

4.6.2.2 Spatial distribution of NDII

The figures 4-18 depict the annual spatial variation of NDII in four regions. Over region A, values were significantly higher in 1994 compared to in 2006, with high values observed for cropland area and water area (Figure 4-18A). In 2008, a strip of high moisture was observed to the east of the study, which can be attributed to the significant water from the period's high rainfall (see Figure 4-18A). Significant dry periods were observed in region B in 2000 and 2005, as illustrated in Figure 4-18B. In 2000 and 2005, a significant dry period characterised by low surface soil moisture was observed over region B, while a significant wet period was observed in 1997 and 2007 (Figure 4-18B). The spatial maps in region B indicate high moisture content observed over

water, cropland, forest, and urban land (Figure 4-18B). Figure 4-18C demonstrates a similar result to that of region B in terms of LULC with high moisture levels observed, whereas urban land did not. Between 1990 and 1995, the area experienced significant dryness, with the exception of water bodies and forested areas (Figure 4-18C). In 1999, 2001, and 2011, the area surrounding the dam water land, which is primarily grassland, regained moisture. Figure 4-18D depicts a forest in region D, which is the only vegetation type that has significant moisture compared to other vegetation types. Significant dryness was observed in 1990, 1992, and 2007 across other LULC types, while moisture levels increased in 1998/99, 2008/09/10, and 2011. Overall, region D spatial maps indicate that the region's surface soil moisture began to increase in 2008, following a period of significant drought in 2007 (Figure 4-18D).

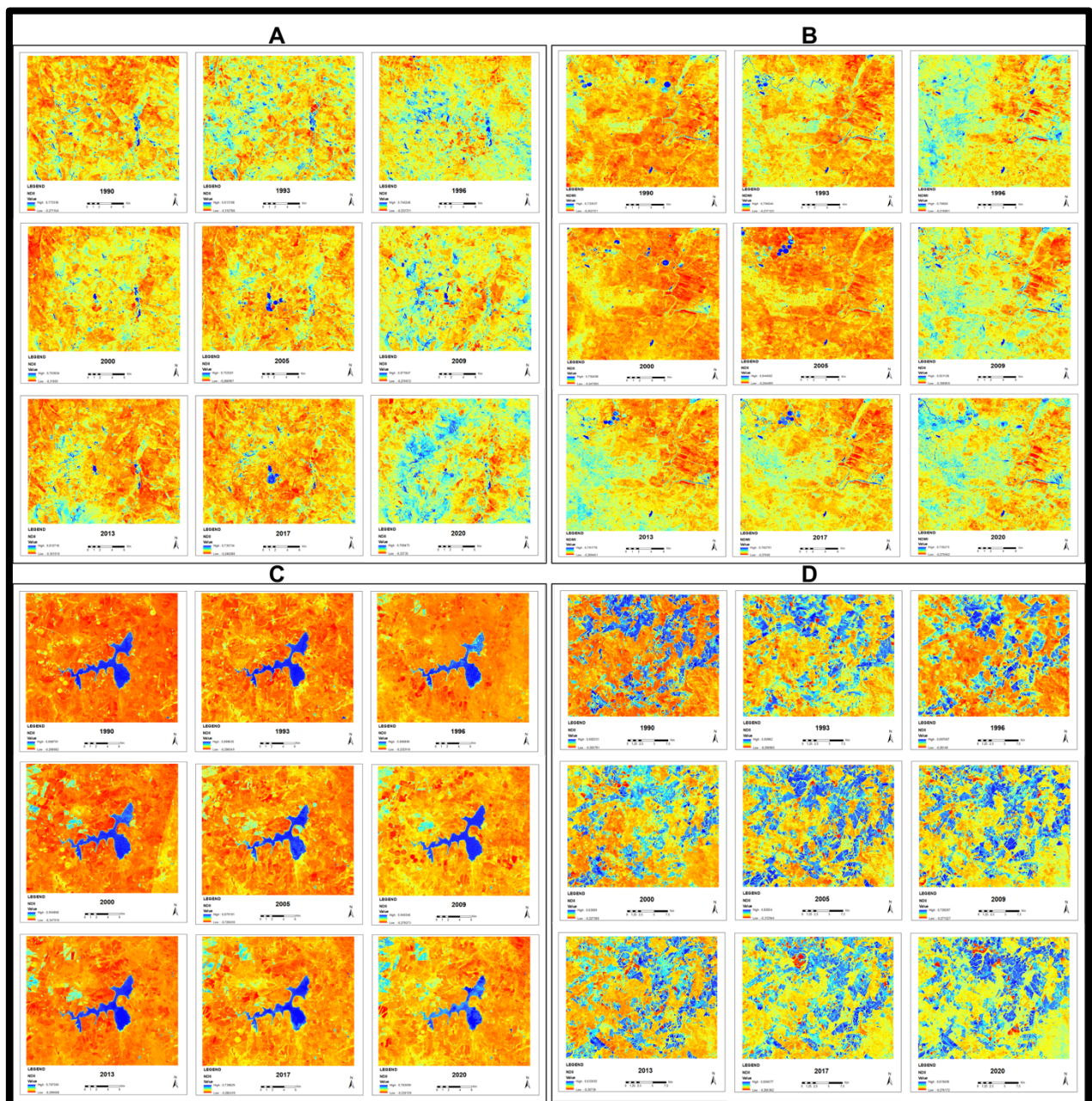


Figure 4-18: Spatial mean Annual distribution of NDII over (A) Region A, (B) Region B, (C) Region C and (D) Region D from 1990 to 2020.

4.6.3 Land Surface Temperature (LST)

4.6.3.1 Temporal analysis of LST

LST is a critical parameter in the calculation of surface energy balance and urban climatology (Khandelwal et al., 2018). It provides critical information about the energy exchange processes that are influenced by the land cover composition (Sayão et al., 2020). This parameter regulates the earth's physical, chemical, and biological processes and is critical for studying urban climate (Solanky et al., 2018). It is the primary determinant of surface radiation and energy exchange, thereby determining how heat is distributed between the surface and atmosphere (Yuvaraj, 2020). It is the critical variable that contributes to the regulation of latent and sensible heat flux.

Figure 4-19 illustrates the long-term variation in both monthly and annual LST. Increased LST is a sign of a dry surface, decreased surface soil moisture, and a high impervious surface which result in local warming (Ngie et al., 2014; Chikoore, 2016; Mohajerani et al., 2017).

LST exhibited a high degree of seasonal variability. It has decreased significantly over the course of the study area, as illustrated in Figure 4-19a, 4-19c, and 4-19d. July 1990, July 1996, and December 2009 had the lowest LST values over region A, with 6.5°C, 7.8°C, and 11.5°C, respectively. region C had LST values of -0.3°C, and 0.05°C, in June 1997, and 2011, respectively. While the lowest temperatures in region D occurred in December 1993, and 2009, with LST values of -10°C, and 10.1°C, respectively. These lowest values were obtained primarily during the winter in regions A and C, but also during the summer in region A and D. Additionally, it is was also necessary to consider the peaks that indicated significant warming, and region B did so in November 1999, December 2002, January 2008, November 2011, and January 2016 with LST values of 37.5°C, 37.8°C, 37.5°C, 36.6°C, and 36.8°C, respectively. Additionally, region D experienced a peak in November 1999, October 2001, 2004, September 2008, and November 2011 with LST values of 36.1°C, 38.1°C, 37°C, 35.9°C, and 37.3°C, respectively (Figure 4-19d).

In both regions, LST values are extremely low in July during the winter season and extremely high in summer. This is supported by Odindi et al. (2015) who discovered significant LST in all seasons however, with highest values observed in summer in eThekwinini than Buffalo city, South Africa. The highest LST peak occurs over Region B, owing to its impervious surface and lack of vegetation in comparison to the other Regions. Yan et al. (2020) found that summer and autumn experienced greater warming and the rate of warming was significantly faster than spring and winter during the 2002-2018 period.

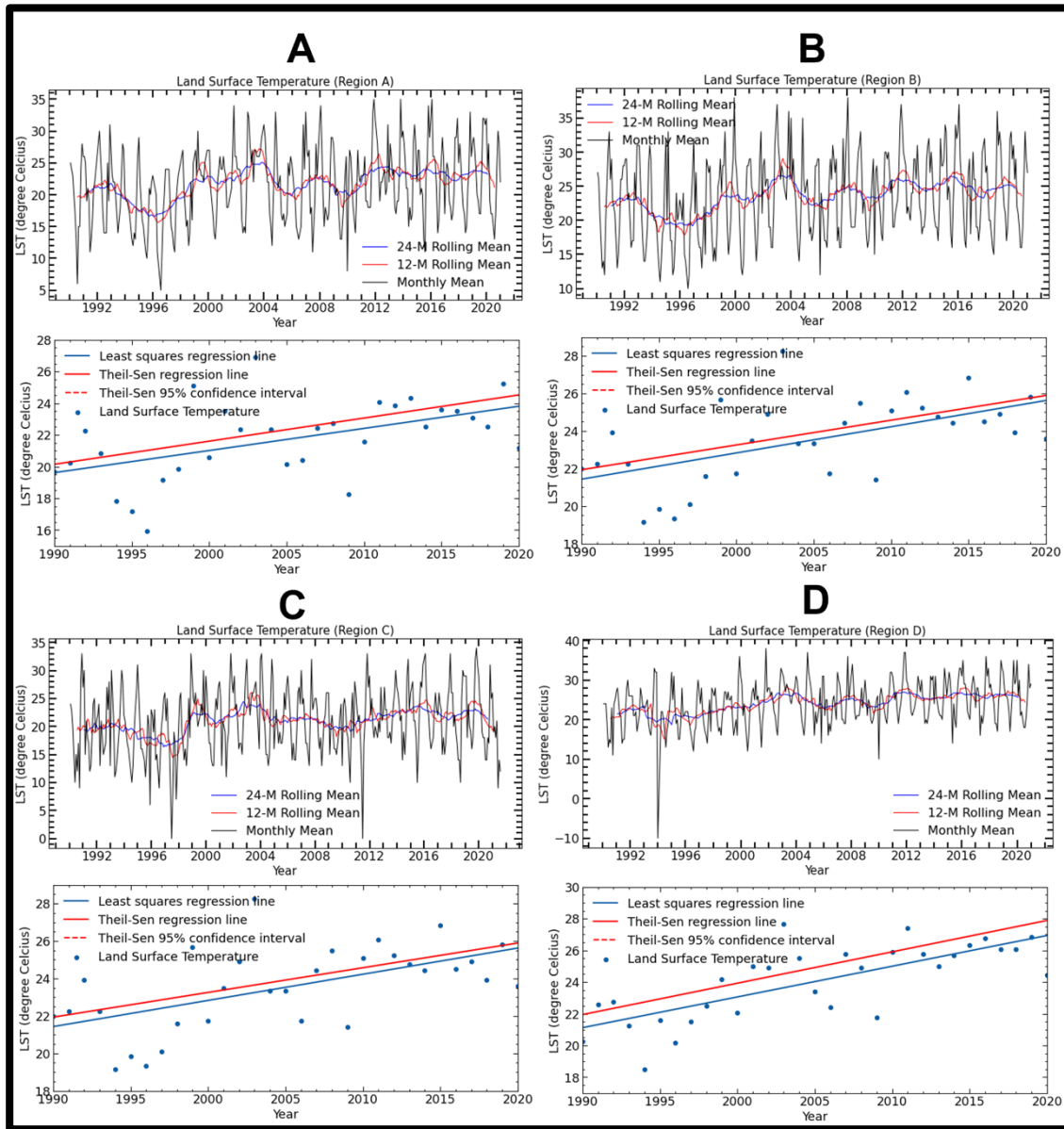


Figure 4-19: Temporal mean monthly, 12 month (annual) and 24 month running trends of LST over (A) Region A (B) Region B (C) Region C and (D) Region D of Eastern South Africa from 1990 to 2020.

4.6.3.2 Spatial distribution of LST

Figure 4-20 depict a spatial distribution of LST in region A, B, C and D respectively. The LST values from satellite images depicted that region B (Figure 4-20A) as expected have the highest LST due to its impervious surface and lack of vegetation in comparison to the other Regions (Zhang et al., 2008). Additionally, the lowest values were observed over forest plantations, which are primarily distributed in Region D (Figure 4-20D) and also water which is in region C (Figure 4-20C). Yan et al. (2020) corroborated these findings by correlating LST with NDVI and soil moisture and finding a negative correlation. Zhang et al. (2008) also discovered a lack of

relationship between NDVI and LST in Shanghai, China, but discovered a strong relationship between LST and impervious surface. In Brazil, the lowest LST values were found in vegetation and water, while the highest values were found in soil cover, implying that water content deficit has an effect on LST values (Sayão et al., 2020). While other studies have established a strong correlation between NDVI and LST, this study also corroborated earlier findings. These confirm the relationship between LULC type and LST as it is clearly visible on the spatial maps, with higher values observed over non-evaporative land cover types and lower values observed over highly evaporative land cover types. The LST variation between vegetation and non-impervious is $\pm 21^{\circ}\text{C}$, which shows the impacts of LULCC on boundary layer climate. Thus, the variation in these LST values over time is primarily due to LULCC, and regions such as B currently have higher values than other regions as a result of land conversion to urban settings. Higher temperatures are common in developed areas, and hotspots are typically concentrated around cities, often coinciding with densely populated/built-up areas, hence Odindi et al. (2015) observed higher LST values distributed in eThekweni than Buffalo city (less vegetated). The spatial distribution of LST is more dependent on the type of LULC than on its proximity to the city center and waterbodies.

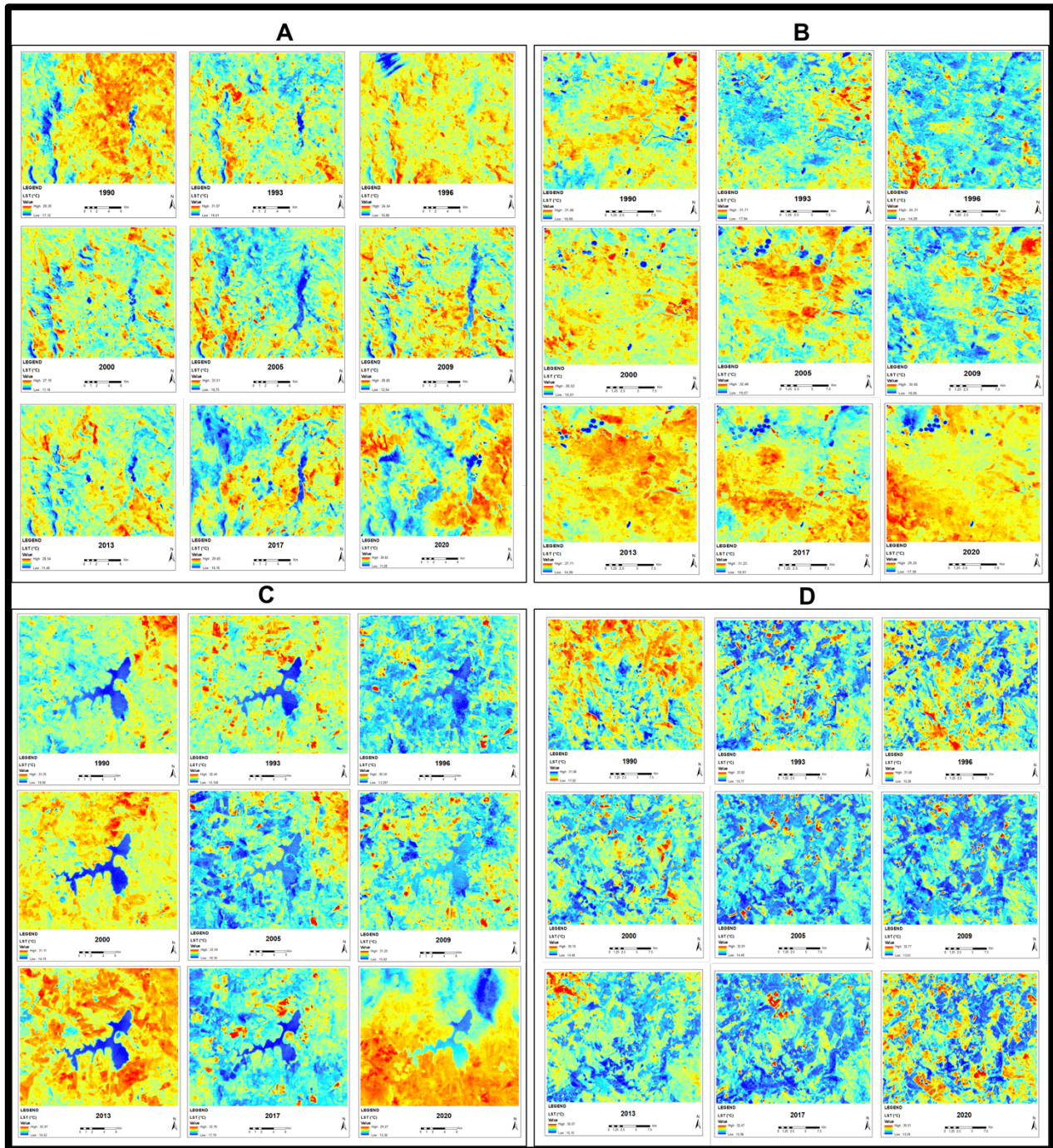


Figure 4-20: Spatial mean Annual distribution of LST over (A) Region A, (B) Region B, (C) Region C and (D) Region D from 1990 to 2020.

