

**SATELLITE-DERIVED ASSESSMENT OF RANGELAND PRODUCTIVITY IN
BLOUBERG MUNICIPALITY IN A CHANGING CLIMATE**

By

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DEDICATION

This dissertation is dedicated to the memory of my beloved mother, whose unwavering love, strength, and guidance continue to inspire me every day. Although she is no longer with us, her spirit and values have been a constant source of motivation and courage throughout this journey.

To my father, your support and belief in my abilities have been a foundation upon which I have built my aspirations.

To my dear grandmother, whose wisdom and kindness have shaped my character, I am forever grateful for the lessons you have imparted. This work is for all of you, with all my love and gratitude

And to my precious daughter, you are my greatest joy and my reason for striving to achieve my dreams. May this work serve as a testament to the importance of education, resilience, and the pursuit of knowledge.

DECLARATION

I declare that the Satellite-derived assessment of rangeland productivity in Blouberg Local Municipality in a changing climate hereby submitted to the University of Limpopo, for the degree of Master of Science In Geography and Environmental Studies has not previously been submitted by me for a degree at this or any other university; that it is my work in design and in execution, and that all material contained herein has been duly acknowledged.

Signature: 

Date: 25 August 2024

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ABSTRACT

This study investigates rangeland productivity in Blouberg Municipality, Limpopo Province, under changing climatic conditions using satellite-derived data. The research employs MODIS-derived vegetation indices, specifically the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), to analyze trends in vegetation health from 2001 to 2022. By integrating climatic variables such as rainfall and temperature, the study assesses their impact on vegetation dynamics. Data processing was conducted using Google Earth Engine (GEE), enabling large-scale temporal monitoring of rangeland productivity. The findings reveal significant inter-annual variability in vegetation indices, driven primarily by climatic fluctuations. While the overall 20-year period does not exhibit a statistically significant long-term trend, selected years show significant variations, with p-values below 0.05. Notably, drought periods in 2002, 2005, and 2016 led to sharp declines in vegetation productivity, while post-drought recovery phases demonstrated the ecosystem's resilience. Correlation analysis confirmed a strong positive relationship between rainfall and vegetation indices, whereas temperature exhibited a weaker negative correlation. Additionally, the study identified specific areas within the municipality that are highly vulnerable to land degradation. These results underscore the critical need for adaptive land management strategies to sustain rangeland ecosystems in the face of climate variability. By providing valuable insights into vegetation-climate interactions and highlighting the significance of short-term climatic impacts, this research contributes to the development of evidence-based policies aimed at promoting the sustainable management of rangelands in semi-arid regions like Blouberg Municipality.

ABBREVIATIONS

AVHRR	Advanced Very High-Resolution Radiometer
BLM	Blouberg Local Municipality
ENSO	El Nino Southern Oscillation
EOSDIS	Earth Observation System Data and Information System
EVI	Enhanced Vegetation Index
GEE	Google Earth Engine
GIS	Geographical Information System
GNDVI	Green Normalized Difference Vegetation Index
IPCC TRA	Third Assessment Report of the Inter-Governmental Panel of Climate Change
LIDAR	Light Detection and Ranging
MODIS	Moderate Resolution Imaging Spectroradiometer
NR	Near Infrared
NDVI	Normalized Difference Vegetation Index
PDO	Pacific Decadal Oscillation
RS	Remote Sensing
SAVI	Soil Adjusted Vegetation Index
SAWS	South African Weather Service
SSA	Sub-Saharan Africa
UAV	Unnamed Aerial Vehicle

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CHAPTER ONE: INTRODUCTION

1.1. Introduction

Rangelands, characterized by vast expanses of grasslands and shrublands, constitute essential ecosystems that support biodiversity, sustain rural livelihoods, and contribute significantly to global food security (Vetter, 2020). The intricate balance of these landscapes, however, is increasingly challenged by the omnipresent forces of climate change (IPCC, 2019). Blouberg Local Municipality (BLM), situated at the nexus of environmental sensitivity and human dependence on rangeland resources, becomes a focal point for exploration in this thesis on the Satellite-Derived Assessment of Rangeland Productivity in Blouberg Municipality in a Changing Climate. This chapter outlines the study's background, articulates the problem statement, explains its rationale, and delineates the purpose of the study.

1.2. Background of Study

According to UNEP (2018), Cheng *et al.* (2020), rangelands are landscapes that are primarily made up of grasslands, woodlands, shrublands, and wetlands. For grazing livestock and wildlife, rangelands offer food, water, and cover. These resources have significant socioeconomic value in many nations (Coppock *et al.*, 2017). Numerous issues have put rangelands in jeopardy worldwide, including soil erosion (Mganga *et al.*, 2015), biodiversity loss (Belnap *et al.*, 2012), frequent habitat-destroying veld fires (Rihan *et al.*, 2021), and—most seriously—climate change (Mani *et al.*, 2021)

Thus, any factor that is affecting these resources has to be recognized and observed. One such factor affecting these ecosystems is climate change, which manifest in altered precipitation patterns, temperature fluctuations, and shifts in vegetation dynamics (IPCC, 2019). As climate change alters precipitation patterns, temperature regimes, and land cover dynamics, there is a pressing need to understand its impact on rangeland productivity (IPCC, 2019).

The global surface temperature increased by 1.09 °C (0.95-1.20 °C) between 2011 and 2020, with the past five years (2016-2020) being the hottest (Ahmed, 2023). An increase of 2 °C in the average world temperature is anticipated over the next 20 years. The most recent projections indicate that by 2100, global temperatures might rise by

1.1°C to 6.4°C (Allen *et al.*, 2018; Kirby, 2014). Climate change is happening, and Africa is the most susceptible continent, according to IPCC (2013). The World Meteorological Organization (2013) states that there is a good chance that this century will see global warming, with drier subtropical parts warming more quickly than the moister tropics. The continent of Africa would see a higher degree of warming.

The average annual temperature of South Africa increased by approximately 0.13°C per decade between 1960 and 2003, with seasonal variations in the increase, according to analyses of climate data from 26 weather stations (Kruger and Shongwe, 2004). Increased temperatures and irregular rainfall patterns with frequent droughts are consequences of climate change (Kruger and Sekele, 2012). Due to its reliance on climate-sensitive economic systems, South Africa is especially susceptible to these fluctuations (Madzwamuse, 2010). According to Ziervogel *et al.* (2014), the nation has seen a marked increase in temperature over the past 60 years, accompanied by a slow and consistent change in climate. The study was conducted in the province of Limpopo, where temperatures are already rising and becoming wetter in the winter and getting hotter and drier in the summer (Tshiala, 2011).

According to the Limpopo Climate Change Response Strategy, 2016–2020, the province is highly susceptible to the effects of climate change, both in terms of variations in extreme events and average temperatures and rainfall patterns. This is not unusual for rural communities in the BLM region, where the majority makes a living primarily from livestock farming. The majority of these communities' grazing areas are overstocked, leading to overgrazing and the biannual drought that results (Blouberg Local Municipality IDP, 2020).

Assessing and monitoring rangelands in the context of climate change is a complex endeavour that requires sophisticated methodologies and technologies. Traditional methods often fall short in capturing the nuances of dynamic ecosystems and fail to provide comprehensive insights into the impacts of climate change on rangeland productivity. In response to these challenges, advanced techniques, such as satellite-derived assessments, have emerged as powerful tools to monitor large-scale changes in vegetation cover, land use, and climate-related variables (Fisher *et al.*, 2016).

In this study, the emphasis will be on elucidating not only the challenges posed by a changing climate on rangelands but also on presenting viable solutions for effective

monitoring and adaptive management. The study will draw from both global perspectives and locally relevant contexts, considering the unique characteristics of regions like Blouberg Local Municipality where rangelands play a crucial role in the socio-economic fabric. Through this approach, the research aims to bridge the gap between theoretical understanding and practical applications, offering a holistic framework for assessing and monitoring rangelands in the dynamic context of climate change.

1.3. Problem Statement

Rangeland productivity is a critical component of sustainable land management, providing essential resources for livestock grazing and supporting biodiversity (Archer *et al.* 2017). Rangelands are generally seen as overgrazed, overstocked, degraded, and unproductive in South Africa (Vetter, 2003). Turner (2014) denotes that climate variability has a significant impact on livelihoods of farmers who practice livestock farming in semi-arid regions. This is due to its effect on rangeland productivity, which is important because it serves as the primary source of feed for livestock.

IPCC (2014) has reported that, by 2050 it is anticipated that the temperature will rise by 1.5 to 3.5 °C in the region of Sub-Saharan Africa (SSA). Additionally, extreme weather and climate are noted to be a major factor in African population displacement (IPCC, 2023). A recent study by Trinity *et al* (2020) indicates that beyond 2050, it is anticipated that the temperature trend will continue to rise, whereas the trends in precipitation vary geographically and between different models. It is anticipated that poor and vulnerable societies, particularly those in SSA, will be badly affected (Trinity *et al.*, 2020).

Thus, it has become crucial to comprehend how climatic factors like temperature and precipitation affect vegetation productivity. Assessing and monitoring rangelands in the context of climate change is a complex endeavour that requires sophisticated methodologies and technologies especially in poor communities of BLM (Blouberg Local Municipality IDP, 2020).

1.4. The Rationale of the Study

Farmers use rangelands as a vital component for livestock grazing. The community farmers of BLM manage a communal land use system based on subsistence and

livestock farming. Additionally, there is a sizable commercial agricultural sector focused on livestock, game, and crop farming (Blouberg Local Municipality IDP, 2020). This municipality has a significant number of livestock, and the availability of vast rangeland complements that support farming in this regard (Agricultural Research Council, 2006).

Rainfall patterns affect the annual growth of grasses and forbs, which is necessary for the survival of livestock. In addition, BLM represents a reasonable grazing area in Capricorn District Municipality and is located in a semi-arid fragile environment, making it susceptible to drought, facing changes in species composition, increasing pressure on range resources, particularly near water sources, expanding cultivation, water scarcity, and overgrazing.

Additionally, due to poverty levels and a lack of awareness about environmental preservation, it is difficult to manage this rangeland and other natural resources in an optimal manner. This is due to the fact that most people depend on natural resources like soil, wood, animals, and plants to survive (Blouberg Local Municipality IDP, 2020).

Several studies have been done on determining how vulnerable and adaptable smallholder farmers are to climate change (Puig *et al*, 2011; Masikati *et al*, 2017). More work still needs to be done to better understand the effects caused by changing climate on rangelands and how farmers of livestock should position themselves to mitigate the risks and shocks. The bottom-up theories of climate change research, which advocate conducting studies at the local scale where impacts and risks are most felt, are becoming more and more prominent (Bardosh, 2014). The Southern African Development Community (SADC) Climate Change Adaptation (2011) affirms that society as a whole must come to a shared understanding of the risks, consequences, and necessary adaptation measures in order to achieve climate change adaptation. Individuals cannot accomplish climate change adaptation on their own.

1.5. The aim of the Study

The primary aim of this study is to examine the dynamics of rangelands (productivity and sustainability) in Blouberg Municipality within the context of the changing climate using Geographic Information System and Remote Sensing applications.

1.6. Objectives

- To characterize the state of rangelands in Blouberg in terms of their productivity (vigour and resilience).
- To assess the rangelands response and trends to changing climate.
- To map out and highlight areas vulnerable to degradation.

1.7. Research questions

- i. What are the trends and patterns of rangeland productivity in Blouberg local municipality over time, as shown by satellite-derived data?
- ii. How are the observed trends and patterns of rangeland productivity in Blouberg local municipality related to climate change?

1.8. Outline of the dissertation

The report is organized into five chapters, the first of which provides an overview of the study's background, problem statement, goals, and limitations. The second chapter reviews relevant literature, focusing on the theoretical frameworks and previous research related to remote sensing, vegetation indices, and change detection methods. The study area, data collection, pre-processing, and the methods for categorization, accuracy evaluation, and change detection are all covered in detail in the third chapter of the approach. The fourth chapter presents the results, along with an in-depth analysis and interpretation of the findings. Finally, the fifth chapter discusses the conclusions, implications for future research, and potential applications, followed by recommendations for improving rangeland management and sustainable farming practices.

CHAPTER TWO: LITERATURE REVIEW

2.1. Introduction

Rangelands are a vital component of global ecosystems, covering nearly half of the Earth's terrestrial surface. They provide critical services, including supporting biodiversity, carbon sequestration, and water regulation, as well as being the main source of livelihood for people in disadvantaged communities around the world ((UNEP, 2018, Wessels *et al.*, 2007). In Sub-Saharan Africa, and particularly in South Africa, rangelands are very important for livestock production, which forms the backbone of the rural economy (Vetter, 2009). However, these rangelands are increasingly under threat from climate change, land degradation, and other anthropogenic factors that reduce their productivity and resilience (Mudau *et al.*, 2022). Assessing the impacts of these changes and managing rangelands sustainably require reliable and timely information about vegetation conditions over large areas.

Recent advancements in remote sensing technologies have enabled more precise monitoring of rangelands. Satellite-derived data, particularly from platforms such as MODIS (Moderate Resolution Imaging Spectroradiometer), offer a means to assess vegetation health, biomass, and land use changes over time and space (Motongera *et al.*, 2021, Huete *et al.*, 2002). This is especially important in the context of a changing climate, where shifts in weather patterns and increased frequency of extreme events can lead to rapid changes in vegetation dynamics (Schulze, 2011). Understanding these dynamics is essential for developing adaptive management strategies that can mitigate the adverse effects of climate change and ensure the sustainability of rangeland ecosystems.

The Blouberg Municipality, located in South Africa's Limpopo Province, provides a valuable case study for assessing rangeland productivity using satellite-derived data. This area is characterized by semi-arid conditions and is heavily reliant on rangelands for livestock farming and other economic activities. The region faces significant challenges due to climate variability and change, which threaten its rangeland resources and the livelihoods of local communities (Sibanda *et al.*, 2016). By employing remote sensing techniques to monitor vegetation indices such as EVI (Enhanced Vegetation Index) and NDVI (Normalized Difference Vegetation Index),

researchers can gain insights into the health and productivity of rangelands in the face of these challenges.

This literature review explores the role of satellite-derived data in assessing rangeland productivity in Blouberg Municipality within the context of a changing climate. It discusses the importance of rangelands in Sub-Saharan Africa and South Africa, the impacts of climate change and variability on these ecosystems, and the application of remote sensing technologies for monitoring rangeland conditions. Furthermore, it addresses the challenges and limitations of using satellite data for rangeland assessment and highlights the potential of platforms like Google Earth Engine for improving vegetation monitoring and management.

2.2. Rangelands in Sub-Saharan Africa Context

Rangelands in Sub-Saharan Africa are diverse and expansive, covering grasslands, savannas, shrublands, and deserts (Liniger *et al.*, 2019). The productivity of these rangelands is highly dependent on climatic conditions, particularly precipitation, which directly influences the growth of grasses and shrubs that serve as forage for livestock and wildlife (Baudron *et al.*, 2017). In regions like Sahel and Horn of Africa, where rainfall is highly variable, rangelands are particularly vulnerable to climate-induced changes.

The socio-economic importance of rangelands in Sub-Saharan Africa cannot be overstated. They support not only pastoral and agro-pastoral systems but also play a critical role in cultural practices and biodiversity conservation (Herrero *et al.*, 2013). However, these rangelands face numerous threats, including overgrazing, land degradation, and invasive species, which reduce their productivity and resilience. Climate change exacerbates these challenges by altering rainfall patterns, increasing temperatures, and contributing to more frequent and severe droughts (Niang *et al.*, 2014). These changes have far-reaching impacts on the health and productivity of rangelands, leading to reduced forage availability, altered plant species composition, and increased soil erosion.

Recent studies have shown that climate variability and change significantly impact rangeland dynamics in Sub-Saharan Africa. For instance, research in the Sahel has demonstrated a strong correlation between changes in rainfall and vegetation

greenness, with periods of drought leading to declines in NDVI, an indicator of vegetation health and productivity (Zeng *et al.*, 2023, Herrmann *et al.*, 2005). Similarly, in East Africa, increased temperature and reduced precipitation have been linked to changes in plant phenology and reduced rangeland productivity (Kimiti *et al.*, 2016). These findings highlight the need for adaptive management practices that consider the effects of climate variability on rangeland ecosystems.

To address the challenges facing rangelands in Sub-Saharan Africa, it is essential to develop sustainable land management strategies that enhance the resilience of these ecosystems to climate change. This requires a comprehensive understanding of the factors driving changes in rangeland productivity and the development of tools and technologies that can monitor these changes effectively. Remote sensing, particularly the use of satellite-derived vegetation indices, provides a powerful means of assessing rangeland conditions and informing management decisions (Bastin *et al.*, 2012). Through the combination of ground-based measurements and satellite data and local knowledge, researchers can develop more robust models for predicting rangeland dynamics and designing adaptive management strategies that promote sustainability.

2.2.1. Importance of Rangelands in South Africa

In South Africa, rangelands are a critical resource for livestock farming, which is a major economic activity in many rural areas (Scholes & Archer, 2020). These rangelands support a wide range of livestock, including cattle, sheep, and goats, which are vital for food security, income generation, and cultural practices (Vetter, 2009). The Blouberg Municipality in Limpopo Province is a prime example of a region where rangelands play a crucial role in the local economy. The area's semi-arid climate and reliance on rain-fed agriculture and grazing make it highly dependent on the health and productivity of its rangelands (Sibanda *et al.*, 2016).

The ecological importance of rangelands in South Africa extends beyond their economic value. These landscapes offer critical ecosystem services, including carbon sequestration, water filtration, and habitat provision for diverse plant and animal species (Reid *et al.*, 2019; Hoffman & Todd, 2000). Recent research, such as that of Mlambo *et al.* (2019), underscores the importance of rangelands as a source of forage for cattle, sheep, and goats. However, the sustainability of South African rangelands is increasingly threatened by factors such as overgrazing, land degradation, and the

spread of invasive species. These issues are compounded by socio-economic pressures, including population growth, poverty, and inadequate land management practices (FAO, 2019; Reed *et al.*, 2007).

Further studies emphasize the ecological significance of South African rangelands in conserving biodiversity. According to Shackleton *et al.* (2018), these ecosystems provide essential habitat for a wide array of wildlife, including threatened and endemic species such as the African wild dog, cheetah, and various antelopes. Protecting rangeland habitats is crucial for preserving South Africa's unique flora and fauna. Rangelands are increasingly recognized as critical areas for carbon sequestration. Barnard *et al.* (2021) demonstrated that well-managed rangelands have the capacity to store substantial quantities of carbon in their soils and vegetation. This contributes to climate change mitigation and helps reduce the country's carbon footprint.

