INTEGRATING LANDSAT AND SENTINEL-2 FOR THE ASSESSMENT OF RANGELANDS VEGETATION DYNAMICS

by

Cathrine Muriva-Makombe
(2514653)

A research report submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science

Geographical Information Systems and Remote Sensing

Supervisor: Dr Cletah Shoko

July 2024

Declaration

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

_______ _______________________________

(Signature of candidate)

____1st_______day of ______July________2024________________at__________

Abstract

Rangelands are vast ecosystems that support biodiversity and livestock grazing. Monitoring species composition in rangelands is vital for assessing ecosystem health and informing management decisions. This study utilized Landsat and Sentinel-2 data to map vegetation composition, monitor vegetation dynamics over time, as well as analyze the relationship between Normalized Difference Vegetation Index, and environmental variables (*temperature and rainfall)* in Gweru district, Zimbabwe. Land use and land cover maps identified *water, forest, bareland, grassland,* and *built-up*. The accuracy of Landsat data was 94.19% in (1985), 93.06% (2015) and 97.06% in (2023). Sentinel's accuracy was lower at 92% in (2016) and 97.99% in (2023). From 1985-2023, bareland increased by 15.01% and 8% increase in built-up areas, while a significant decline of forest -25%. NDVI showed a strong relationship with rainfall ($R^2 = 0.9748$) and a weaker relationship with temperature ($R^2 = 0.3333$), highlighting the importance of integrating remote sensing in rangeland management.

Key words

Biodiversity; Ecosystems; Landsat; Rangelands; Sentinel.

Dedication

I dedicate this research to Agapao, my son, whom I left when he was still a baby, as well as to my parents, husband, and siblings.

Acknowledgement

I would want to begin by expressing my gratitude to God for providing me with the strength and provision that I required to continue with my studies. I would also want to convey my most sincere appreciation to my supervisor Dr. Cletah Shoko, for the extraordinary assistance and direction that she provided. The level of commitment that she showed for her position as a supervisor has been nothing short of motivational. She was consistently and dedicated above the call of duty, always making time to assist me. I would want to express my sincere gratitude for the countless hours she spent assisting me in overcoming obstacles, as well as the vital advice and critical feedback she provided, without these the research would not have been possible. I express my gratitude. A monument to the love that never wavered and the sacrifices that were made, this accomplishment is a credit to both. To Noah, my husband, whose unflinching support, and unshakable faith in me have been a consistent source of strength throughout this journey. I would like to express my gratitude to my parents, whose love, support, and direction enabled me to develop into the person I am today. I would also like to express my gratitude to my brother and sister, who have never failed to provide me with constant support and friendship. Obtaining this degree is not only a reflection of the effort I put in, but also of the love and support I received from those who are close to me. I am grateful to you.

Contents

List of figures

List of tables

Acronyms

GEE: Google earth engine

ETM: Enhanced Thematic Mapper +

IDW: Inverse distance weighting

LAI: Leaf Area Index

LULC: Land use Land cover

NDVI: Normalised difference vegetation index

NDWI: Normalised Difference Water Index

OLM: Operational Land Imager

SVM: Support Vector Machine

TM: Thematic Mapper

UTM: Universal transverse Mercato

CHAPTER ONE: GENERAL INTRODUCTION

1.1 Introduction

Rangelands are large tracts of land with native flora, primarily grasses, forbs, and shrubs, grazed by domesticated and wild animals (Abdullah et al., 2023). Except for Antarctica, every continent in the world has rangelands, which make up nearly half of the planet's total area (Abeysinghe et al., 2018). According to the Rangelands Atlas, rangelands cover 54% of the global terrestrial surface, or about 79.5 million square kilometres. Rangelands occupy roughly 28% (around 8,300,000 km2) of Africa and provide a vital ecosystem (D'Adamo, 2020). Millions of people who depend on tourism, livestock production, hunting, and gathering rely on rangelands for their livelihoods. They provide feed and habitat for cattle and wildlife, which helps ensure food security, livelihoods, and biodiversity protection. Rangelands also promote cultural norms and leisure pursuits that promote human happiness and well-being (Reid et al., 2014).

Rangelands are particularly important because they are responsible for delivering key ecological services such as the preservation of soil, the sequestration of carbon, the maintenance of biodiversity, and the regulation of water. According to Reid et al. (2014), these ecosystems provide support for millions of people all over the world. These people rely on rangelands for their livelihoods, which are based on activities such as the production of livestock, tourism, hunting, and gathering as well. Furthermore, rangelands are responsible for the maintenance of a wide variety of wildlife populations, which in turn ensures the preservation of biodiversity, cultural practices, and food security, making a substantial contribution to the well-being and pleasure of humans.

However, rangelands are subject to numerous kinds of threats that put their well-being and long-term viability at risk. Invasive species pose a serious threat because they displace local flora and upset the equilibrium of the ecosystem. On the other hand, overgrazing, which primarily results from domesticated livestock and wildlife, can cause soil erosion, decreased vegetation cover, and general degradation (Kayet et al., 2016). According to Kayet et al. (2016) unsustainable land use practices, such as excessive mining and urbanization, further exacerbate these difficulties by modifying the structure and function of rangelands, which in turn reduces the rangelands' productivity and ecological value. In addition, the effects of climate change, which include changing patterns of precipitation and an increase in the frequency of extreme weather events, further intensify these pressures, which in turn lead to changes in the distribution and composition of vegetation (D'Adamo, 2020).

The deterioration of rangelands has far-reaching consequences, as it has an impact on millions of people who are dependent on these ecosystems for grazing, agriculture, and tourism. Furthermore, according to Kayet et al. (2016), the reduction of ecosystem services and the loss of biodiversity may have major implications for the water and food security of both specific regions and the entire world. There are several documented cases of rangeland degradation consequences, which can be found in a variety of regions, including the Sahel in Africa (Xie et al., 2019), the Great Plains in the United States (Kayet et al., 2016), and the Tibetan Plateau in Asia (Zhou et al., 2020). These locations serve as significant examples of the issue and demonstrate the significant impact that rangeland degradation has had on ecosystems, livelihoods, and biodiversity.

When it comes to keeping track of the dynamics of rangelands, satellites like Landsat and Sentinel-2 have unmatched remote sensing capabilities. According to Jonsson et al. (2018), these satellites can provide high-resolution, multispectral imagery, which makes it possible to evaluate a variety of biophysical factors that are essential for comprehending the health and production of rangelands. In addition, the combination of unmanned aerial vehicles (UAVs) and space-borne sensors improves the collection of data at finer spatial scales, which in turn makes it easier to conduct extensive assessments of the status of rangelands (Jonsson et al., 2018).

Moderate Resolution Imaging Spectroradiometer (MODIS) and other multispectral sensors offer frequent revisits and broad coverage, which can be used to gather additional data for monitoring rangeland conditions (Abdullah et al., 2019). Additionally, hyperspectral sensors like Hyperspectral Infrared Image (HyspIRI), Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), Light Detection and Ranging (LiDAR), and Hyperspectral Thermal Emission Spectrometer (HyTES) offer better spectral resolution, which makes it easy to fully understand plant features and ecosystem processes (Alcaraz-Segura et al., 2010). The sensors can capture a broad spectrum of specific wavelengths, which enables the detection of small differences in the composition, health, and stress levels of vegetation (Ustin et al., 2004). According to Pickup et al. (1993), Landsat satellites are particularly useful for doing long-term trend research in rangeland ecosystems. These satellites are known for their enormous data archives, worldwide coverage, and multispectral imaging capabilities. Landsat sensors can quantify a wide variety of vegetation characteristics, such as its productivity, biomass, moisture levels, and sensitivity to disturbances such as fire and invasive species (Masek et al., 2020). This is because Landsat sensors have spectral bands that cover a wide range of wavelengths. Similarly, Sentinel-2 satellites provide high-resolution images, which makes it possible to conduct extensive monitoring of rangeland conditions and makes it easier to evaluate the dynamics of vegetation (Zhou et al., 2020). Furthermore, the thermal infrared band of Landsat data makes it possible to monitor the temperature of the land surface, which is helpful in determining the severity of drought conditions and the amount of water that is available inside rangelands (Graetz et al., 1988).

The capabilities of rangeland monitoring have been greatly improved in recent years because of developments in remote sensing techniques, the appearance of high-resolution imagery, and the development of machine learning algorithms (Zhou et al., 2020). These advancements present the innovative potential they bring for research as well as practical applications in rangeland management and conservation. Through remote sensing, one can use spectral bands and vegetation indices for rangeland monitoring (Eddy et al., 2017). Enhanced vegetation indices (EVI), the NDVI, the Soil Adjusted Vegetation Index (SAVI), LAI, and the NDWI are some of the commonly used indices to monitor vegetation. These indices can reveal details about a plant's phenology, health condition, and vigor. Other variables like net primary production (NPP) and fractional cover can also be estimated using vegetation indices (Qin et al., 2021) to understand vegetation dynamics.

1.2 Problem Statement

Rangelands face a range of multifaceted challenges, such as climate change, land degradation, excessive grazing, invasive species, and human activities. Pullanagari et al. (2016) did a study on

AisaFENIX hyperspectral images projected zinc, sulphur, sodium, copper, manganese, and magnesium in uneven mixed pastures rangeland in Mauritania. Except for Knox et al. (2011), all other studies simulated models which had accuracies of $R^2 > 0.5$. Knox et al. (2011) model predicted N in the dry season ($R^2 = 0.41$). Another study by Vina et al., (2019) utilised hyperspectral remote sensing to assess the nutritional quality of forage in a semiarid rangeland in Uganda. They collected data in the visible and near-infrared regions of the electromagnetic spectrum. The study accurately predicted these parameters, with a root mean square error of 0.80 for crude protein content. Although there have been significant advancements, most studies have mostly concentrated on the dynamics of vegetation quality, with less research conducted on the patterns of vegetation dynamics in rangelands. In their study, Skidmore et al., (2010) utilized HyMap imagery to map N, P, and polyphenols in an African savanna, in accordance with hyperspectral airborne sensors. They were able to assess forage quality.