4.7 Assessment of Land Use/Land Cover Change

4.7.1 DBEST

The resource bases of developing countries, such as forest, land, and water, are dwindling significantly (Lambin & Meyfroidt, 2011). However, data on the rate of reduction is frequently lacking. Accurate LULCC information is required to comprehend the underlying cause and the associated environmental cost. All classified classes across all the regions required special

consideration because they are subjected to spatial and temporal change, which can affect the biogeochemical and hydrologic cycles of land cover patterns (Mahmood et al., 2014). Extreme and rapid changes in land cover as a result of anthropogenic pressures have the potential to have serious consequences for the environment's ecological functioning and can result in land degradation (Musetsho et al., 2021). It is pertinent to enquire here about the extent to which land cover changed during the interim periods and the factors that influenced change. It is not inconceivable that significant land cover changes and examples of land degradation occur in the study area in a rapidly growing country. The method of land cover change detection that was chosen and selected is determined by the user's needs and the purpose of the investigation. Below is a DBEST results of 6 LULC across four regions.

DBEST was able to detect abrupt LULCC over the 31-year period (Table 4-2). These changes were attributed to both anthropogenic and natural forcing. Most significant change across the land cover occurred during the same period of well-known global phenomenon such as the ENSO phase and IOD. Abrupt change was detected between 1994 and 2000, where increase of water in region B, forest in region A, B and D, cropland in all regions and grassland in region A was observed (Table 4-2). This abrupt increase occurred over different period and the time it took for transition also varies. Grassland in region D decreased abruptly from 1990 to 2000 by 7 907,9 Ha, which can be attributed to the increase in both forest and cropland during this period. Furthermore, region Cs' bare land decreased significant by 10 061 Ha from 1995 to 1997 as more land was used for the increasing cropland. Most importantly all the changes occurred concurrently with the La Niña phase which include the 1996/97, 1998/99 and 1999/2000 (Moeletsi et al., 2011; Ficchi et al., 2021). La Niña phase is a cool phase which is known to bring above normal rainfall and flooding (Ndlovu et al., 2021) over southern Africa, providing sufficient surface soil moisture which enables vegetation growth. Region C saw a benefit in grassland growth due to the same condition that occurred also in 2008/2009.

Abrupt decrease was also observed between 2000 and 2010, with water in region A and C, forest in region A and D and grassland in region A and D experiencing the decline. Water decreased significantly over this period (2000-2004) and was the highest decline (501.9 Ha) in comparison to other areas over the 31-year period (Table 4-2). Water decreased regardless of the tropical cyclone Eline in 2000 that dropped significant amount of rainfall (Ndlovu & Demlie, 2020). This decline can be attributed to the occurrence of El Nino phase, which is a dry spell associated with drought which occurred in 2002/03, 2004/05, 2006/2007 which affected the growth in vegetation as it accelerated evapotranspiration which declined surface moisture and waterbodies (Mpandeli & Maponya, 2013; Maponya & Mpandeli, 2016; Xulu et al., 2018). Drought enhances the removal of vegetation through livestock grazing as there is no sufficient vegetation to satisfy the livestock on the ground. The decrease in vegetation cover in region D exposed the surface cover as bare

land also increased abruptly from 2006 to 2008. Positive abrupt change in bare land indicates an increase in unvegetated surface cover, which indicates that more vegetation was removed during this time period.

Water continued to decrease, while bare land in region A increase with the decrease in grassland due to 2011, 2012 positive IOD (Ficchi et al., 2021) and the 2014/15/16 El Niño and drought condition (Maponya & Mpandeli, 2016; Xulu et al., 2018; Ficchi et al., 2021). The 2015/16 was the most severe and intense drought that occurred in southern Africa and causing significant amount of impact (Chikoore & Jury, 2021). After this drought bare land decreased significantly in region B which was the highest decrease across all the areas and LULC classes. This decrease is due to vegetation recovery following the 2015/16 drought period (Mbatha & Xulu, 2018). Furthermore, cropland also increased significantly after the 2015/2016 drought, which may be due to a massive demand of crop for food following one of the country's worst droughts. During this period farmers needed to plant more crops to meet the high demand, which the 2019 tropical cyclone Idai was able to supply. Forest increased in region A during the one of southern Africa's most severe and prolonged droughts (Ndlovu & Demlie, 2020). The recorded increase was due to forest unlike grassland does not depict the short-term climate extreme immediately hence no impact was recorded (Mbatha & Xulu, 2018).

Urban land saw abrupt increase across region A, B and D which resulted in also the decline in natural land cover as a result of its increase. over the 31-year period region B saw two most abrupt increase of 2 117 and 1 912.2, which was the most highest compared to other areas which saw a < 300 Ha of increase (Table 4-2). However, regardless of magnitude, the increase in urban land is serious. The 31-year change represents a period of significant increasing abrupt change, indicating a period of significant anthropogenic LULCC as a result of human settlement demand and also the construction of new structures and roads networks (Gillson et al., 2012; Mudau et al., 2014). However, this is a critical LULCC that requires significant attention because it demonstrates a commitment to ecosystem protection and climate change mitigation.

Table 4-2: DBEST LULCC analysis over Eastern South Africa from 1990 to 2020

LULC Classes	Region A		Region B		Region C		Region D	
	Period	Area (Ha)	Period	Area (Ha)	Period	Area (Ha)	Period	Area (Ha)
Water	2003-2005 2014-2016	-160 -112.3	1998-2000	+269.5	2000-2004 2011-2016	-501.9 -466.7	2014-2017	-162,3
Bare land	2012-2015	+4 367.3	2016-2018	-11 811.1	1995-1997 2000-2004 2007-2008	-10 061.9 +5 332.3 +7 911.7	2006-2008 2010-2012	+4 858,5 -2 937.1
Urban	2002-2009	+98.1	1997-2005 2013-2020	+2 117.6 +1 912.2			2010-2019	+243,7
Forest	1998-1999 2003-2006 2015-2016	+156.3 -2 336 +160.7	1996-1998 2007-2010	+260.3 +567.9			1999-2000 2007-2010	+9067.3 -2 518.4
Cropland	1996-1999	+3 872.9	1999-2000 2017-2019	+483.3 +1 742	1998-1999	+5 979.6	1999-2000 2010-2011	+760.1 +1 699.2
Grassland	1994-1996 2004-2005 2011-2015	+4 839.2 -2 629 -5 050.9	2014-2015	+8 706.5	1998-2003 2009-2011	-11 025.6 +8914.6	1999-2000 2006-2007 2016-2018	-7 907,9 -3370 +2 823,8

4.7.2 Overview of Land Use/Land Cover change

LULCC is a global phenomenon that has established itself as a significant issue throughout the world (Idowu et al., 2019; Thapa, 2020), including eastern South Africa (Odindi et al., 2012; Mudau et al., 2014; Mushore et al., 2017; Musetsho et al., 2021). This study, across four areas, found that change occurs on a yearly basis, with some significant changes occurring in different geographical areas. Analysis of change using time series enables a thorough examination and comprehension of change, in contrast to image differencing, which focuses exclusively on changes occurring before and after a specified period without regard for what occurs in between. Numerous studies in South Africa have used image differencing to detect LULCC (Mudau et al., 2014; Xulu, 2014; Tizora et al., 2016), but DBEST has not been used to analyse multiple LULC except for Xulu et al. (2021), focusing on vegetation cover over mining areas. DBEST has demonstrated its robustness in detecting LULCC and in detecting change during periods of extreme climate conditions. Temperature and rainfall extremes during these climate conditions have been demonstrated to significantly fragment and impact LULC, as previously demonstrated in the previous section.

Water availability decreased significantly during the 2014–2016 drought in Regions A, C, and D. The findings are corroborated by a study conducted in eastern South Africa, which indicating significant hydrological crisis as a result of the drought (Ndlovu & Demlie, 2020). During drought seasons, vegetation productivity is reduced (Akinyemi, 2021). Cropland loss can affect food production as drought phenomenon occurs. All significant abrupt increases in cropland cover have occurred during the La Niña phase and tropical cyclone period, which are associated with high rainfall and extreme wetness. Throughout southern Africa Sazib et al. (2020) discovered that

crop yields increased during the La Niña event. The association of La Niña with precipitation has shown to increase food production and security, and this is as a result of its effect on root zone soil moisture, which represents water in the root zone of plants and regulates vegetation growth and density (Sazib et al., 2020; Ndlovu et al., 2021). Maize production increased by 11% in South Africa during the La Nina years, because crops require adequate moisture and avoidance of extreme temperatures in order to produce a high yield, which is likely to occur in South Africa and Zimbabwe. However, during the 2010/11 drought, region D saw a significant increase in cropland. In comparison, eastern Africa experienced cropland loss during the same period, resulting in food insecurity for 20 million people (Sazib et al., 2020). Decrease in cropland due to climate conditions is significant and poses a significant risk to food production.

Urban development has increased significantly and abruptly, as Akinyemi (2021) indicated, because of increased land demand caused by significant population growth and economic development. Urbanisation is an anthropogenic phenomenon that is also influenced by climatic factors. Drought's effect on grassland, forest, and water implies a detrimental effect on livestock and biodiversity (Ndlovu et al., 2021). During droughts, water crises occur as a result of low erratic rainfall, which lead to lower water levels and inflows. Mbatha & Xulu (2018) assessed the impact of the El Niño droughts in 2003 and 2015/16 on vegetation status in South Africa's Hluhluwe-Imfolozi park. ENSO events were found to be significant drivers of LULCC; however, anthropogenic influence also plays a role in abrupt change.

4.8 Summary

This chapter examined the long term LULCC in the eastern South Africa over four regions with a variety of LULC composition and distribution. The objective was to classify Landsat imagery and assess the changes across the regions using DBEST algorithm, furthermore, to also perform the spatiotemporal analysis of NDVI, NDII and LST. The presented result shows that LULCC occurred over four regions at a greater scale and the significance of change varies across the area and over time. The results show that the GEE-based RF classifier is a reliable machine learning algorithm, with an average 98% classification accuracy using the confusion matrix. This provided clear and reliable evidence of LULCC across all six LULC classes. Furthermore, DBEST has shown its robustness in detecting change. From the analysis, the following was noted over eastern South Africa : -

- a) Urban settlement increased significantly in all regions, bare land increased significantly in region A, B, and D, while increasing insignificantly in region C. Whereas, cropland decreased significantly in region A and B with region C and D insignificantly decreasing.
- b) Furthermore, water increased insignificantly in region B and D, while decreasing insignificantly in region A and C. Grassland only increased significantly in region A while

decreasing significantly in region B, C and D. Forest on the other hand decreased significantly in region A, insignificantly decreased in region B, and increasing insignificantly in region C and D

- c) Significant abrupt changes were detected across the LULC and all the significant changes over the 30-year period are in correspondence with the period of extreme climate, in exception of urban areas as there is no climate relationship found between these classes.
- d) NDVI and LST increased significantly across all regions, while soil moisture decreased insignificantly in regions A, B, and C but increased significantly in region D. Furthermore, this variable showed strong seasonality, with high distribution observed in summer and a decrease over winter

CHAPTER 5 : ATTRIBUTING IMPACTS OF LAND USE/LAND COVER CHANGE ON THE BOUNDARY LAYER CLIMATE

5.1 Introduction

Land-atmosphere-interactions have an important role in modification of the climate (Boisier et al., 2012). Climate variability depends on the state on the land surface, how frequently and the extent at which they are transformed (Mahmood et al., 2014). Modification of temperature and rainfall have been found to have been caused by changes in land surface characteristics (Legates et al., 2011). Moisture and heat fluxes are also sensitive to the change of the LULC in several regions of the world (Boisier et al., 2012; Mahmood et al., 2014; Pielke et al., 2011). However, significance of these changes depends upon a variety of surface features which include the soil type, topography, land cover type and climate condition across the area.

The aim of this chapter is to establish relationships between land cover classes by attributing impacts of LULC change on the local climate in the eastern escarpment in South Africa from 1990 to 2020. The chapter discusses the trends in surface heat and moisture fluxes and the local climate. It considers the variable that is mostly vulnerable/sensitive to change in LULC and identifies the land cover type that significantly influences this important variable. Additionally, it analyses the role played by the Indian Ocean Dipole (IOD) and El-Niño/La Niña Southern Oscillation (ENSO) phenomenon on the climate system.

5.2 Trends or changes in heat and moisture fluxes and local climate

The variables' trends and changes have been depicted by time series and spatial distribution map across all the regions. The time series and spatial map analysis begins in 1979, with the exception of rainfall and surface heat flux, which have data availability since 1981 and 1982, respectively. Furthermore, the spatial maps displayed a four-year interval for visualization, but annual maps for each variable from 1979 to 2020 were computed but not included. Furthermore, the spatial resolution of the dataset was high, and it restricted the spatial visualisation of each region individually for all the variable hence there is a shift in spatial scale of map generated.

5.2.1 Temporal analysis of variables

The long-term monthly and annual MK trend analysis of LHF, SHF, ET, PET, Tmax and rainfall are shown in Table 5-1. There is a clear seasonality, whereby high values of LHF are observed in winter while low values are in summer Months. On the other hand high SHF, ET, PET, Tmax and rainfall values are observed in summer and low values in winter. Table 5-1 show that all regions are characterised by annual insignificant decreasing trend for LHF ($p > 0.05$ and negative

z value) and significant increasing trend for SHF ($p < 0.05$ and positive z value) for region B, C and D, while region A increase insignificantly ($p > 0.05$ and positive z value). ET in region B, C and D depicted a similar trend to that of SHF, with region A however showing an insignificant increasing trend. PET and Tmax depicted significant increasing trend ($p < 0.05$ and positive z value) in all the regions (Table 5-1). Table 5-1 also show that rainfall is characterised by insignificantly decreasing trend in region B, C and D, while insignificantly increasing in region A. This demonstrate that region B, C and D is becoming dry over time while region A is becoming wetter as it receives an increasing rainfall.