Rangelands are integral to the livelihoods of many rural communities in South Africa. Twine *et al.* (2019) highlight the importance of rangelands in providing food security through livestock farming and the gathering of edible plant resources. The resilience of these communities often depends on the sustainability of rangeland ecosystems. According to the Department of Environmental Affairs and Tourism (2019), animal production in South Africa's rangelands is correlated with the availability of fodder, which translates to the growth of the economy through tourism and contributed to an employment rate of about 9% in 2019. Rangelands hold cultural and spiritual importance for many indigenous communities in South Africa. Nxele *et al.* (2021) highlighted the spiritual and cultural connections of local communities to rangeland landscapes, underscoring their cultural significance beyond economic and ecological aspects.

One of the key challenges facing rangelands in South Africa is land degradation, which is often driven by overgrazing and improper land use practices. Overgrazing reduces the vegetation cover, loss of soil fertility, leading to soil erosion, and reduced water infiltration, which in turn decreases the land's productivity and resilience (Gonzalez *et al.*, 2021, Wessels *et al.*, 2007). The invasion of alien plant species further exacerbates these problems by outcompeting native vegetation, reducing biodiversity, and altering ecosystem processes (Kumar Rai *et al.*, 2020). A comprehensive approach to land

management that strikes a balance between the demands of livestock production, and the preservation of rangeland ecosystems is necessary to address these issues.

Given the importance of rangelands in South Africa, there is a need for effective monitoring and management strategies that can ensure their sustainability. Remote sensing technologies offer a valuable tool for assessing rangeland conditions and identifying areas at risk of degradation. By using satellite-derived data, researchers can monitor changes in vegetation cover, biomass, and land use, providing critical information for land managers and policymakers (Wessels *et al.*, 2012). This information can be used to develop adaptive management practices that promote the sustainable use of rangelands and enhance their resilience to environmental changes.

2.3. Climate Change and Variability

Climate change and variability are among the most significant challenges facing rangeland ecosystems globally. Climate change denotes enduring alterations in temperature and precipitation patterns, while climate variability encompasses short-term fluctuations in these climatic parameters (IPCC, 2014). Both phenomena have profound implications for rangelands, which are highly sensitive to changes in climate. Increased temperatures and altered rainfall patterns can lead to shifts in plant species composition, reduced forage availability, and increased vulnerability to pests and diseases (Niang *et al.*, 2014). These changes threaten the productivity and sustainability of rangeland ecosystems, particularly in semi-arid regions like Blouberg Municipality.

In Sub-Saharan Africa, climate variability is a defining characteristic of the region's climate, with significant year-to-year and decadal fluctuations in rainfall that can lead to periods of drought or excessive rainfall (Boko *et al.*, 2007). These fluctuations have a direct impact on rangeland productivity. Changes in precipitation and temperature influence vegetation growth, soil moisture, and forage availability (Schulze, 2011). During droughts, reduced rainfall leads to declines in vegetation cover and biomass, which in turn reduces the carrying capacity of rangelands and increases the risk of land degradation (Moyo *et al.*, 2018).

Climate change is anticipated to intensify these challenges by raising the frequency and severity of extreme weather events, including droughts, heat waves, and floods

(Engelbrecht *et al.*, 2015 In South Africa, projections indicate that temperatures will continue to rise, and rainfall patterns will become more erratic, with longer dry spells and more intense rainfall events (Schulze, 2011). These changes will have a considerable impact on rangeland ecosystems, especially in locations like Blouberg Municipality, where residents rely significantly on rain-fed agriculture and grazing for a living (Sibanda *et al.*, 2016).

Addressing the impacts of climate change and variability on rangelands requires a multi-faceted approach that includes improving our understanding of climate-rangeland interactions, developing adaptive management strategies, and enhancing the resilience of rangeland ecosystems (Reed *et al.*, 2011). Remote sensing technologies, such as satellite-derived vegetation indices, play a crucial role in this process by providing reliable and timely information on vegetation conditions and trends. By integrating remote sensing data with climate models and socio-economic data, researchers can develop more robust frameworks for predicting rangeland responses to climate change and designing effective adaptation strategies (Pettorelli *et al.*, 2005).

2.3.1. Climate Change in South Africa

The climate of South Africa is changing significantly, with increased frequency of extreme weather events, changing precipitation patterns, and rising temperatures (MacKellar *et al.*, 2014; Schulze, 2011). According to Rögelj *et al.* (2016), semi-arid and arid regions have been warming at a rate of approximately 2°C per century or higher. This is thought to be more than twice the pace of growth in global temperature. In Blouberg Municipality, located in Limpopo Province, climate change poses a serious threat to rangeland productivity and the livelihoods of local communities who depend on these lands for grazing and agriculture (MacKellar *et al.*, 2014).

According to IPCC (2014), temperatures in Southern Africa are expected to rise significantly faster than the average global temperature. This warming is expected to lead to more frequent and intense heat waves, prolonged dry spells, and increased evaporation rates, which will reduce soil moisture and exacerbate water scarcity (Engelbrecht *et al.*, 2015). These changes have profound implications for rangeland ecosystems, particularly in regions like Blouberg Municipality, where water is a limiting factor for vegetation growth and productivity (Hoffman & Todd, 2000).

Due to the influence of the ocean and interior plateaus, South Africa has a mix of temperate and subtropical climates. The northeast has a warm, subtropical climate, while the Drakensberg region has a cool, rainy climate. While the central west and north-west have warm, dry desert climates, the south-west enjoys a Mediterranean climate. The majority of the country's 464 mm of yearly rainfall falls in the Western Cape during the winter. In summer, temperatures can reach up to 36°C, while in winter, they can drop as low as -2°C. South Africa in particular, is susceptible to climate change because of its reliance on natural resources and rain-fed agriculture. The monthly temperature ranges from 22°C to 11°C, with an annual mean temperature of 17.5°C (World Bank, 2017).

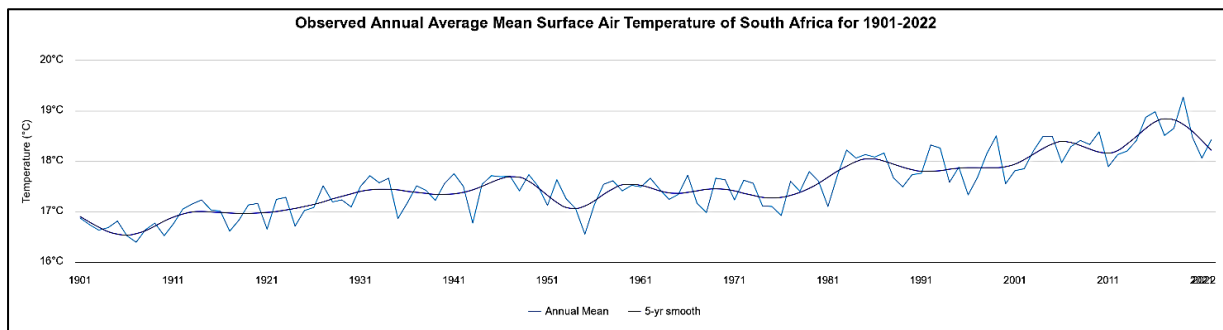


Figure 2.1: Average yearly temperature in South Africa (1901–2022) Source: World Bank (2017)

South Africa's climate is categorized as semi-desert and desert; the eastern provinces (Gauteng, Free State, KwaZulu-Natal, and Mpumalanga) get the most annual rainfall, with amounts up to 900 mm. The western and northwestern regions experience semi-desert and desert climates, while the central region receives about 400 mm of annual rainfall. With 515 mm of annual rainfall, the Western Cape's southern region experiences a Mediterranean climate (World Bank, 2017). Nevertheless, the trend indicates that there hasn't been much of a shift between 1901 and 2015 (see Figures 1.2 and 1.3).

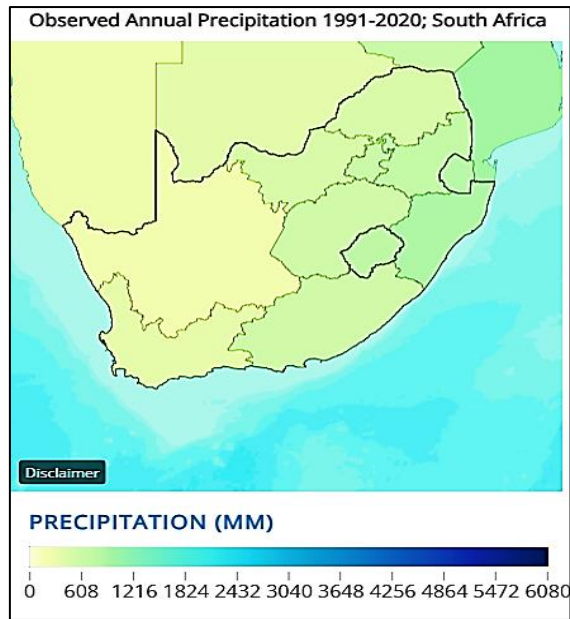


Figure 2.2: Average yearly precipitation in South Africa (1901–2022) Source: World Bank (2017)

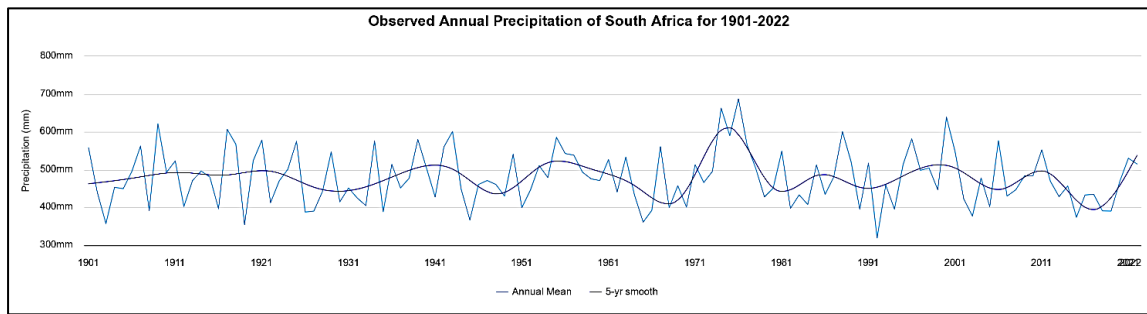


Figure 2.3: Average yearly precipitation in South Africa (1901–2022) Source: World Bank (2017)

In addition to rising temperatures, climate change is also expected to alter precipitation patterns in South Africa. While some areas may experience increased rainfall, others are likely to see declines, leading to greater spatial and temporal variability in water availability (Schulze, 2011). This variability poses a significant challenge for rangeland management, as it increases the risk of both droughts and floods, which can cause severe damage to vegetation and soil health (Wessels *et al.*, 2007). In Blouberg Municipality, where rainfall is already highly variable, these changes could further destabilize the region's rangeland ecosystems and reduce their resilience to environmental stressors (Sibanda *et al.*, 2016).

2.4. Occurrence and Impacts of Climate Change and Climate Variability on Rangelands

The occurrence of climate change and climate variability has significant impacts on rangeland ecosystems, particularly in semi-arid and arid regions like Blouberg Municipality. Numerous studies (Derner *et al.*, 2009; Knapp *et al.*, 2008; Snyman, 2013) have highlighted the adverse effects of climate change on rangeland productivity. Changes in temperature, precipitation, and the frequency of extreme weather events can alter the structure and function of these ecosystems, leading to reduced productivity, changes in species composition, and increased vulnerability to degradation (Niang *et al.*, 2014). In South Africa, these impacts are already being observed, with evidence of declining rangeland productivity and shifts in vegetation dynamics in response to changing climatic conditions (Sibanda *et al.*, 2016).

Alterations in precipitation patterns have a direct impact on rangelands by influencing the amount of water available for vegetation development. In semi-arid regions like Blouberg Municipality, where water is a limiting factor, changes in rainfall can have profound effects on rangeland productivity (Schulze, 2011). During periods of drought, reduced rainfall leads to declines in soil moisture, which in turn reduces vegetation growth and forage availability for livestock (Ponce-Campos *et al.*, 2013; Vetter, 2009). Conversely, excessive rainfall can lead to flooding and waterlogging, which can also damage vegetation and reduce rangeland productivity (Wessels *et al.*, 2007).

In addition to changes in precipitation, rising temperatures associated with climate change can also have significant impacts on rangeland ecosystems. Higher temperatures increase evaporation rates, reducing soil moisture and exacerbating water scarcity in already dry regions (Engelbrecht *et al.*, 2015). Jewitt *et al.* (2020) focus on water scarcity in South African rangelands, demonstrating that climate-related shifts in precipitation patterns can intensify competition for limited water resources, affecting both wildlife and livestock. Changes in precipitation patterns can lead to increased competition for water resources between livestock, wildlife, and human populations. Water scarcity exacerbates the challenges faced by rangeland communities (Seely *et al.*, 2011).

The combined impacts of climate change and climate variability pose a significant challenge for rangeland management, particularly in regions like Blouberg

Municipality, where most communities rely heavily on rain-fed agriculture and grazing for their livelihoods. In a more forward-looking study, Jones *et al.* (2022) assess various adaptive strategies employed by local communities in response to the changing climate. These strategies include altering livestock management practices, introducing drought-resistant forage species, and diversifying income sources. South African rangelands contribute significantly to carbon sequestration. Changes in land use due to climate-related shifts can affect the carbon balance, impacting global climate systems and biodiversity (Snyman *et al.*, 2018).

2.5. Overview of Remote Sensing Application in Rangeland Assessments

One very useful tool for assessing rangeland productivity and monitoring changes in vegetation dynamics over time and space is remote sensing. It involves the use of satellite or aerial imagery to collect data on various aspects of the Earth's surface, including vegetation cover, land use, and soil conditions (Gao, 2000). In rangeland ecosystems, remote sensing technologies have been widely used to monitor vegetation health, assess land degradation, and inform management decisions (McGranahan *et al.*, 2013, Harmse *et al.*, 2022, Hunt *et al.*, 2003). By providing a synoptic view of large areas, remote sensing allows researchers to detect changes in rangeland conditions that may not be visible from the ground.

The application of remote sensing in rangeland assessment has been greatly enhanced by the development of various vegetation indices, which are mathematical combinations of different spectral bands designed to highlight specific properties of vegetation (Justice *et al.*, 1985). The most widely used indices in rangeland assessment are the Normalized Difference Vegetation Index and the Enhanced Vegetation Index, both of which are derived from the red band and near-infrared band of satellite imagery (Huete *et al.*, 2002). The NDVI is especially helpful for tracking the greenness of the vegetation and identifying changes in its cover over time, while EVI provides improved sensitivity in areas with dense vegetation and reduces the influence of atmospheric conditions (Harmse *et al.*, 2022; Pettorelli *et al.*, 2005).

Remote sensing technologies have been applied in various rangeland ecosystems around the world to assess vegetation dynamics and monitor the impacts of environmental changes. For example, in the Sahel region of Africa, satellite-derived NDVI has been used to assess the impacts of drought and land degradation on

vegetation productivity, revealing significant declines in greenness during periods of reduced rainfall (Herrmann *et al.*, 2005). Remote sensing has been used to monitor the impacts of grazing and fire on rangeland ecosystems, providing valuable information for land managers and policymakers (Maphanga *et al.*, 2022; Thamanga *et al.*, 2024).

Despite the many advantages of remote sensing for rangeland assessment, there are also several challenges and limitations associated with its use. One of the main challenges is the difficulty in interpreting satellite data in heterogeneous landscapes, where variations in vegetation cover, soil conditions, and land use can affect the accuracy of vegetation indices (Wessels *et al.*, 2012). Additionally, remote sensing data are often limited by spatial and temporal resolution, with some satellites providing coarse-resolution imagery that may not capture fine-scale changes in vegetation dynamics (Li *et al.*, 2013). To address these challenges, researchers are increasingly using advanced techniques, such as data fusion and machine learning, to increase the precision and reliability of remote sensing-based assessments (Gorelick *et al.*, 2017).

Remote sensing is a useful tool for evaluating how grazing affects rangeland productivity. By comparing vegetation indices between grazed and ungrazed areas, it is possible to detect changes in vegetation cover and productivity caused by livestock grazing. Remote sensing allows for the continuous monitoring of vegetation phenology, including the identification of critical stages and shifts in vegetation growth patterns. This information is valuable for managing grazing practices and predicting forage availability (Wang *et al.* 2022)

Almalki *et al* (2022), provide a comprehensive review of remote sensing applications in change detection. They discuss the use of various remote sensing techniques such as multispectral and hyperspectral imagery, LIDAR, and thermal imaging in monitoring vegetation cover, biomass, and water resources. The article highlights the importance of remote sensing for rangeland assessment and suggests the integration of different data sources for improved accuracy and efficiency.

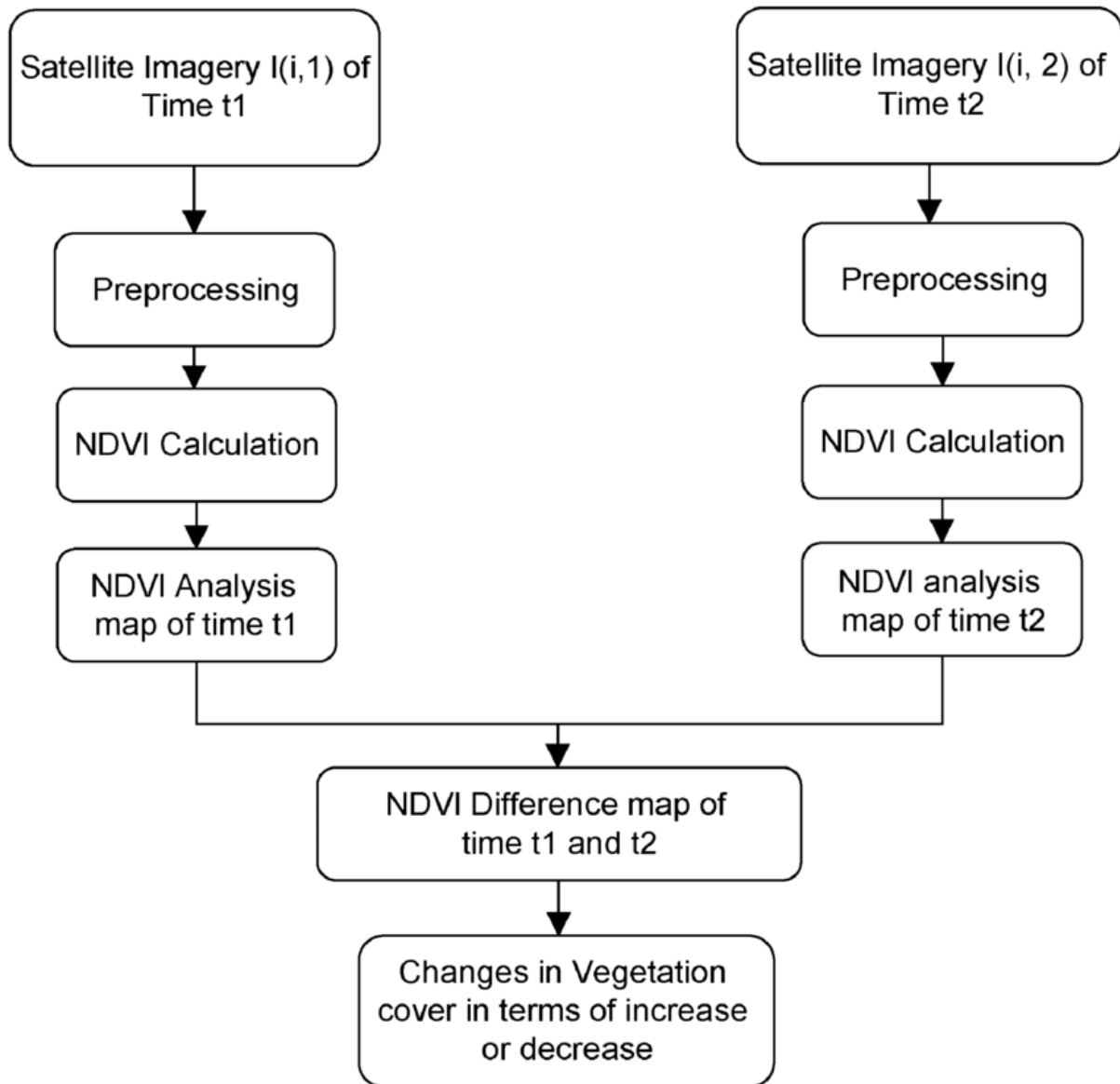


Figure 2.4: Comprehensive review of remote sensing applications in change detection.