The absence of research in this field poses a challenge to comprehending the evolving patterns within rangeland ecosystems over time, potentially impeding informed decision-making regarding land management and conservation endeavours. Currently, there is a dearth of studies that have effectively integrated Landsat and Sentinel-2 data to investigate vegetation dynamics patterns in rangeland environments (Micijevic et al., 2022). This study aims to bridge this gap by amalgamating data from both sensors, thereby facilitating a more thorough examination of vegetation dynamics in rangelands in Gweru district. The limited availability of comprehensive research on vegetation dynamics restricts insight into the temporal transformations occurring within rangeland ecosystems, potentially hindering the ability to make well-grounded decisions regarding land management practices and impeding conservation efforts.

1.3 Aim

To assess Landsat and Sentinel-2's efficacy in mapping rangeland vegetation composition, detecting temporal changes in vegetation dynamics, and exploring the relationship between NDVI and environmental factors

1.4 Specific Objectives

- To identify trends and changes in rangeland vegetation dynamics over time in Gweru district.
- To assess Landsat and Sentinel 2's potential for identifying and mapping rangeland vegetation composition.
- To analyse the relationship between rangeland vegetation dynamics using NDVI and environmental factors.

1.5 Structure of the Report

The report has 5 chapters which are as follows:

Chapter one

This chapter provides a thorough overview of the research topic, including the background and context of the problem statement, the aim and specific objectives of the study, and the structure of the report. Subsequently, it sets the foundation for the subsequent sections of the paper.

Chapter two

This chapter critically reviews the literature on rangeland assessment, emphasizing the importance of and threats to rangeland vegetation. The chapter also examines several techniques for monitoring rangelands, specifically emphasizing remote sensing, and evaluates previous studies conducted on rangelands.

Chapter 3

This chapter describes the research design, the study area, and the methods and techniques utilized to gather and analyze the data. It additionally justifies the methodologies and techniques employed in the study.

Chapter four

This chapter presents the findings from the data analysis. Tables, graphs, and maps visually display the classification, change detection, and regression analysis.

Chapter five

This chapter presents a complete analysis of the results. It assesses the importance of the findings in comparison with previous studies as well as offers a summary of the main findings, clarifying the original research aims and objectives. Additionally, it provides recommendations for future research.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter investigates and understand the complexities of the rangelands in Sub-Saharan Africa. The decision to concentrate on Sub-Saharan Africa was made due to the distinctive qualities of the region as well as the difficulties it encounters in the process of managing and maintaining its rangelands. The specific focus areas include the importance of rangelands in Sub-Saharan Africa, threats to the sustainability of rangelands, and rangelands monitoring using remote sensing. Considering recent technological developments, remote sensing emerges highly effective instrument for the monitoring of rangelands. The chapter also discusses the utilization of remote sensing techniques in monitoring the dynamics of the rangelands vegetation as well as approaches to remote sensing of rangelands dynamics, image classification for rangeland vegetation dynamics, and regression analysis for rangeland vegetation dynamics assessment.

2.2 Importance of Rangelands in Sub-Saharan Africa

Rangelands are vital to the preservation of biodiversity because they are habitats for an extensive variety of plant and animal species, which contribute significantly to the region's biodiversity. (Naidoo et al., 2013). Not only do these diversified ecosystems provide a home for common wildlife, but they also serve as vital homes for endangered species, such as the African wild dog and several different species of antelope (Vågen et al., 2005). The complex balance in these ecosystems makes it possible for many species to depend on each other(Group, 2019), which is good for the health of the environment The Kalahari Desert, encompassing both Botswana and Namibia, boasts unique flora and animals that have evolved to thrive in extreme dry conditions (McKay, 1968), demonstrating the incredible adaptability of life in these locations.

The biggest grazing areas for cattle are rangelands, which are essential to the survival of pastoral communities and the traditional way of life they have maintained (McGranahan & Kirkman, 2013). To provide fodder for their cattle, goats, and sheep, nomad herders are extremely reliant on these wide regions (Binot et al., 2009), Not only is the sustainable management of cattle on rangelands an economic necessity, but it is also a cultural practice that is deeply embedded in the way of life of tribes (Kiage, 2013) such as the Maasai in Kenya and Tanzania. Despite their traditions dating back hundreds of years, the Maasai, with their nomadic existence closely linked to the rangelands, continue to find a means of subsistence and cultural identity.

By absorbing carbon dioxide from the atmosphere, rangelands serve as significant carbon sinks, which are an essential component in the process of reducing the consequences of rising temperatures (Musekiwa et al., 2022). Grasses and shrubs that are found in these habitats play a vital role in the process of storing carbon in their roots and soil, which ultimately results in a reduction in the emissions of greenhouse gases (Mapfumo et al., 2021). The ability to comprehend and preserve this carbon sequestration function is necessary for the purpose of preserving the stability of the global climate. A study by Kuntu-Blankson (2019) compared soil organic carbon (SOC) stocks for depth intervals of 30 cm or less in grasslands and rangelands in Sub-Saharan Africa with the default reference condition of SOC stocks to 30 cm for different climates and soil types, as defined by the IPCC. In degraded semi-arid savannas, the levels of soil carbon declined by 40% after a span of 3 to 5 years on sandy soils and within 5 to 10 years on clay soils due to farming. A review of the potential for carbon sinks and greenhouse gas emissions in rangeland ecosystems of Eastern Africa revealed that some strategies that improve the process of carbon capture offer encouraging advantages (Tessema et al., 2020), with a sink capacity ranging from -0.004 to 13 Mg C ha-1 year -1.

To maintain the health of watersheds and regulate the flow of water, rangelands are an extremely important component (Amede et al., 2009). Rangelands have a natural barrier in the form of vegetation cover, which helps to prevent soil erosion and ensures a sustainable water supply farther downstream (Miller & Doyle, 2014). The protection of water supplies and the preservation of the ecological equilibrium of the regions are two of the most important functions that this perform, not only do the Drakensberg Mountains in South Africa offer stunning scenery, but they also serve as protectors of water supplies (Taylor et al., 2016), which allows them to provide sustenance to millions of people further downstream.

It is important to note that rangelands are a source of revenue for local economies since they attract tourists who are looking for genuine wilderness experiences (Mureithi et al., 2016). Wildlife tourism is a significant source of revenue in numerous countries characterized by substantial proportions of savannah-based rangelands, particularly in East and Southern Africa. In 2017, Kenya witnessed an influx of 1.5 million tourists, which accounted for 9.7% of the nation's total gross domestic product (GDP) and 3.4% of its overall employment (Liniger, 2021). The rangelands in Kenya play a crucial role in supporting various economic endeavors, including livestock production, wildlife conservation, and associated activities (Kariuki et al., 2018). Additionally, to a lesser extent, these rangelands also contribute to crop farming, mining, the production of cosmetics, and the creation of handicrafts (Omondi et al., 2014).

(Brinkmann et al., 2023)extends beyond the physical realm; it is profoundly rooted in the practices, rites, and narratives that are practiced by some societies . There are certain rangeland regions that are revered as sacred, and they play an important role in the maintenance of cultural traditions and spiritual procedures. Not only do the San people of Namibia live in these rangelands (Ekblom et al., 2019), but they also hold certain locations in high regard, highlighting the spiritual and cultural connection they have with the environment.

Rangelands provide access to the harvesting of medicinal plants in most African countries (Galloway et al., 2016), an example are the Himba women in Namibia, who collect wild herbs and resins for traditional medicine . In Zimbabwe, rangelands play a pivotal role in supporting various livelihood opportunities, such as tourism and conservation, livestock production for commercial purposes, and smallholder livestock systems (Gororo, 2013). Rangelands serve as the predominant means of sustenance for numerous rural communities in Zimbabwe, where a significant proportion of the populace (Muir, 1989), exceeding 70%, resides in rural regions and depends on agriculture and natural resources for their economic well-being. Zimbabwe boasts numerous national parks and game reserves, which attract visitors from around the world (Tavirimirwa et al., 2019) . In 2018, the tourism sector in Zimbabwe emerged as the third most significant source of foreign currency, generating a substantial contribution of $1.4 billion to the national economy.

2.3 Threats to the Sustainability of Rangelands

2.3.1 Threats to Rangelands from natural factors

Rangelands are subject to a significant amount of influence from climate change and the variability that is associated with it (Mccollum et al., 2017). Changes in temperature, patterns of precipitation, and extreme weather have the potential to change the composition of vegetation, the moisture content in the soil, and available nutrients (Mapfumo et al., 2021). If such changes occur, the quality and availability of forage may decrease, affecting livestock and wildlife that are dependent (Shiferaw et al., 2014) on rangeland resources.

Aridity and desertification Sudanese regions are especially susceptible to the impact of rangeland degradation (Pfeiffer et al., 2019). Dry spells that last for an extended period make soil erosion worse, reduce plant cover, and harm the fertility of dirt. The practice of desertification, which is characterized by the expansion of conditions like deserts (Dodd, 1994), poses a threat to rangelands because it renders them unproductive and inhospitable for animals that graze on them.

Periods of drought, whether short-term or prolonged, directly impact rangelands (Vetter, 2009). Insufficient rainfall stunts plant growth, disrupts nutrient cycling, and weakens the soil's structure erosion of the soil becomes more pronounced as vegetation withers, which ultimately results in the degradation of the land (Fava & Vrieling, 2021). Erosion of the Soil leading to land degradation can be accelerated by natural processes such as wind and water erosion (Snyman, 1998), which are both examples of soil erosion. The loss of soil leaves the ground bare, lowers the fertility of the soil (Hoffman & Vogel, 2008)and interferes with the establishment of plants. Another way in which erosion impacts water quality is through the movement of sediment and nutrients further downstream. Concentration of salts in the soil during periods of high evaporation in arid regions initiates the salinization process (Siyabulela et al., 2020). as well as on the productivity of plants and the roots' ability to absorb water (Tully et al., 2015). Large swaths of rangeland may become unfit for grazing because of this phenomenon.