Table 5-1: Monthly and annual trend analysis of LHF, SHF, ET, PET, Tmax and rainfall

Variable	Period	Region A			Region B			Region C			Region D		
		ZMK	P-value	Slope	ZMK	P-value	Slope	ZMK	P-value	Slope	ZMK	P-value	Slope
LHF	Monthly	-0.239	0.811	-0.02	-0.750	0.4528	-0.34	-0.517	0.6051	-0.21	-1.2298	0.2188	-0.34
	Annual	-0.072	0.9421	-0.0316	-1.427	0.1535	-0.113	-1.427	0.1535	-0.1658	-1.7661	0.077	-0.2427
SHF	Monthly	0.470	0.6382	0.04	0.997	0.3184	0.17	0.772	0.4404	0.16	1.6529	0.098	0.28
	Annual	0.943	0.3454	0.115	2.056	0.03974 *	0.157	1.911	0.0559 *	0.215	2.1049	0.0353 *	0.2516
ET	Monthly	-0.428	0.669	0.03	0.709	0.478	0.39	0.706	0.4799	0.39	0.382	0.7026	0.27
	Annual	1.040	0.2982	4×10^{-08}	2.601	0.00929 **	8.4×10^{-08}	2.189	0.02859 *	7.556×10^{-08}	2.0808	0.0374 *	6×10^{-08}
PET	Monthly	7.056	1.7×10^{-12} ***	1.24	7.820	5.3×10^{-15} ***	1.49	5.089	3.587×10^{-07} ***	0.8	5.8066	6.4×10^{-09} ***	0.89
	Annual	4.421	9.8×10^{-06} ***	1.440	4.465	8.0×10^{-06} ***	1.616	3.793	0.000148 ***	0.9356	4.0098	6.1×10^{-05} ***	0.9374
Tmax	Monthly	3.084	0.002036 **	0.25	2.984	0.002842 **	0.21	3.153	0.00162 **	0.25	1.3971	0.1624	0.13
	Annual	4.421	9.8×10^{-06} ***	0.0387	4.519	6.2×10^{-06} ***	0.0378	4.400	1.08×10^{-05} ***	0.0388	4.1832	2.8×10^{-05} ***	0.0256
Rainfall	Monthly	-0.008	0.993	-0.02	-0.481	0.63	-0.18	0.0037	0.997	0.09	0.98146	0.3264	0.43
	Annual	1.293	0.1959	1.121	-1.060	0.289	-1.449	-0.570	0.5681	-1.249	-0.4544	0.6495	-2.724

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Over time all the variable has undergone significant change and fluctuations as a result of severe climatic condition and extremes. LHF, SHF, ET, PET, Tmax and rainfall in all the regions responded to the climatic condition such as the 1993/1994, 2002/03, and 2015/16 drought, and during wet spell such as the 1987/88, 1995/96 and 2006 and is depicted by Figure 5-1. Furthermore, significant decrease in SHF was observed in June 1997 with region A, B, C and D recording 14.3W/m^2 , 11.9W/m^2 , 5.5W/m^2 and 1.2W/m^2 respectively. During this period region A was warmer, while Region D is cooler. Furthermore, it also shows significant peak in October 1994, January 2001, October 2002, December 2003, October 2004 and in November 2015 (Figure 5-1). These peaks represented a period on significant dry spell and high temperature due to significant climatic conditions with 2015 as the most recent period and most significant one. PET significantly dropped in 1988, and also a peak in 2015 which is approaching a 400W/m^2 mark

for region A, B and C, while D approaches 350W/m^2 during the same period. High PET results from lack of ET (high SHF) (Figure 5-1) as a result of low soil moisture which has resulted in significantly increased temperatures (Figure 5-1) across all regions over the same period. PET is the atmospheric demand of moisture from the surface hence the area saw significant PET increase corresponding to low ET. However during the same period, region A saw significant high PET but low ET in comparison to other regions.

The high Tmax values are in region D, with a range from 26°C to 28°C , while low values are in region A ranging from 22°C to 25°C . It is worth noting that the warmest region is characterised by abundance of forest land distribution in comparison to other regions, with high surface soil moisture observed above the forest, but unforested land depicting dryness. In July 1996, there is a significant temperature drop, with region A recording 15.1°C , region B recording 17.2°C , and region C recording 16.3°C (Figure 5-1). Tmax values were highest in the summer (November-January), with lower values in the winter (May-July), and Tmin values were similar. Increase in ET due to temperature depends on surface water availability hence high temperature in 2015 depict low ET response compared to 2019 (Figure 5-1). A drier climate results in increased climate variability as a result of decreased rainfall and increased ET (Omoyo et al., 2015; Recha et al., 2012).

Rainfall showed fluctuations throughout the year, with peaks observed during the austral summer in all regions (Figure 5-1). The peak indicated the intense rainfall occurred and likelihood for flooding. The peak was observed across the regions with a significant peak over region D in 1984, 1988 and 1996, recording more than 1100mm of rainfall (Figure 5-1). The peak corresponds to the significant phenomenon such as the 1984 tropical cyclone Domoina in January and Imboa in February and 1996 tropical cyclone Bonita. Figure 5-1 also showed that significant dryness in 1983 was severe in region D, whereas 2002, 2011, and 2015, which corresponded to the worst drought ever recorded in southern Africa, were severe in region B. Study by Moses (2021) observed maximum rainfall in March and virtually no rainfall from May to September. Very little rainfall is received during the winter and lack of rainfall exposes the area to dry spells and drought.

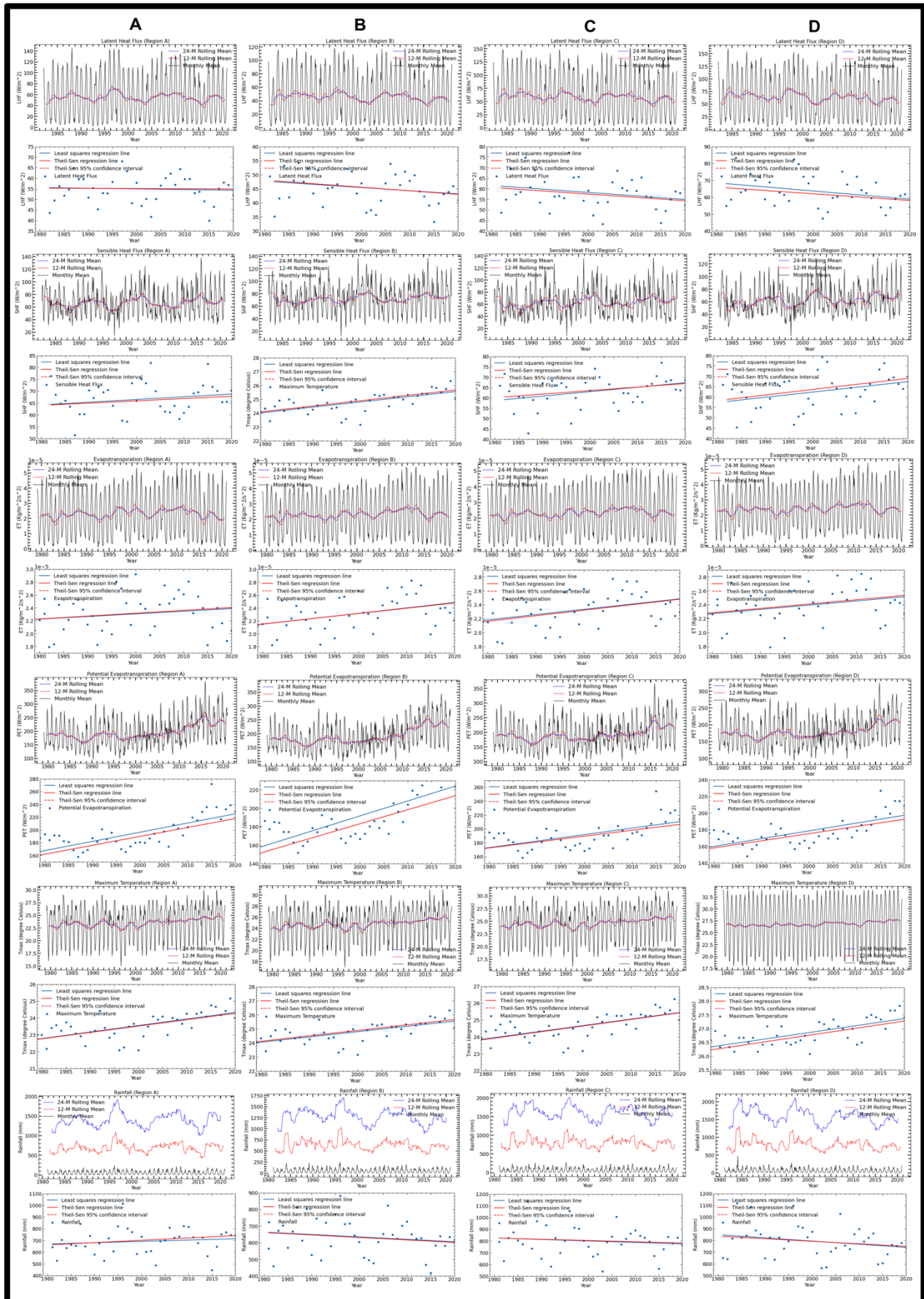


Figure 5-1: Temporal monthly, 12 month (annual) and 24 month running trends of LHF, SHF, ET, PET, Tmax and Rainfall over (A) Region A (B) Region B (C) Region C and (D) Region D of Eastern South Africa from 1979 to 2020.

5.2.2 Spatial distribution analysis of variables

LHF and SHF has depicted an inverse relationship over the study (Figure 5-2) and this is because energy at the surface during partitioning either favours LHF during high surface moisture or SHF when the is surface moisture deficit. Overall, high LHF (low SHF) are observed over the east of the study and over the escarpment and coastal regions (Figure 5-2). In 2000 high LHF is observed south of the study which is where region C is located, while in 2008 high values are over the western side covering region A and C. In 1981, 1984, 1988, 1996 and 2000 the is $< 40 \text{ m/w}^2$ which is the lowest SHF observed corresponding to high LHF of $> 65 \text{ m/w}^2$ during the same period (Figure 5-2). However, the highest LHF values are observed in 2008. Spatial trend showed that LHF was significantly lower in 2000, 2001 followed by 2015 and significantly higher in 1984, 1996, 1998 and 2008 (Figure 5-2) and it can be observed that the region B which is located 27.8S , 30.5E had the lowest LHF from 1982 to 2020 with $< 48 \text{ w/m}^2$. Furthermore, the result has shown that region B's low LHF value may be attributed to the impervious surface dominance and as a result of urban land expansion.

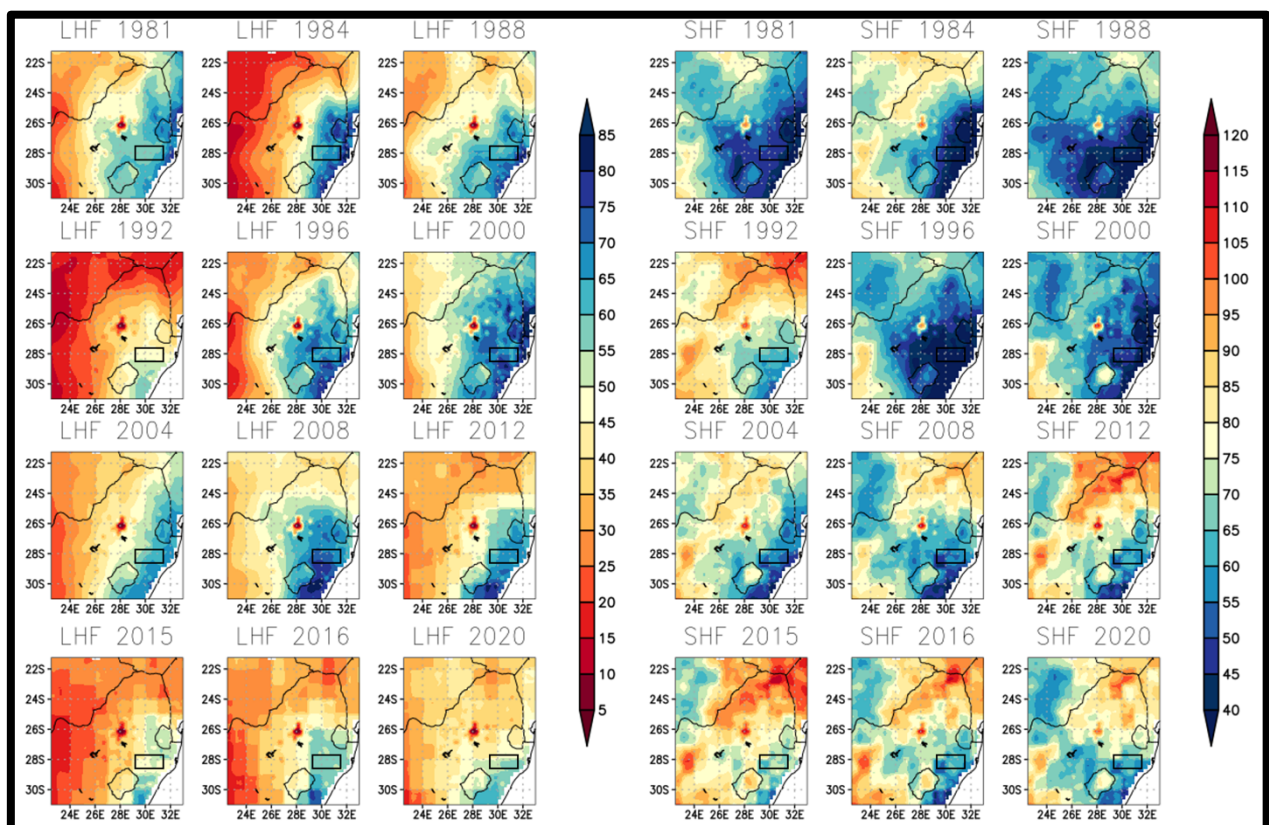


Figure 5-2: Spatial mean annual variation of LHF and SHF over Eastern South Africa from 1981 to 2020; black rectangle in the study area.

ET is depicting an increase towards the eastern side, while PET is decreasing also eastwards of the study (Figure 5-3). The highest ET (lowest PET) is observed over the escarpment that runs

from Lesotho crossing toward east of the study and running to Limpopo province (Figure 5-3). Furthermore, similar observations are observed along the coastal region, with moisture fed from oceans. ET (PET) shows a similar trend with LHF (SHF) with low/ high values observed over the same region. The ET observed towards the eastern region were high over high vegetation located in the area. Low topography, high soil moisture and high experienced temperature, which is associated with increased ET may account for observed high values.

PET has been increasing over the years, which according to Abera et al. (2018) promote ET on land and accelerate the drying of soils. Figure 5-3 summarises the spatial distribution of the PET trend. So, PET has the inverse relationship with ET, where low ET results in high PET values (Figure 5-2). Climate change vulnerability globally is due to high PET which then influences temperature variability. Furthermore, increased PET reduces ET as a result of low surface soil moisture. Figure 5-3 have shown high PET values over the west and low towards the east, with the highest value observed in 2015 reaching more than 280 w/m^2 , while the lowest was observed in 1988 reaching 180 w/m^2 .

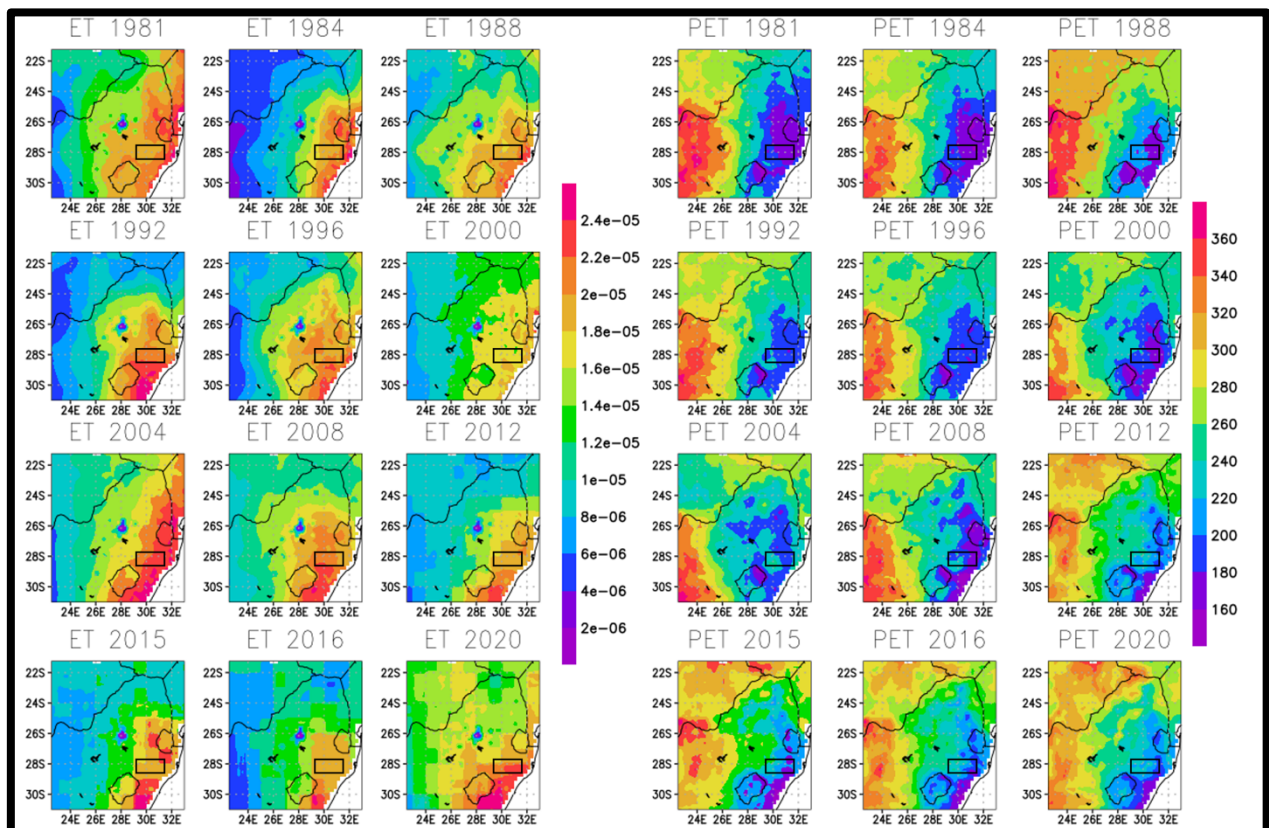


Figure 5-3: Spatial mean Annual variation of ET and PET over eastern South Africa; black rectangle is the study area.