Using multispectral remote sensing data, Liu et al. (2019) developed optimal techniques for mapping high-resolution forage production. By offering spatially detailed and almost real-time estimates of fodder yield, they illustrated the value of satellite and aerial remote sensing technology in assisting adaptive rangeland management, especially in the face of climate extremes. A 10-hectare deferred grazing rangeland was the subject of monthly Small Unmanned Aerial System (sUAS) flights. More frequently occurring 3-m PlanetScope satellite observations were combined with monthly 30-cm sUAS data to create daily maps of NDVI at 30-cm resolution. A combination of light uses efficiency (LUE), which was tuned for topography and climate stressors, and absorbed photosynthetically active radiation

(APAR), which was determined from NDVI, was used to estimate aboveground net primary productivity.

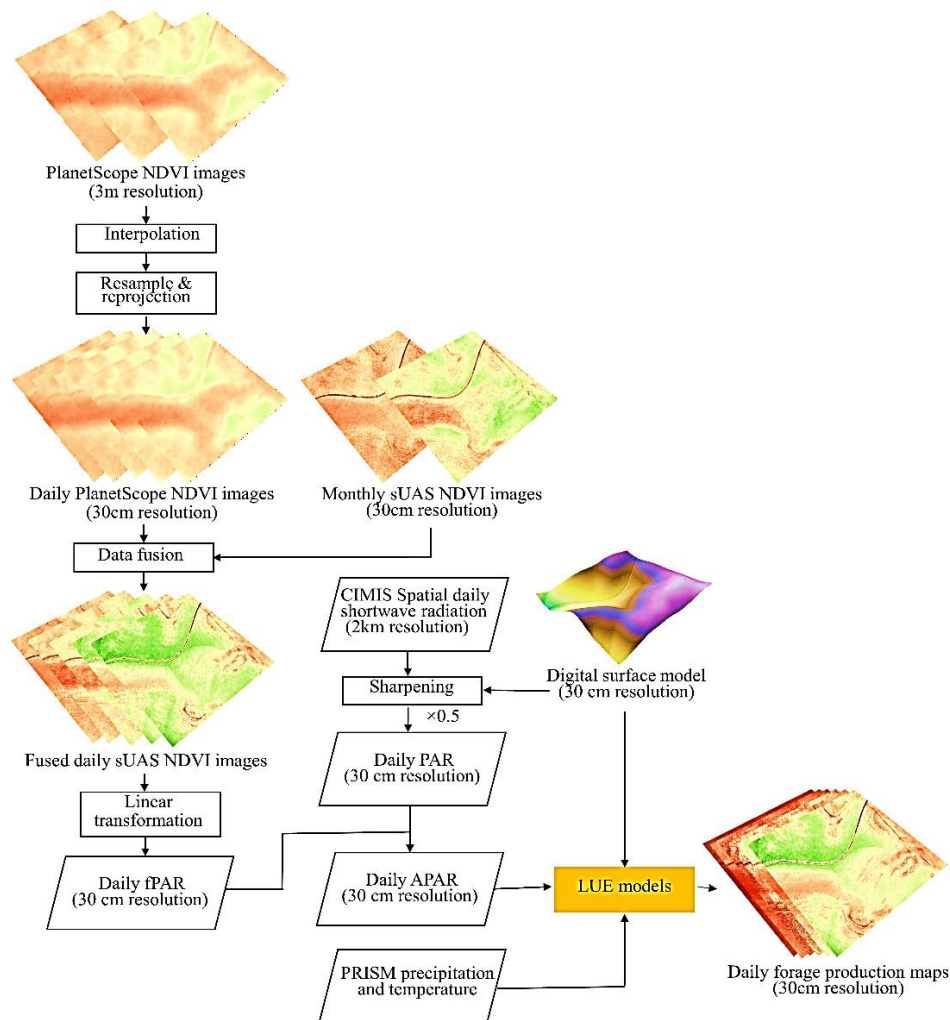


Figure 2.5: methodology flow used to develop optimize methods to map high resolution forage production

Wessels *et al.* (2007) investigated the influence of grazing intensity on vegetation indices in a semi-arid savanna in South Africa using both field-based measurements and remote sensing data. By analyzing relationships between in-situ measurements of vegetation, as well as remotely sensed NDVI and EVI, the study revealed how grazing pressure impacts vegetation cover and productivity. The findings emphasize the value of remote sensing in assessing the effects of grazing in South African rangeland ecosystems.

Mutanga *et al.* (2012) focus on estimating high-density biomass for wetland vegetation in South Africa using WorldView-2 satellite data. The study demonstrates the potential of high-resolution remote sensing data for accurately assessing biomass, which is vital for rangeland management. By utilizing a combination of vegetation indices and regression models, the authors successfully estimated biomass, providing valuable insights into wetland vegetation dynamics and ecosystem health in South Africa.

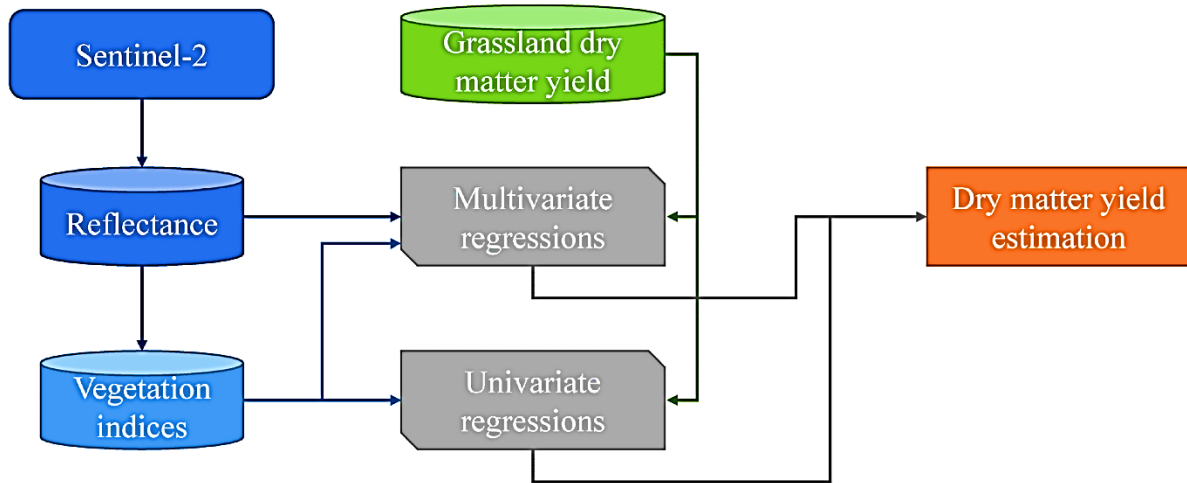


Figure 2- 6: flow chart of the estimation of biomass for forage.

Although focused on Mozambique, Ndambuki *et al.* (2016) evaluated the potential of spectral vegetation indices for monitoring rangelands in Urema National Park, which is located near the South African border. The study used Landsat imagery to assess vegetation cover, biomass, and other indicators of rangeland health. The findings demonstrate the applicability of remote sensing techniques to monitor rangelands in neighboring regions of South Africa.

Through the analysis of various studies, it is evident that remote sensing techniques, including satellite imagery, UAVs, and machine learning algorithms, provide valuable tools for monitoring vegetation dynamics, assessing grazing impacts, estimating biomass, and characterizing rangeland condition in diverse South African ecosystems.

2.5.1. Role of Vegetation Indices

Vegetation indices play a crucial role in remote sensing-based assessments of rangeland productivity, providing a quantitative measure of vegetation health and cover that can be used to monitor changes over time (Huete *et al.*, 2002; Dymond *et*

al., 1992; Kogan *et al.*, 2004; Wessels *et al.*, 2006). The red and near-infrared bands of satellite images are the source of two of the most popular vegetation indices: the NDVI and the EVI (Pettorelli *et al.*, 2005). NDVI is particularly useful for detecting changes in vegetation greenness and has been widely used to monitor the impacts of drought, land degradation, and other environmental changes on rangeland ecosystems (Herrmann *et al.*, 2005).

EVI, on the other hand, provides improved sensitivity in areas with dense vegetation and reduces the influence of atmospheric conditions, making it a valuable tool for monitoring vegetation dynamics in a variety of ecosystems (Huete *et al.*, 2002). By combining data from different spectral bands, vegetation indices can highlight specific properties of vegetation, such as chlorophyll content, leaf area, and biomass, providing valuable information for assessing rangeland productivity and health (Li *et al.*, 2023; Almalki *et al.*, 2022; Marín *et al.*, 2020; Amsalu *et al.*, 2018; Gao, 2000). This information can be used to inform management decisions, such as identifying areas at risk of degradation, assessing the impacts of grazing and fire, and monitoring the effectiveness of restoration efforts (Hunt *et al.*, 2003).

In addition to EVI and NDVI, there are several other vegetation indices that have been developed for specific applications in rangeland assessment. For example, the Soil-Adjusted Vegetation Index (SAVI) is designed to minimize the influence of soil background on vegetation measurements, making it useful for monitoring vegetation in areas with sparse cover or exposed soil (Huete, 1988). The Normalized Difference Water Index (NDWI) is another index that can be used to assess vegetation water content and monitor drought conditions in rangeland ecosystems (Gao, 1996). By selecting the appropriate vegetation index for a given application, researchers can obtain more accurate and meaningful assessments of rangeland conditions.

However, the use of vegetation indices in rangeland assessment is not without challenges. One of the main limitations is the sensitivity of these indices to atmospheric conditions, such as clouds, aerosols, and dust, which can affect the accuracy of satellite-derived data (Justice *et al.*, 1985). Additionally, vegetation indices may be influenced by factors such as soil colour, topography, and land use, which can complicate the interpretation of satellite imagery in heterogeneous landscapes (Wessels *et al.*, 2012). To address these challenges, researchers are increasingly

using advanced techniques, such as atmospheric correction, data fusion, and machine learning, to improve the accuracy and reliability of vegetation index-based assessments (Gorelick *et al.*, 2017).

2.5.2. MODIS NDVI for Vegetation Monitoring Using Google Earth Engine

The MODIS (Moderate Resolution Imaging Spectroradiometer) sensor, onboard NASA's Terra and Aqua satellites, provides key data for vegetation monitoring, particularly through the NDVI. NDVI is a widely used remote sensing index that measures the density and health of vegetation by comparing the reflectance of visible red light, which chlorophyll absorbs, with near-infrared light, which plant cells reflect (Huete *et al.*, 2002). The MODIS NDVI data products, available at various spatial resolutions, are invaluable for large-scale vegetation monitoring, offering near-daily global coverage, which is crucial for detecting changes in rangeland productivity over time (Vova, 2021; Justice *et al.*, 2002).

Google Earth Engine (GEE) has revolutionized the accessibility and analysis of MODIS NDVI data. Through the cloud-based platform GEE, users can access a sizable collection of geospatial datasets and satellite images, including MODIS data, and it offers powerful computational tools for large-scale environmental analysis (Gorelick *et al.*, 2017). By using GEE, researchers can easily access and analyze MODIS NDVI data to monitor vegetation dynamics, assess land degradation, and evaluate the impacts of climate change on rangeland ecosystems (Hansen *et al.*, 2013).

In the context of rangeland assessment in Blouberg Municipality, MODIS NDVI data, accessed via Google Earth Engine, can be used to track changes in rangeland production over time and measure the greenness of the vegetation. By analyzing trends in NDVI, researchers can identify periods of drought or excessive rainfall, assess the impacts of grazing and land use changes, and develop adaptive management strategies to enhance the resilience of rangeland ecosystems (Sibanda *et al.*, 2016). Furthermore, the integration of MODIS NDVI data with other geospatial datasets, such as soil moisture and land use data, can provide a more comprehensive understanding of the factors driving changes in rangeland productivity and inform more targeted management interventions (Pettorelli *et al.*, 2005).

2.5.3. Challenges and Limitations

While remote sensing offers significant advantages for assessing rangeland productivity, it is not without challenges and limitations. One of the main obstacles is the problem of temporal and spatial resolution. Many remote sensing platforms, such as MODIS, provide data at relatively coarse spatial resolutions, which may not capture fine-scale variations in vegetation cover and biomass (Pettorelli et al. 2014; Li *et al.*, 2013). This limitation can be particularly problematic in heterogeneous landscapes, where small-scale differences in vegetation and land use can have significant impacts on rangeland productivity and sustainability (Wessels *et al.*, 2012).

Another challenge associated with remote sensing is the influence of atmospheric conditions, such as clouds, aerosols, and dust, on satellite-derived data. These conditions can affect the accuracy of vegetation indices and other remote sensing products, leading to errors in the assessment of rangeland conditions (Justice et al., 1985). Additionally, variations in soil color, topography, and land use can complicate the interpretation of satellite imagery, particularly in areas with sparse vegetation or exposed soil (Turner *et al.*, 2015; Huete, 1988). To address these challenges, researchers often use techniques such as atmospheric correction, data fusion, and machine learning to increase the precision and reliability of remote sensing-based assessments (Gorelick *et al.*, 2017).

However, the use of MODIS NDVI data for vegetation monitoring in Google Earth Engine is not without challenges. One of the main limitations is the relatively coarse spatial resolution of MODIS data, which may not capture fine-scale variations in vegetation cover and biomass, particularly in heterogeneous landscapes (Li *et al.*, 2013). Additionally, the accuracy of NDVI measurements can be affected by atmospheric conditions, such as clouds and aerosols, which can introduce errors into the analysis (Moravec et al., 2021). To address these challenges, researchers often use advanced techniques, such as cloud masking and atmospheric correction, to improve the quality of MODIS NDVI data and enhance its utility for rangeland assessment (Gorelick *et al.*, 2017).

Remote sensing also faces limitations in terms of data availability and accessibility. While there are numerous satellite platforms providing data for rangeland assessment, access to high-resolution imagery and other specialized products can be limited by

cost and licensing restrictions (Li *et al.*, 2013). This can be a significant barrier for researchers and land managers in developing countries, who may lack the resources to acquire and analyze remote sensing data (Reed *et al.*, 2011). To overcome these limitations, initiatives such as Google Earth Engine have been developed to provide free and open access to satellite data and analytical tools, enabling researchers to conduct remote sensing-based assessments at little or no cost (Gorelick *et al.*, 2017).

Finally, remote sensing is limited by the need for ground-based validation and calibration. While satellite-derived data can provide valuable information on rangeland conditions, it is often necessary to validate these data with ground-based observations to ensure their accuracy and reliability (Huete *et al.*, 2002). This can be a time-consuming and labor-intensive process, particularly in remote or inaccessible areas, where collecting ground-based data may be challenging (Pettorelli *et al.*, 2005). Despite these challenges, remote sensing remains a valuable tool for assessing rangeland productivity and informing management decisions, particularly when combined with ground-based observations and other sources of data.

2.6. Summary

The literature review has explored the existing body of knowledge on satellite-derived assessment of rangelands in the context of the research topic, highlighting its ability to capture vegetation dynamics and land cover changes with enhanced spatial and temporal resolution, offering a promising alternative to traditional ground-based methods. The review also examined global trends in rangeland productivity, focusing on climate change, land use practices, and human interventions. The review emphasizes the integration of satellite data with ground-based measurements and local knowledge for accuracy and reliability. The review identifies research gaps and knowledge needs, justifying the importance of leveraging satellite-derived data for sustainable land management and policy development.

CHAPTER THREE: METHODOLOGY

3.1. Introduction

This chapter outlines the study area, the research design, and the methods that were employed to carry out the investigation. Additionally, it offers a particular approach that is applied to the gathering, processing, and display of data.

3.2. Study Area

The study area is Blouberg Municipality, which is approximately 95 km north of Polokwane in the Capricorn District Municipality of Limpopo Province. The municipality's total area is approximately 9,248.44 km² (Blouberg Municipality, 2020). The estimated total population is 172 601 and there are approximately 43,747 households. About 5.72 people live within each household on average (Community Survey, 2016). Polokwane, Molemole, Makhado, Lephalale, Mogalakwena, and Musina municipalities are its southern, western, northeastern, southwest, and northern neighbors, respectively (Blouberg Municipality, 2020).

BLM has a predominantly rural landscape, with significant portions of land dedicated to subsistence and commercial agriculture. The municipality collaborates with traditional authorities to manage communal land under customary tenure, ensuring that land use practices support local livelihoods while adhering to government regulations (Masipa, 2021).

Blouberg Local Municipality (BLM) in Limpopo Province has a diverse land-use structure that supports various socio-economic activities. According to the Integrated Development Plan (IDP) 2023–2024 and the Spatial Development Framework (SDF), the municipality's land is primarily used for agriculture, residential settlements, commercial activities, conservation, mining, and public infrastructure (Blouberg Local Municipality, 2023). Agriculture plays a dominant role, with large portions of land dedicated to subsistence and commercial farming, contributing to local food security and economic stability. Residential areas include both formal housing developments and informal settlements, with the latter requiring urgent intervention for infrastructure development and service delivery. Commercial and industrial zones are concentrated in key economic hubs, providing business and employment opportunities, though industrial development remains limited. Additionally, conservation areas are

designated to preserve biodiversity and promote eco-tourism, which is an emerging sector in the municipality. The mining sector also influences land use, as Blouberg has significant deposits of platinum and diamonds, though environmental sustainability remains a concern. Lastly, public land use includes schools, healthcare facilities, and transportation networks essential for social and economic development. The IDP and SDF aim to ensure that these land uses are well-coordinated to promote sustainable growth and balanced development in Blouberg Local Municipality (Blouberg Local Municipality, 2023).