2.3.2 Anthropogenic Factors affecting rangelands.

There is a significant cause for concern regarding the destruction of habitat, as human populations continue to grow (Dube & Pickup, 2001), they are increasingly converting rangelands for activities such as agriculture, urban development, and infrastructure development (Getabalew & Alemneh, 2019). Consequently, this results in the destruction of native vegetation, the erosion of soil, and the fragmentation of their habitats (Jiao et al., 2009). Livestock overgrazing exacerbates the degradation by reducing the amount of plant cover and soil stability.

Compaction of the soil, decreased plant diversity, and altered nutrient cycling are all potential outcomes of grazing that are not under control (Shah et al., 2017). Inappropriate grazing practices, such as grazing animals continuously without taking breaks, contribute to the further degradation of rangeland ecosystems (Oba et al., 2000). In the Eastern Cape Province of South Africa, the issue of overgrazing has been widely observed because of the presence of high livestock densities and the limited availability of alternative grazing areas (Archer, 2004) . Consequently, there has been a decrease in the availability of forage and an escalation in land degradation. Rangelands frequently overlap with areas where inhabitants engage and areas with high density in activities that are recreational in nature (Getabalew & Alemneh, 2019). Activities such as hiking, camping, and off-road driving are known to agitate and disrupt the rangelands.

The process of agricultural expansion poses a substantial anthropogenic threat as it involves the conversion of rangelands into agricultural fields and settlements (Sibanda et al., 2011). The reduction of available rangeland for livestock and wildlife leads to habitat loss (Senda et al., 2020) and fragmentation. In the country of Zimbabwe, there has been a continuous process of agricultural expansion into rangelands primarily driven by population growth and the demand for cultivable land (Peel & Stalmans, 2018), also the encroachment of human activities results in a reduction of available rangelands.

2.3.3 Alien Invasive species and bush encroachment

A plant species that is not native to the ecosystem has the potential to outcompete native vegetation in rangelands (O’Connor & van Wilgen, 2020). This phenomenon is referred to as an "alien species invasion." The cycling of nutrients is altered, ecological processes are disrupted, and biodiversity is decreased because of these invaders (Ehrenfeld, 2010) presence of alien species frequently results in a decline in the quality of the forage and alterations in the properties of the soil.

The presence of these factors has the potential to pose a significant risk to the long-term viability of rangelands, which serve as critical habitats for both livestock grazing and the preservation of wildlife (Holou et al., 2013). In the regions of Sub-Saharan Africa and specifically Zimbabwe, the presence of invasive species presents a multitude of challenges in the context of rangeland management in Sub-Saharan Africa, specifically Zimbabwe (Mujaju et al., 2021). O’Connor & van Wilgen (2020) did a study on the impacts of alien invasive species in South Africa and found that, numerous invasive alien plants have a significant impact on South African rangelands, which account for more than 70 percent of the country's total land area. On an annual basis, these rangelands contribute approximately 30 billion ZAR to the economy; however, they are infested with hundreds of plant species that are not native to the area Trees reduce the amount of grass cover and support for livestock (Birhane et al., 2017). According to estimates, the value of livestock production is reduced by 340 million ZAR annually due to the presence of invasive species (De Lange & van Wilgen, 2010). Even though there are some invasive plants that are beneficial, the negative impact that they have necessitates creative solutions that go beyond biological control and clearing programs.

When it comes to rangelands, invasive alien species present a significant risk to the native biodiversity that exists there (DiTomaso, 2000). During the process of establishing themselves, these non-native plants frequently take precedence over native vegetation in terms of competition for resources such as water, nutrients, and sunlight (Marchante et al., 2021). Therefore, the loss of native plant diversity can disrupt the functioning of ecosystems, which can have an impact on the cycling of nutrients the stability of soil (Gichure et al., 2023), and the overall resilience of ecosystems Invasive species have the potential to change the interactions between plants and pollinators, which can result in additional ecological imbalances. Invasive alien plants have the potential to make water conditions in rangelands even more difficult to manage (Honda & Durigan, 2016). The rapid growth of these plants uses up a significant amount of water, which leads to the depletion of groundwater reserves and a decrease in streamflow. As the amount of water that is available decreases, it becomes increasingly difficult for the ecosystem (Eriksen & Watson, 2009). Additionally, changes in the composition of vegetation can influence the rates of water infiltration, which in turn can influence the overall health of the watershed (Du Preez & Van Huyssteen, 2020).

2.4 Approaches to Rangelands Monitoring

2.4.1 Conventional approach of Rangelands Monitoring

The conventional method of monitoring rangelands entails the methodical observation and evaluation of ecological conditions in grazing lands (Oba et al., 2000) for the purpose of managing and maintaining the productivity of these environments. Conventional rangelands and assessment ground-based monitoring techniques are also frequently utilized. A study on the comprehensive assessment of methods for monitoring the condition of grasslands in regions with low rainfall by Wolfaard (2017) did a full study on the different ways to check on the health of grasslands in places with little rain. The study looked at a lot of different conventional rangeland monitoring strategies, such as the Multiple Indicator Monitoring (MIM) method. Which regarded the MIM approach as an effective and rigorous survey technique for obtaining comprehensive information on the health and condition of rangelands in semi-arid savannas in southern Africa. Friedel et al. (2000) conducted another study on vegetation sampling in rangelands, revealing the common use of vegetation attributes in rangeland inventory or monitoring projects. The properties encompass biomass, cover, density, and frequency. The study also highlighted the benefits and drawbacks of different field sampling methods for quantifying these characteristics.

Transects and quadrats are two methods that researchers can use to collect detailed information about the composition of plant species, the amount of biomass, and the characteristics of the soil (Nichols et al., 2009). By conducting this approach on the ground, researchers can gain a deeper understanding of the local ecosystem, thereby assisting land managers in making informed decisions about stocking rates and grazing rotation (Sangeda & Maleko, 2018). Field-based assessments can also include the monitoring of invasive species, which can significantly impact rangeland ecosystems by competing with native vegetation and changing the dynamics of the habitat (Lake & Minteer, 2018).

Metrics that have been used traditionally to evaluate livestock performance are essential components of rangelands monitoring (Sannier, 2000). Managers can evaluate the impact of grazing practices on livestock by monitoring parameters such as animal weight gain, reproductive rates, and health indicators. This allows managers to adjust management strategies in accordance with the findings of the evaluation (Onyango et al., 2021). As a result of the fact that rangelands frequently face challenges associated with drought and water scarcity, monitoring the availability and quality of water is equally important. It is possible to gain a better understanding of the rangeland ecosystem's overall resilience through the implementation of water monitoring systems (Birhane et al., 2017). These systems may include groundwater wells or surface water gauges.

The monitoring of rangelands also includes conducting regular evaluations of the state of the soil (Tully et al., 2015). The process of sampling and analyzing soil yields essential information regarding the levels of nutrients, the structure of the soil, and the potential for degradation (Bekunda et al., 2010). The utilization of these data is beneficial in the process of formulating appropriate land management practices, such as the application of fertilizers or the implementation of erosion control measures (Mutuku et al., 2021), with the goal of preventing soil erosion and managing soil fertility. Conventional rangelands monitoring helps to foster a holistic understanding of ecosystem dynamics and provides information that can inform sustainable land management strategies (Reed et al., 2015). This is accomplished by taking into consideration the interaction between vegetation, livestock, and soil.

One of the most important aspects of conventional rangelands monitoring is the involvement of the community and the utilization of local knowledge (Roba & Oba, 2009). To achieve a comprehensive understanding of the socio-economic and cultural factors that influence rangeland dynamics, it is necessary for researchers, land managers, and local communities to work together (Finca et al., 2023). Indigenous knowledge about traditional grazing practices, seasonal variations, and local ecological indicators is a valuable source of information that contributes to the monitoring process. Through the integration of scientific expertise with the knowledge of those who have a profound connection to the land (Hunt Jr et al., 2003), this participatory approach helps to ensure that rangelands are used in a manner that is environmentally responsible.

2.5 Rangelands monitoring using remote sensing

An efficient way to evaluate vegetation characteristics like biomass, leaf area index (LAI), phenology, and productivity is by remote sensing (Dube et al., 2019), because of its ability to capture spatially explicit and temporally consistent data on various biophysical aspects of rangelands (Booth & Tueller, 2003). This allows for a less subjective form of monitoring rangeland landscapes Additionally, remote sensing can provide data over large areas in short periods, especially on sites that are remote and hard to access on the ground (Thamaga et al., 2022).

2.5.1 Multispectral Remote sensing for rangelands monitoring.

Multispectral imagery is generated by sensors that measure reflected energy within several distinct bands of the electromagnetic spectrum (Navulur, 2006). Images generated by multispectral sensors typically contain between three and ten distinct band measurements per pixel (Mngadi et al., 2022). Typical band examples for these sensors include near-infrared, visible green, and visible red. Multispectral satellite sensors include Landsat, Sentinel, QuickBird, IKNOS, RapidEye and Spot satellites Multispectral 2016 (David et al., 2022). Some notable multispectral satellite systems, differentiate between commercial and freely available. The able 2.1 below shows different multispectral sensors which can be used for rangeland monitoring.