The spatial trend of Tmax follows the similar trend to that of Tmin from 1979 to 2020. The spatial map shows that the eastern part of South Africa has the highest average temperature of $> 25^\circ\text{C}$,

while the western part has the lowest average temperature of $< 24^{\circ}\text{C}$ (Figure 5-4). The highest average T_{max} was experienced in the eastern part, which is where region D is located, just as it was in the time series analysis (Figure 5-4). The results show that due to orographic lifting, which modulates temperature, the low topography in the east is warmer than the high topography which is depicted in Figure 5-4 where the lower temperature ($< 21^{\circ}\text{C}$) is observed over Lesotho extending into Mpumalanga along the escarpment/Drakensberg mountain range. Temperature rises are expected to have an impact on livelihood, health, and heatwaves in the future. The highest temperature change occurring over the eastern part of the region that have the most homogenous topography, or the least complex topography.

The rainfall spatial trend depicts its distribution across the eastern South Africa. It revealed that rainfall over the east vary from 600mm to 1100mm, while the west received less than 800mm of rainfall (Figure 5-4). Most rainfall is seems to be experienced over east low laying region which is towards the ocean which can be playing a significant role in supplying the region with moisture which enhance rainfall. In 1996 the study area experienced rainfall $> 1100\text{mm}$, which was the highest rainfall period (Figure 5-4). The great escarpment also show to play a significant role throughout the years as more rainfall ($> 1200\text{mm}$) are observed even during the 2015/2016 drought. However, high topographic area in 1992 and 2020 observed significantly less rainfall which is 200mm less than the other drought period particularly the 2015/16. Areas that experience a decrease in rainfall become drier and trigger both drought and heatwave. According to Abera et al. (2018) rainfall exert more important control on drought events than PET. This also alters the rainfall pattern and may result in intense rainfall that trigger flooding and cause significant damage to the environment, infrastructure and human lives.

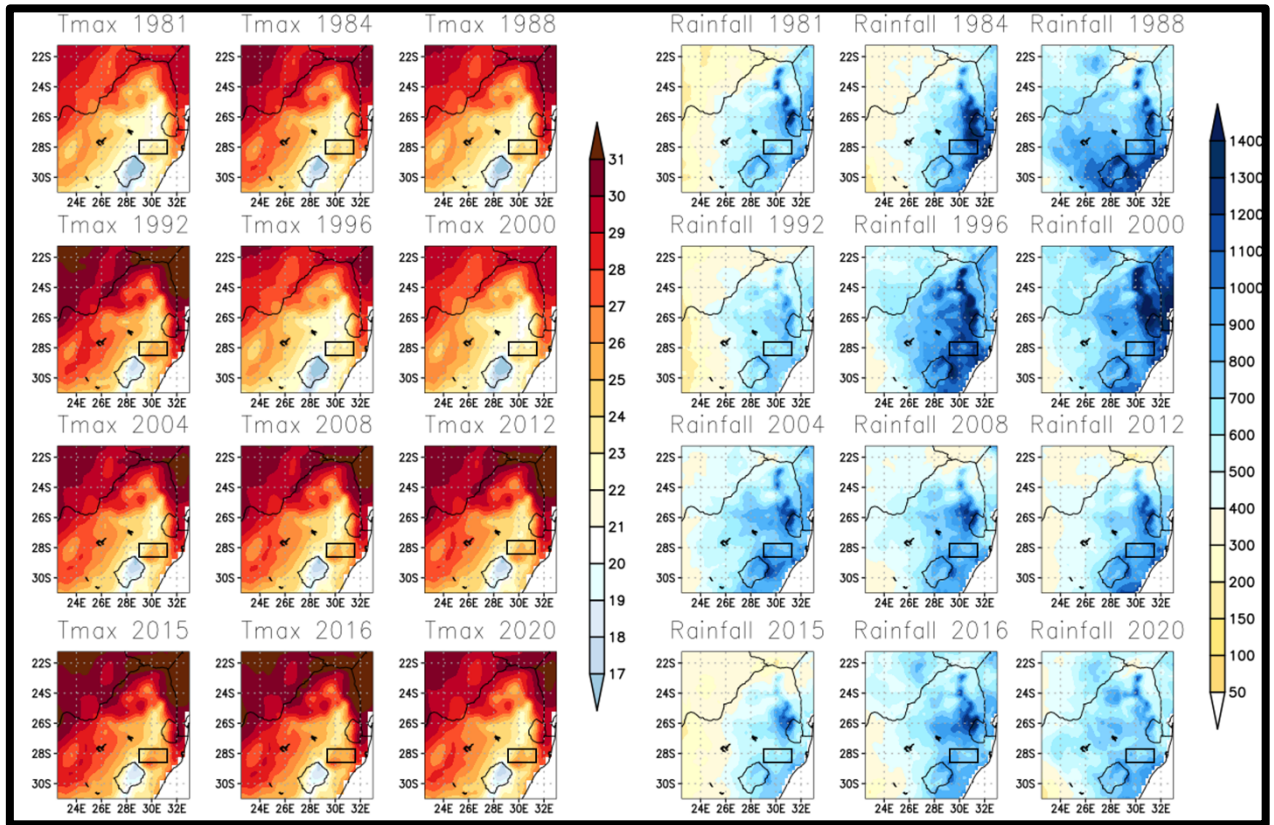


Figure 5-4: Spatial mean of annual Tmax and total rainfall over Eastern South Africa from 1981 to 2020.

5.2.3 Overview of overall changes in heat and moisture fluxes and local climate

Solar radiation is a major driver of the climate system, a portion of solar radiation is reflected back to the atmosphere while the remainder is absorbed by the surface or partitioned into sensible or latent heat (Ban-Weiss et al., 2011; Bo Huang et al., 2020). The pertaining is dependent on the surface cover over the area, and it is mostly influenced by vegetation cover (Boisier et al., 2012). The overall increase in LHF correspond with NDII, and NDVI results, however, region D received the highest LST despite having high values of LHF parameters that influences both rainfall and temperature. SHF values are observed to be high in region B, which is consistent with LHF results. An increase in SHF signifies the warming of the atmosphere as it increased at the expense of LHF resulting in increasing warm climate (Mahmood et al., 2014). Region B is an urbanised area and has experienced high SHF compared to the other regions at expense of LHF. The non-evaporative surfaces that are distributed across the area increased SHF and decrease LHF, corresponding to high LST and low soil moisture value in region B. It is well understood that an increase in SHF reduces LHF, which influences evaporative cooling. The results show that SHF has an inverse relationship with LHF, as evidenced by the period of both dry and wet spells, where inverse fluctuations in both parameters are observed (Figure 5-1 and Figure 5-2). It has been documented that areas with forest tend to experience low SHF (Ban-Weiss et al., 2011). As a

result of the forest dominance in region D, lower SHF values were observed compared to the urban dominance in region B. Figure 5-1 also demonstrated that deep forest roots can supply moisture during periods of significant dry spell, and therefore NDII result depicted significant high surface moisture over forest land over a 31-year period and was less influenced by extremes.

ET is a key element in surface water budget and helps determine humidity in the lower atmosphere. The ET process recycles rainwater into the atmosphere. It involves transfer of moisture from surface to the atmosphere resulting in atmospheric water vapour. ET is the water that is lost from the surface to the atmosphere, and it decreases in the absence of water particularly over the impervious surface. ET showed an overall increase across all regions with the increase. According to Sinha & Kumar (2019) the increase in ET is exacerbated by the increase in temperatures, which alter the surface soil moisture. Increased ET results in the formation of lower clouds, which results in evaporative cooling and initiate rainfall (Ban-Weiss et al., 2011). PET on the other hand depicted a significant increasing trend across all the area, despite of the overall increase in ET. PET is low when vegetation is at its peak. While when vegetation is brown and unhealthy, the demand for water vapour is greatest. This indicates that the atmosphere demand for moisture across all Regions is increasing and the surface doesn't have sufficient moisture for its demand and it's getting drier. Hence the increase in ET was unable to satisfy the atmosphere and decreased PET. Overtime PET depicted a similar pattern as Tmax and Tmin values which shows a significant increasing trend. Tmax is in line with the LST as discussed in the previous chapter, which showed an significant increase in all regions. Soil moisture is known to supply the atmosphere with vapour to cool the climate (Legates et al., 2011), however it was not sufficient to reduce warming. Tmax follows the same pattern as ET as temperature enhances evaporation in the presence of surface soil moisture. The increase in ET is consistent with the increase in temperature. This finding is consistent with previous research indicating that increasing global average surface temperature increases ET across the land and alters the global hydrological cycle, with wet areas becoming wetter, dry areas becoming drier, and rainfall becoming more intense (Huang et al., 2012).

Increased temperatures have an effect on water availability and surface soil moisture, as they will increase evaporative water losses (Ogutu & Owen-Smith, 2003), further exacerbating an area's dryness hence surface soil moisture over the eastern South Africa observed a decreasing trend during climate extremes. Study in northern Europe found that higher evaporation from warm summers decreased precipitation (Huang et al., 2020). The overall result has shown that both Tmax and Tmin have been increasing over time since 1979, this means that South Africa is becoming warmer. Several studies have also established that warm conditions are becoming more intense. This is consistent with findings by Mbokodo et al. (2020) who indicated that the number of cold days are decreasing while warm days are increasing in South Africa. Furthermore,

Engelbrecht et al. (2015), also showed that Africa's temperature is becoming warmer. Thapa (2020), also discovered that Tmin and Tmax showed an increase over a period of 8 years. When temperatures rise, a water vapour shortage occurs as a result of increased ET, threatening the surface water moisture (Chikoore & Jury, 2010; Mahmood et al., 2014).

The observed increasing temperature in all regions, with insignificant decreasing rainfall trend in region B, C and D is critical in the environment and society because it has a direct impact on agriculture and biodiversity. Rainfall is also the most important meteorological parameter over South Africa, and which has a profound impact on the environment and human activities. It can impact society and the livelihood through alteration of agriculture and food security and human health and the economy (Chikoore, 2005). It acts as a source of soil moisture required by vegetation to grow as a result act as heat sink mitigating climate change. Green vegetation can be used as mitigation strategy to reduce heat and enhance rainfall (Odindi, 2015), however for it to grow it require moisture/rainfall. Meer & Mishra (2020) and Masroor et al. (2022) also found decrease in precipitation in India. Understanding the distribution and variability of precipitation throughout South Africa increases accuracy and reliability of forecasting which is aimed at saving lives and livelihood and also minimising the destruction of infrastructure and agricultural production. It also assists on how to adapt particularly in a rain fed agriculture reliance areas (Ogwang et al., 2020).

5.3 Impact of Land Use/Land Cover change on surface energy, moisture flux and hydrometeorological variables

LULCC is one of the important phenomena that continues to occur globally as humans try to satisfy their daily need and also livelihood (Rounsevell et al., 2014; Musetsho et al., 2021). It is well documented that LULCC interacts with the lower atmosphere and as a result influences the climate (Mahmood et al., 2010, 2014). Below is an analysis of the impact of LULCC on the local climate through correlation analysis. A Pearson correlation analysis was performed to ascertain the relationship between LULCC, surface energy, moisture flux and the hydrometeorological variables over four regions from 1990 to 2020. The results for different regions are presented below in Figure 5-5 and Table 5-2.

Figure 5-5 depicts the annual variability of Pearson linear correlation between LULC class and hydrometeorological variables, while Table 5-2 depicts its significance for four study regions. The LULCC has been shown to have a significant correlation on the spatiotemporal pattern of the variable over eastern South Africa between 1990 and 2020, as illustrated below. However, the results have shown that the significance differs per region, while some correlations are significant to other regions and not significant in others. The result revealed that a positive significant

correlation was found between Bare and PET and also strong negative significant correlation with ET and LHF in region A. Urban land have a positive significant correlation with Tmax in all the regions (A, B, C and D), Tmin in region D, PET in region C and D, and LST in region B. Furthermore, grassland have positive significant correlation with LHF and Rainfall in region A and PET in region D (Table 5-2).

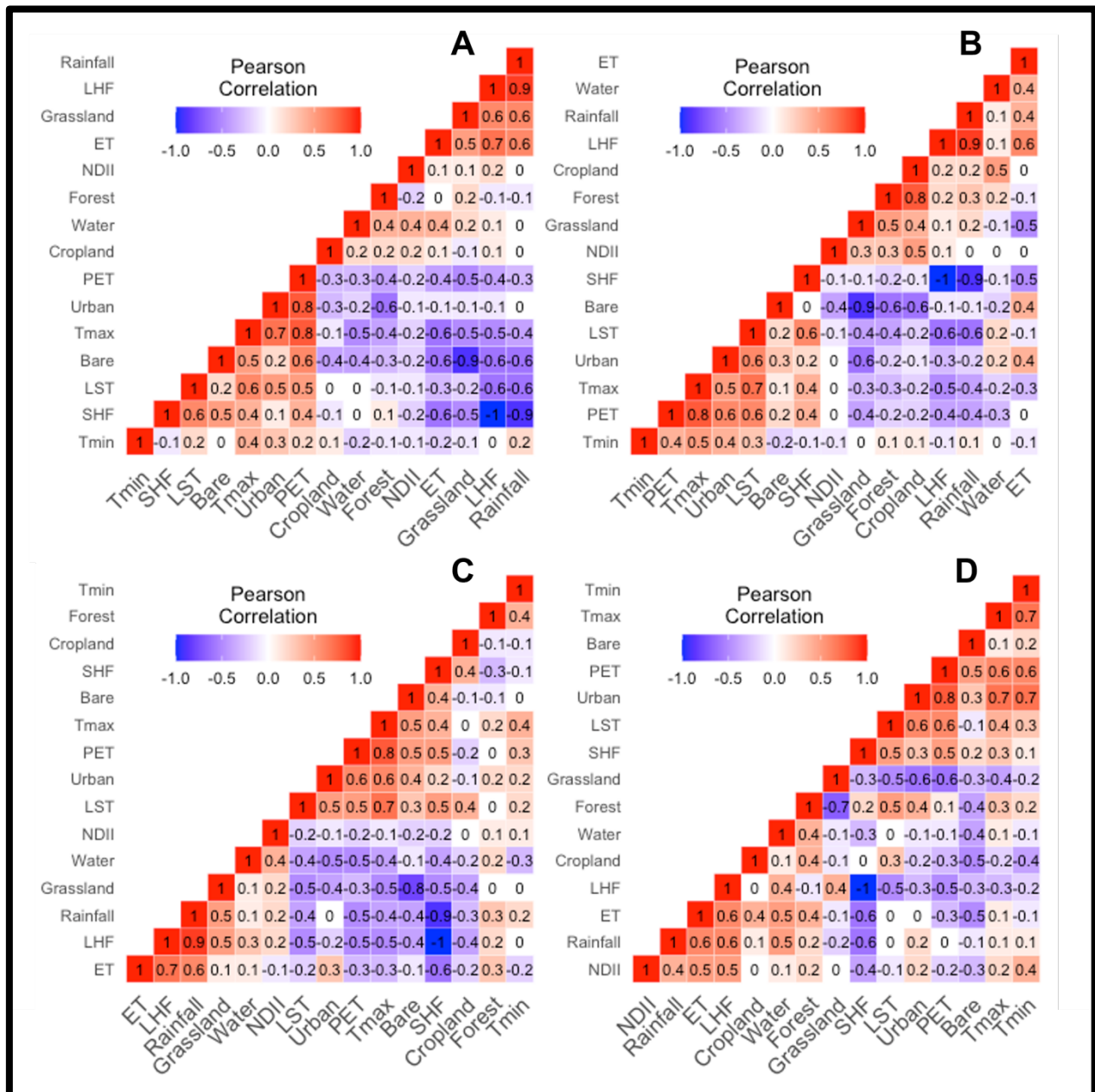


Figure 5-5: The heat map of Pearson correlation coefficients for LST, SHF, PET, MDI, LHF, NDVI, NDII, Rainfall, Tmax, ET and Tmin over (A) Region A, (B) Region B, (C) Region C and (C) Regio D.

Table 5-2: Impact of LULCC on surface energy, moisture fluxes and hydrometeorological variable in region A (A), region B (B), region C (C) and region D (D).