BLM is within the semi-arid region where summer seasons are warm, dry, lasting from October, with winter season being dry, lasting from April to September. During summer, BLM receives 410 millimeters of precipitation annually on average. Due to Soutpansberg Mountain's location, the region experiences seasonal drought and orographic rainfall between May and October, with temperatures between 16 to 40 °C in temperature (Constance, 2014).

BLM has some areas with a mixture of sour and sweet grass, but the majority of the region is covered with sweet veld. The most common kinds of grass are annual types, which disappear quickly in the winter and leave the ground bare (Zwane, 2006).

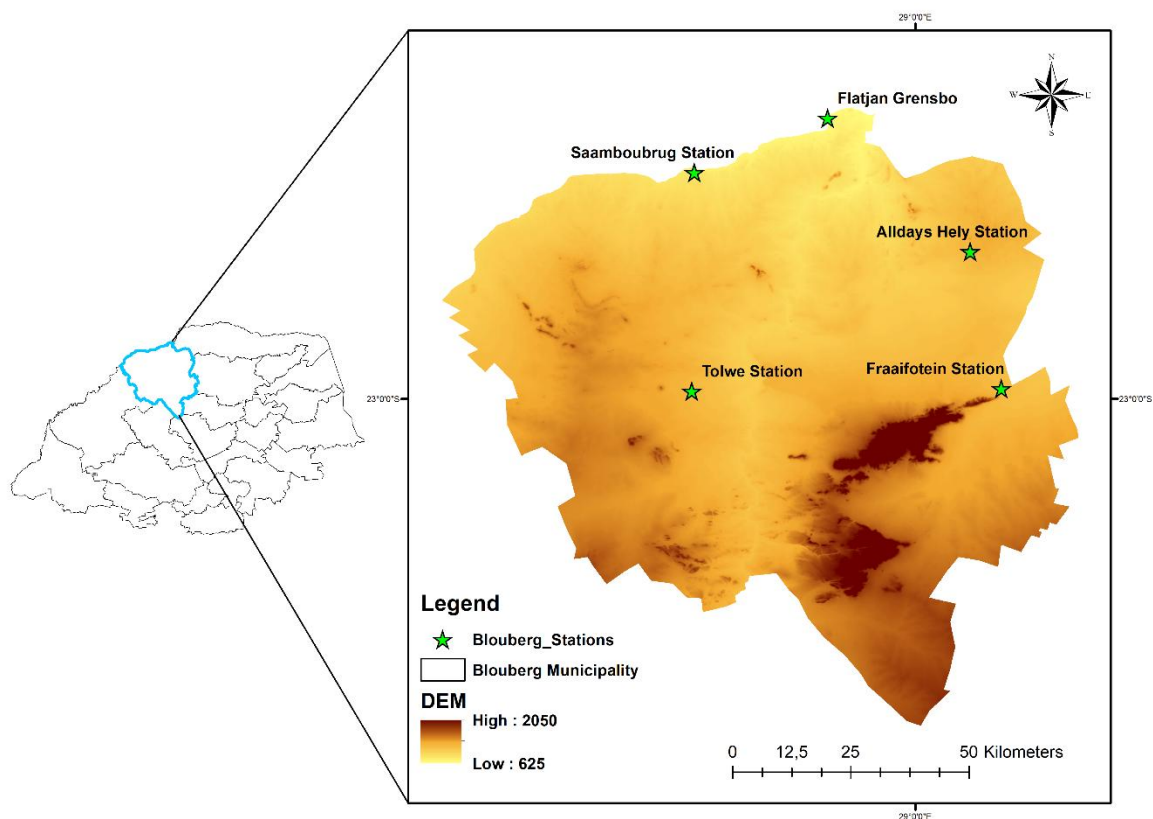


Figure 3. 1: Locality map of study area

3.3. Research approach

This study adopted the use of remote sensing (RS) integrated with machine learning. Remote sensing involves using aerial or satellite imagery to assess rangeland productivity. NDVI is a widely used remote sensing index for calculating vegetation greenness based on the difference between near-infrared and red light reflectance. It provides an estimate of vegetation density and vigor, which can be correlated with rangeland productivity (Tong *et al.* 2019).

According to Tong *et al.* (2019), the use of RS provides a broad-scale assessment of rangeland conditions over large areas, allows for frequent monitoring and tracking of changes over time, and is cost-effective compared to extensive field sampling, especially with freely available satellite data (Matongera *et al.*, 2021). RS is therefore a well-established and useful technique for evaluating rangelands. Assessing rangeland productivity using RS can provide valuable insights into vegetation dynamics and biomass estimation (Robinson *et al.*, 2019). However, it is important to note that the accuracy of the data depends on various factors, including sensor characteristics, data processing techniques, and validation.

For example, Advanced Very High-Resolution Radiometer (AVHRR) (Fontana *et al.* 2008), Landsat (Tomaszewska *et al.* 2020; Nguyen *et al.* 2020), Sentinel-2 (Vrieling *et al.* 2018), and Moderate Resolution Imaging Spectroradiometer (MODIS) (Cao *et al.* 2015) have been used in monitoring vegetation. This study used remotely sensed data (MODIS) from 2000 to 2023 in order to evaluate the study area's rangeland production.

3.3.1. Data Collection

Satellite Data:

In order to analyse NDVI and EVI trends in Blouberg Local Municipality in response to climatic conditions, we opted to use the MOD13Q1 Version 6 dataset on Google Earth Engine (GEE) for the period from 2001 to 2022 (21 years). Because of the size of the geographic area, MODIS images were the most suitable for this study due to their significant time resolution (roughly images per month) when compared to other satellites. The MOD13Q1 dataset provides 16-day composites of vegetation indices

derived from the Terra/Aqua satellite. Each composite includes multiple bands, but for this analysis, the focus is on the NDVI and EVI. Both indices are crucial for monitoring vegetation health, but they serve slightly different purposes. NDVI is widely used for assessing vegetation density and greenness, whereas EVI improves sensitivity in areas with dense vegetation and reduces atmospheric influences, making it more reliable in areas with high biomass.

The MODIS data used for the study are available in the GEE collection. The GEE platform (<https://earthengine.google.com/>) was used to extract and process the data (see Appendix A). Even for very vast study areas, this platform offers the capacity for big data processing and parallel computing. In addition to the NDVI, which is our main parameter for this study, we also considered the Enhanced Vegetation Index (EVI) as one of the vegetation indices. The following formulas were used to calculate these spectral indices:

:

$$NDVI = \frac{NIR - R}{NIR + R} \quad (1)$$

$$EVI = 2.5 \frac{NIR - R}{NIR - 6R - 7.5B + 1} \quad (2)$$

In the near-infrared (700–1300 nm), blue (450–500 nm), red (600–700 nm), and shortwave infrared (1550–1750 nm) regions, the spectral bands R, NIR, and B are correspond.

Weather data:

In this study, climatic data, including rainfall and soil temperature, were crucial for understanding environmental conditions within the research area. The South Africa Weather Service provided the rainfall data (SAWS), while the temperature data were sourced from NASA's POWER (Prediction of Worldwide Energy Resource) project.

The raw data for both variables were collected from meteorological stations strategically located within the study area. To create a comprehensive spatial representation, these point data were interpolated using ArcMap (see Appendix B). Interpolation was performed to estimate the mean values of rainfall and soil temperature across the entire study region for the period under investigation. This

process involved spatially distributing the point-based observations over the study area, allowing for the generation of continuous surface maps that reflect the variability of these climatic variables across the landscape.

Inverse distance weighting (IDW) was applied, the interpolation technique applied allowed for more accurate predictions of rainfall and soil temperature in areas between the measurement stations. This method ensured that the spatial patterns of climatic conditions were captured effectively, providing a more precise dataset for further analysis, including its influence on vegetation dynamics as part of the study's broader objectives.

The vegetation indices (VI) data and climatic data were temporally aligned to ensure that the time series of NDVI, EVI, rainfall, and temperature are consistent. This involves averaging the climatic variables to match the temporal resolution of the VIs (e.g., 16-day, monthly, or seasonal composites). Ensuring temporal alignment is crucial for an accurate correlation analysis.

3.3.2. Analysis and Interpretation

3.3.2.1. Linear Regression Analysis

This study employed a linear regression analysis to examine the temporal trends in vegetation indices (VIs) using the MODIS NDVI and EVI datasets. Additionally, specific years representing extreme conditions-both dry and wet periods were selected based on the mean VI values.

For each pixel within the study area, NDVI and EVI time series have been constructed. A linear regression model was applied to each pixel's time series data to determine the trend over the 21 years. The regression equation used:

$$VI(t) = \beta_0 + \beta_1 \times t \quad (3)$$

Where $VI(t)$ represents the vegetation index (NDVI or EVI) at time t , β_0 is the intercept, and β_1 is the slope, representing the trend. The slope β_1 indicates whether there is an increasing, decreasing, or stable trend in vegetation over time.

To assess the statistical significance of the trends over the 21 years, the Mann-Kendall test was applied. This non-parametric test is widely used to detect monotonic trends in time-series data while minimizing the influence of outliers (Bouizrou *et al.*, 2022; Lioi, 2024).

For identifying extreme conditions, mean annual NDVI and EVI values were calculated for each year across the study area. Two years with the lowest mean VI values, representing the most significant vegetation stress or reduction, were identified as the dry years. Two years with the highest mean VI values, representing periods of optimal vegetation growth, have been selected as the wet years. To compare vegetation dynamics between these extreme conditions, a t-test was performed to evaluate whether the mean difference in NDVI and EVI between wet and dry periods was statistically significant.

The mean and standard deviation of NDVI and EVI for the selected year were compared to assess the magnitude of variation between extreme years and the overall trend. The findings are presented through maps, graphs, and statistical summaries.

Given the importance of accurate long-term vegetation monitoring, the MODIS vegetation products, specifically NDVI and EVI, have been extensively validated globally. Studies such as those by Huete *et al.* (2002) and Jiang *et al.* (2008) demonstrated the reliability of these indices across various ecosystems, confirming their utility in detecting subtle changes in vegetation dynamics. Didan *et al.* (2015) further validated MODIS vegetation products, highlighting their consistency and accuracy when compared with ground-based observations. These general validations of MODIS data provide a strong foundation for their use in this study, ensuring that the trend analysis conducted is based on reliable and accurate data.

3.3.2.2. Correlation Analysis of NDVI and Climate Factors

The study conducts a correlation analysis between vegetation indices (VIs) and climatic factors using the Pearson correlation coefficient to understand the relationship between vegetation dynamics and climatic variables such as rainfall and temperature. This technique has been extensively used to examine the connection between climatic factors and the NDVI (The Jiang group, 2017). The degree of influence on VI patterns was assessed over 21 years, from 2001 to 2022.

The Pearson correlation coefficient r is calculated using the formula:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}} \quad (4)$$

Where x and y represent the VI and climatic variable values, respectively, and n is the number of paired observations.

The correlation analysis is conducted at different spatial scales (e.g., pixel, region) and temporal scales (e.g., monthly, seasonal, annual). This allows for the identification of spatial patterns and temporal variability in the strength of the correlations. For instance, stronger correlations during specific seasons or in certain regions can highlight areas where vegetation is more responsive to climatic factors.

Based on the Pearson correlation coefficient (r), which has a range of -1 to 1, the results are interpreted. Strong positive correlation is indicated by a value near 1, which means that when the climatic factor rises, the VI rises as well. A strong negative correlation is indicated by a value near -1, meaning that a rise in the climatic factor is correlated with a fall in the VI. A value around 0 suggests little to no linear relationship. Statistical significance tests are conducted to determine whether the observed correlations are significant.

The results are visualized through correlation maps that show the spatial distribution of Pearson correlation coefficients across the study area, as well as graphs that illustrate the relationship between VIs and climatic factors over time.

3.4. Validation and Uncertainty Analysis

The accuracy of the MODIS-derived NDVI and EVI indices used in this study is further validated through recent studies conducted in South Africa and across the African continent, including those by Sifiso Xulu, which have demonstrated the effectiveness of these indices in similar contexts.

Sifiso Xulu's research has been instrumental in evaluating the application of MODIS vegetation indices in South African rangelands. In Xulu (2019), Xulu investigated the utility of MODIS NDVI and EVI in detecting vegetation changes in the KwaZulu-Natal province, specifically focusing on their ability to monitor rangeland degradation and

recovery processes. His findings demonstrated that both NDVI and EVI from MODIS are reliable indicators of vegetation health, correlating well with ground-based measurements and effectively capturing the seasonal and interannual variability in vegetation cover.

Similarly, in Xulu and Mafongoya (2021), the role of MODIS EVI was emphasized in assessing the impact of climate variability on rangelands in semi-arid regions of South Africa. The study highlighted EVI's strength in providing more nuanced insights into vegetation changes in areas with dense vegetation compared to NDVI. These findings are supported by other recent studies, such as Venter *et al.* (2018), which validated MODIS NDVI data in South Africa by comparing it with field measurements of rangeland productivity, finding strong correlations and reinforcing the index's utility for long-term vegetation monitoring.

Owuor *et al.* (2021) confirmed the reliability of MODIS EVI in East Africa, particularly in detecting vegetation responses to climatic variability, which is critical for understanding rangeland dynamics in the face of climate change. Akinyemi and Mashame (2020) in Botswana further validated MODIS NDVI and EVI against ground-based observations, underscoring their effectiveness in capturing seasonal and interannual vegetation changes across diverse landscapes in southern Africa.

By incorporating these studies, including those by Sifiso Xulu, the current research methodology is well-supported by recent literature, ensuring that the analysis of rangeland dynamics using MODIS-derived NDVI and EVI is accurate and reliable. The findings of this study are therefore grounded in a solid foundation of validated remote sensing techniques, particularly in the context of climate change impacts on rangeland ecosystems in South Africa and beyond.

3.5. Conclusion

This chapter covered the study area, data collection methods, and analysis techniques. The study topic, Satellite-Derived Assessment of Rangeland Productivity in Blouberg Municipality in a Changing Climate, was the main focus.

CHAPTER 4: RESULTS AND DISCUSSION

4.1. Introduction

This chapter presents and discusses the findings of the study. Using MODIS vegetation indices, which were generated on 16-day intervals and at several spatial resolutions, two vegetation indices were developed using atmospherically-corrected reflectance in the Red, Near-infrared, and Blue wavebands. These indices are the NDVI, which offers continuity with NOAA's AVHRR NDVI time series record for historical and climatic applications, and the EVI, which increases sensitivity over dense vegetation conditions and minimizes canopy-soil variations.

These two vegetation indices are crucial indices when it comes to assessing vegetation health, biomass, and the overall ecosystem productivity. The two pairs (NDVI and EVI) of analysis have been provided to illustrate the productivity dynamics in terms of annual mean values of EVI and NDVI from 2001 to 2022. Analysing these trends in the Blouberg Municipality, especially in light of changing climate conditions, offers insights into the ecological dynamics and potential impacts of climate variability on rangeland ecosystems.

Pearson's correlation coefficient has been used to study the relationship between the responses of rangelands in the study in question against climate variables: temperature and rainfall. This demonstrated a comparative analysis of the relationship between Annual Mean Vegetation Indices (EVI and NDVI), Annual Mean Rainfall, and Annual Mean Temperature in the context of assessing the rangeland in the study in question has been provided. These analyses provide an understanding of how climate variables impact vegetation health and productivity, which is a critical aspect of rangeland management and sustainability. The results also account for intraseasonal dynamics for selected dry and wet seasons. 2003 & 2005 are selected dry years, and 2010, 2022 are selected wet years.

4.2. Results

4.2.1. MODIS NDVI and EVI derived rangeland productivity (2001-2022)

4.2.1.1. Temporal Analysis

Figure 4.1 below shows the combined annual mean NDVI and EVI from 2001 to 2022. The vegetation indices (NDVI and EVI) have been calculated using the formula: $NDVI = (NIR - Red) / (NIR + Red)$ and $EVI = 2.5 * (NIR - Red) / ((NIR + 6 * Red - 7.5 * Blue + 1))$, respectively. Both vegetation indices values range from -1 to 1, with higher values near 1 indicating vigorous and more productive vegetation.

The NDVI values in the graph are consistently higher than EVI values, ranging between 0.30 and 0.45, indicating relatively healthy vegetation cover throughout the period. Both indices show similar patterns of variability, though NDVI appears less volatile compared to EVI.

The parallel trends of NDVI and EVI suggest that both indices are responding similarly to external influences such as climate variability and anthropogenic activities. The observed patterns imply that rangelands in Blouberg Municipality have experienced periods of both stress and recovery, influenced by climatic factors and potentially by land use changes and management strategies.

Statistical analysis further supports this observation. For NDVI, the calculated p-value is 0.204294, which is above the significance threshold of 0.05, indicating that any observed changes are not statistically significant. The S-Statistic of 46 and a Z-Score of 1.269412 suggest only a weak upward movement that does not qualify as a trend. Similarly, for EVI, the p-value of 0.175552 also exceeds 0.05, reinforcing the absence of a significant trend. The S-Statistic of 49 and a Z-Score of 1.354578 indicate minor fluctuations but no definitive increase or decrease.

Table 1: Man-Kendall Significance test for NDVI and EVI from 2002-2022

Index	Trend	p-value	S-Statistic	Z-Score
NDVI	no trend	0,204294	46	1,269412
EVI	no trend	0,175552	49	1,354578

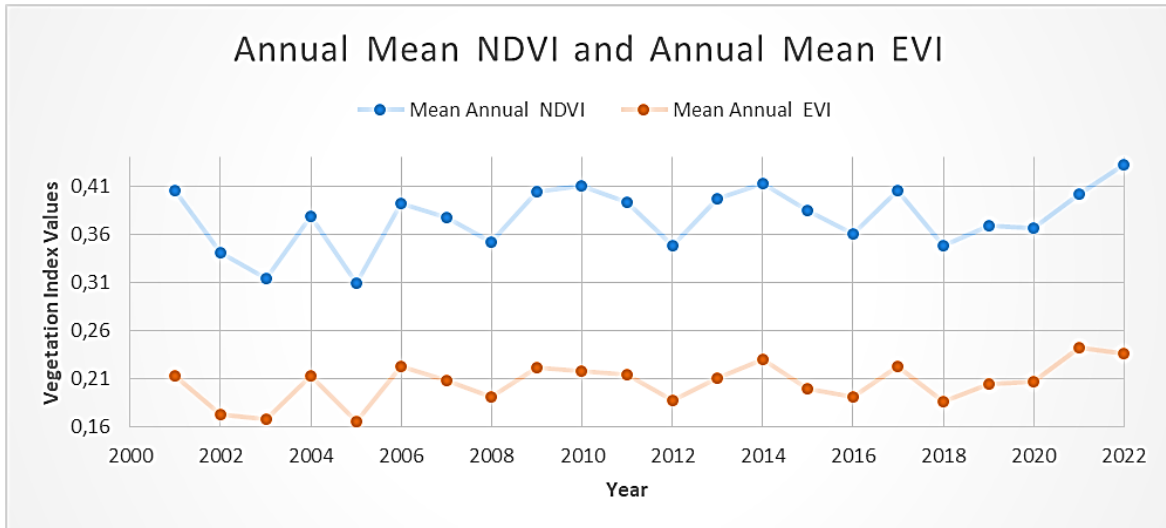


Figure 4.1: Scatter plot graph with values of Annual Mean NDVI and EVI from 2001 to 2022 for Blouberg Local Municipality.