Table 2.1: Multispectral sensors available for rangeland monitoring

Satellite	Sensor	Spatial Resolution	Temporal Resolution	Bands (specific for vegetation studies)
Landsat 8	OLI/TIRS	30m	16 days	Band 2 (Blue), Band 3 (Green), Band 4 (Red), Band 5 (Near-Infrared), Band 6 (Short-Wave Infrared 1), Band 7 (Short-Wave Infrared 2)
Sentinel 2	MSI	10 m, 20 m, 60 m	5 days	Band 2 (Blue), Band 3 (Green), Band 4 (Red), Band 5 (Red-Edge), Band 6 (Red-Edge), Band 7 (Red-Edge), Band 8 (Narrow Near-Infrared), Band 8A (Narrow Near-Infrared), Band 11 (Short-Wave Infrared), Band 12 (Short-Wave Infrared)
MODIS	MODIS	250 m, 500 m, 1000 m	1-2 days	Band 1 (Red), Band 2 (Near-Infrared), Band 3 (Blue), Band 4 (Green), Band 5 (Red), Band 6 (Near-Infrared), Band 7 (Mid-Infrared), Band 8 (Upper Atmosphere), Band 9 (Water Vapor), Band 10 (Thermal Infrared), Band 11 (Thermal Infrared)

QuickBird	Panchromatic & Multispectral	0.61 m (Panchromatic), 2.44 m (Multispectral)	1-3 days	Blue, Green, Red, Near-Infrared
IKONOS	Panchromatic & Multispectral	0.82 m (Panchromatic), 3.2 m (Multispectral)	1-3 days	Blue, Green, Red, Near-Infrared
RapidEye	5 identical multispectral imagers	5m	1-3 days	Blue, Green, Red, Red-Edge, Near-Infrared
SPOT	HRG	1.5 m (Panchromatic), 6 m (Multispectral)	1-3 days	Blue, Green, Red, Near-Infrared

Despite, their high temporal resolution, and coarse spatial resolution in remote sensing images such as MODIS, have proven effective in monitoring expansive rangelands. Ibrahim et al., (2015) used satellite derived NDVI data to identify soil erosion in Benin. The residual trend (RESTREND) of an NDVI time-series was proportional of the variance between the predicted and observed NDVI using climatic data. NDVI3g, generated by the NASA-Goddard Space Flight Centre GIMMS served as a satellite-derived substitute for vegetation productivity in conjunction with the CPC soil moisture index, CRU rainfall data. Prince et al. (2009) implemented the method of local net primary productivity scaling (LNS) across Zimbabwe on a national level, employing MODIS NDVI at 250-meter resolution. Their findings demonstrated an annual loss of approximately 17.6 teragrams of carbon due to degradation. Nevertheless, the utilization of remote sensing data characterized by low spatial resolution presents constraints, particularly in regions characterized by extensive fragmentation and heterogeneity within rangeland environments.

Studies have shown that using high resolution images such as Quick, IKONOS and SPOT improve accuracy in rangeland monitoring. Everitt et al. (2008) utilized QuickBird imagery to identify the invasion of giant reed (Arundo donax) in Mauritania, achieving an overall accuracy of 86%. Additionally, Sant et al., (2014) assessed sagebrush-steppe rangeland in northern Utah in 2010 using IKONOS data, which revealed 5% greater variation in shrub cover compared to using

MODIS data exclusively. Al-Bakri and Abu-Zanat (2007) investigated west Mauritanian rangeland biomass using SPOT-5 HRV data at 10-meter spatial resolution. They revealed a robust correlation (R^2 = 0.77) between vegetation biomass and NDVI, underscoring the utility of this imagery for comprehensive rangeland assessment. However, the utilization of optical sensors with enhanced spatial resolution, especially for large-scale applications regionally and globally, may face constraints due to their considerable expenses, extensive data volumes, and infrequent data capture, particularly exacerbated in tropical areas with frequent cloud cover (Lehmann et al., 2015).

In contrast, the Sentinel 2 and Landsat offer a distinctive blend of global coverage, well-maintained calibration, and frequent revisits, making them valuable assets for rangeland monitoring purposes over large areas (Gascon et al., 2017; Micijevic et al., 2022). Several studies (Brink & Eva, 2011; Dube et al., 2019; Masemola et al., 2016; Mngadi et al., 2022; Winowiecki et al., 2018) have utilized Landsat products in monitoring rangelands with better accuracies Serra et al. (2003) employed Landsat MSS and Landsat TM data, employing a protocol allowing dependable post-classification assessments to identify land cover and land use (LCLU) changes in Spanish rangelands spanning 30 years. Their findings indicate that utilizing the protocol for change detection achieved an accuracy of 85.1%, surpassing the accuracy of 43.9% attained with a direct overlay method.

The small size of smallholder woodlots can hinder their differentiation from neighboring land cover with similar spectral signatures (Kimambo & Radeloff, 2023) which varies over the woodlot's establishment stages. Higher spatial resolution images like those from ESA's Sentinel-2 at 10-meter resolution, offer a potential solution, providing nine more pixels per woodlot compared to Landsat (Drusch et al., 2012). Despite Sentinel-2's short time series, studies in Tanzania have shown that its inclusion improves rangeland vegetation mapping accuracies in single-date analyses. However, the efficacy of Sentinel-2's higher spatial resolution in vegetation mapping warrants evaluation while considering the time series duration (Hurni et al., 2017).

2.5.2 Hyperspectral Remote Sensing for rangelands

Hyperspectral sensors, in contrast to multispectral sensors, have the remarkable ability to capture energy across many contiguous spectral bands, usually more than 200 (Shippert, 2003). Their wide coverage allows them to consistently sample the whole electromagnetic spectrum, leading to increased sensitivity to minor variations in reflected energy (Xiaoping et al., 2011). Hyperspectral images provide a higher level of resolution and discrimination compared to multispectral photos, allowing for accurate differentiation between different land and water features (Gaffney et al., 2021).

Table 2.2 hyperspectral sensors available for rangelands monitoring

Sensor type	**Satellite sensor**	**Spectral band information**	**Spatial resolution (m)**	**Revisit period (days)**
	NOAA-9 AVHRR LAC	R, NIR, 3TIR	1100	14.5/day
	PRISMA	VNIR: 400–1010 nm (66 bands) SWIR: 920–2500 nm (173 bands)	30	29
	MODIS - Moderate Resolution Imaging Spectrometer	0.405 - 14.385 µm (36 bands)	250, 500, 1000	1 - 2
	MERIS/Envisat	VIS - NIR (18 selectable bands)	230 x 300	3
	Hyperion/EO-1	VIS - TIR (36 bands)	250-1000	16

A study by Ullah et al. (2017) used hyperspectral data from the Hyperion sensor on board the Earth Observing-1 (EO-1) satellite to estimate the nutritional quality of forage in a rangeland ecosystem in California. The study utilized partial least squares regression to estimate the nutritional quality parameters of the forage, including crude protein, neutral detergent fiber, acid detergent fiber, and ash content. The study found that hyperspectral approach was able to accurately predict these parameters, with R^2 values ranging from 0.60 to 0.82. However, the use of hyperspectral images in rangeland monitoring has been limited since they are not easily accessible to those outside the scientific community. Moreover, existing hyperspectral missions suffer from infrequent revisits, and relatively small fields of view constraining their applicability for global-scale monitoring (Bioucas-Dias et al., 2013).

2.6 Approaches to the remote sensing of rangelands dynamics

Various approaches are utilized in this context. They include digital image classification for mapping land cover, regression analysis to evaluate quality, and the use of vegetation indices to assess productivity, phenology, and health (Eddy et al., 2017). These techniques are applicable to both classification and regression tasks. Moreover, the requirement for careful and detailed planning before obtaining data creates difficulties in regions with limited resources.

2.6.1 Image classification for rangelands vegetation dynamics using remote sensing.

In remote sensing applications, unsupervised classification involves employing algorithms to categorize data without prior knowledge of the classes, aiding in data analysis and interpretation When dealing with intricate data or lacking clear class specifications in advance (Jensen, 2005), this strategy proves especially beneficial. Unsupervised classification algorithms detect patterns or groupings in the data by analyzing statistical qualities like spectral characteristics or geographical correlations (Oyekola & Adewuyi, 2018). Unsupervised classification frequently employs clustering, a method that organizes data points that share similarities into clusters without pre-established labels (Lu et al., 2017).

Supervised classification relies on labeled training data to categorize new observations. Training a classifier with a dataset in which each sample is assigned a predetermined class label constitutes this method (Muñoz-Marí et al., 2007). The classifier acquires the ability to distinguish between classes by analyzing the features derived from the training data. Popular supervised categorization techniques encompass support vector machines (SVM), random forests, and neural networks(Perumal & Bhaskaran, 2010). Supervised classification is a commonly employed technique in remote sensing for the purpose of land cover mapping, object recognition (Rogan & Chen, 2004) and other applications that require the availability of labeled training data.

Pixel-based classification, is the process of categorizing individual pixels in a picture separately, solely based on their spectral properties. Remote sensing data, such as multispectral or hyperspectral imaging (Khatami et al., 2016), typically provides the spectral signature that assigns each pixel in the image to a specific class. Pixel-based categorization algorithms approach each pixel as an individual unit and do not consider the spatial connections between adjacent pixels (Stuckens et al., 2000).

Object-based classification, as opposed to pixel-based classification, considers not only the spectral characteristics of individual pixels but also their spatial connections and contextual information (Walter, 2004). Object-based categorization refers to the process of segmenting an image into uniform objects or regions using criteria such as spectral similarity, texture, and shape (Blaschke, 2010). Segment information, such as average spectral values, textural parameters, and spatial qualities, categorizes the objects into various classes. Object-based classification is generally more precise than pixel-based approaches (Yu et al., 2006), particularly in intricate landscapes with diverse land cover.

Parametric classifiers and non-parametric classifiers are two different types of classifiers used in machine learning (Abedi, 2020). Parametric classifiers make assumptions about the underlying distribution of the data, while non-parametric classifiers do not make any assumptions (Hubert-Moy et al., 2001). This distinction affects how the classifiers learn and make predictions. Parametric classifiers assume that the data follows a particular probability distribution and then use the training data to estimate the parameters of this distribution (Bruzzone et al., 2002). Two often used parametric classifiers are the Maximum Likelihood Classifier. and the Gaussian Mixture Model (GMM). These classifiers rely on significant assumptions about the underlying data distribution, which can restrict their usefulness in complex or non-standard situations (Mancino et al., 2023) Contrarily, non-parametric classifiers do not rely on explicit assumptions regarding the underlying data distribution (Serpico et al., 1996). Instead, they depend on the training data exclusively to produce predictions. Non-parametric classifiers encompass k-Nearest Neighbors (k-NN), decision trees, and random forests (Bruzzone et al., 2002) . Non-parametric classifiers are more adaptable and can find complex relationships in data without making strict assumptions about how the data is distributed (Lakhankar et al., 2009).