LULCC	VARIABLES' p-value (A)								
Variable	PET	ET	LHF	SHF	Tmax	Tmin	NDII	Rainfall	LST
Water	0.11	0.018*	0.78	0.84	-0.0024**	-0.25	0.032*	0.85	0.98
Bare Land	0.00068***	-0.00073***	-0.0001***	0.0041**	0.0039**	0.96	-0.22	-0.0012**	0.3
Urban	2.2x10 ⁻⁰⁹ ***	-0.75	-0.45	0.44	4.8 x10 ⁻⁰⁹ ***	0.096*	0.53	-0.91	0.0073**
Forest	-0.013*	0.93	-0.56	0.52	-0.019*	-0.064*	0.34	-0.58	0.61
Cropland	-0.064*	0.56	0.74	-0.68	-0.64	0.45	0.26	0.82	0.85
Grassland	-0.011*	0.0014**	0.00039***	-0.0022**	-0.0066**	0.75	0.48	8.6 x10 ⁻⁰⁵ ***	-0.18

LULCC	VARIABLES' p-value (B)								
Variable	PET	ET	LHF	SHF	Tmax	Tmin	NDII	Rainfall	LST
Water	-0.062*	0.028*	0.51	-0.54	-0.22	0.96	0.98	0.52	0.4
Bare Land	0.18	0.048*	-0.74	0.94	0.45	-0.37	-0.018*	-0.44	0.19
Urban	7.9 x10 ⁻⁰⁵ ***	-0.03*	-0.17	0.21	0.0028***	0.034*	0.8	-0.24	0.00046***
Forest	-0.25	-0.73	0.2	-0.24	-0.09*	0.75	0.15	0.1	-0.032*
Cropland	-0.38	0.83	0.41	-0.46	-0.26	0.72	0.0059**	0.29	-0.35
Grassland	-0.016*	-0.0031**	0.55	-0.73	-0.14	0.97	0.08*	0.37	-0.02*

LULCC	VARIABLES' p-value (C)								
Variable	PET	ET	LHF	SHF	Tmax	Tmin	NDII	Rainfall	LST
Water	-0.0037**	0.62	0.065*	-0.049*	-0.016*	-0.077*	0.023*	0.43	-0.015*
Bare Land	0.0033**	-0.74	-0.03*	0.042*	0.002**	0.91	0.19	-0.02*	0.1
Urban	0.00042***	0.095*	0.42	0.4	0.00068***	0.26	-0.48	0.9	0.0078**
Forest	0.94	0.13	0.32	-0.14	0.41	0.021*	0.77	0.16	0.85
Cropland	-0.25	-0.33	-0.052*	0.021*	0.88	-0.71	0.91	-0.09*	0.035*
Grassland	-0.064*	0.52	0.0026**	-0.0026**	-0.006**	0.96	0.31	0.0025**	-0.0086**

LULCC	VARIABLES' p-value (D)								
Variable	PET	ET	LHF	SHF	Tmax	Tmin	NDII	Rainfall	LST
Water	-0.48	0.0052**	0.049*	-0.057*	0.77	-0.79	0.57	0.0053**	0.83
Bare Land	0.0024**	-0.0091**	0.16	0.3	0.73	0.41	-0.15	-0.46	-0.63
Urban	2.2 x10 ⁻⁰⁹ ***	0.93	-0.076*	0.11	0.000002***	3.9 x10 ⁻⁰⁵ ***	0.25	0.25	0.0035**
Forest	0.45	0.036*	-0.43	0.36	0.082*	0.41	0.23	0.21	-0.0035**
Cropland	-0.15	0.039*	0.91	0.86	-0.26	-0.025*	0.79	0.57	0.14
Grassland	-0.00093***	-0.74	0.046*	-0.072*	-0.044*	-0.19	1	-0.4	-0.0054**

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

The effects of LULCC on past and present-day climate have been thoroughly evaluated. According to Pearson Correlation Coefficients, LULCC have an effect on and influence hydro-meteorological variables. LULCC has been shown to have an anthropogenic climate forcing effect, and its effects vary by geographical region, as the results demonstrate. As a result, this demonstrates that the impact of LULCC is not solely determined by the type and magnitude of the LULC but also by the location in which it occur, implying that correlations between similar LULC vary across regions.

5.4 Attributing LULCC to local climate variability and change

5.4.1 Variable of importance

Rainfall and temperature are vital variables that are often used in describing how the climate changes (Huang et al., 2012). This is so we can be able to understand the climate and also which variables are sensitive to change as a result of altering the climate. Figure 5-6 shows a variable of importance, which outlines the meteorological variables that are of significant importance and causes most influence on temperature and rainfall. The variables are presented in descending importance from two qualitative measures produced by the model, which are the Increased Mean Square Error (%IncMSE) and the Increased Impurity Index (IncNodePurity). The model has shown in result that an increasing %IncMSE for temperature-PET was 10.79%, 10.33%, 16.22% and 7.85% for region A, B, C, and D, respectively (Figure 5-6). While the %IncMSE for rainfall-LHF is 12.13%, 11.79%, 14.1% for region A, B and C respectively, while rainfall-SHF was 5.27% for region D. This suggests that PET and LHF are variable which significantly influence temperature and rainfall respectively over eastern South Africa. Moreover, analysis also showed that rainfall in region A and D was also significantly influenced by SHF (Figure 5-6H), while B is influenced by LST (Figure 5-6).

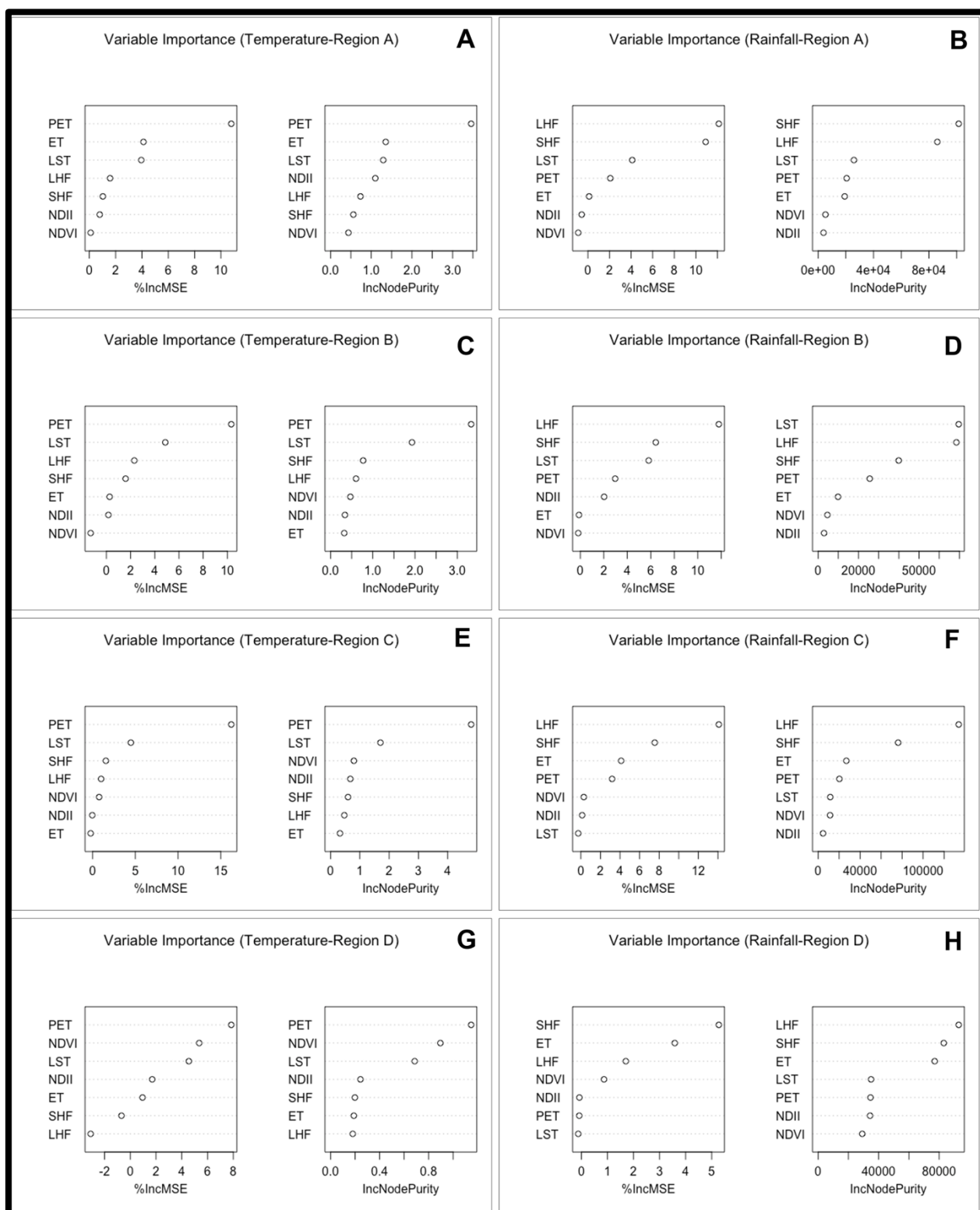


Figure 5-6: Mean Decrease Accuracy (%IncMSE) and Mean Decrease Gini (IncNodePurity) of attributes as assigned by the RF for Temperature and Precipitation over Region A, B, C and D.

The variable of importance was able to rate the variable based on the important variable that is sensitive to change and influences climate variability the most. It is also important to test the

significance of these variables of importance as a variable can be important, but the influence is insignificant, as observed in the study by Mathivha & Mbatha (2022).

Figure 5-7 shows correlation of temperature and PET and this is because variable of importance have determined PET as the most significant variable that influences change in temperature over the study area. It was found that there is a moderate positive correlation between the variables, indicating that the increase in PET results in the increase in temperature as depicted by the R-value in Figure 5-7. The result further showed that the positive correlation is significant between temperature and PET as depicted by p-value < 0.05 in all the study regions. It is clear from p-value that correlation significance in region B is greater followed by C, A and lastly region D.

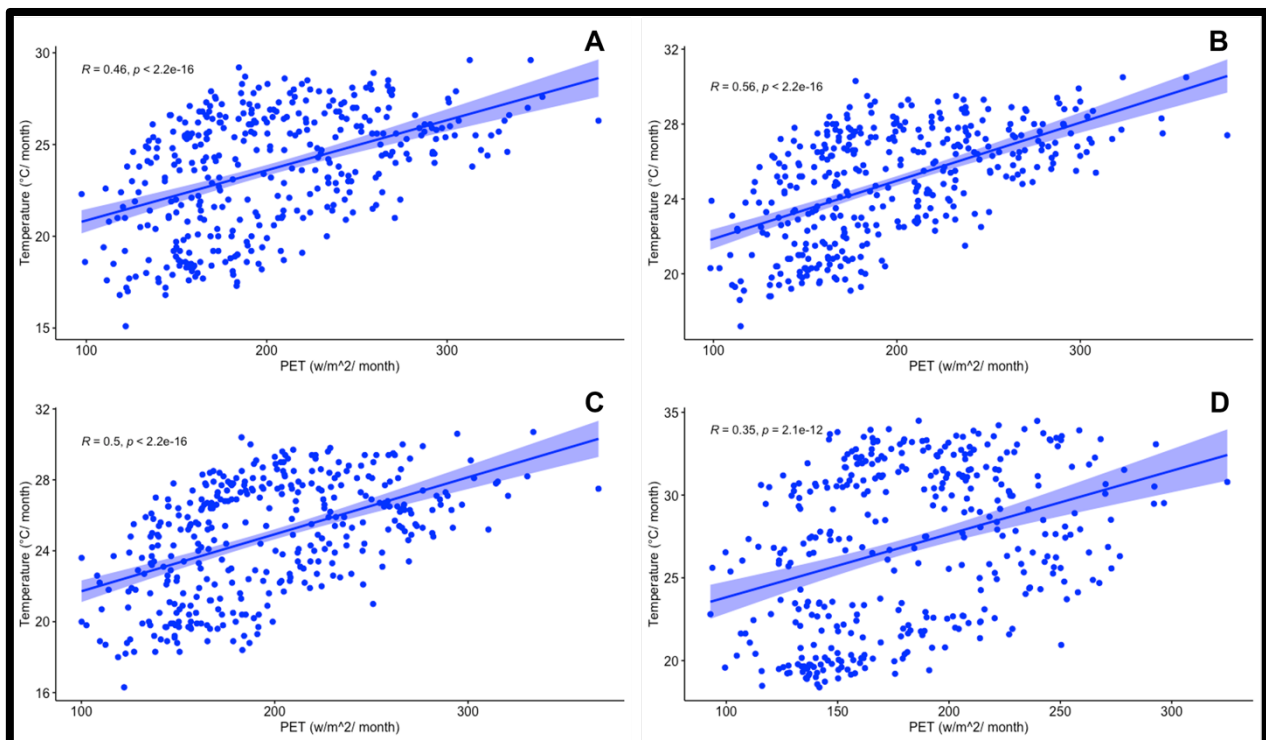


Figure 5-7: Correlation of temperature and PET variable importance over the study area; region A (A), region B (B), region C (C) and region D (D).

Correlation analysis was further done between rainfall, LHF, SHF and LST as per variable of importance result. Variable of importance showed that rainfall in region A, B and D was influenced by SHF and LHF. Therefore, Figure 5-8 has shown that there is a significant correlation between rainfall and all the variables tested as depicted by p-value < 0.05. Furthermore, Pearson R and p-value showed that strong positive significant correlation exists between rainfall and LHF in all the study regions. While SHF and LST in region A, B and D (see Figure 8B, D and F) depicted a significant strong correlation as shown by Pearson R-values. This suggests that the increase in LHF influences rainfall more in comparison with SHF and LST in region A, B and D.

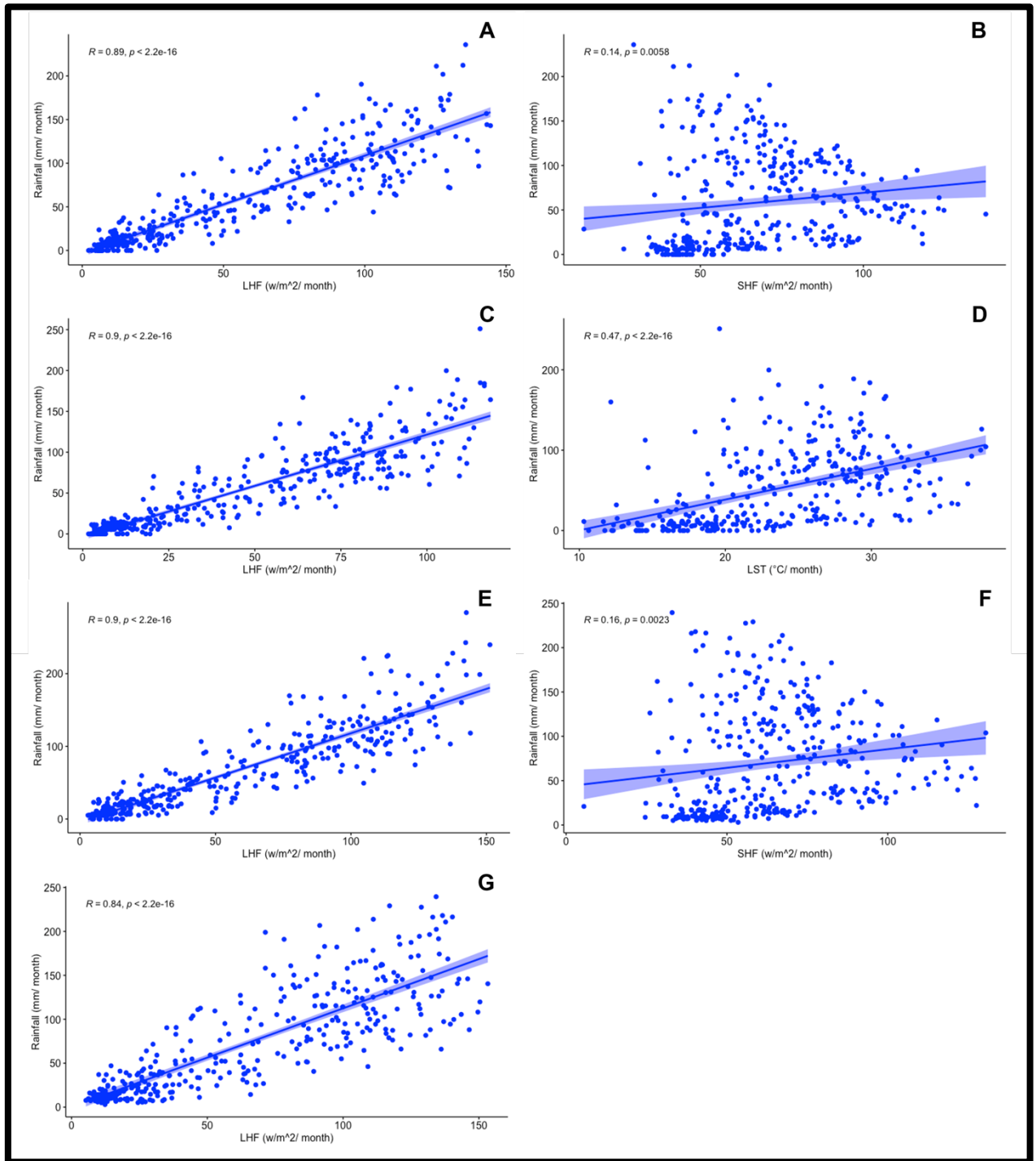


Figure 5-8: Correlation of rainfall, LHF, SHF and LST variable importance over the study area; region A (A, B), region B (C, D), region C (E) and region D (F, G).