Figure 4.2 below shows the calculated annual mean NDVI values of the study area from 2001 to 2022 using MODIS Vegetation indices, produced on 16-day intervals at 250m spatial resolution. The figure displays a notable fluctuation over the period of time being investigated. During the period of 2005 and 2003, having the lowest NDVI values of 0.309 and 0.315, respectively, which suggests the period of stress or degradation. 2014, 2021, and 2022 have higher NDVI values of 0.413, 0.42, and 0.432, respectively, which indicate the period of improvement in vegetation vigour.

The overall trend shows a general increase in NDVI values in recent years, which might reflect positive ecological changes or improved climatic conditions conducive to vegetation growth. This trend aligns with global observations where some regions experience greening due to factors such as an increase in Carbon Dioxide (CO₂) fertilisation, better patterns of precipitation, and longer growing seasons.

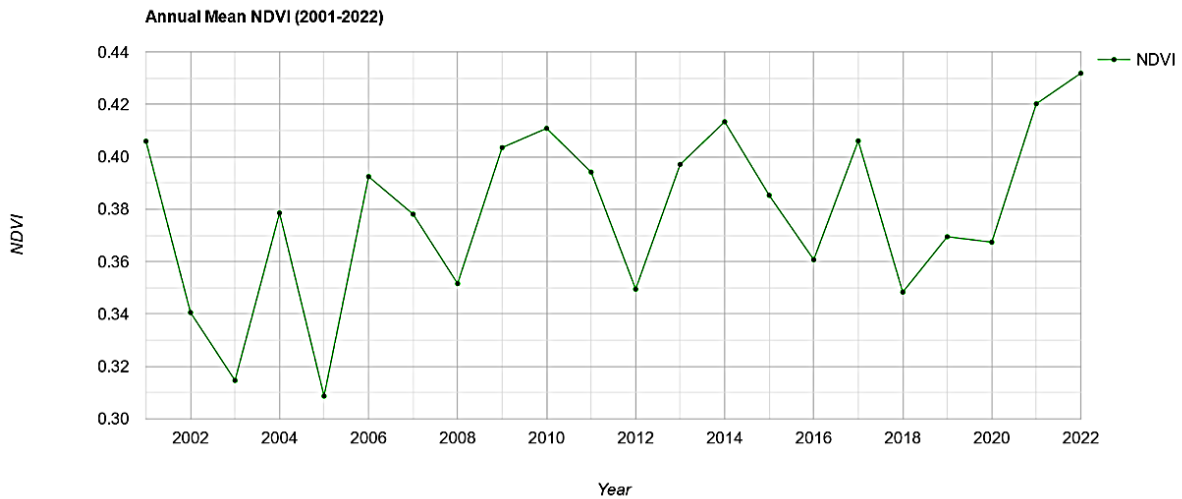


Figure 4.2: Scatter Plot showing time series of annual mean NDVI from 2001 to 2022

Figure 4.3 shows the calculated annual mean EVI values of the study area from 2001 to 2022, the MODIS Vegetation indices, produced on 16-day intervals at 250m spatial resolution. This vegetation index is an optimized index designed to enhance the vegetation signal by reducing atmospheric influences and soil background signals.

The graph shows a significant inter-annual variability, with EVI values fluctuating between approximately 0.16 and 0.26. Lowest values in EVI appear around 2005, 2003, and 2002 with the values of 0.166, 0.168, and 0.173, respectively. This indicates the period of potentially reduced vegetation vigour. Conversely, higher values appear around 2015, 2022, and 2021 with EVI values of 0.231, 0.236, and 0.243, respectively. This suggests a period of more robust vegetation.

This variability can be attributed to several factors, including climatic conditions such as precipitation patterns, temperature fluctuations, and extreme weather events. The increase in EVI values in recent years might indicate a positive response of vegetation to favourable climatic conditions or improved land management practices.

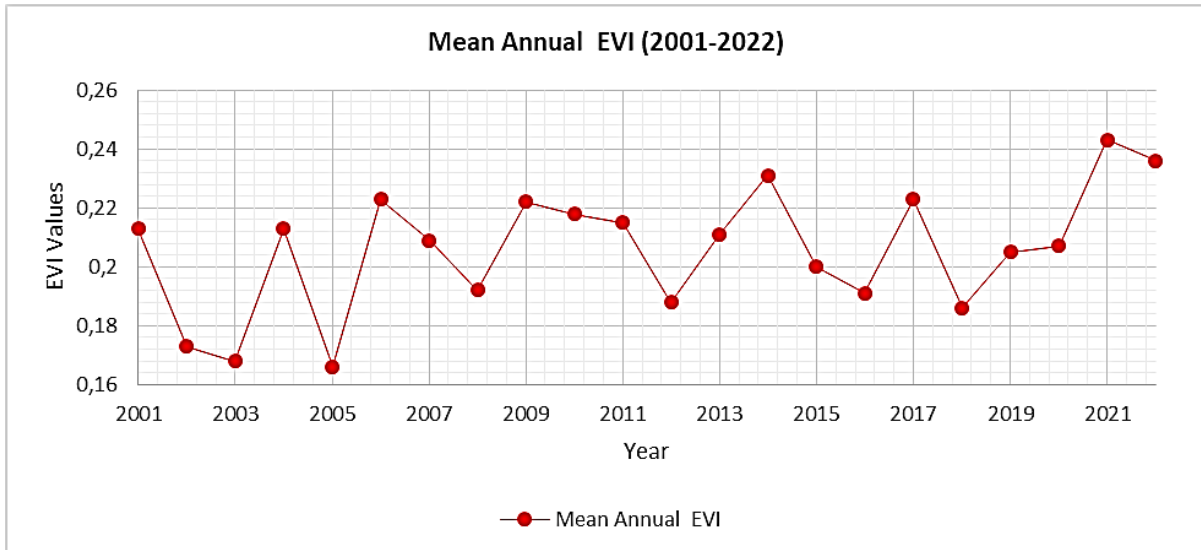


Figure 4.3: Scatter Plot showing time series of annual mean EVI from 2001 to 2022

Figure 4.4 displays monthly NDVI values for the years 2003, 2005, 2010, and 2022, offering a detailed view of seasonal and interannual vegetation trends. In all four years, NDVI values follow a similar seasonal pattern, peaking during the summer months (November to March) and declining during the winter (May to August). However, there are notable differences in NDVI values between these years. For instance, 2003 shows the lowest NDVI values throughout the year, indicating poor vegetation health, likely due to less favourable climatic conditions. In contrast, 2022 stands out with the highest NDVI values, particularly in January and March, which suggests a particularly strong growing season, likely to be influenced by the La Niña event that year.

The scatter plot further reveals that, while all four years experience a sharp decline in NDVI values from March to May, corresponding to the end of the rainy season, the overall vegetation health in 2022 remained higher than in other years, especially compared to 2003. This pattern highlights the influence of both seasonal rainfall and interannual climatic variability, such as ENSO, on vegetation dynamics in Limpopo Province. The 2022 data, with its significantly higher NDVI values, underscores the importance of wetter conditions brought by La Niña, in contrast to the drier years marked by El Niño, which result in vegetation stress and lower NDVI values.

To ensure these patterns weren't just random, a T-test was conducted for NDVI between the selected years. The results confirmed a significant difference with the p-value of 0,000701, with the trend showing p-values well below 0.05.

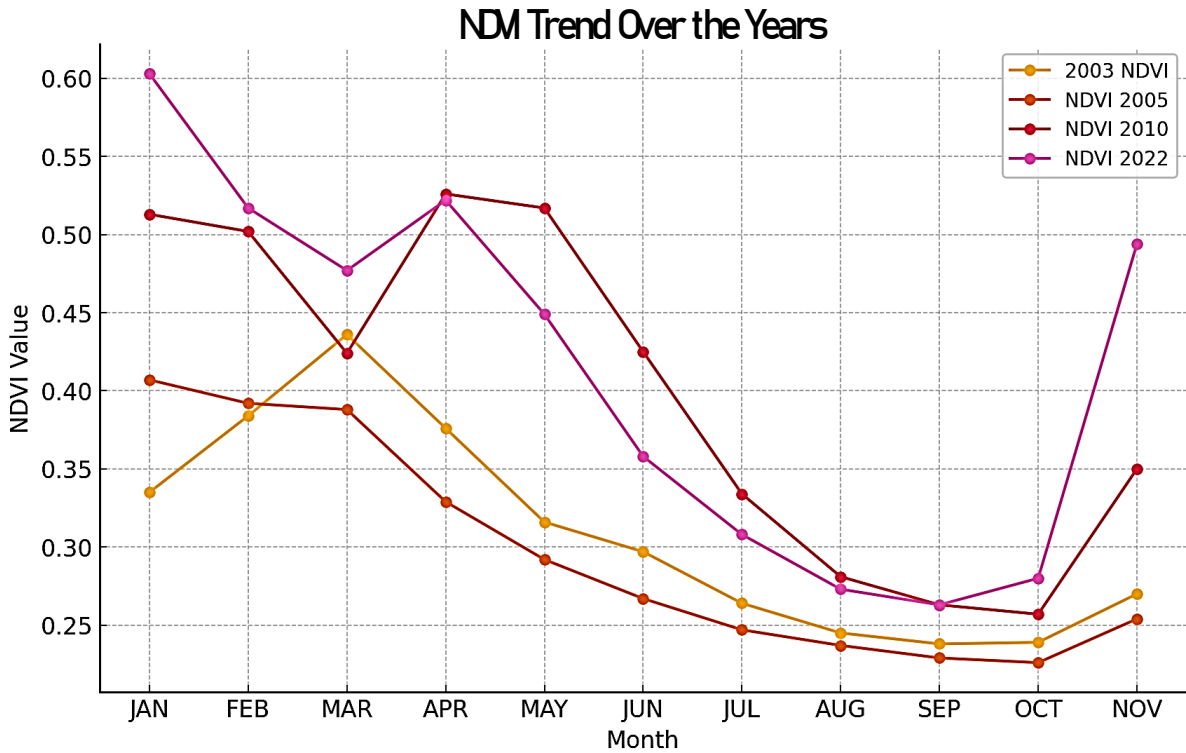


Figure 4.4: Monthly NDVI trends over the years 2003, 2005, 2010 and 2022.

Figure 4.5 displays the Enhanced Vegetation Index (EVI) trends over January to November for 2003, 2005, 2010, and 2022. The highest values are observed in 2022, particularly in early months (January to April) and November, indicating better vegetation conditions. The graph also shows moderate EVI values in 2003, with a peak in March and a gradual decline throughout the year. The lowest EVI values are seen in 2005, particularly in April through September, suggesting lower vegetation activity during these months.

Seasonal trends in vegetation activity include winter (June-August), with 2022 having the highest EVI values, indicating better vegetation growth. In spring, there is a noticeable peak in vegetation activity, particularly in 2003, 2010, and 2022. However, 2005 lags behind, indicating less favourable conditions. In summer, EVI values decline across all years, with the lowest points typically occurring in July or August. In autumn, EVI values begin to recover in October and November, particularly in 2010 and 2022. November shows a significant spike in EVI for all years, indicating a late-season recovery in vegetation.

The figure shows clear seasonal trends in vegetation activity, with early-year peaks, mid-year declines, and late-year recoveries. 2022 stands out with the highest EVI

values, indicating robust vegetation growth, while 2005 had the lowest, suggesting less favourable conditions. The consistent late-season recovery across all years suggests a typical pattern of vegetation regrowth before winter. To ensure these patterns weren't just random, a T-test was conducted for the EVI. The results confirmed a significant difference of 0.0049, with the trend showing p-values well below 0.05.

Table 2: T-test for NDVI and EVI for selected years (2003, 2005, 2010 and 2022)

Index	T-Statistic	P-Value	Significance
NDVI	-3,722874562	0,000701	Significant
EVI	-3,007879494	0,004901	Significant

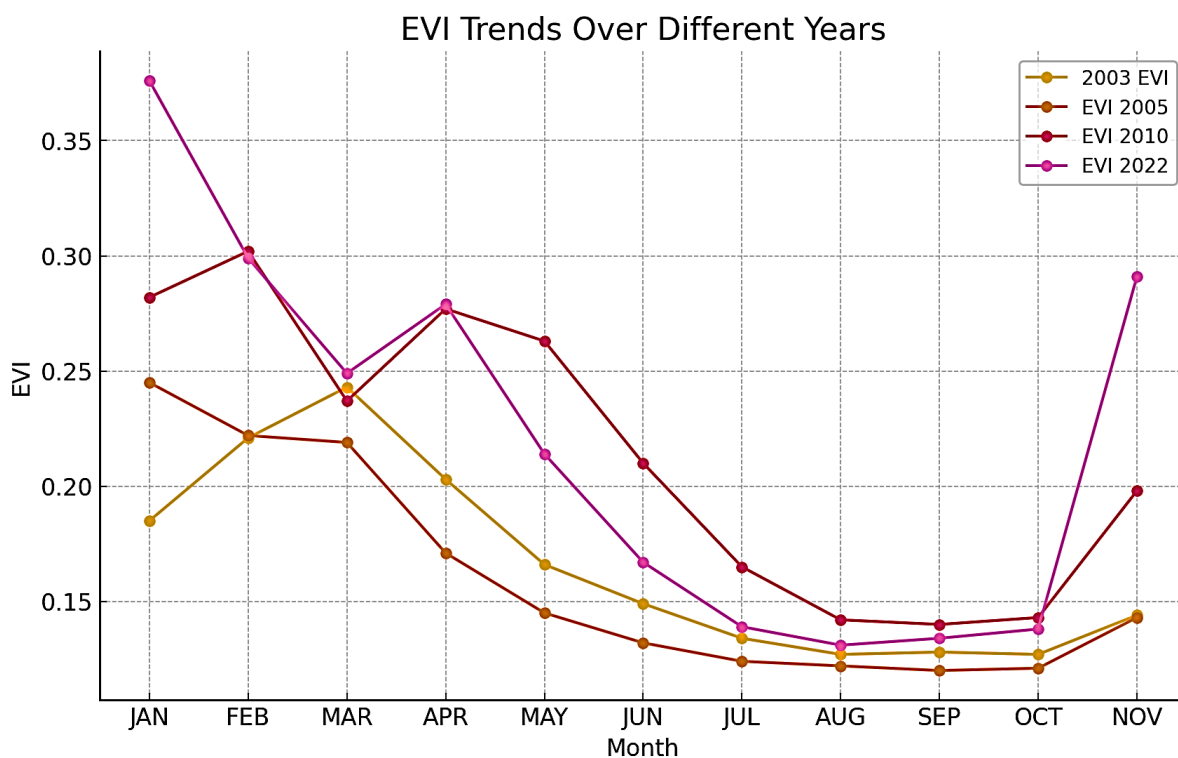


Figure 4.5: Monthly EVI trends over the years 2003, 2005, 2010 and 2022.

4.2.1.2. Spatial Analysis

Figure 4.6 depicts a time series of NDVI (Normalized Difference Vegetation Index) maps for Blouberg Local Municipality in Limpopo Province, South Africa, covering the years 2001 to 2022. NDVI is used to measure vegetation health, where values closer

to 1 (green) indicate dense, healthy vegetation, while values closer to 0 (yellow, orange, and red) represent sparse or stressed vegetation. Over the years, the region generally appears in shades of yellow, signifying moderate vegetation levels, with a prominent green belt that consistently shows higher NDVI values, indicating healthier or denser vegetation in that specific area.

Year-to-year fluctuations in vegetation health are visible across the time series. From 2001 to 2004, NDVI values were mostly moderate to low, reflecting potential dry conditions. From 2005 to 2012, the region appeared more stable, though still with predominantly moderate NDVI. However, between 2013 and 2016, there seems to be a decline in vegetation health, suggesting a period of drought or reduced rainfall. The years from 2017 to 2022 show some recovery, with an increase in vegetation density in certain areas, although the overall NDVI remains moderate.

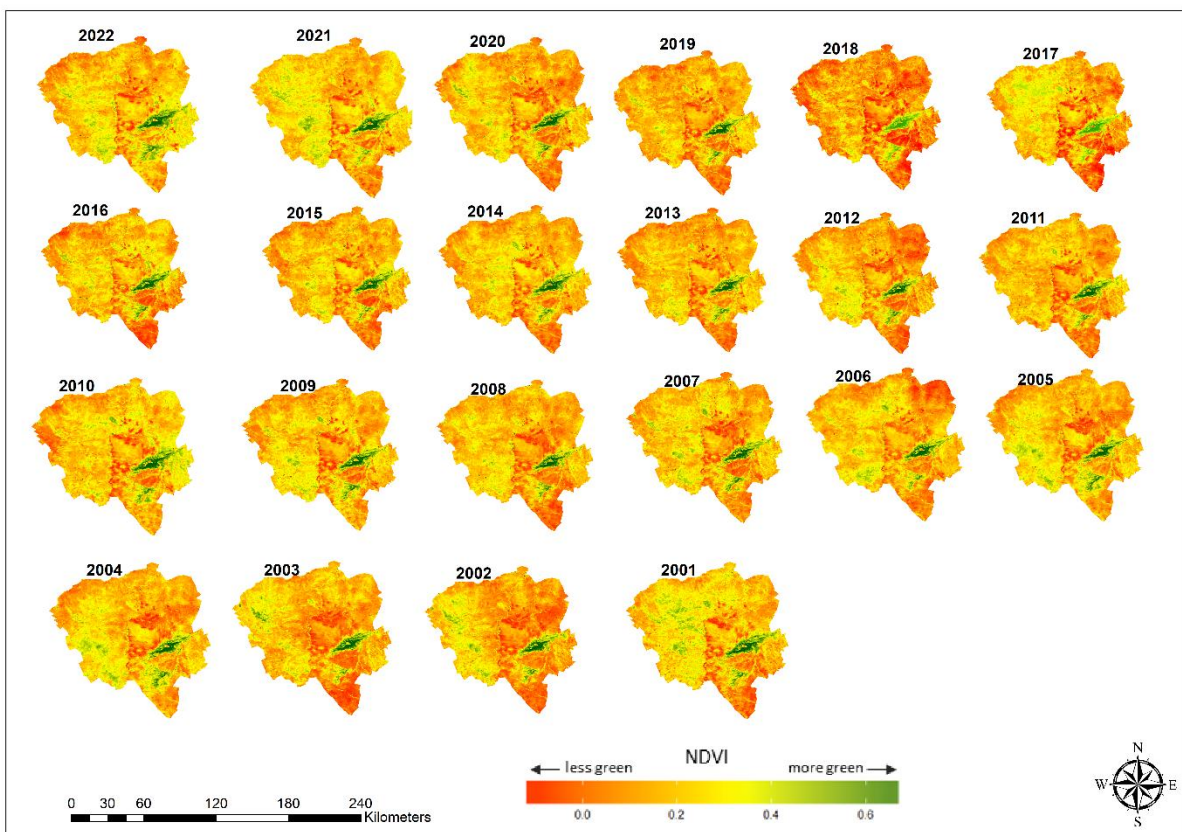


Figure 4.6: NDVI maps of Blouberg Municipality from 2001-2022 reflecting rangeland greenness.