The Multi-Label Classification (MLC) is a classification algorithm that relies on statistical probability (Sumbul & Demİr, 2020). The process involves allocating pixels or data points to assign the observed data to a particular class based on the class that is most probable to produce it. Within the realm of image classification, MLC computes the likelihood of a pixel being associated with each individual class and designates it to the class with the greatest probability (Shao et al., 2018). This approach, especially valuable for addressing multi-class classification issues, assumes that each class generates the observed data from a distinct statistical distribution.

Decision trees are hierarchical structures utilized for the purposes of both classification and regression tasks (Kotsiantis, 2013). Feature thresholds recursively divide the data, creating a hierarchical structure where each node represents a decision based on a specific feature (Xu et al., 2005). Decision trees possess the quality of interpretability and can capture non-linear relationships within the data (Friedl & Brodley, 1997). While challenges like overfitting and data quality exist, these can be addressed through techniques like pruning, ensemble methods, and data preprocessing (Moustakidis et al., 2011). Recent advancements in machine learning integration, big data, and high-resolution multispectral data further enhance the effectiveness of decision trees (Maabreh et al., 2023) in remote sensing applications.

Support Vector Machines (SVM) is a robust algorithm primarily employed for binary classification tasks (Pavlidis et al., 2004). Its functionality involves identifying the most effective hyperplane that efficiently separates the data points belonging to different classes within the feature space. (SVM) algorithm is particularly efficient when applied to datasets with many dimensions. Its decision boundary is defined by support vectors which are the data points that are nearest to the hyperplane (Sweeney et al., 2015). SVM have the capability to handle non-linear relationships by utilizing kernel functions (Bhaga et al., 2020). These functions enable SVM to transform the data into higher-dimensional spaces where a hyperplane can effectively separate the different classes.

Random forests are ensemble learning techniques that integrate multiple decision trees to enhance overall performance and resilience (Breiman, 2001). Every tree is trained on a randomly selected subset of the data and features (Speiser et al., 2019). Either a majority vote or an averaging of the results from all the individual trees determines the final classification. Random forests address the problem of overfitting that is commonly observed in individual decision trees and improve the model's ability to generalize (Joelsson et al., 2006). They possess a high level of proficiency in managing extensive datasets and can comprehend intricate connections within the data by consolidating outcomes from numerous decision trees.

Convolutional neural networks (CNNs) are a type of deep learning algorithm that are specifically designed for analysing visual data. They are widely used in computer vision tasks such as image classification, object detection (Kattenborn et al., 2021) and image segmentation. CNNs, initially developed for image recognition, have demonstrated remarkable efficacy in acquiring intricate spatial patterns, rendering them invaluable for the analysis of remotely sensed data (Li et al., 2022). CNNs, in the context of vegetation mapping, can automatically extract hierarchical features from high-resolution satellite or aerial imagery. This allows them to classify various types of rangeland vegetation (Al-Najjar et al., 2019) . CNNs excel at capturing local patterns and spatial dependencies, making them highly suitable for tasks like land cover classification.

Recurrent Neural Networks are particularly ideal for analysing time series data, making them highly valuable for capturing the temporal relationships within vegetation dynamics (Salehinejad et al., 2017). RNNs can analyse sequential data and acquiring knowledge about growth, phenology, and other temporal aspects (Mou et al., 2017), making them suitable for monitoring changes in vegetation over time RNNs are highly advantageous for tasks such as forecasting changes in vegetation cover (Ienco et al., 2017), comprehending seasonal fluctuations, and examining prolonged patterns in vegetation well-being.I

SegNet is a deep learning architecture specifically designed for semantic segmentation. The purpose of this design is to effectively divide images into individual pixels while preserving spatial intricacies (Du et al., 2018). SegNet employs an encoder-decoder architecture and utilizes max-pooling indices to efficiently perform up-sampling during the decoding stage. This architectural approach has been implemented in the field of vegetation mapping (Badrinarayanan et al., 2017), enabling the precise identification and demarcation of distinct vegetation categories in remote sensing imagery. Gandhi et al. (2015) extracted features using the Normalised Difference Vegetation Index (NDVI) technique with various threshold values and data from remote sensors. Their research revealed that, despite varying threshold levels, the percentage of vegetation remained largely constant. Additionally, they discovered that plants with varied densities and dispersed distributions responded favourably to the NDVI technique. Table 2.3 below shows studies which have used classifiers.

Table 2.3 summary of key results demonstrating the role of remote sensing in rangeland monitoring

Author (Year)	Purpose	Classifier	Application	Research Findings
(Sisodia et al., 2014)	to assess the performance and accuracy of MLC in the context of remote sensing image analysis.	Maximum Likelihood Classifier (MLC)	Image Classification	Effective for multi-class classification problems
(Kotsiantis,2013)	To examine the accuracy, efficiency, and suitability for decision trees on crop type mapping.	Decision Trees	Classification and Regression Tasks	Can capture non-linear relationships within the data

(Pavlidis et al., 2004)	To assess the effectiveness of Support Vector Machines in handling high-dimensional remote sensing data	Support Vector Machines (SVM)	Binary Classification Tasks	Efficient when applied to datasets with many dimensions
(Speiser et al., 2019)	To investigate how Random Forests can address overfitting issues and improve model generalization in landuse and land cover classification.	Random Forests	Classification and Regression Tasks	Addresses overfitting and improves model’s ability to generalize
(Kattenborn et al., 2021)	To develop transferable multi-trait models from heterogeneous and sparse data to map multiple plant traits using hyperspectral remote sensing of plant canopies	Convolutional Neural Networks (CNNs)	Image Classification, Object Detection, Image Segmentation	Excels at capturing local patterns and spatial dependencies

(Salehinejad et al., 2017)	to evaluate the estimates of foliar and ground cover for, erosion prediction, and land management decisions.	Recurrent Neural Networks (RNNs)	Time Series Analysis	Captures temporal relationships within vegetation dynamics
(Du et al., 2018)	The study explored how the simulated ecosystem carbon storage capacity varied with different commonly used schemes of carbon-nitrogen coupling in the terrestrial ecosystem model.	Segnet	Semantic Segmentation	Precisely identifies and demarcates distinct vegetation remained largely constant

2.7 Regression analysis for rangeland vegetation dynamics assessment in relation to environmental changes

Advanced regression analysis is essential for evaluating the quality and quantity of rangeland using remote sensing data (Karl, 2010). Various regression techniques have been applied to investigate the relationships between different vegetation dynamics with environment or remote sensing. Traditional linear regression has been widely used to analyze the relationships between different environmental factors and vegetation dynamics (Geerken & Ilaiwi, 2004). Traditional Linear regression enables researchers to analyze the linear relationships between predictor variables and vegetation dynamics offering valuable information about the direction and magnitude of these connections (Faramarzi et al., 2010). For instance, it can be utilized to evaluate the impact of precipitation, temperature, and grazing intensity on the composition and productivity of vegetation in rangelands over a period (Karl, 2010). Although linear regression has demonstrated its utility in revealing fundamental relationships, it may encounter difficulties in capturing intricate nonlinear patterns and interactions that are inherent in rangelands (Kakinuma et al., 2014). Furthermore, it presupposes that the relationships are strictly linear, which may not be accurate in the complex dynamics of rangeland ecosystems.

Recently, the field of rangeland vegetation dynamics assessment has seen an increase in the use of advanced machine learning techniques, specifically Partial Least Squares Regression (PLSR) and Sparse Partial Least Squares Regression (SPLSR) (Kiala et al., 2016). Partial Least Squares Regression (PLSR), for example, is highly skilled at managing multicollinearity and extracting latent variables that effectively capture intricate connections between predictors and vegetation responses (Ramoelo et al., 2013). This ability is essential for comprehending the intricate interaction of factors that influence rangeland ecosystems**.** Multiple linear regression can be used to analyze the influence of a mixture of remote sensing variables, including NDVI, Land Surface Temperature (LST), and precipitation data, on rangeland production (Zou et al., 2003). This methodology enables a more thorough comprehension of the variables that impact the quality of rangelands. PCR can be used to reduce the complexity of remote sensing data, particularly when working with a high number of spectral bands (Ergon et al., 2014). PCR can be employed by researchers to ascertain the primary factors that impact rangeland parameters such as vegetation cover or soil moisture. Partial Least Squares Regression (PLSR) can be utilized to reveal the correlations between several remote sensing indices and indicators of rangeland health (Ramoelo et al., 2013). For instance, a study done by Salazar et al., (2008) utilized to evaluate the correlation between combinations of vegetation indices obtained from Sentinel-2 imagery and the quality of fodder on rangelands.

Table 2.4 Case studies of key results demonstrating the role of linear regression modelling in rangelands

Study	Regression Technique	Purpose	Findings
(Karl 2010)	Traditional Linear Regression	Assessing linear relationships between environmental factors and vegetation dynamics in rangelands.	Revealed linear connections between precipitation, temperature, grazing intensity, and vegetation dynamics.
(Zou et al., 2003)	Multiple Linear Regression	Analysing the influence of remote sensing variables (NDVI, LST, precipitation) on rangeland production.	Provided insights into variables impacting rangeland quality, aiding in understanding ecosystem dynamics.
(Ergon et al., 2014)	Principal Component Regression (PCR)	Decreasing complexity of remote sensing data to understand factors impacting parameters like vegetation cover.	Identified primary factors influencing rangeland parameters, facilitating better management strategies.
(Chang et al., 2021)	Partial Least Squares	To examine if PLSR does not consider the grouping structure of	illustrated model performance using real-world leaf spectra data to

Study	Regression Technique	Purpose	Findings
	Regression (PLSR)	the full spectrum, where spectral subsets may have distinct relationships with response variable.	indirectly quantify leaf traits and demonstrated superior prediction performance, higher R-squared values, and faster computation time compared to other PLS variations.
(Shoko 2018)	Sparse Partial Least Squares Regression (SPLSR)	Establishing a model correlating spectral reflectance with aboveground biomass of C3 and C4 grasses.	Outperformed traditional regression techniques in accuracy and variable selection, improving understanding of grass biomass.