5.4.2 The influence of LULCC on the local climate

Table 5-3, 5-4, 5-5 and 5-6 show a comprehensive summary of the MLR analysis LULC classes, PET and LHF. This was conducted using PET and LHF as the most important variables that significantly influence temperature and rainfall respectively as informed by variable of importance. Therefore, was used to attribute the impact of LULCC. The MLR results revealed that over region A, forest decrease showed an increasing influence on temperature (Table 5-3A) and decreasing influence on rainfall (Table 5-3B) over a 30-year period. This suggests that the decrease in forest increased temperature while decreasing rainfall in region A. Meer & Mishra (2020) discovered decrease in rainfall as a result of forest modification. According to Lobell et al. (2006) and Hu et al. (2019) clearing of forested land can cause extreme warming. Thapa (2020) observed an increase in both T_{max} and T_{min} and a decrease in rainfall due to forest loss in Kathmandu. Yang et al. (2009) stated that for forests to be able to lower temperature and increase precipitation, forest moisture must reach a particular altitude in order to induce essential change of characteristics to influence the parameters. The study result has shown that forest can be used as a mitigation measure for climate warming. However, climate warming and rainfall enhancement mitigation measures may vary per region due to a variety of factors.

Grassland decreased in region B was found to negatively influence rainfall as shown in Table 5-4B. Less surface moisture occur due to decreased grassland, as a result less energy would be partitioned as LHF. Native vegetation, such as grassland, transpires more, resulting in increased LHF and rainfall; thus, vegetation alteration and decline influenced rainfall negatively (Abera et al., 2018).

The Increase of urban area has positively influenced temperature over region A, B and D (Table 5-3A, 5-4A and 5-6A), as well as negatively influencing rainfall over region B (Table 5-3). Study by Cao et al. (2020), found that urbanisation and agricultural development are exerting pressure significantly on temperature change generally between 1 and 2 °C. Zhou et al. (2016) noted that urban land substantially affects the climate, particularly temperature by both biogeophysical and biochemical effects. This signifies that anthropogenic activities have a major climate impact. This is because urban surface cover enhances surface temperature as it increases PET and surface heat energy (Zhou et al., 2016). Over region A and D the urban area coverage is a small proportion however its significance to climate changing and variability was observed in this study. This is exactly in line with what Zhou et al. (2016) stated by indicating that regardless of urban cover accounting for a small portion in the global land cover, its impact however to local, regional, and global warming is significant. Urban sprawling always contributes to temperature increase (Huang et al., 2020) and decreased precipitation significantly (Li et al., 2018; Masroor et al., 2022).

Bare land increase also showed that it has a positive influence on temperature in region A, C and D as depicted on Table 5-3A, 5-4A and 5-5A and negative influence on rainfall in regions A and C (Table 5-3B and 5-5B). This is supported by Yang et al. (2009) who found barren land to show greater climate warming than construction land over China. Bare land is sensitive to climate warming (Yang et al., 2009) and highly prone to heat absorption (Masroor et al., 2022). Due to limited moisture and insignificant evaporation feedback, bare land increases temperature due to increase in PET (Yang et al., 2009). Masroor et al. (2022) also found that barren negatively affected rainfall over India, as it acted as a barrier to local hydrological cycle as a result lowering precipitation. Reduced plant cover increases the albedo of the surface, resulting in less precipitation.

Table 5-5B shows that cropland loss has a significant negative influence on rainfall in region C. Cropland can increase LHF by supplying water vapour, which influences climate.(Ban-Weiss et al., 2011). Overall cropland decreased in region C, and fluctuation has shown change, negatively influencing rainfall. Study conducted by Ge et al. (2013) found that rainfall over Eastern China was reduced as a result of cropland expansion. Furthermore, the atmosphere also as a result became 0.6°C warmer, while surface net radiation and SHF increased. Lobell et al. (2006) noted that cropland expansion over natural vegetation has vital climatic consequences. It is worth noting Zhou et al. (2016) who stated that agricultural land is an important surface parameter with a potential to influence the climate more than greenhouse gas. However, its influence depends on the geographic location. This is because dense vegetation and forest are being replaced by cropland, altering the surface roughness, albedo, leaf conductance, and other properties as a result alter the climate (Zhou et al., 2016). Cropland can influence the climate due to lack of irrigation (Zhou et al., 2016). Irrigation is the most significant human water use that can affect the climate, because it has the potential to enhance cloud cover and rainfall of a region (Cook et al., 2015). This is as a result of favouring LHF over SHF during surface energy partitioning.

Waterbodies have the highest LHF (Huang et al., 2020) and have heat capacity compared to other LULC (Li et al., 2018). Water in region C and B significantly negatively influenced temperature (Table 5-5A) and rainfall in region D (Table 5-6B). Huang et al. (2020) discovered wetland drying and as a result increased summer temperature significantly over Europe. This is also supported by Meer & Mishra (2020), who discovered decrease in rainfall as a result of waterbodies fragmentation. Soil moisture and water lower the albedo which then increase rainfall (Ge et al., 2013). The increase in moisture/water increases the LHF, and subsequently alters the partitioning of energy in the surface energy budget. The increased SHF makes more moisture available to the atmosphere from the surface which is of vital importance in cloud and rain formation (Ge et al., 2013).

Table 5-3: The output of Multiple Linear Regression (MLR) model over Region A in which (A) PET and (B) LHF are dependent variable and Water, Bare Land, Urban, Forest, Cropland and Grassland are independent variables.

Variable	Estimate	Std. Error	t-Value	p-value	Sig
Water	-4.300×10^{-05}	7.328×10^{-05}	-0.587	0.5626	
Bare Land	2.911×10^{-05}	4.810×10^{-06}	6.051	2.54×10^{-06}	***
Urban	1.241×10^{-03}	1.117×10^{-04}	11.107	3.70×10^{-11}	***
Forest	1.926×10^{-04}	9.088×10^{-05}	2.119	0.0442	*
Cropland	5.401×10^{-06}	9.520×10^{-06}	0.567	0.5755	
Grassland	NA	NA	NA	NA	

(A)

Variable	Estimate	Std. Error	t-Value	p-value	Sig
Water	-1.257×10^{-04}	1.932×10^{-04}	-0.651	0.520983	
Bare Land	-5.443×10^{-05}	1.268×10^{-05}	-4.292	0.000233	***
Urban	-4.584×10^{-04}	2.946×10^{-04}	-1.556	0.132259	
Forest	-5.367×10^{-04}	2.396×10^{-04}	-2.240	0.034199	*
Cropland	-2.786×10^{-05}	2.510×10^{-05}	-1.110	0.277498	
Grassland	NA	NA	NA	NA	

(B)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Table 5-4: The output of Multiple Linear Regression (MLR) model over Region B in which (A) PET and (B) LHF are dependent variable and Water, Bare Land, Urban, Forest, Cropland and Grassland are independent variables.

Variable	Estimate	Std. Error	t-Value	p-value	Sig
Water	-3.151×10^{-04}	6.960×10^{-05}	-4.527	0.000138	***
Bare Land	6.995×10^{-06}	4.780×10^{-06}	1.463	0.156347	
Urban	5.355×10^{-05}	7.671×10^{-06}	6.981	3.22×10^{-07}	***
Forest	-1.919×10^{-05}	1.555×10^{-04}	-0.123	0.902782	
Cropland	4.934×10^{-05}	3.004×10^{-05}	1.642	0.113559	
Grassland	3.337×10^{-06}	2.754×10^{-06}	1.212	0.237469	

(A)

Variable	Estimate	Std. Error	t-Value	p-value	Sig
Water	1.772×10^{-04}	1.143×10^{-04}	1.550	0.1342	
Bare Land	-6.561×10^{-07}	7.852×10^{-06}	-0.084	0.9341	
Urban	-2.751×10^{-05}	1.260×10^{-05}	-2.183	0.0391	*
Forest	3.911×10^{-04}	2.554×10^{-04}	1.531	0.1388	

Cropland	-3.614×10^{-5}	4.934×10^{-5}	-0.732	0.4710	
Grassland	-9.320×10^{-6}	4.523×10^{-6}	-2.060	0.0504	.

(B)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Table 5-5: The output of Multiple Linear Regression (MLR) model over Region C in which (A) PET and (B) LHF are dependent variable and Water, Bare Land, Urban, Forest, Cropland and Grassland are independent variables.

Variable	Estimate	Std. Error	t-Value	p-value	Sig
Water	-1.443×10^{-0}	7.028×10^{-5}	-2.054	0.0506	.
Bare Land	7.883×10^{-6}	3.682×10^{-6}	2.141	0.0422	*
Urban	1.186×10^{-3}	8.804×10^{-4}	1.348	0.1899	
Forest	-2.087×10^{-6}	3.092×10^{-5}	-0.067	0.9467	
Cropland	-8.040×10^{-6}	5.623×10^{-6}	-1.430	0.1652	
Grassland	NA	NA	NA	NA	

(A)

Variable	Estimate	Std. Error	t-Value	p-value	Sig
Water	1.753×10^{-4}	1.068×10^{-4}	-1.642	0.1130	
Bare Land	-1.459×10^{-5}	5.593×10^{-6}	-2.608	0.0151	*
Urban	1.191×10^{-3}	1.337×10^{-3}	0.890	0.3819	
Forest	2.717×10^{-7}	4.697×10^{-5}	0.006	0.9954	
Cropland	-1.981×10^{-5}	8.542×10^{-6}	-2.319	0.0288	*
Grassland	NA	NA	NA	NA	

(B)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Table 5-6: The output of Multiple Linear Regression (MLR) model over Region D in which the (A) PET and (B) LHF are dependent variable and Water, Bare Land, Urban, Forest, Cropland and Grassland are dependent variables.

Variable	Estimate	Std. Error	t-Value	p-value	Sig
Water	6.207×10^{-5}	7.735×10^{-5}	0.802	0.4299	
Bare Land	1.371×10^{-5}	5.350×10^{-6}	2.563	0.0168	*
Urban	7.150×10^{-4}	1.086×10^{-4}	6.583	6.76×10^{-7}	***
Forest	-3.056×10^{-6}	4.928×10^{-6}	-0.620	0.5407	
Cropland	1.346×10^{-5}	2.565×10^{-5}	0.525	0.6045	
Grassland	NA	NA	NA	NA	

(A)

Variable	Estimate	Std. Error	t-Value	p-value	Sig
Water	3.898 x 10 ⁻⁰⁴	2.173 x 10 ⁻⁰⁴	1.794	0.0849	.
Bare Land	-1.292 x 10 ⁻⁰⁵	1.503 x 10 ⁻⁰⁵	-0.860	0.3981	
Urban	-1.820 x 10 ⁻⁰⁴	3.051 x 10 ⁻⁰⁴	-0.596	0.5563	
Forest	-1.429 x 10 ⁻⁰⁵	1.384 x 10 ⁻⁰⁵	-1.033	0.3117	
Cropland	-2.809 x 10 ⁻⁰⁵	7.206 x 10 ⁻⁰⁵	-0.390	0.7000	
Grassland	NA	NA	NA	NA	

(B)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

5.5 The role of remote phenomena on local boundary layer climate

The ENSO and IOD are one of the most significant phenomena in the Earth's climate, which explains climate variations globally. They have been affecting the climate regime of southern Africa, causing frequent drought, heatwaves and flooding during past decades, and acted as the main natural hazard that contributes to food insecurity and poverty.

The time series of DMI and ENSO anomalies is shown on Figure 5-9A and 5-9B. Both the positive DMI and El Niño events are shaded in red, whereas the negative DMI and La Niña are shaded in blue. The study adopted the threshold applied by Mbatha & Xulu (2018) in identifying the strength of ENSO which include weak (0.5-0.9), Moderate (1.0-1.4) and strong (≥ 1.5) SST anomaly. Figure 5-9A shows that 2018/19 was one of the strongest positive DMI followed by 1997/98 and then 1994/95. Whereas strongest El Niño was in 2014-2016, followed by 1997/98 which co-occur with positive DMI, then 1982/83, 1992/93 and 2009/10. When positive IOD and El Niño co-occur, a major drought is highly probable and heavy rain is unlikely to happen (Chikoore et al., 2021). There are positive IOD events that occurred the same time with severe drought such as the 1992 drought, whilst negative IOD occurred during 1995 drought (Chikoore, 2016). Furthermore, strongest La Nina was recorded in 1988/89, then 2000 and 2011. Extreme rainfall tends to be more common during La Niña events (Chikoore et al., 2021). These are the events that have been known to cause serious impact in terms of severe drought and flooding over southern Africa. In North America, 2015/16 El Niño event had a significant impact on LST, causing the temperature to reach its highest level (Yan et al., 2020).

The natural phenomenon are large-scale global events that have had a noticeable impact. Its evaluation cannot be limited to a global scale; it must also consider its impact on a local scale.

This is to comprehend its impact and develop locally-based solutions, as global assessments cannot generate local impact solutions. This is due to the fact that the impact of this phenomenon varies with latitude, LULC type, climate condition, and altitude.

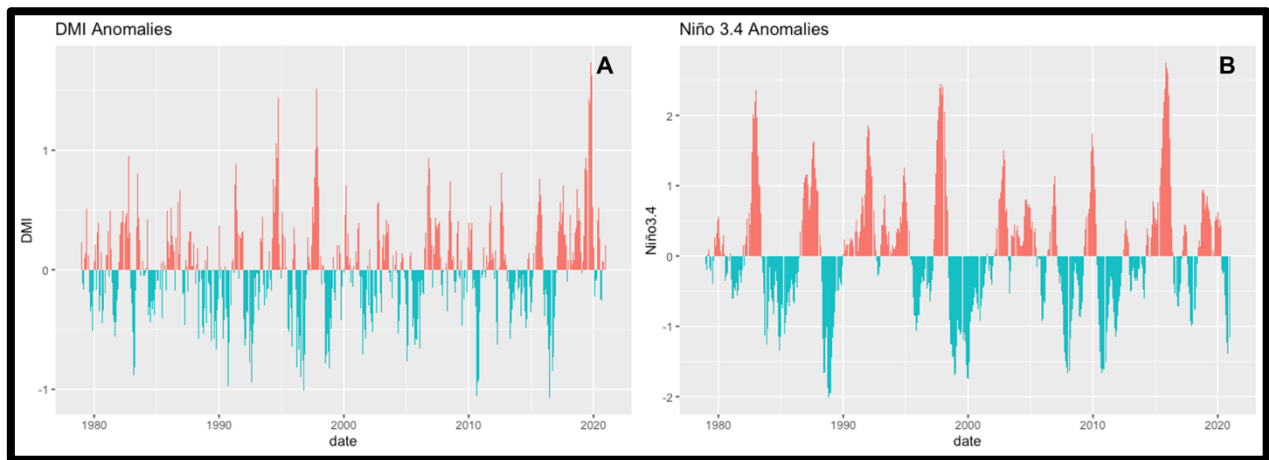


Figure 5-9: The standardized monthly ERSST Niño3.4 (a) and dipole mode index (DMI) for a period from 1980 to 2020.

Analysis of the link between remote phenomenon and temperature and rainfall extreme occurrence was performed. It was found that there is statistically significant and positive correlation that exists between Niño3.4 SST anomalies and extreme temperature and rainfall (Figure 5-10). Moreover, DMI SST has a statistically significant and positive correlation with temperature (Figure 5-11), but weak correlation with rainfall (Figure 5-13). This demonstrated that El Niño and positive IOD influence temperature extremes across all regions, with a greater influence observed in region D. The influence of La Niña has increased rainfall over eastern South Africa, as shown in Figure 5-12. Negative IOD had no correlation with rainfall in regions A and B, while positive IOD had a weak positive insignificant correlation in region C and negative IOD had a weak negative insignificant correlation in region D (Figure 5-13). This demonstrates how complex remote phenomena are. Because of differences in land surface characteristics, the statistical significance of the correlation varied across regions.