4.2.2. Comparative analysis of satellite-derived vegetation indices to climate dynamics

Figure 4.7, generated from the Pearson correlation matrix, offers a detailed view of the relationships between Mean Rainfall, Mean Temperature, Mean NDVI, and Mean EVI. A key observation is the strong positive correlation between Mean NDVI and Mean EVI (0.94), indicating a close relationship between these two vegetation indices. Both NDVI and EVI, derived from similar spectral bands in remote sensing data, differ in their sensitivity to factors like soil background and atmospheric conditions.

It also reveals moderate negative correlations between Mean Temperature and the vegetation indices, with -0.55 for NDVI and -0.65 for EVI. These negative correlations suggest that higher temperatures may negatively impact vegetation health and greenness in the study area, potentially due to increased evapotranspiration, heat stress, and reduced soil moisture availability during warmer periods.

Interestingly, the correlations between Mean Rainfall and the vegetation indices are weak, with 0.069 for NDVI and 0.0024 for EVI. This near-zero correlation suggests that rainfall alone is not a strong predictor of vegetation health in the dataset. Various factors, such as the timing and distribution patterns of rainfall, soil moisture retention, or the potential influence of irrigation, might contribute to this weak relationship. Additionally, other environmental factors, such as soil type, topography, or human activities, could be playing a more significant role in determining vegetation health, thus diminishing the apparent influence of rainfall.

The heat map also shows a moderate negative correlation between Mean Rainfall and Mean Temperature (-0.26), indicating that higher temperatures tend to coincide with lower rainfall in the study area.

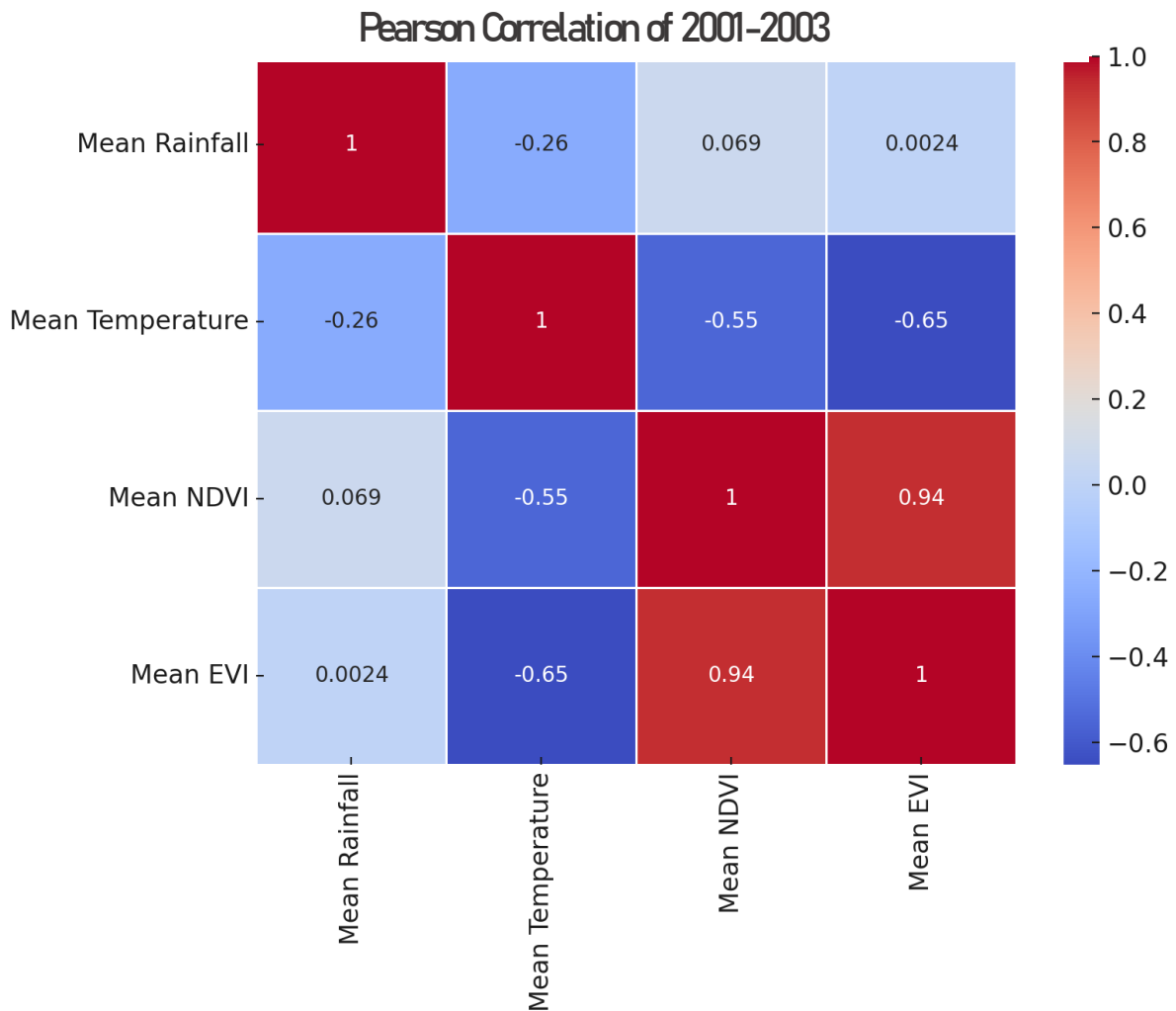


Figure 4.7: Heat map of Pearson correlation coefficients for NDVI, EVI, Temperature and Precipitation from 2001 to 2022.

In Figure 4.8 analysis of the relationship between vegetation indices (EVI and NDVI) and climatic variables (rainfall and temperature) reveals varying degrees of correlation. In Figure 4.8 (a), the correlation between Mean Annual EVI and Mean Annual Rainfall is extremely low, with an almost negligible correlation coefficient, indicating no significant linear relationship between these two variables. The trend line in the graph is nearly flat, suggesting that changes in rainfall do not have a noticeable impact on the EVI values.

In contrast, Figure 4.8 (b) shows the relationship between Mean Annual EVI and Mean Annual Temperature shows a moderate negative correlation, with an R^2 value of approximately 0.4246. This suggests that as temperature increases, the EVI tends to decrease, implying that higher temperatures may be associated with reduced

vegetation vigour. The negative slope of the regression line further supports this observation.

Similarly, the analysis in Figure 4.8 (c) of Mean Annual NDVI versus Mean Annual Rainfall also shows a very low correlation coefficient ($R^2 = 0.0047$), indicating a weak or negligible relationship between NDVI and rainfall. The nearly flat regression line in this case suggests that the annual rainfall has little impact on the NDVI values.

Finally, the relationship between Mean Annual NDVI and Mean Annual Temperature in Figure 4.8 (d) also exhibits a weak negative correlation, similar to the EVI-Temperature relationship. The negative slope of the regression line indicates that higher temperatures tend to reduce NDVI values, although the correlation is not very strong.

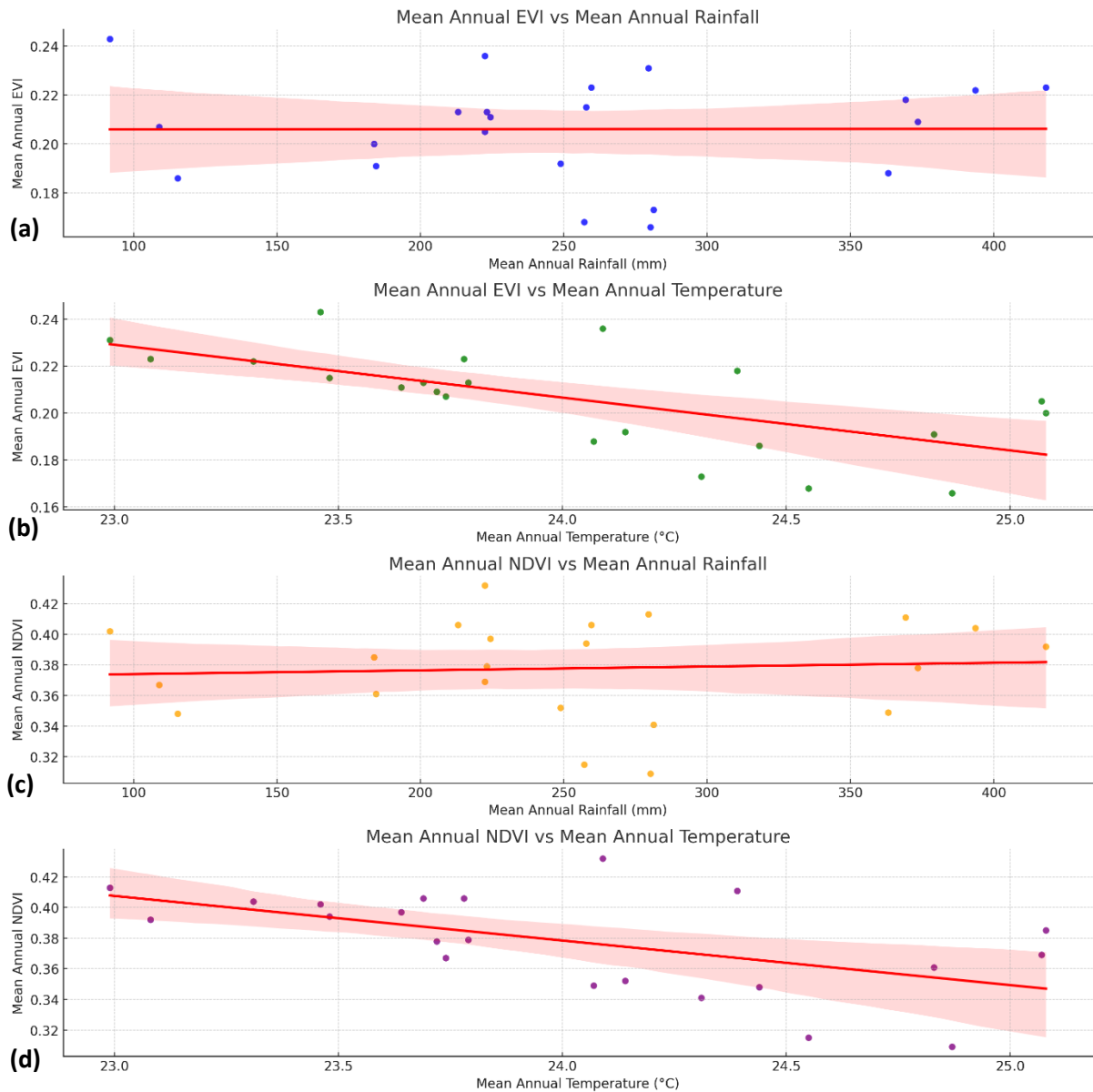


Figure 4.8: Correlation between mean annual vegetation indices (NDVI and EVI) with mean annual rainfall (mm) and mean annual temperature (°C) from 2001 to 2022.

Figure 4.9 reveals that vegetation conditions are heavily influenced by rainfall, with high correlations between NDVI and EVI with Mean Rainfall. Changes in precipitation patterns, such as those due to climate change, could significantly impact vegetation greenness and health. Temperature has a moderate influence on vegetation, but its impact is not as strong as rainfall. Temperature might indirectly influence vegetation through evaporation rates, soil moisture, or phenology. The almost perfect correlation between NDVI and EVI suggests that either index can be used to monitor vegetation, but using both might not provide significantly different information. EVI's slight sensitivity to structural and health aspects of vegetation might be advantageous in

specific contexts. The study highlights the complex interplay between climate variables and vegetation, with water availability emerging as a dominant driver.

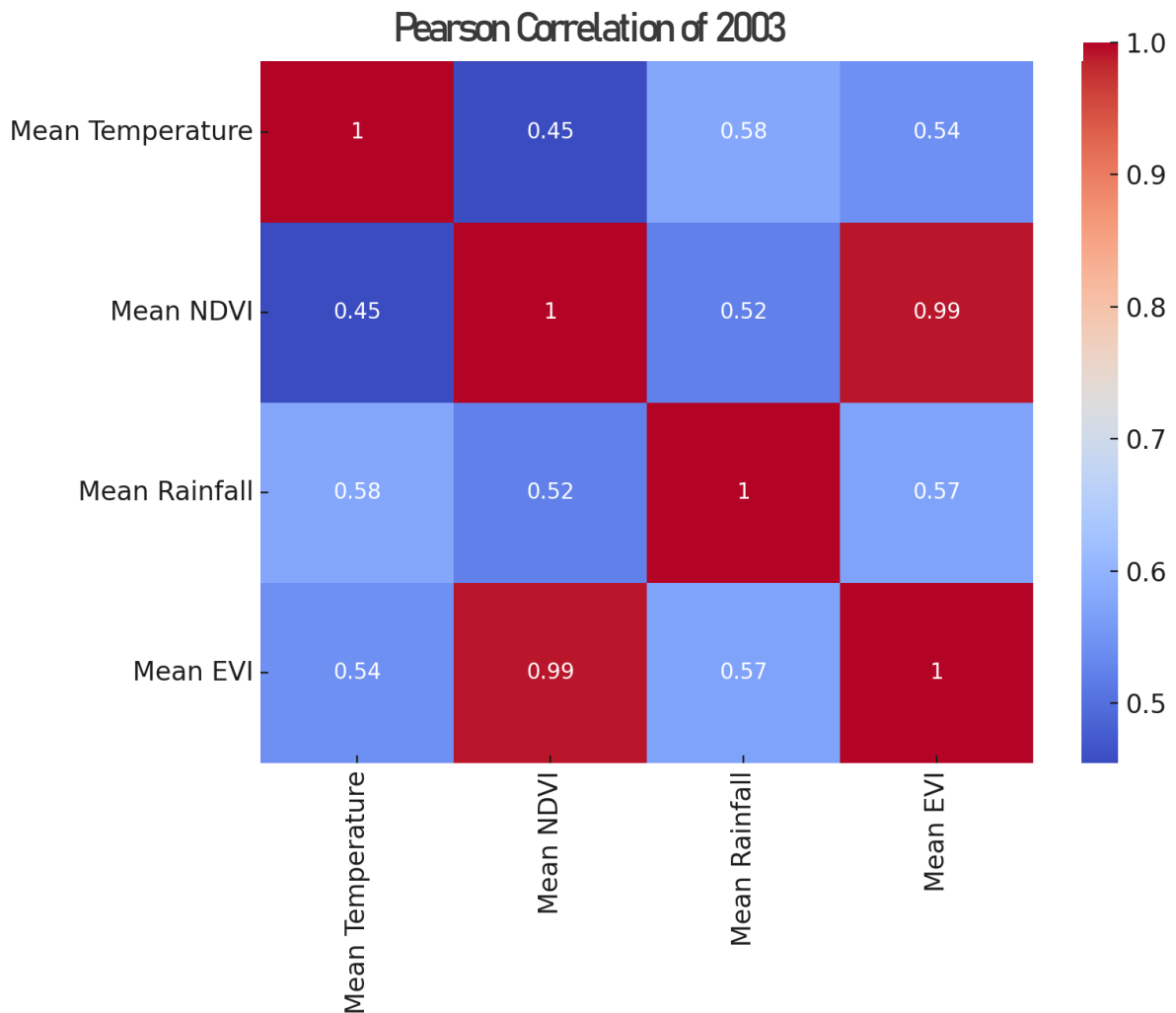


Figure 4.9: Heat map of Pearson correlation coefficients for NDVI, EVI, Temperature and Precipitation for 2003.

Figure 4.10 reveals a moderate positive correlation between mean temperature and NDVI, suggesting that temperature is an important factor influencing vegetation growth. The correlation between mean temperature and EVI (vegetation health) is slightly higher, suggesting that EVI is more influenced by temperature. Rainfall has a significant impact on NDVI, highlighting the importance of water availability for maintaining or increasing vegetation greenness. The correlation between NDVI and EVI is very high, almost perfect, at 0.98, suggesting that changes in NDVI are almost entirely mirrored by changes in EVI. The moderate positive correlation between mean temperature and rainfall suggests that warmer temperatures are somewhat associated

with increased rainfall, but this relationship is not strong, suggesting other climatic or environmental factors may play a role.

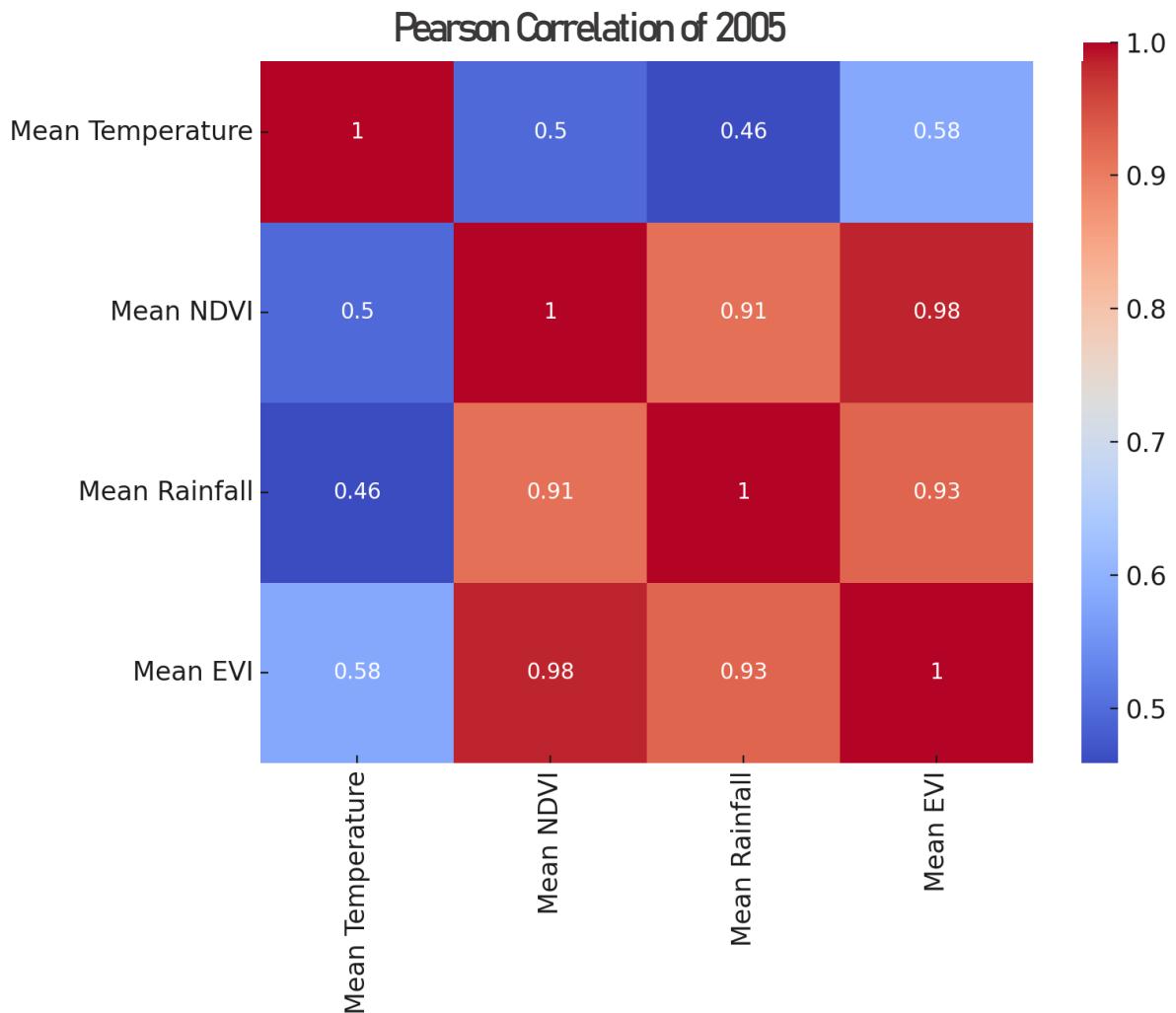


Figure 4.10: Heat map of Pearson correlation coefficients for NDVI, EVI, Temperature and Precipitation for 2005.