2.8 The use of vegetation indices in assessing rangeland vegetation dynamics.

Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) and others, are valuable tools for assessing rangeland vegetation (Ediz et al., 2014). These indices depend on the principle that plants reflect and absorb light differently in various wavelengths, providing insights into their productivity, phenology, quality, and cover. Below is table 2.5 showing of some of the vegetation indices used for vegetation assessment in rangelands.

Table 2.5 Review of vegetation indices case studies for rangelands vegetation dynamics

Index	**Aim of Study**	**Satellite Used**	**Major Finding on Performance**	**Author (Year)**
NDMI (Normalized Difference Moisture Index)	Predicts soil moisture content in vegetation	Sentinel-2	Model showed predictions close to ground MAE0.0325, RMSE 0.0447model accurately predicted	(Habiboullah & Louly, 2023)
SAVI (Soil-Adjusted Vegetation Index)	Adjusts for soil brightness to improve sensitivity in low vegetation areas	Landsat	MSAVI optimizes soil adjustment factor per pixel, effective in assessing rangeland degradation	(Belhadj et al., 2023)
NDVI (Normalized Difference Vegetation Index)	Measures the difference between near-infrared and red reflectance,	MODIS	RDST created using MODIS NDVI data for monitoring Kenyan rangelands	(Ndungu et al., 2019)

Index	Aim of Study	Satellite Used	Major Finding on Performance	Author (Year)
	indicating vegetation health			
NDWI (Normalized Difference Water Index)	Monitor and assess impacts on climate variability and droughts on water	Various remote sensors	Found various most effective indices for drought and water including SPI, PDSI and that remote sensing advancements play a major role.	(Bhaga et al., 2020)
EVI (Enhanced Vegetation Index)	incorporates a soil background adjustment	Landsat, MODIS,	Study examined how topography affects EVI and NDVI	(Matsushita et al., 2007)

2.9 Conclusion

This chapter revealed that rangelands monitoring through remote sensing highlights the transformative role of technology in understanding and managing these critical ecosystems. Remote sensing provides exceptional insights into vegetation dynamics, land cover changes, and environmental interactions using multispectral and hyperspectral data, as well as advanced classification and regression techniques. Remote sensing is highly efficient and has a wide range of applications, making it possible to thoroughly assess rangeland landscapes across large areas. This technology enables to monitor various vegetation characteristics, including biomass, leaf area index, phenology, and productivity, using data that is both spatially explicit and temporally consistent. Additionally, using machine learning algorithms like support vector machines, decision trees, and convolutional neural networks makes classification more accurate and helps recognize different types of vegetation, which helps to learn more about rangeland ecosystems.

Moreover, using vegetation indicators like the Normalized Difference Vegetation Index offers significant knowledge on the well-being, productivity, and extent of vegetation. This allows stakeholders to evaluate the quality and quantity of rangelands. Advanced regression techniques, such as partial least squares regression (PLSR) and sparse partial least squares regression (SPLSR), enhance the analysis of remote sensing data by examining the connections between environmental factors and vegetation changes. These techniques provide a more precise approach to understanding the intricate interactions within rangeland ecosystems. The combination of these methods and results highlights the significance of remote sensing in promoting sustainable rangeland management practices.

CHAPTER THREE: METHODS AND MATERIALS

3.1 Introduction

Chapter 3 delves into the materials and methods employed in this study to achieve the outlined objectives. The chapter elaborates on the utilization of Landsat and Sentinel-2 data for mapping rangeland vegetation composition and tracking temporal changes in vegetation dynamics. Through a detailed exploration of the methodology, this chapter lays the foundation for a robust analysis and assessment of rangeland ecosystems using remote sensing techniques.

3.2 Study Area

The study area is in Gweru district, which is geographically located within the latitudinal range of 19°27′41″S and the longitudinal range of 29°48′08″E, with reference to the Greenwich Mean Time (Mutsvangwa, 2010). The region is situated in the central part of the country. The city of Gweru is situated in Zimbabwe's Midlands Province in southern Africa (Mutsvangwa, 2010). Gweru is situated along the banks of the Gweru River. The topography of the area is characterized by predominantly flat to moderately sloping terrain, slightly undulating with hills and ridges surrounding it (Innocent et al., 2019), at an elevation varying between 1,420 and 1,520 meters above sea level.

The rangeland is comprised of *brachysteg, balsam, acacia,* and *Terminalia-Combretum* trees (Matsa et al., 2022). The soil comprises black basalt soils, red loams, sands, and gravel. Red grass *(Themeda triandra),* star grass (*Cynodon spp.), hyparrhenia rufa*, and *Rhodes grass* (Chloris gayana) are the three most prevalent grass species (Matsa et al., 2022). The subtropical climate in Gweru has distinct rainy and dry seasons. The rainy season, which normally lasts from November to March, is characterized by high temperatures and heavy downpours of rain; between April and October (Innocent et al., 2019), there are lower temperatures and little rain. The farming of sheep, goats, and cattle is a key component of Gweru's socio-economic structure. Livestock production is a major source of livelihood and revenue for many communities (Mutsvangwa, 2010). Gweru acts as an economic, transportation, and administrative centre for the outlying rural districts. The region around Gweru's rangelands has several environmental difficulties (George & Steven, 2022).

Overgrazing due to poor grazing management and land degradation, such as illegal mining (Munhenzva et al., 2019), puts natural vegetation in danger. Fig. 3.1 below shows the study area map of Gweru.

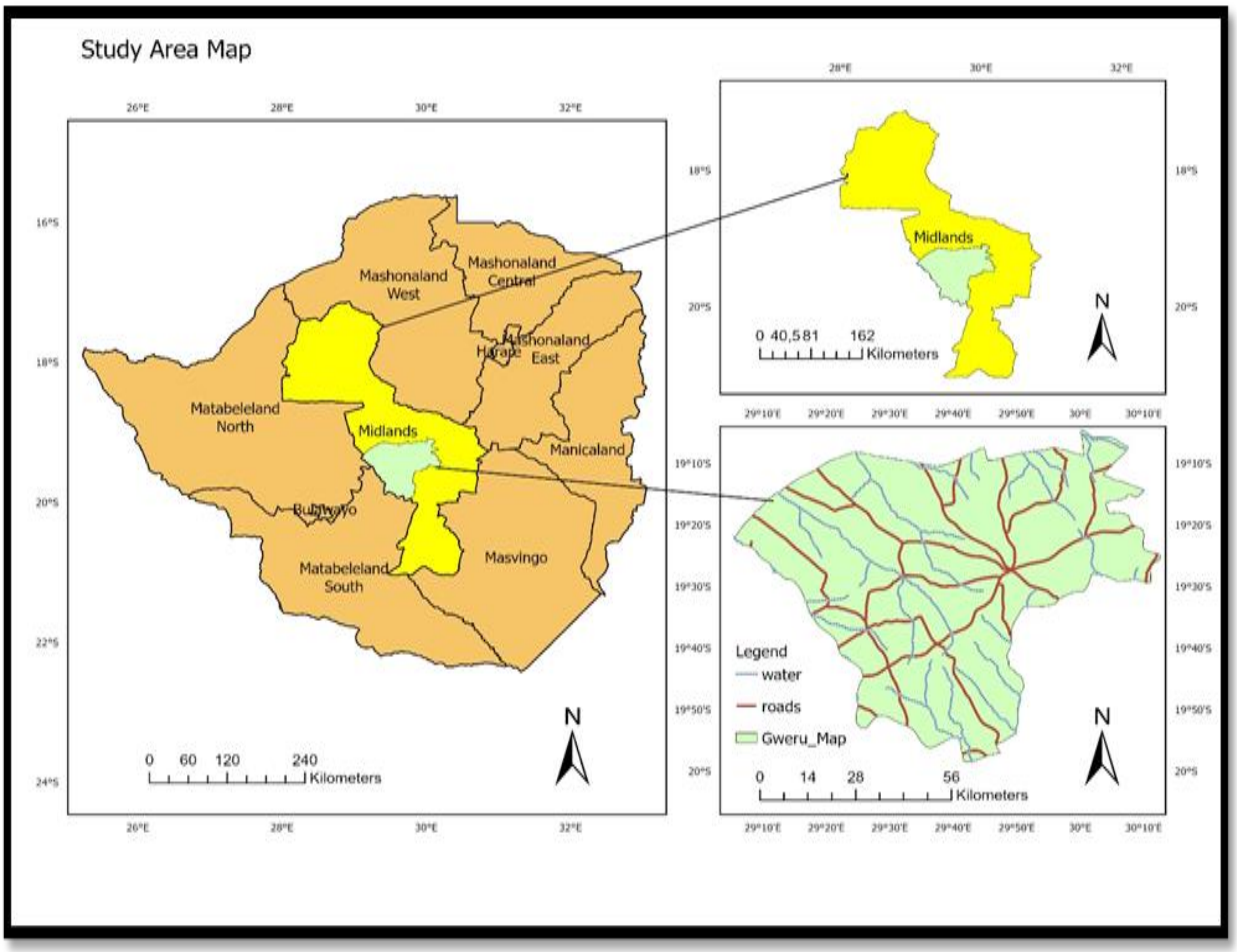

Figure 3.1: location of the study area map Gweru, Zimbabwe

3.3 Field Data Collection

The study was employed in 3 field campaigns, conducted on July 14 and 15, 2023, which included a total of 5 sampling sites (3 in the grazing area and 2 in the forest area). The sample strategy involved the deliberate selection of sampling sites across the rangeland, employing judgmental sampling techniques (Munyati, 2022) to ensure comprehensive coverage. The sampling sites possessed sufficient size to represent a pixel of at least 30m. The Universal Transverse Mercator coordinates of the sampling sites GPS coordinates were recorded to ensure accurate tracking of their exact locations (Munyati, 2022). These were documented using a Garmin eTrex 10 Global Positioning System (GPS) with an accuracy of within 3m. For the years 1985- 2020 for Landsat and 2016 -2020 for sentinel where ground truth was not available. Below is Figure 3.2 showing a flowchart of the methodology of this research.