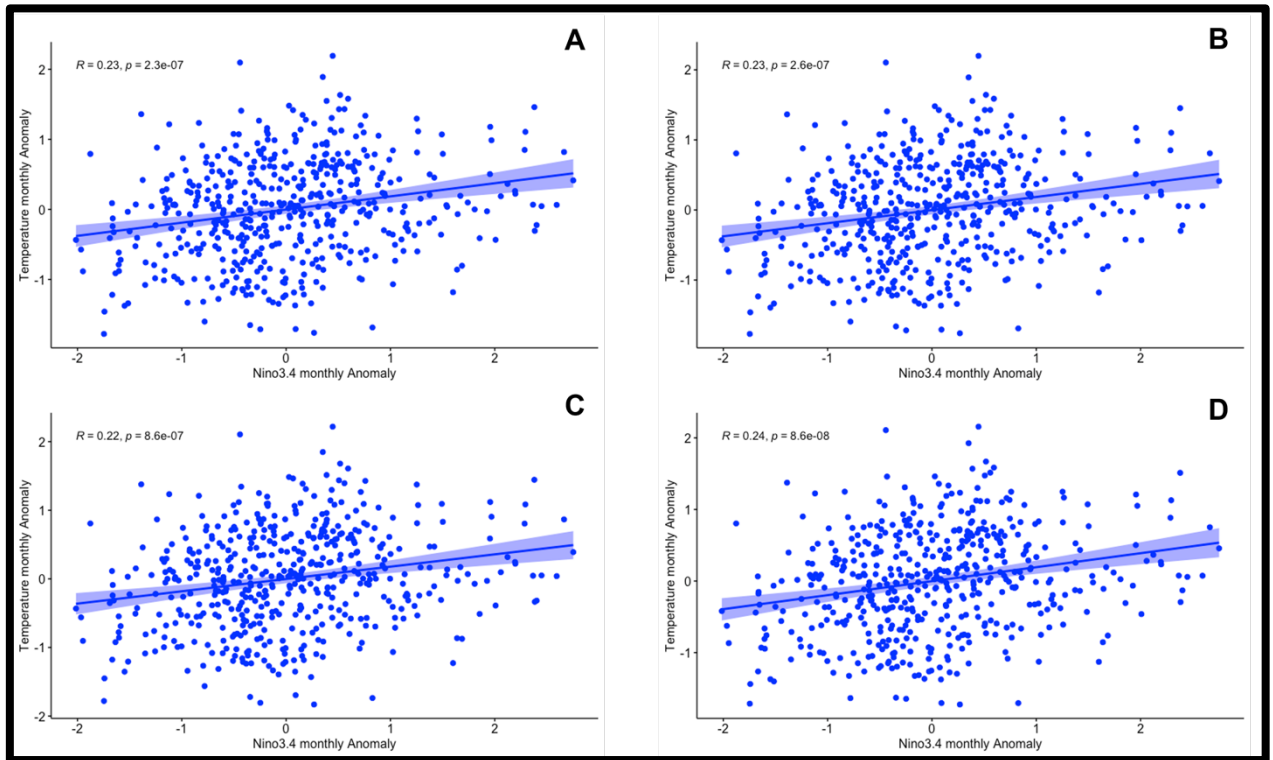


Figure 5-10: Correlation of Niño3.4 with temperature over the study area; region A (A), region B (B), region C (C) and region D (D) from 1979 to 2020.

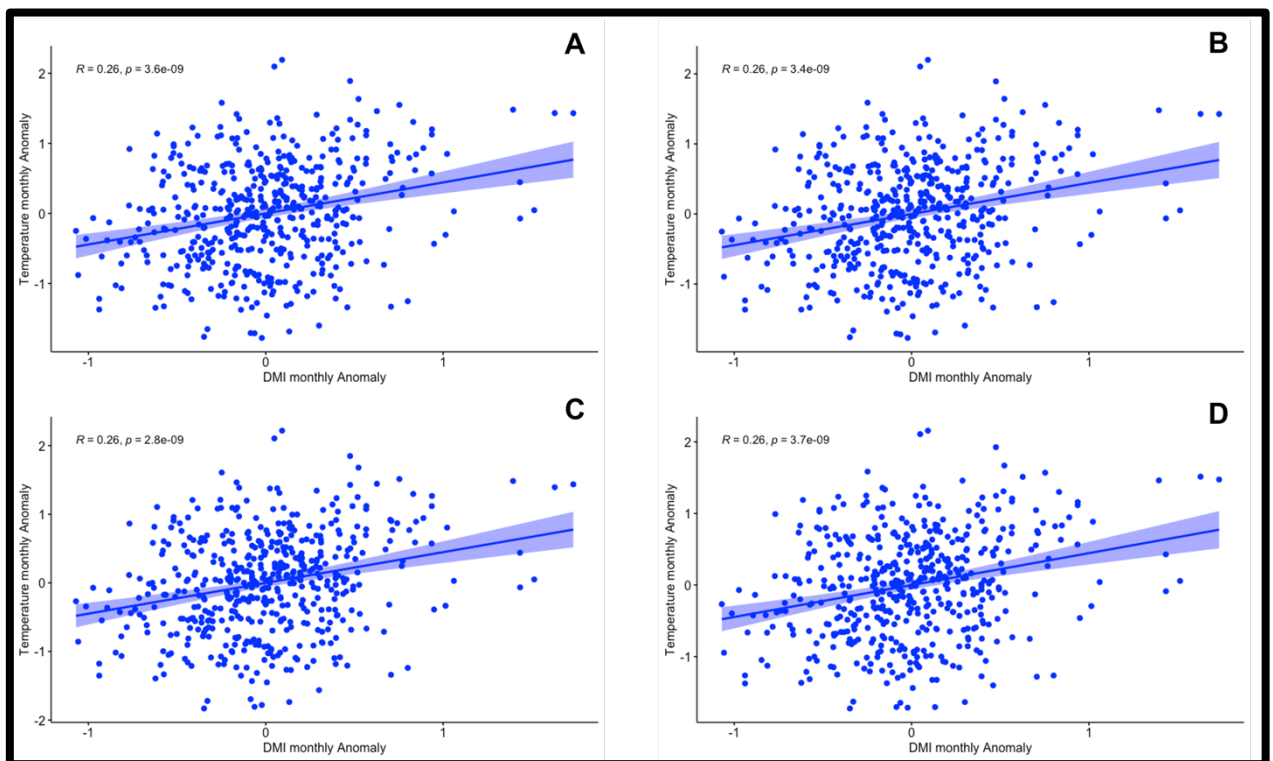


Figure 5-11: Correlation of DMI with temperature over the study area; region A (A), region B (B), region C (C) and region D (D) from 1979 to 2020.

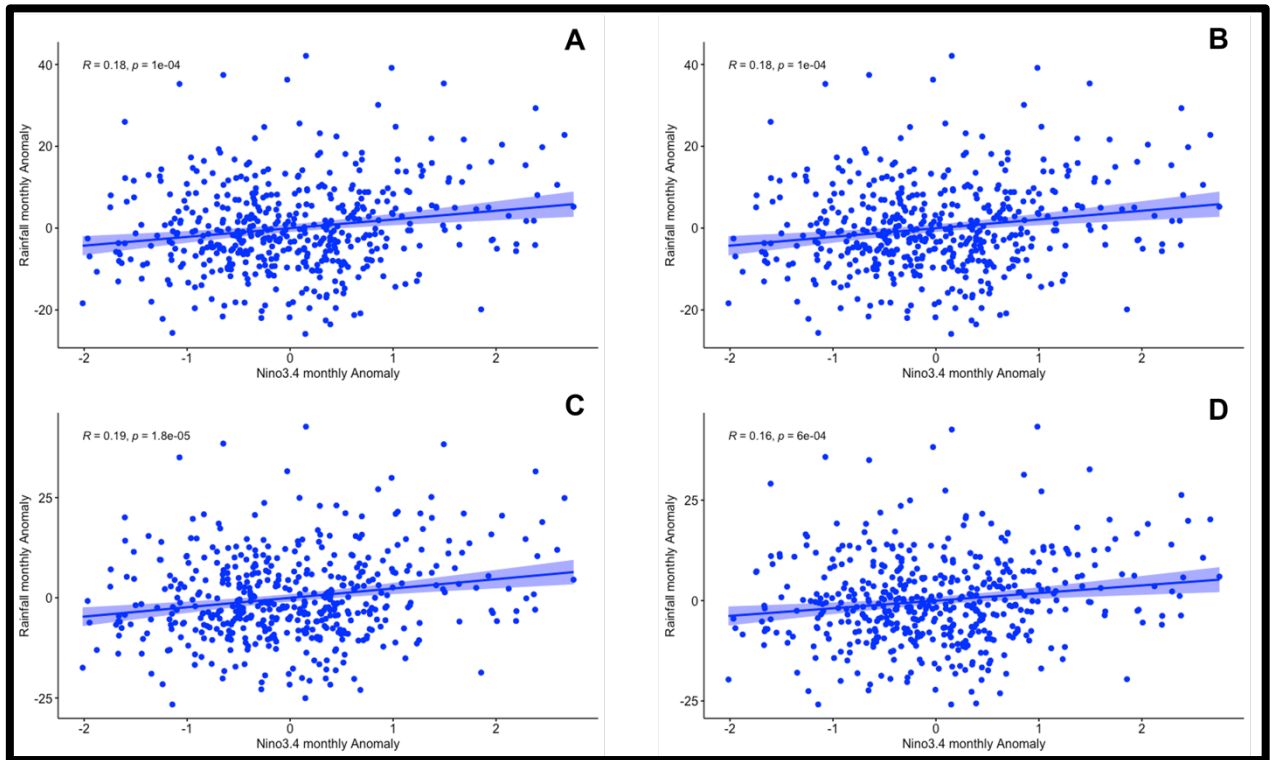


Figure 5-12: Correlation of Niño3.4 with rainfall over the study area; region A (A), region B (B), region C (C) and region D (D) from 1979 to 2020.

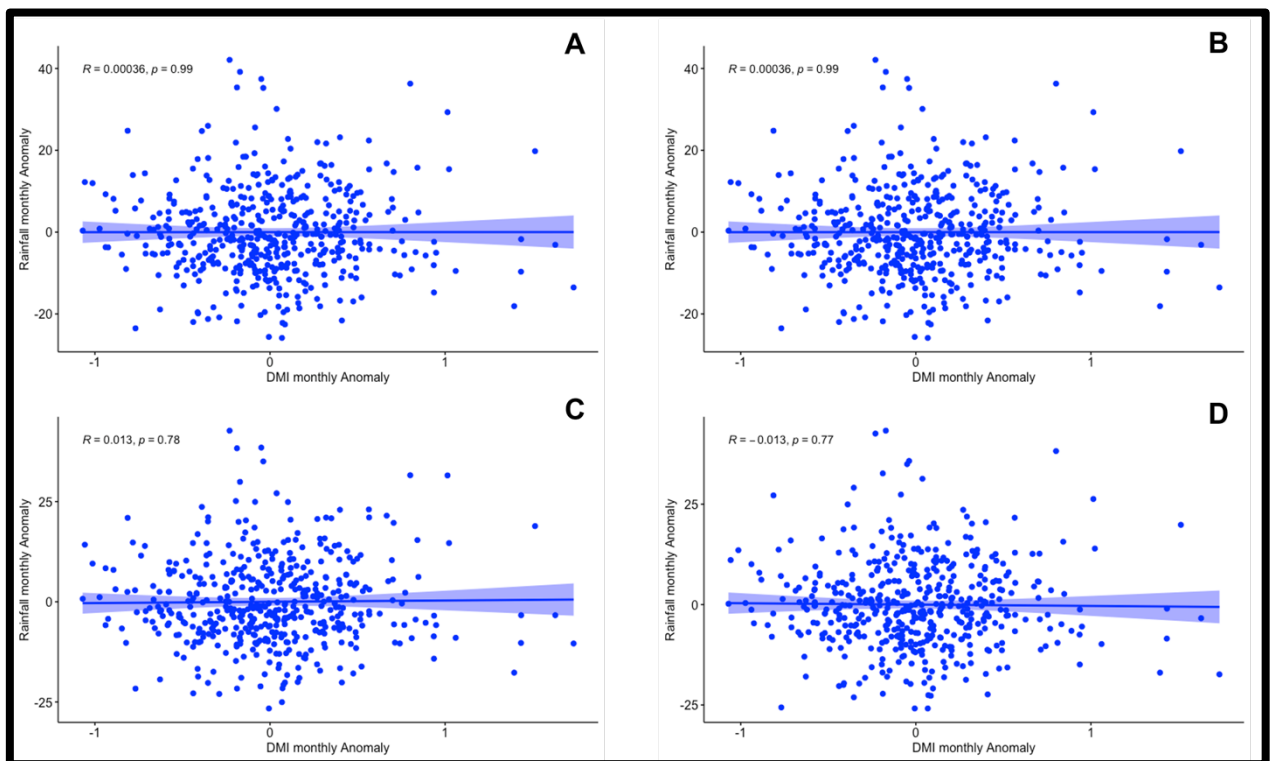


Figure 5-13: Correlation of DMI with rainfall over the study area; region A (A), region B (B), region C (C) and region D (D) from 1979 to 2020.

5.6 Summary

Temperature, SHF, ET, and PET all increased insignificantly between 1979 and 2020, while rainfall and LHF decreased insignificantly. Correlations between different land cover types and these variables have revealed that LULCC is very much significantly altering the climate condition via these variables. Additionally, the results indicate that PET and LHF are the most sensitive variables to change. While LULC type shows a significant influence of boundary layer climate, with urban and bare land showing dominance in negative climate influence across the regions. Most importantly water showed a positive influence and as a land cover type to be used for climate impact mitigation. As a result of this finding, it can be said that LULCC is a threat to the climate and its impact cannot be ignored; consequently, mitigation and management policies are required for South Africa's future climate change and variability to be contained. Additionally, the study examined the ENSO and IOD phenomena and discovered that there is correlation between both phenomenon, temperature, and rainfall changes in eastern South Africa. This demonstrates the importance of LULCC and remote phenomenon in the boundary layer climate and the urgency with which it must be addressed as population grows. Understanding how the land surface and SST anomaly interacts with the local climate is critical for fully comprehending and developing strategies for mitigating climate change. This is because different surfaces exhibit a range of physical properties, which affects its heat storage and moisture capacity. This LULCC has enabled the explanation of eastern South Africa's temperature and rainfall variability.

CHAPTER 6 : CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

The aim of this study was to analyse the nature, extent and effect of land use/land cover change (LULCC) on surface heat and moisture fluxes and hence the local climate of the eastern escarpment of South Africa from 1979 to 2020. This aim was achieved by mainly making use of Google Earth Engine, QGIS and ArcGIS as a remote sensing tool for Landsat imagery data classification and analysis and the use of python for observation and reanalysis data. Furthermore, RStudio was used to analyse LULCC, surface heat and moisture flux variables and to attribute LULCC to these variables that play a significant role to the local boundary layer. In this section each objective is revisited to reflect on how they were achieved through the result generated.

The aim of this chapter is to provide a synthesis and conclusion of the study findings detailed in chapters 4 and 5, and how they contribute to science knowledge. The chapter follows the structure of the dissertation's objectives. As a result, the first section discusses and evaluates the overall research objectives. Thereafter the conclusion of the study is drawn. It also recommends and provides suggestions on what can be done on future studies/ researchers to further analyse and improve the understanding of LULCC and its impact on the local boundary layer. It is believed that this study contributes to knowledge of science about LULCC and climate science over the country. The subsequent sections summarise key findings of the study.

6.2 Discussion of key findings

6.2.1 Classification and quantifying of temporal changes in land use and land cover types

6.2.1.1 Mapping Land Use, Land Cover and change (LULCC)

The land surface of the eastern South Africa was classified into six land cover types: waterbodies, grassland, cropland, forest, urban land, and bare land, using a RF classifier and Landsat data within GEE cloud platform. It was discovered that LULC types changed significantly over time, and eastern South Africa experienced significant anthropogenic as well as natural influence. From 1990, when the study began, all regions were predominantly covered by natural surfaces. Over a 31-year period, grassland maintained a dominant but significant decrease in region B, C, and D, while increasing insignificantly in region A. Changes in livestock numbers may have an effect on grassland change, as more grass may be required to satisfy the livestock (Meng et al., 2020), of course, climatic conditions also have an effect on grassland change. Additionally, during droughts, livestock may have a significant impact on vegetation, as it rely heavily on vegetation

for grazing (Serneels et al., 2007). Cropland showed a significant decreasing trend in regions A and B, but insignificant decreasing trend in regions C and D. Forest cover decreased significantly in regions A and B, but increased insignificantly in regions C and D. Because vegetation is critical for intercepting rainfall, slowing runoff, and increasing infiltration, a loss of grassland, cropland, and forest will exacerbate soil erosion, affect river sediments, modify soil moisture, and alter the climate (Huang et al., 2021). Cropland loss indicates insufficient soil moisture and favourable climate conditions to support crop production, on the grounds that the population is exploding, resulting in increased demand for food and biofuel production. It is worth noting that, while expanding cropland is necessary for ensuring food security and alleviating poverty, it may result in degradation of soil resources that are already stressed due to intensive management practices and changes in surface temperature (Sayão et al., 2020).