Figure 4.11 examines the relationship between temperature, rainfall, and vegetation greenness in a dataset. The correlation between mean temperature and NDVI is weak, suggesting that temperature has little direct influence on vegetation greenness. The correlation between mean temperature and EVI is weak but stronger, suggesting that temperature has a slightly more significant impact on vegetation health or density. Rainfall plays a more significant role in influencing vegetation greenness compared to temperature. The correlation between mean rainfall and EVI is slightly higher, indicating that rainfall has a more pronounced effect on vegetation health or structure. The strong correlation between NDVI and EVI confirms that they are closely related

indices, capturing similar aspects of vegetation conditions. The moderate and positive correlation between mean temperature and rainfall suggests that higher temperatures are somewhat associated with increased rainfall, possibly due to increased evaporation and condensation.

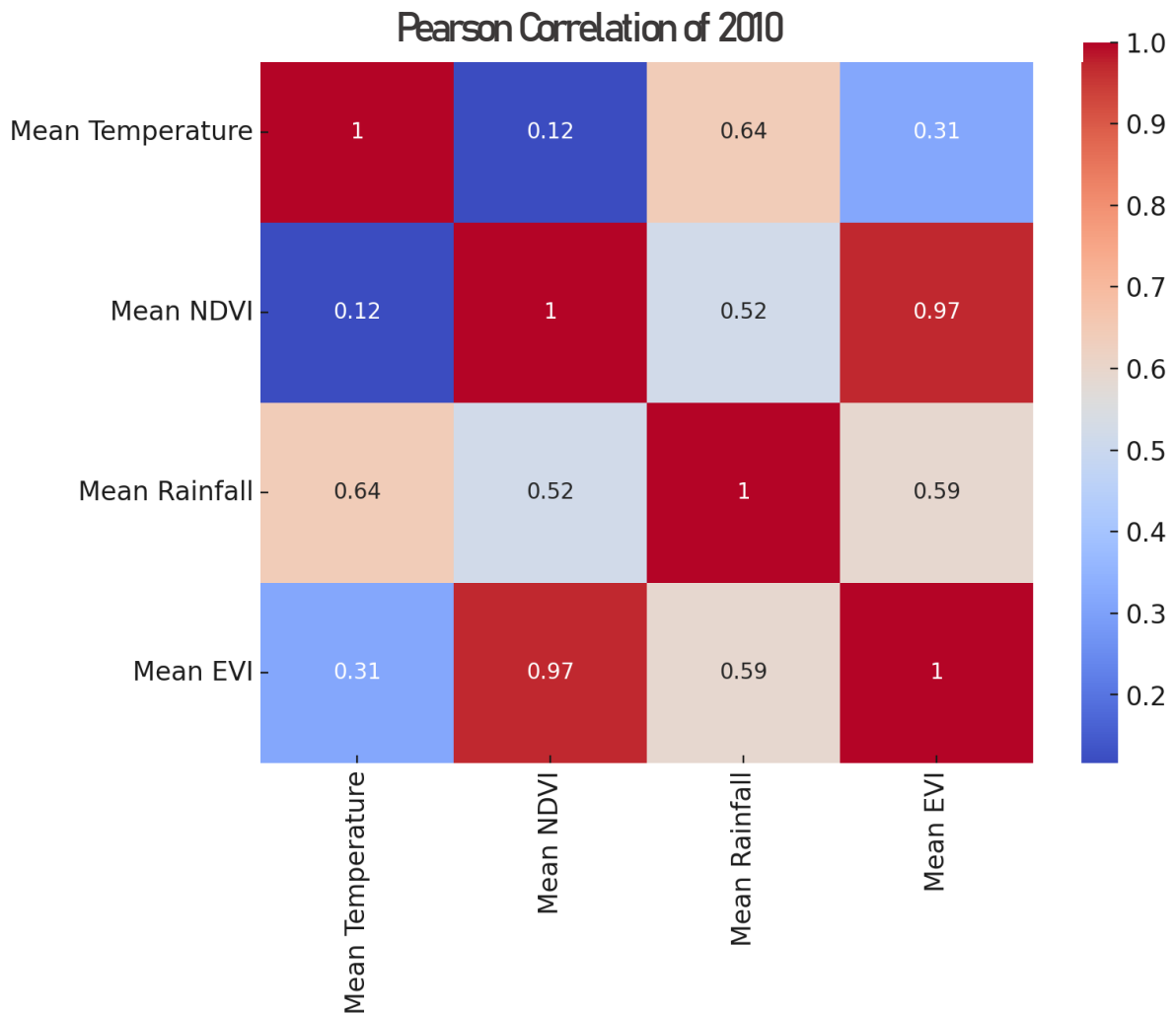


Figure 4.11: Heat map of Pearson correlation coefficients for NDVI, EVI, Temperature and Precipitation for 2010.

Figure 4.12 reveals a strong positive correlation between the mean NDVI and Mean EVI, which measure vegetation greenness. This is expected due to their close relationship with satellite imagery. As rainfall increases, NDVI tends to increase, aligning with the understanding that vegetation greenness typically increases with more rainfall due to better water availability for plant growth. EVI, like NDVI, also increases with increased vegetation health and density, which can be influenced by rainfall. The relationship between temperature and NDVI is weaker, suggesting that

temperature has some impact on vegetation greenness but is not as strong as the influence of rainfall. The correlation between temperature and EVI is slightly stronger but still moderate, indicating that temperature plays a role in affecting vegetation health, but is not the dominant factor compared to rainfall.

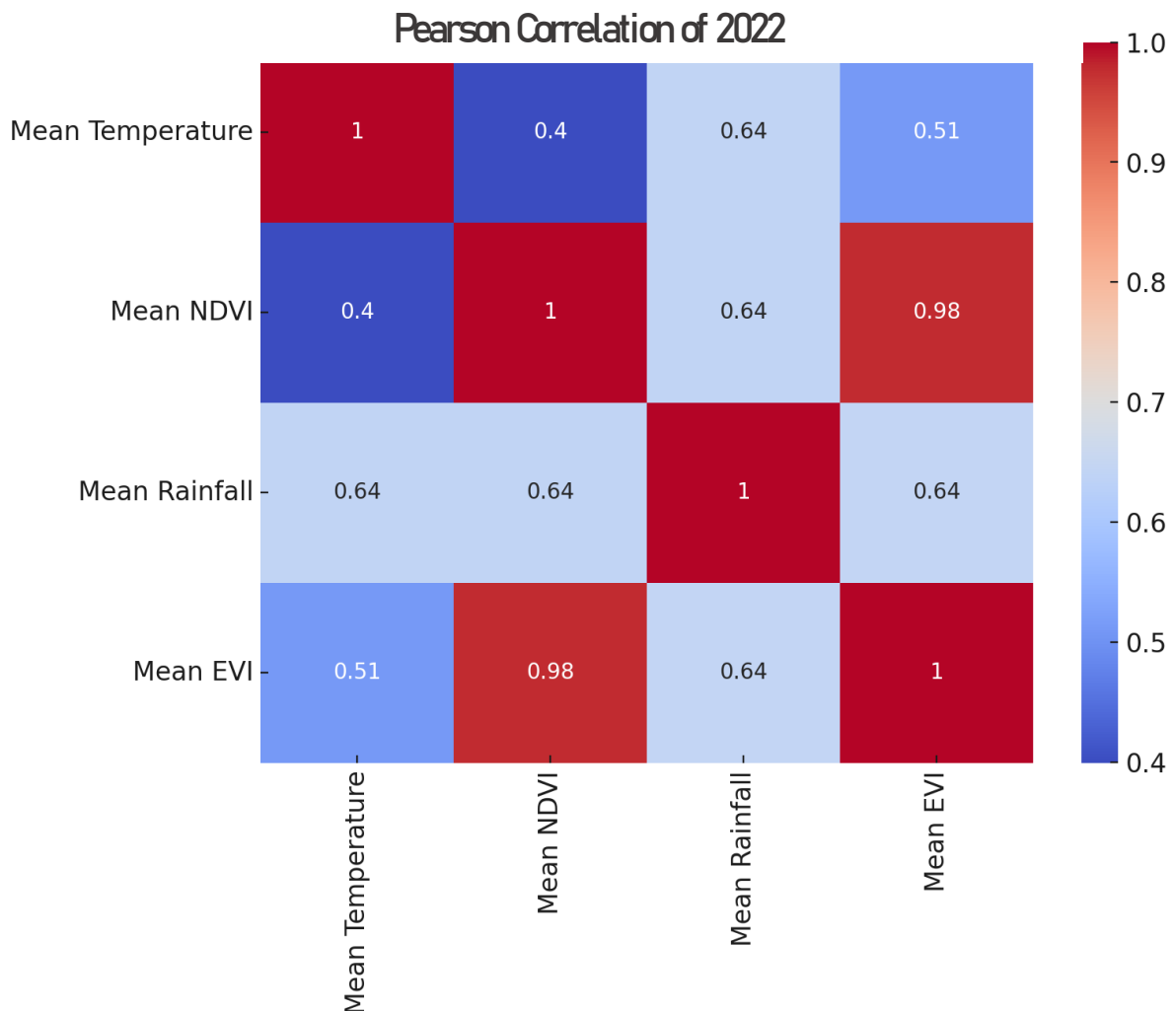


Figure 4.12: Heat map of Pearson correlation coefficients for NDVI, EVI, Temperature and Precipitation for 2022.

4.2.3. Areas vulnerable to degradation

The map of areas at risk of degradation in Blouberg Local Municipality provides a visual overview of the severity of degradation across the landscape. The colour gradient, ranging from green (less vulnerable) to red (high vulnerable), effectively communicates the severity of degradation. However, a critical analysis reveals several important considerations for land management and policy planning. The spatial distribution of degradation risk is uneven, with high-risk areas predominantly located

in the northern and eastern regions of Blouberg. The red and orange zones, indicative of high vulnerability, may correspond to areas with steeper slopes or fragile soils prone to erosion, and may also experience higher pressure from human activities. The green areas, indicating lower vulnerability, are concentrated in the central and southern parts of the municipality.

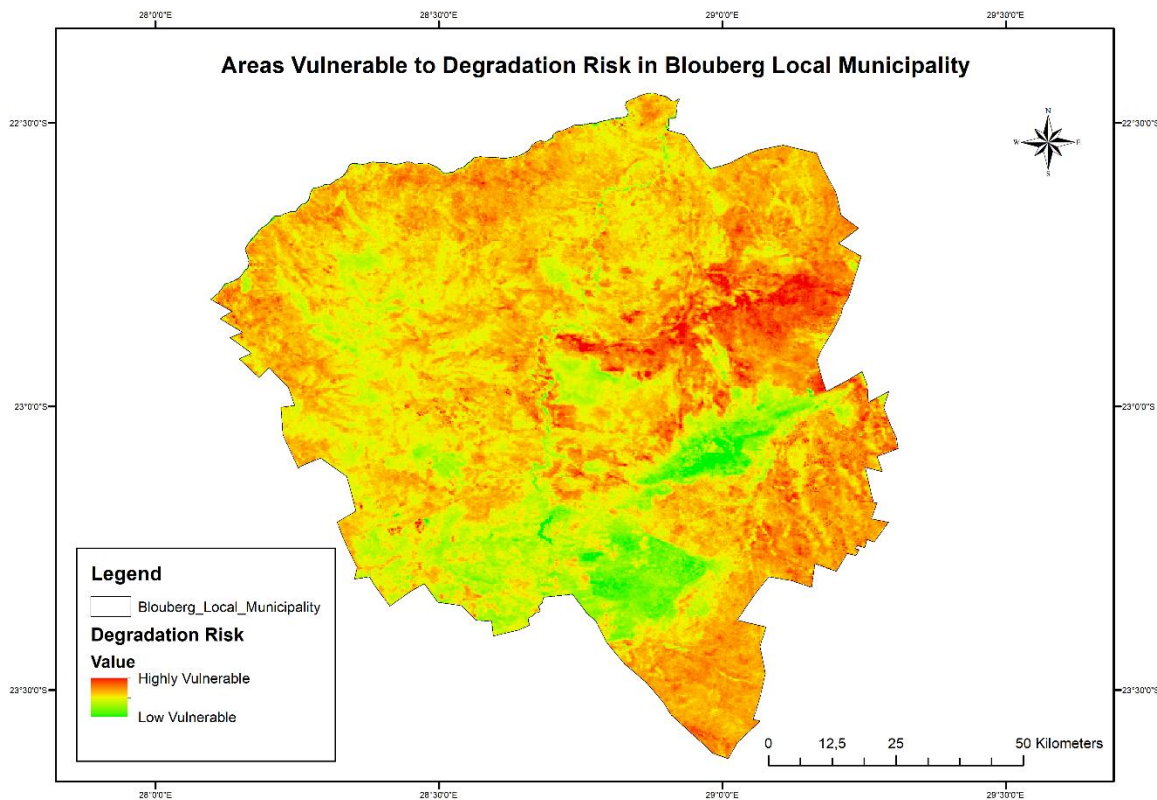


Figure 4.13: NDVI Trend from 2002 to 2022 in Blouberg Local Municipality highlighting areas vulnerable to degradation.

4.3 Discussion

Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) are crucial tools in assessing the health, productivity, and dynamics of vegetation across temporal and spatial scales. These indices are widely used to monitor vegetation cover, assess ecosystem responses to environmental stress, and track land cover changes over time. Both NDVI and EVI are derived from satellite data, offering a long-term perspective on vegetation trends. NDVI, which measures the difference between near-infrared (vegetation reflects strongly) and red light (vegetation absorbs strongly), serves as a general indicator of

vegetation health and biomass. EVI, on the other hand, incorporates additional adjustments for atmospheric conditions and canopy structure, making it more responsive to areas with dense vegetation and less sensitive to soil background signals (Zeng *et al.*, 2022).

NDVI values range from -1.0 to 1.0. Values less than zero typically represent non-vegetated surfaces, such as water bodies, barren land, or snow and ice. These surfaces reflect more in the red spectrum and absorb more in the NIR spectrum (Tucker, 1979). Values from 0 to 0.2 indicate areas with little to no vegetation, such as bare soil, rock, or sparse vegetation. The low reflectance in NIR and higher reflectance in the red spectrum result in lower NDVI values (Pettorelli *et al.*, 2005). Values from 0.2 to 0.5 generally correspond to areas with shrubs, grasslands, or crops, indicating some vegetation presence but not very dense (Pettorelli *et al.*, 2005). Higher NDVI values represent areas with dense vegetation, such as forests or well-managed cropland, reflecting healthy, green vegetation with high photosynthetic activity (Mathur & Pandey, 2016).

Vegetation Indices (NDVI & EVI) provided illustrate time series over the period from 2001 to 2022. Findings suggest that annual mean EVI values fluctuate between approximately 0.16 and 0.24, while the annual mean NDVI values range from about 0.30 to 0.44. Both Vegetation Indices show clear inter-annual variability, reflecting changes in vegetation conditions over the 21 years.

The discrepancy between EVI and NDVI values, where EVI consistently reports lower values compared to NDVI, can be attributed to the structural differences between the two indices. While both are used to assess vegetation health, NDVI is more sensitive to the difference between red and near-infrared light, making it effective in detecting changes in vegetation biomass. However, NDVI has certain limitations in densely vegetated regions or where atmospheric effects and soil background noise may interfere with its accuracy (Xu *et al.*, 2023; Huete *et al.*, 2002).

In contrast, EVI is designed to minimize atmospheric distortions, such as those caused by aerosols, and reduce the influence of soil background reflectance. EVI achieves this by using the blue spectral band in its formulation and incorporating a canopy background adjustment factor, which makes it less responsive to variations in soil and

more accurate in densely vegetated areas. As a result, EVI generally provides lower values compared to NDVI, particularly in areas where vegetation cover is dense and biomass levels are high. This is evident in the time-series graphs, where NDVI shows higher peaks than EVI, especially in years with better vegetation conditions.

Moreover, EVI is less prone to saturation in regions with dense vegetation. NDVI tends to saturate in such areas, particularly when leaf area index (LAI) exceeds a certain threshold, leading to an overestimation of vegetation health. EVI, by contrast, remains more sensitive in these situations, offering a more nuanced perspective of canopy conditions in regions with high biomass (Zhu *et al.*, 2016). This explains why, in densely vegetated areas such as forest regions or well-managed rangelands, NDVI values might appear higher while EVI values remain lower and more stable.

Results on the EVI graph reveal noticeable fluctuations without a clear increasing or decreasing trend, though a general recovery can be observed following specific dips, indicating resilience in vegetation conditions. Similarly, the NDVI graph follows a comparable pattern, with a slight upward trend particularly evident from 2018 onwards, suggesting an overall improvement in vegetation health. The year-to-year variations observed in both indices are likely influenced by a combination of factors, including climatic conditions such as rainfall, temperature fluctuations, and drought periods, as well as anthropogenic influences like land use changes and deforestation. Specific years, such as 2002, 2003, and 2005, show marked decreases in both EVI and NDVI, possibly linked to significant environmental stressors during those periods.

The trends observed in these indices suggest that while there are periods of stress or decline, overall vegetation health appears to recover over time, indicating stable ecological processes or effective management practices in the study area. The increasing trend in NDVI after 2018 could signal a positive shift in environmental conditions, potentially due to increased rainfall, reforestation efforts, or natural regrowth following disturbances.