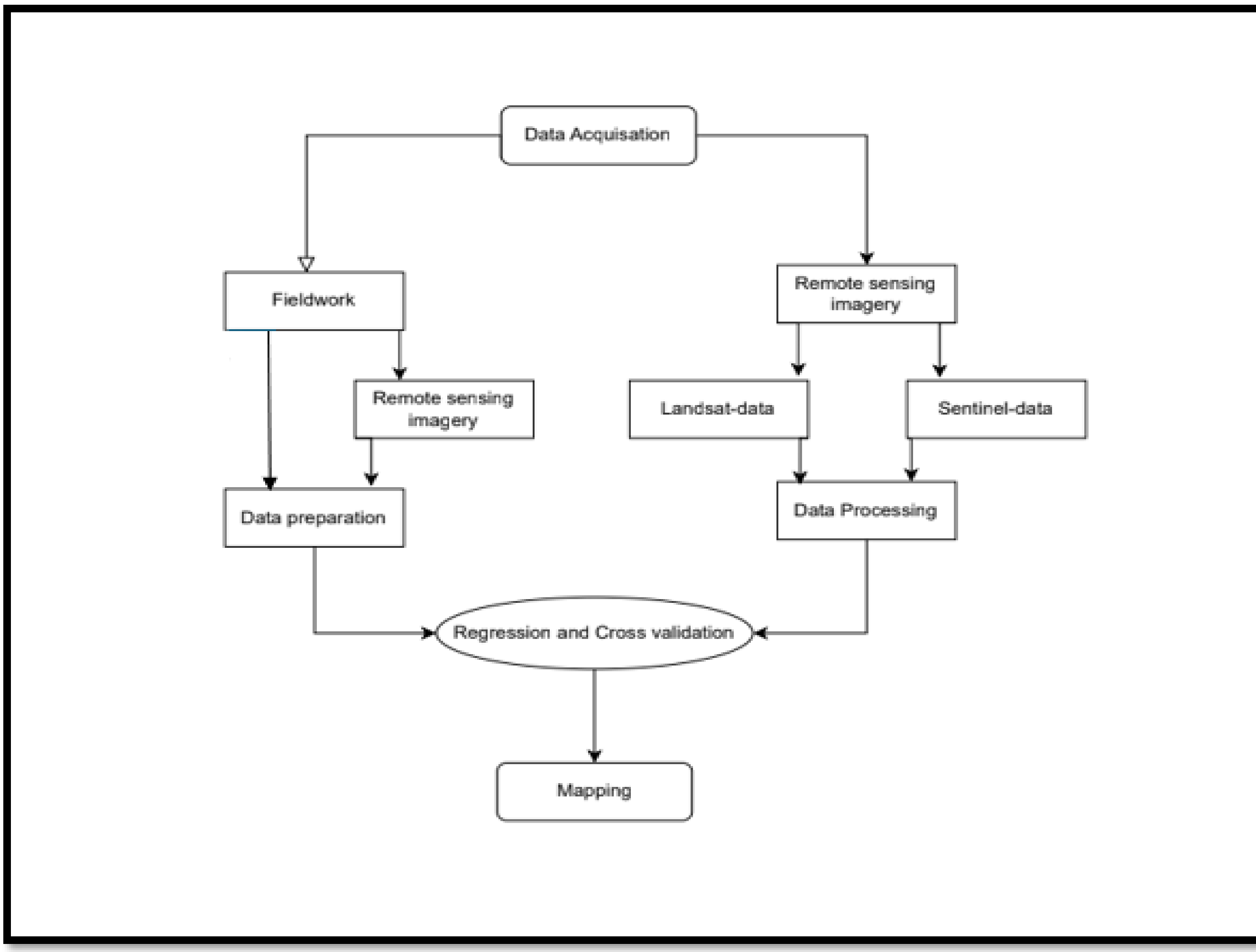

Figure 3.2: summary of the flow of the methodology of this research.

(a)

(b)

(c)

(d)

Figure 3.3: some of the visited sites showing: (a) hyparrhenia rufa grass (b) sweet thorn trees (d) illegal mining being done: Photo credits:Cathrine.

3.4 Data acquisition

3.4.1 Temperature and Rainfall

Temperature and rainfall were collected online on the climate data websites https://data.chc.ucsb.edu/products/CHIRPS-2.0/ and http://www.worldclimate.com/ respectively The temperature was averaged from the monthly temperatures to get the yearly average. The temperature has an impact on plant growth and phenology, which impacts when plants develop and are productive (Hatfield & Prueger, 2015). Extreme temperatures can affect the health and survival of vegetation. Water availability directly affects plant growth and biomass output and depends on precipitation. It affects the distribution and composition of the vegetation (Hatfield & Prueger, 2015).

The average values were tabulated to understand the relationship between vegetation dynamics rainfall and temperature. The study examined the correlation between the NDVI and meteorological factors, namely temperature and rainfall.

3.4.2 Satellite data

The acquisition of satellite data from Landsat and Sentinel 2 was facilitated through the utilization of Google Earth Engine (https://earthengine.google.com/), a cloud-based platform facilitating access, analysis, and visualization of satellite imagery (Zhao et al., 2021). The Landsat and Sentinel 2 datasets Landsat satellites, namely Landsat-5 (TM), and Landsat-8 (OLI), captured multispectral images with a spatial resolution of thirty meters and revisited the same location every 6 to 16 days (Roy et al., 2019). Landsat-5 data collected between 1985 and 2010 included Blue, Green, Red, and Near-Infrared bands to estimate surface reflectance and Landsat-8 2015 and 2023 incorporated additional bands (Roy et al., 2019). Sentinel 2 images for the years 2016 and 2023 were downloaded from Copernicus Open Access Hub https://scihub.copernicus.eu/dhus/#/home. Table 3.1 and 3.2 presents a succinct summary of the and bands utilized in the research for Landsat and Sentinel 2 respectively.

Table 3.1: Landsat sensors used.

Sensor	Bands	Wavelength µm
Landsat 5	Visible Blue	0-45-0.52
	Visible Green	0.52-0.60
	Visible Red	0.63-0.69
	Near Infrared	0.76-0.90
	Shortwave Infrared	1.55-1.75
	Thermal Infrared	10.40-12.50
	Shortwave Infrared 2	2.08-2.35
Landsat 8	Coastal Aerosol	0.43-0.45
	Blue	0-45-0.51
	Green	0.53-0.59
	Red	0.64-0.67
	Near Infrared	0.85-0.88
	Shortwave Infrared 1	1.57-1.65
	Shortwave Infrared 2	2.11-2.29
	Panchromatic	10.60-11.19
	Cirrus	1.36-1.38
	Thermal Infrared 1	10.60-11.19

As a means of improving the overall quality of the data, Table 3.2 shows the sentinel 2 bands used for the study.

Table 3.2: Sentinel 2 bands used.

Bands	Wavelength µm	Spatial Resolution
Coastal aerosol	400-453	60
Blue	455-520	10
Green	530-570	10
Red	630-680	10

Red Edge 1	698-73	10
Red Edge 2	733-748	20
Red Edge	773-793	20
Narrow Near Infrared	780-2500	10
Water Vapour	935-955	60
Shortwave Infrared-Cirrus	1360-1390	60
Short Wave Infrared-1	1610-1660	20
Short Wave Infrared-2	2100-2190	20

3.5 Preprocessing of remote sensing data

Landsat images come in Universal transverse Mercator (UTM) zone 35 N for the scenes in Zimbabwe hence, they must be reprojected. All Landsat scenes were reprojected to UTM zone 35S. Both sentinel and Landsat images were corrected atmospherically. Landsat datasets, obtained via GEE, were analyzed using the Landsat Surface Reflectance Code (LaSRC) to adjust for atmospheric conditions and convert top-of-atmosphere reflectance to surface reflectance (Vermote et al., 2016). Atmospheric correction procedure for Sentinel 2 was implemented, using SNAP in conjunction with the Sen2Cor plugin. Rainfall data was interpolated using the Inverse Distance Weighting (IDW) method to calculate the year-average rainfall. The IDW approach gives larger weights to data points closer to the target location and lower weights to those farther away, resulting in a weighted average.

3.6 Image Classification

The significance of designing a classification system that aligns with the research domain and objectives has been emphasized in multiple studies (Abrams et al., 1996; Congalton, 1991). Consequently, all satellite images were classified utilizing the supervised classification system and the Google Earth engine. To accomplish this, the Support Vector Machine (SVM) was implemented for image classification. From the 200 collected field samples, two groups were randomly formed for validation and training samples. One hundred and sixty were used for training, which is 80%, and forty were used for validation, which is 20%, for the year 2023, for both summer and winter. For the years 1985–2020 for Landsat and 2016–2020 for Sentinel, where ground truth was not available, training sites were identified based on the information obtained from Google earth.

3.7 Accuracy Assessment

To assess the accuracy of the image classification, the study employed Kappa statistics. Kappa statistics are measured on a scale of 0 to 1, with 0 representing random agreement and 1 representing perfect agreement. The Kappa statistics were computed by utilizing the confusion matrix (Adepoju & Adelabu, 2020), which compares the identified pixels with the reference pixels for each land cover class. User and producer accuracy were also identified, and the results for each year are illustrated in tables 3.3 to 3.7.