Water decreased insignificantly in regions A and B, but significantly in regions C and D. Most significantly, urbanisation increased significantly across regions A, B, C, and D, whereas bare land increased insignificantly in regions A, B, and D and increased significantly in regions C. Urban expansion was one land cover that demonstrated noticeable change in region B, with dominance and a high rate of change, at the expense of natural vegetation and surface cover. It increased year after year for a period of 31 years, whereas other land uses fluctuated annually. The increase in population resulted in an increase in urban expansion to meet the growing population's demand for urban settlements. This urban change is critical because it permanently alters the most critical natural surface, which is critical for sustaining life and modulating the local boundary layer.

DBEST demonstrated its robustness by identifying significant LULCC that occurred between the 31-year period. The LULCC were discovered to have occurred during a period of climate extremes over southern Africa. Each LULC class reacted differently to climate extremes such as tropical cyclones, flooding, and drought, as well as other natural phenomena such as ENSO and IOD that occurred over time. The climate extreme that influenced LULCC in eastern South Africa include Tropical cyclone Bonita (1996), La Niña phase (1998/99), Tropical cyclone Eline (2000), 2002/03/04/5 drought, Tropical cyclone Dando (2011/12), 2015/16 drought, Tropical cyclone Dineo (2017), and Tropical cyclone Idai (2019). Urbanisation was mainly due to anthropogenic influence, whereas changing of natural land cover types such as water, bare ground, and vegetation was due to natural phenomenon. Of course, human activities contributed also to the abrupt change in natural land cover type. Cropland and urban land change was due to significant increase in human demand for resources use. Soil moisture deficits and high temperatures also played a significant role in disrupting cropland growth, resulting in the observed decrease in cropland. Forests, on the other hand, are drought resistant (Mbatha & Xulu, 2018), and can be

abruptly induced by humans through high demand for wood used for energy, building houses, and fence poles.

6.2.1.2 Normalized Difference Vegetation Index

NDVI provides quantitative and reliable information about the physical characteristics of the surface and has been successfully used to map the abundance and health of vegetation (Mushore et al., 2018). NDVI was used as a proxy for vegetation cover in this study because it correlates with vegetation growth and can be used to determine the surface vegetation condition accurately (Sun et al., 2020). The overall finding indicated that NDVI has increased significantly over a 31-year period in regions A, B, C, and D. This demonstrates that vegetation is regaining and increasing in the study area over time. Region D had the highest NDVI values, followed by A, C, and finally B. The high values in region D are a result of forest dominance relative to other areas, whereas the low values in region B are a result of urban and bare land dominance relative to other regions. This demonstrated that NDVI is influenced by surface change as well as groundwater availability and given that eastern South Africa has undergone significant transformation, this notion is substantiated. This is because vegetation is highly susceptible to change as a result of the influence of climate, geomorphology, soil, and other natural and anthropogenic factors (Sun et al., 2020). Mlenga et al. (2019) used this index to assess moisture and vegetation production, and Mlenga et al. (2019) noted that it is useful for drought monitoring and early system warming. Additionally, this study demonstrated the index's significance by demonstrating its ability to successfully monitor vegetation. Increased vegetation may have aided in the enhancement of the ecological environment, material circulation, and energy conservation (Sun et al., 2020).

6.2.1.3 Surface soil moisture

Due to the robustness of the NDII as a proxy for soil moisture and its ability to assess moisture within the root zone of vegetation (Sriwongsitanon et al., 2015). Soil moisture has changed, primarily as a result of LULCC and extreme climatic conditions. Over a 31-year period, surface soil moisture has decreased in region A and C, with the exception of region B and D, which has increased. This indicates that regions A, and C are becoming drier as surface soil moisture levels decrease insignificantly, while region B and D are becoming wetter as surface soil moisture levels increase insignificantly. In addition to modulating climate, surface soil moisture is a critical factor affecting the spatial and temporal distribution of vegetation and is also critical for vegetation growth (Huang et al, 2021). The NDII has been demonstrated to be a robust and capable indicator of drought, flooding, and excessive rainfall, as fluctuations were detected across the study in predominantly drier and wet periods. Water stress variations across regions are a sign of declining water availability and a sign of deteriorating water scarcity (Ndlovu et al., 2021). Reduced soil

moisture levels are either a result of decreased rainfall or an increase in evaporation (LHF). However, additional factors such as soil type, orography, and vegetation all had an effect on soil moisture retention. Additionally, soil temperature decreases soil moisture due to increased evaporative losses of surface soil.

6.2.1.4 Land Surface Temperature

Land surface temperature (LST) is critical for understanding energy exchange processes that are influenced by LULC (Sayão et al., 2020). The LULCC altered LST, particularly in urban and bare land areas. The LST increased significantly with the highest values observed in the summer and over region B, which is located in the study's easternmost region and has a low altitude. The impervious urban land and bare land LULC classes have a high LST (+29°C) because of their physical characteristics, which include a lack of moisture. For each of the LULC classes, the LST value varies according to vegetation and climate conditions, with forest-dominated and low-lying region D experiencing the lowest LST values ($\pm 12^{\circ}\text{C}$). Forested areas, such as those found in this region, are expected to have low LST values due to their ability to absorb and reflect solar radiation energy, as well as reduce heat retained by the soil through transpiration (Sayão et al., 2020). This study was able to show that vegetation plays a significant role in the boundary layer climate. It is important to note that while forested cover had the lowest LST, dry bare land and urban areas had a significantly higher LST, indicating their influence on LST. Vegetation conversion to urban and bare land also contributed to the rise in LST. Shade provided by vegetated areas and trees in various parts of the area helps lower LST and lowers air temperature through ET, the process by which plants release water into the surrounding air. The highest LST values were found in urban areas, bare land, and dry grassland.

6.3 The impact of land cover changes on trends in surface energy and moisture fluxes and hydrometeorological variables

Different land surface properties, such as heat storage and moisture capacity, influence the boundary layer climate in various ways. Humans play a significant role in the impact of surface energy and soil moisture fluxes, as well as hydrometeorological variables, due to their influence on LULCC. This study demonstrated not only human-induced influence, but also natural influence, as both played a role in LULCC. The time series and MK trend test revealed that rainfall, and LHF all decreased insignificantly while SHF, Tmax, ET and PET increased significantly across all regions. However, over time, there were fluctuations that correlated with or depicted periods of significant dry and wet spells.

ET is a component of the boundary layer climate that connects the hydrological cycle to the energy balance on the surface. Since decreased ET results in LHF as a result of soil moisture deficits, rainfall also decreased. The increase in temperature, on the other hand, suggests that

SHF may have increased. This is because an increase in SHF results in an increase in temperature; thus, the LHF decreased, and decreased rainfall (Ban-Weiss et al., 2011). When the surface is unable to supply moisture to the atmosphere, PET increases, and as surface soil moisture decreases in the study regions, PET increases. Reduced rainfall has resulted in water scarcity, forcing residents of Kathmandu to rely on tankers and water jars (Thapa, 2020). This has also been observed in most South Africa's communities, indicating that eastern South Africans are susceptible to future water scarcity as a result of climate variability. This variable changed in response to the change in the land surface. The LULCC has altered surface soil moisture and surface energy flux, thereby altering the local climate (Ban-Weiss et al., 2011). Correlation with LULCC was used to evaluate and determine the LULCC's effect on these variables. The results indicated that LULCC had a significant impact on the spatiotemporal pattern of the variable in eastern South Africa between 1990 and 2020. The impact of LULCC on these variables varies per region. Due to the study's purposeful division into four areas, high values associated with increasing temperature are observed toward the eastern region, while the highest rainfall values are observed toward the west with high elevation, indicating that the climate is sensitive to mountainous topography (Aik et al., 2020).

Topography played a significant role in enhancing the climate conditions in areas with high topography. While it has long been recognized that high topography has an effect on climate conditions, Chikoore et al. (2021) demonstrated the Soutpansberg mountain range enhancing low-level convergence and lifting, resulting in 300mm of sub-daily rainfall. While Singleton & Reason (2006) demonstrated how the Drakensberg mountains increased rainfall intensity during cut-off lows along the eastern cape coast. Overall, the decrease and increase in this variable are cause for concern because they indicate climate variability and change, which will have a significant impact on vulnerable communities in the future and probably already have.

6.4 The important land cover classes driving change in the boundary layer climate

Climate Research Unit (CRU) observational temperature data showed an increase in warming, while CHIRPS Meteosat and station observations showed a decrease in rainfall in eastern South Africa over the last 31 years. Additionally, the LULCC has occurred in the last 31 years across all land cover types, implying that climate change is consistent with the LULCC results. Temperature and rainfall differences between regions over time can be attributed to differences in land cover type and surface change. As a result, the land cover types that have a significant impact on and influence the boundary layer climate were identified. Most importantly, before determining the critical land cover influencing the boundary layer climate, the critical surface moisture and heat fluxes, as well as the hydrometeorological variables that most influence rainfall and temperature, were determined. PET and LHF are the most sensitive parameters affecting temperature and rainfall variability in regions A, B, C, and D respectively, in eastern South Africa.

It was discovered that the major LULC types influencing boundary layer climate vary across the study. Urban land had a positive influence on temperature in regions A, B, and D and a negative influence on rainfall in region B. Bare land had a positive influence on temperature in regions A, C, and D, but had a negative influence on rainfall in regions A and C. The influence of urban and bare land is a result of its high susceptibility to heat absorption and severe surface moisture deficits (Peña, 2009; Tarawally et al., 2018; Meer & Mishra, 2020). Expansion of urban land warms the climate regardless of the previous LULC type (Huang et al., 2020). Urban areas tend to have a lower sky-view factor, less heat removal via wind, and the ability to store a significant amount of energy absorbed by the walls and buildings (Mushore et al., 2018), all of which influence the local boundary climate. This LULC type had a greater impact than other land cover types, which is cause for concern because it results in permanent fragmentation, which invites continued impact.

Forest showed a positive and negative influence on temperature and rainfall respectively in region A, while cropland negatively influenced rainfall in region C. Forest cover is known to increase infiltration and storage capacity in soil, absorbing excess rainwater and releasing it during dry periods (Abera et al., 2018). Furthermore, it helps capture moisture to supply the atmosphere. Cropland on the other hand also has a larger evaporative cooling effect (Boisier et al., 2012), due to irrigation that makes water accessible to the boundary layer climate influencing climate. Therefore, when cropland and forest fragmentation occur it has a considerable effect on the climate due to changing of surface roughness which directly enhances SHF during partition of energy decreasing low clouds associated with decreased evaporation (Ban-Weiss et al., 2011).

Water has a negative influence on temperature in region C and a positive influence on rainfall in region D, whereas grasslands has a negative influence on rainfall in region B. According to the study, water in eastern South Africa is the only LULC that decreases temperature and increases rainfall, thereby positively influencing the climate. This is because it provide the necessary moisture to the atmosphere, which aids in energy partitioning to favour LHF over SHF (Mushore et al., 2018), thereby lowering temperatures and enhancing cloud and rainfall formation (Meer & Mishra, 2020). Additionally, water has a high heat capacity, which means that a substantial amount of heat will be required to raise the temperature (Mushore et al., 2018). This demonstrates that water can be used to cool the climate during this period of climate vulnerability.

6.5 The influence of external remote phenomena (i.e. ENSO and Indian Ocean Dipole) on variability in the boundary layer climate

The effect of ENSO and IOD on temperature and rainfall was assessed using Pearson Correlation Coefficient. It has been demonstrated that both ENSO and IOD have a significant effect on climate variability in southern Africa (Ndlovu et al., 2021). This phenomenon has exacerbated heatwaves,

flooding, and drought throughout southern Africa (Chikoore, 2016; Chikoore & Jury, 2021). The study also showed a similar and supportive finding which discovered a statistically significant positive correlation between ENSO phenomena, temperature, and rainfall, with correlation p-values > 0.05 . The El Niño phase is more influential in causing hydro-climatological changes than the La Niña or neutral phase (Tamaddun et al., 2019). In eastern South Africa, rainfall demonstrated weak vulnerability to IOD, whereas temperature showed the greatest influence from positive IOD. On the contrary, El Niño demonstrated significant influence on temperature, while La Niña influenced rainfall increased. Consequently, region D's vulnerability and risk to climate extreme is greatest in comparison to other regions. Variation in LULC types and topography had a significant effect on climate influence. Mbatha & Xulu (2018), similarly noted that topography and different LULCC influenced the impact of remote phenomenon. On the other hand, rainfall is more susceptible to ENSO in region A and IOD in region D.

6.6 Conclusion

The findings corroborate previous research and add to global knowledge about LULCC and its influence on climate variability and change. Additionally, this study adds to scientific knowledge about LULCC and its influence on climate variability and change. Moreover, it will contribute to our understanding of the significance of remote phenomena in southern Africa's local boundary layer climate.

Over a 31-year period, this study discovered a significant LULCC over the eastern escarpment. These changes were influenced by both natural and human-caused factors. Cropland, grassland, urban areas, and barren land have all been shown to have a significant effect on the climate, which has been attributed to the widespread LULCC across all regions, as they influence both temperature and rainfall. However, the significance of this land cover class varies significantly across areas, owing in part to the orographic factor and to the type of vegetation present. Urban land is a source of concern because it is an irreversible activity that will continue to have an effect on our lives. Throughout the study, LULCC, ENSO, and IOD all had an effect on climate variability. The study's vulnerability to climate extremes will increase as the population grows in the future, resulting in more permanent LULCC. Additionally, remote phenomena are linked to drought, heat waves, and flooding, wreaking havoc on human health, agricultural production, infrastructure, and the environment throughout southern Africa (Mbokodo et al., 2020; Mavume et al., 2021). As it was correlated with any change in this study, it demonstrates the importance of understanding the impact of LULCC and remote phenomena on climate to develop effective and appropriate plans and strategies for mitigating and overcoming climate change in the future.

This study has provided comprehensive detail that aids in comprehending the land-atmosphere interaction, which can aid various entities in avoiding future warmer climates and intense rainfall.

It is well established that climate variability in the region has an impact on food security, livelihoods, and water availability (Ogwang et al., 2020), and thus requires an understanding of the various factors that influence its variability and change. By examining the relationship between each land cover type, remote phenomenon, and various climatic variables, this study demonstrated the importance of land surface and ocean phenomena in boundary layer climate. Additionally, and perhaps most importantly, the study discovered that water can be used as a mitigation strategy for both reducing temperature and increasing rainfall in eastern South Africa. As with Abera et al. (2018), vegetation cover can be used to mitigate local warming and increase rainfall, thereby reducing the severity of heatwaves, droughts, and flooding. This necessitates additional research and attention in this area at various latitudes, as the impact of LULCC on the climate can be equivalent to that of CO₂, and in some cases, even double or greater (Manhmood et al., 2014). This places LULCC as a primary concern when assessing climate change, implying that additional research is necessary.

6.7 Recommendations

Eastern South African climate has changed for years, and it has been attributed to the LULCC. Therefore, understanding of LULCC should be followed by proper programs that teach people about how the environment should be treated and proper policies that enhance natural vegetation restoration. The following recommendation was made in view of the study conclusion:

- Further research needs to be conducted across South Africa to understand LULCC influence on climate variability and change to be able to find strategies for individual different geographical areas to combat its impact in the future.
- During this era of extensive urban growth and global warming, there must be a continuous mapping of these expanding settlements so that it can be restrained, or rather growth be redirected to a direction of no vegetation to protect the sensitive surface from been transformed.
- There is a need to incorporate both the biogeophysical and biogeochemical characteristics of the land surface and how the change in these properties both influence climate, so that a comprehensive understanding on Land-climate is enhanced.
- Future studies need to investigate the role of different soil, and vegetation types, and monitor how irrigation patterns across cropland influence the local boundary layer.
- These studies are significant to human and the local climate, so it is important that future studies are not limited to current and previous LULCC.

- Furthermore, future studies should project future LULCC using models and how the climate will be influenced in the future by such change. As it will assist in planning for future devastating events.

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