The Mann-Kendall significance test was performed to determine the presence of a long-term trend in NDVI and EVI values from 2002 to 2022. The results (Table 1) indicate that there is no statistically significant trend in NDVI (p -value = 0.204294) or EVI (p -value = 0.175552), suggesting that vegetation conditions have remained

relatively stable over the study period. The S-statistics (46 for NDVI and 49 for EVI) and corresponding Z-scores further confirm the absence of significant upward or downward trends.

While the lack of a significant long-term trend suggests relative stability, the inter-annual fluctuations observed in the time-series analysis indicate that vegetation dynamics are influenced by short-term climatic variations such as rainfall and temperature anomalies. These results align with previous studies indicating that semi-arid rangeland ecosystems exhibit high inter-annual variability rather than sustained trends in vegetation cover (Mishra & Kar, 2021).

The T-test results (Table 2) comparing vegetation indices for selected years (2003, 2005, 2010, and 2022) indicate significant differences between these years. NDVI and EVI show statistically significant variations, with t-statistics of -3.72 ($p = 0.000701$) for NDVI and -3.01 ($p = 0.004901$) for EVI. These findings highlight that vegetation conditions differ significantly between dry years (2003 and 2005) and wet years (2010 and 2022). This pattern supports the hypothesis that rainfall variability plays a dominant role in determining vegetation health in semi-arid regions, as confirmed by recent studies emphasizing the strong influence of precipitation on vegetation indices (Zhang *et al.*, 2022).

The variability observed in both EVI and NDVI is likely driven by a combination of climatic factors, such as inter-annual variability in rainfall, drought events, or temperature anomalies, which directly impact vegetation growth and greenness. Additionally, human activities, including deforestation, agricultural expansion, urbanization, and conservation efforts, may also contribute to the observed trends. These activities likely vary in their impact across different years, leading to the fluctuations seen in the graphs.

These temporal patterns in vegetation indices align with the spatial distribution maps, which provide a visual representation of vegetation cover across Blouberg Local Municipality over the same period. The NDVI spatial distribution maps illustrate the geographic variability in vegetation health, with certain areas consistently displaying higher or lower vegetation cover. The central and south-eastern parts of Limpopo show higher NDVI values, indicating denser vegetation, likely due to favourable rainfall

patterns and possibly better land management practices in these areas. In contrast, the northern and western regions exhibit lower NDVI values, reflecting sparser vegetation, which could be attributed to a combination of lower rainfall, land degradation, or intensive land use practices such as overgrazing or agriculture.

Existing studies support the connection between rainfall variability and spatial vegetation patterns. For example, Fensholt and Proud (2012) emphasize that in semi-arid regions, rainfall is the primary driver of vegetation greenness, and the spatial distribution of vegetation indices often reflects underlying patterns of water availability. This study showed that areas receiving more consistent or higher amounts of rainfall tend to support more robust vegetation, as evidenced by higher NDVI values. Conversely, areas prone to water stress, particularly those in the north and west, exhibit lower NDVI values, suggesting that water availability is a limiting factor for vegetation productivity (Mishra & Kar, 2021).

The consistently green belt visible in the spatial NDVI map likely represents a region with stable and dense vegetation throughout the year. This could be attributed to either a natural feature, such as a forested area, riparian zone, or protected parkland, or it could result from human land management practices, such as irrigated agriculture or a sustainable grazing system.

If the green belt corresponds to a natural feature, it could be a forest, a riparian zone (area adjacent to rivers or wetlands), or an area with naturally high water availability, such as a mountainous region that receives more rainfall than the surrounding areas. Riparian zones tend to remain green even during dry periods due to access to groundwater sources. Forests and other well-established ecosystems, especially if protected from human interference, can maintain higher NDVI values year-round due to their perennial nature (Fensholt *et al.*, 2013).

Alternatively, this green belt could be the result of human intervention, such as irrigation or protected land management. In regions where water resources are controlled or irrigation systems are used, crops or pastures can remain green and productive despite surrounding areas experiencing water stress. In some cases, this might represent agricultural lands or conservancies where controlled grazing or agroforestry practices help maintain vegetation cover (Wessels *et al.*, 2007).

The fact that this green belt remains consistently visible across multiple years suggests a resilience to environmental fluctuations such as droughts or dry periods. This might be due to a combination of natural resilience (e.g., proximity to water bodies, higher elevation, or dense canopy structure) and effective land management practices that mitigate the effects of external stressors, such as drought or land degradation, on vegetation health. The green belt might also provide ecosystem services, such as acting as a carbon sink, which contributes to the stability of vegetation in the region.

Moreover, the spatial variability observed in the maps also points to the influence of other environmental and anthropogenic factors. For instance, land use changes such as agricultural expansion and deforestation can significantly impact vegetation cover. Studies have shown that human activities, including farming, grazing, and urbanization, can lead to soil degradation and reduced vegetation health, as indicated by persistently low NDVI values in some areas (Engelbrecht *et al.*, 2015). Areas with intensive agricultural practices may exhibit lower NDVI values due to soil degradation, while areas with better land management may show higher values due to the preservation of natural vegetation.

In summary, the NDVI and EVI time series graphs provide a quantitative overview of vegetation changes over time, while the spatial distribution maps offer a detailed view of how these changes are manifested across the landscape. Together, these tools reveal the complex interplay between environmental factors such as rainfall, temperature, and human activities in shaping the vegetation dynamics of Blouberg. The use of vegetation indices in combination with spatial analysis is critical for understanding long-term trends in vegetation health, informing sustainable land management practices, and adapting to the impacts of climate change in semi-arid regions.

To understand the variability observed in both Vegetation Indices (NDVI & EVI), climatic factors including inter-annual rainfall and temperature have been used. Using both long-term trend and intra-seasonal trend allows for a comprehensive understanding of vegetation-climate interactions. Long-term provides a broad overview of the trend and relationship, while intra-seasonal dynamics offer insights into specific events and their impacts on vegetation.

Results from the long-term trend annual mean showed a weak correlation between EVI and rainfall. This suggests that the vegetation vigor in the study area may not be strongly influenced by the amount of annual rainfall. This could be due to factors such as soil moisture retention, vegetation type, and other environmental variables that may mitigate the impact of rainfall variability. Additionally, it is possible that the study area receives adequate rainfall for the existing vegetation types, leading to a saturation effect where additional rainfall does not significantly enhance vegetation greenness. Similarly, the weak correlation between NDVI and rainfall reinforces the idea that annual rainfall may not be the primary driver of vegetation greenness in the region. Other factors, such as the timing and distribution of rainfall events, or possibly irrigation practices, may play a more critical role than the total annual rainfall.

The results have indicated a moderate negative correlation between EVI and temperature indicates that higher temperatures may stress the vegetation, resulting in reduced vigor. This could be due to increased evapotranspiration rates, lower soil moisture availability, or direct heat stress on plant physiology. The findings suggest that temperature could be a limiting factor for vegetation health in this region, particularly in years with higher-than-average temperatures. The weaker correlation between NDVI and temperature compared to EVI and temperature might indicate that NDVI, which primarily measures greenness, may not capture vegetation stress as effectively as EVI, which also accounts for the structural condition of vegetation.

A key observation is the strong positive correlation between Mean NDVI and Mean EVI at 94%, indicating a close relationship between these two vegetation indices. Both NDVI and EVI, derived from similar spectral bands in remote sensing data, differ in their sensitivity to factors like soil background and atmospheric conditions. The strong correlation suggests that in this dataset, both indices respond similarly to changes in vegetation health and coverage, implying that either index could be used reliably for monitoring vegetation. However, EVI might be preferable in environments where soil background and atmospheric conditions are significant concerns due to its ability to minimize noise.

Higher temperatures can lead to increased plant respiration rates, water loss, and overall stress, resulting in lower EVI values, which reflect less healthy or less dense vegetation. Elevated temperatures can reduce soil moisture through higher

evapotranspiration, leading to water stress for vegetation. This is particularly critical in semi-arid regions like Blouberg Municipality, where water availability is a major limiting factor for plant growth. Increased temperatures can alter the timing of vegetative growth phases, potentially leading to a mismatch between the availability of water and nutrients and the periods of peak plant demand.

Conversely, the 2003 correlations show moderate positive correlations across most variables, suggesting that temperature, rainfall, and vegetation indices are positively linked and may work together to influence ecological outcomes.

The correlation reveals that vegetation conditions are heavily influenced by rainfall, with high correlations between NDVI and EVI with Mean Rainfall. Changes in precipitation patterns, such as those due to climate change, could significantly impact vegetation greenness and health. Temperature has a moderate influence on vegetation, but its impact is not as strong as rainfall. Temperature might indirectly influence vegetation through evaporation rates, soil moisture, or phenology. EVI's slight sensitivity to structural and health aspects of vegetation might be advantageous in specific contexts.

The correlation reveals that temperature has a limited influence on vegetation, with weak correlations between temperature and vegetation indices (NDVI and EVI). However, a stronger correlation between temperature and rainfall suggests that indirect effects of temperature on vegetation may have been mediated through its impact on precipitation. Rainfall is considered a more crucial factor for vegetation health and greenness, as indicated by moderate correlations with both NDVI and EVI. Correlation heat maps of intra-seasonal dynamics suggest that rainfall is the primary factor influencing vegetation conditions, while temperature plays a more indirect role through its effects on rainfall. The moderate correlation between temperature and rainfall suggests a possible climatic linkage, where warmer temperatures are associated with higher rainfall, which supports vegetation growth.

The overall interpretation is that vegetation indices (NDVI and EVI) are more strongly correlated with rainfall than with temperature, highlighting the importance of water availability for vegetation health in the study area. The weaker correlation with temperature suggests that temperature alone is not the most significant driver of

vegetation changes, at least not within the temperature range observed in the dataset. Given the area's average annual precipitation of 410 mm, along with the seasonal drought and orographic rainfall patterns (Constance, 2014), it is expected that the vegetation indices will show a stronger correlation with rainfall than with temperature.

The identification of degradation-prone areas is crucial for rangeland management in Blouberg Municipality. By focusing on the regions highlighted in red, local authorities and land managers can implement targeted strategies to mitigate further degradation. This may include practices such as controlled grazing, reforestation, soil conservation techniques, and sustainable land use planning. Additionally, the map can be used to monitor the effectiveness of these interventions over time by comparing future NDVI trends.

The degradation risk map in Blouberg Local Municipality highlights the significant role of land use in shaping vulnerability. High-risk zones are more likely to appear due to intensive agricultural activities and a lack of sustainable practices, while areas managed sustainably through controlled grazing, conservation practices, or afforestation show lower vulnerability. This spatial relationship highlights the need for targeted land management strategies considering both environmental and human factors.

Identifying high-risk areas has implications for land management and policy planning. Prioritizing these regions for intervention can help mitigate the risk, while policies that promote land stewardship and provide incentives for sustainable land use can reduce vulnerability. Green areas, although currently at low risk, should not be neglected. Continuous monitoring and promoting best practices can maintain their resilience and prevent future degradation.

The map's effectiveness could be enhanced by addressing certain limitations, such as the scale and resolution appropriate for municipal-level planning, finer resolution data for localized interventions, and the inclusion of contextual information like roads, rivers, and administrative boundaries. Integrating this map with socioeconomic data, such as population density, income levels, and land tenure systems, could provide a more nuanced understanding of the degradation impact on local communities and inform more equitable policy responses.

The degradation risk map in Blouberg Local Municipality serves as a critical tool for identifying vulnerable areas and guiding land management decisions. However, for more effective planning and intervention, the map could be enhanced with finer resolution, additional contextual layers, and integration with socioeconomic and temporal data.

One of the significant applications of NDVI time series is in monitoring vegetation responses to climatic variations. For instance, studies have shown that NDVI is closely linked to precipitation patterns, particularly in arid and semi-arid regions where water availability is a critical determinant of vegetation growth (Wang *et al.*, 2003). This relationship is evident in regions such as the Sahel, where NDVI has been used to monitor vegetation recovery following periods of drought (Anyamba & Tucker, 2005). These studies have demonstrated that NDVI can effectively track changes in vegetation cover in response to variations in rainfall, providing valuable information for managing water resources and assessing the impacts of climate change.

Furthermore, the NDVI time series has been applied to understand the impact of temperature on vegetation dynamics. In temperate and boreal regions, NDVI has been used to assess the effects of rising temperatures on the growing season length and the timing of vegetation phenology (Myneni *et al.*, 1997). These studies reveal that temperature increases can lead to earlier onset of spring greening and a longer growing season, as reflected by higher NDVI values during the growing period. However, in regions where temperature increases are coupled with reduced precipitation, NDVI time series data have shown a decline in vegetation health, indicating stress due to heat and water scarcity (Zhou *et al.*, 2001).

The use of NDVI time series has also been instrumental in detecting land cover changes, particularly in the context of land degradation and deforestation. For example, Tucker *et al.* (2005) employed NDVI data to analyse deforestation trends in the Amazon, revealing significant losses in forest cover over time. Similarly, studies in dry land regions have used NDVI to monitor desertification processes, where a consistent decline in NDVI values over time indicates a loss of vegetation cover and soil degradation (Prince *et al.*, 1998). These findings underscore the utility of NDVI as a robust tool for assessing vegetation changes across different biomes and climatic conditions.

4.4. Summary

The study examined the dynamics of rangelands (productivity and sustainability) in Blouberg Municipality within the context of the changing climate using Geographic Information System and Remote Sensing applications.

The analysis examined the inter-annual variability of vegetation conditions in the study area, assessed using MODIS-derived Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). These vegetation indices are critical in remote sensing for evaluating vegetation health, coverage, and dynamics over time.

The analysis of NDVI and EVI values from 2001 to 2022 shows that annual mean EVI fluctuated between approximately 0.16 and 0.24, while NDVI ranged between 0.30 and 0.44. Both indices display noticeable variability over the years, without a distinct increasing or decreasing trend. However, a general recovery in vegetation conditions was observed following specific dips in the indices, reflecting the resilience of the vegetation in the study area.

The year-to-year fluctuations in the indices were influenced by various factors, including climatic conditions (such as rainfall and temperature fluctuations) and anthropogenic influences (such as deforestation and land use changes). Specifically, the years 2002, 2003, and 2005 saw significant decreases in both NDVI and EVI, possibly linked to environmental stressors like drought.

EVI, due to its design, exhibited more pronounced fluctuations compared to NDVI, which captures a more averaged vegetation state. This suggests that EVI might be more sensitive to small changes in vegetation health, making it a valuable tool for detecting subtle variations, particularly in areas with atmospheric or soil background noise.

The overall trends in these indices suggest that, despite periods of stress, vegetation health appears to recover over time, indicating stable ecological processes or effective land management practices in the region. Notably, NDVI displayed an increasing trend after 2018, hinting at possible improvements in environmental conditions, which could be due to increased rainfall, conservation efforts, or natural regrowth.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This study sought to analyse the relationship between vegetation indices (NDVI and EVI) and climatic factors (Mean Rainfall and Mean Temperature) within the context of understanding vegetation dynamics in the study area. The findings provide valuable insights into the complex interactions between vegetation health and climatic variables, contributing to the broader discourse on environmental monitoring and management, particularly in the face of climate change.

The strong positive correlation between NDVI and EVI indicates that both indices are reliable indicators of vegetation health, reflecting consistent patterns in vegetation dynamics. However, EVI's enhanced sensitivity to atmospheric conditions and soil background effects suggests that it may be a more precise tool in environments where these factors are significant.

The analysis revealed a moderate negative correlation between Mean Temperature and the vegetation indices, indicating that higher temperatures are associated with a decline in vegetation health. This underscores the critical role that temperature plays in influencing vegetation dynamics, particularly in regions where temperature extremes may lead to increased stress on plant life.

Contrary to common assumptions, the correlation between Mean Rainfall and vegetation indices was weak, suggesting that rainfall alone is not a primary determinant of vegetation health in the study area. This highlights the complexity of environmental interactions and suggests that factors such as rainfall distribution, soil moisture retention, and anthropogenic influences may mediate the impact of rainfall on vegetation.

The findings indicate that rising temperatures, rather than changes in rainfall patterns, may pose a greater threat to vegetation health in the study area. This finding has significant implications for the management of natural resources, as it suggests that strategies aimed at mitigating the effects of climate change on vegetation should prioritize addressing temperature-related stressors.

5.2 Recommendations

Given the strong performance of EVI (Enhanced Vegetation Index) in capturing vegetation health, it is recommended that EVI be prioritized in future vegetation monitoring efforts, particularly in areas where atmospheric conditions or soil background effects might influence the accuracy of NDVI (Normalized Difference Vegetation Index). Integrating EVI into remote sensing practices can provide a more nuanced understanding of vegetation dynamics. Additionally, the Vegetation Condition Index (VCI), which compares current vegetation conditions to historical averages, can also be a valuable tool in assessing the extent of vegetation stress or recovery. Incorporating VCI into vegetation monitoring can help identify regions at risk and guide interventions for sustainable land management. The weak correlation between rainfall and vegetation indices suggests that a more holistic approach is needed when managing vegetation health. This should involve considering not only climatic factors but also soil properties, land use practices, and human interventions. Incorporating these factors into vegetation management plans will lead to more effective and sustainable outcomes.

While the NDVI trend map provides valuable insights, it is essential to consider its limitations. NDVI, though a robust indicator of vegetation health, can be influenced by factors such as soil background, atmospheric conditions, and non-photosynthetic vegetation. Therefore, ground-truthing and the use of complementary indices such as the Enhanced Vegetation Index (EVI) and Vegetation Condition Index are recommended for a more accurate assessment. Future research could also explore the socio-economic drivers of land degradation and incorporate them into the analysis to develop holistic management strategies.

While Pearson correlation provides useful insights, it does not capture non-linear or more complex interactions between vegetation and climatic factors. Future research should explore advanced statistical and machine learning techniques to better understand these relationships. Additionally, studies should focus on the temporal dynamics of vegetation responses to climatic factors, including seasonal variations and extreme weather events.

It is essential to integrate the findings of this study into policy frameworks aimed at environmental conservation and climate change mitigation. Engaging stakeholders, including local communities, government agencies, and NGOs, in the development and implementation of these policies will ensure that strategies are context-specific and have broad support.

To effectively implement the recommended strategies, there is a need for educational and capacity-building programs aimed at raising awareness about the impacts of climate change on vegetation. Training programs for local farmers, land managers, and policymakers can facilitate the adoption of best practices in vegetation management and climate adaptation.

This study provides a foundation for understanding the intricate relationships between vegetation health and climatic factors in the study area. The insights gained underscore the importance of considering both climatic and non-climatic factors in environmental management and highlight the need for adaptive strategies to mitigate the impacts of climate change on vegetation. By advancing our understanding of these relationships and implementing the recommended strategies, it is possible to promote more resilient ecosystems and ensure the long-term sustainability of vegetation in the face of global environmental change.

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APPENDIX

Appendix A