3.8 NDVI for regression analysis with temperature and rainfall

The Normalized Difference Vegetation Index (NDVI) is an important measurement that is utilized to evaluate the health of vegetation. The reflectance values the red band and the near-infrared band (Tucker, 1979), The index is calculated as:

NDVI = (NIR-RED)/(NIR+RED) (Tucker, 1979).

Where NIR and R represents reflectance in the near infrared and red bands.

In essence, the NDVI provides an understanding of the amount of healthy green vegetation that is present in a particular area (Abdullah et al., 2023). This study employed ArcGIS Pro to extract NDVI average annual values from satellite imagery. Points that were extracted from rainfall were interpolated. The values were used for regression; hence, it was essential to ensure that the NDVI and rainfall data were spatially aligned (Garai et al., 2022) to achieve a proper correlation.

3.9 Data analysis

3.9.1 Image analysis

The summary statistics such as species composition an area of LULC in each image and were automatically generated from the Google Earth engine. LULC area statistics were used to calculate LULC percentage change for trend analysis.

3.9.2 Regression Analysis

Regression analysis was performed using from SAS software to determine relationship between NDVI and climatic variables such as rainfall and temperature. Graphs and R-Square statistics obtained from this process were used to in the analysis.

CHAPTER FOUR: RESULTS

4.1 Introduction

In this chapter, the results of the investigation into the potential of Landsat and Sentinel-2 for identifying and mapping rangeland vegetation composition are presented. In addition, the chapter sheds insight on the temporal patterns that influence the composition and distribution of vegetation by showing the trends and changes that have been observed in the dynamics of rangeland vegetation throughout time.

4.2 Vegetation Composition Mapping using Landsat 8 and Sentinel 2

Figure 4.1 shows the classification map of vegetation composition for Gweru using the SVM classifier for both Landsat and Sentinel. *Rhodes*, which is a prevalent grass covering 20% of the area, and *Rufa* grass, which contributes to the overall vegetation cover with a percentage of 30%, *Mopane* has 10% coverage, *Acacia* has 5% coverage, *Miombo* has 25% coverage, *Terminalia* has 1% and others cover 9%. For sentinel the values are slightly different from those of Landsat *Rhodes* grass having 23% coverage, *Rufa* grass with 28% coverage, *Mopane* 29,5% coverage, *Miombo* of 15% coverage, *Accacia* 4% and, *Terminalia* 0,5%. Based on the percentages, in terms of the vegetation distribution significant presence of grasslands and woodlands can be found in the northern region. The woodlands become more densely forested, interspersed with areas of grass, proceeding eastward. In addition to a combination of grasslands and woodlands, the western region has a marginally greater concentration of grasslands. A varied ecosystem is signified by the presence of woodlands and vegetation in the southern region.

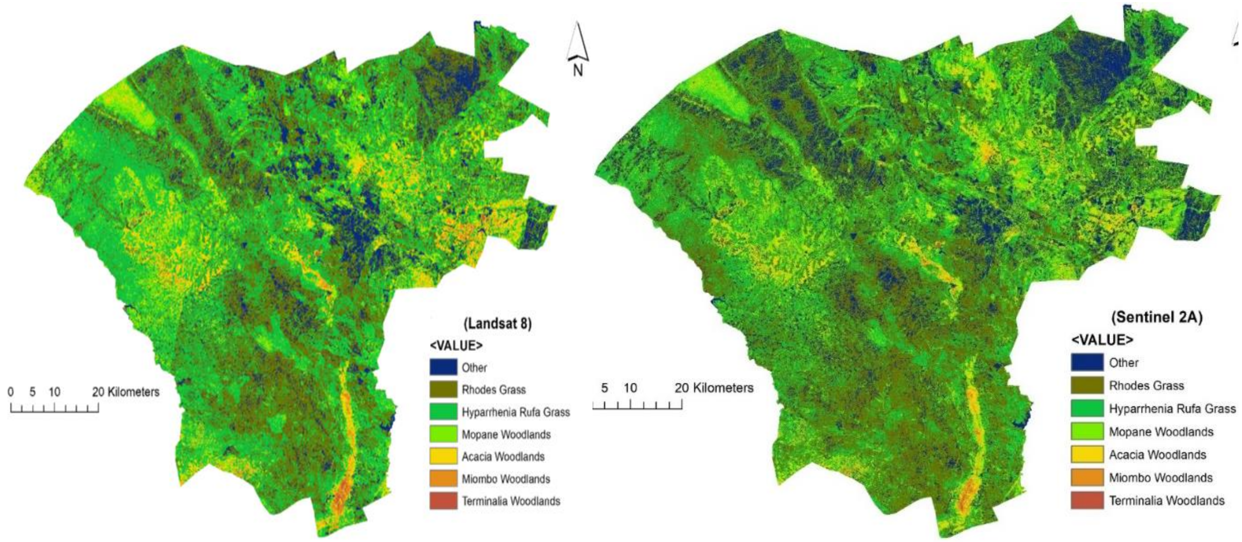

Figure 4.1: Sentinel 2 and Landsat 8 derived vegetation composition map for 2023 for the study area.

4.3 Trend and change analysis of land use and landcover images.

Figure 4.2: shows the classified LULC images for Landsat images between 1985 to 2023. The images show broad LULC classes that have potentially reduced vegetation in the study area. In 1985, the study area was characterized by a substantial forest cover, particularly in the western and northern areas. In 1995, there was an increased prevalence of grassland in the eastern region. Since 2005, there has been a general rise in grassland areas and a decline in forest areas, with the changes being most pronounced in the eastern and southern regions. Bareland begins to emerge sharply in 2015, as forested regions continue to decline, and grassland expands further. In 2023, built-up areas become more prevalent in the southern region, suggesting the emergence of urban development. Forest areas have experienced a substantial reduction, while grassland and bareland have grown. A transition from forest to grassland and desolate terrain is indicated by these trends, as well as the formation of built-up regions, especially in the southern part, which is suggestive of urbanization. This could be the result of a multitude of factors, including economic development, climate change, or human activities.

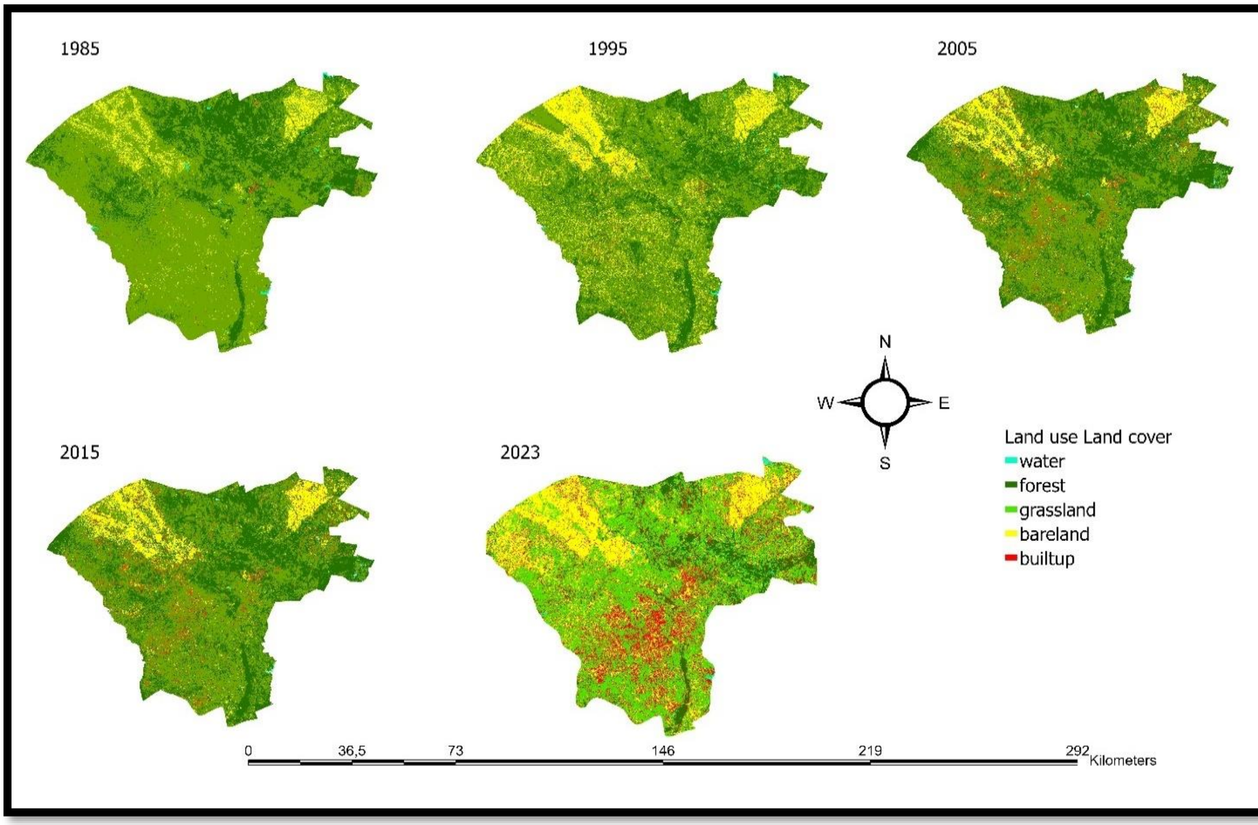

Figure 4.2: show the classified LULC images for Landsat images between 1985 to 2023.

Figure 4.3: show the classified LULC images for sentinel images between 1985 to 2023.In 2016, a substantial proportion of the study area is covered by forest, particularly in the western and northern regions. The built-up class increases in 2023, especially in the eastern and southern regions of the area. The class of grassland exhibits a decrease. A transition from forested to built-up is suggested by these trends, which also point to urbanization, especially in the eastern and southern portions. The water shows a decrease in every part of the city, this could be due to high temperatures and human activities.

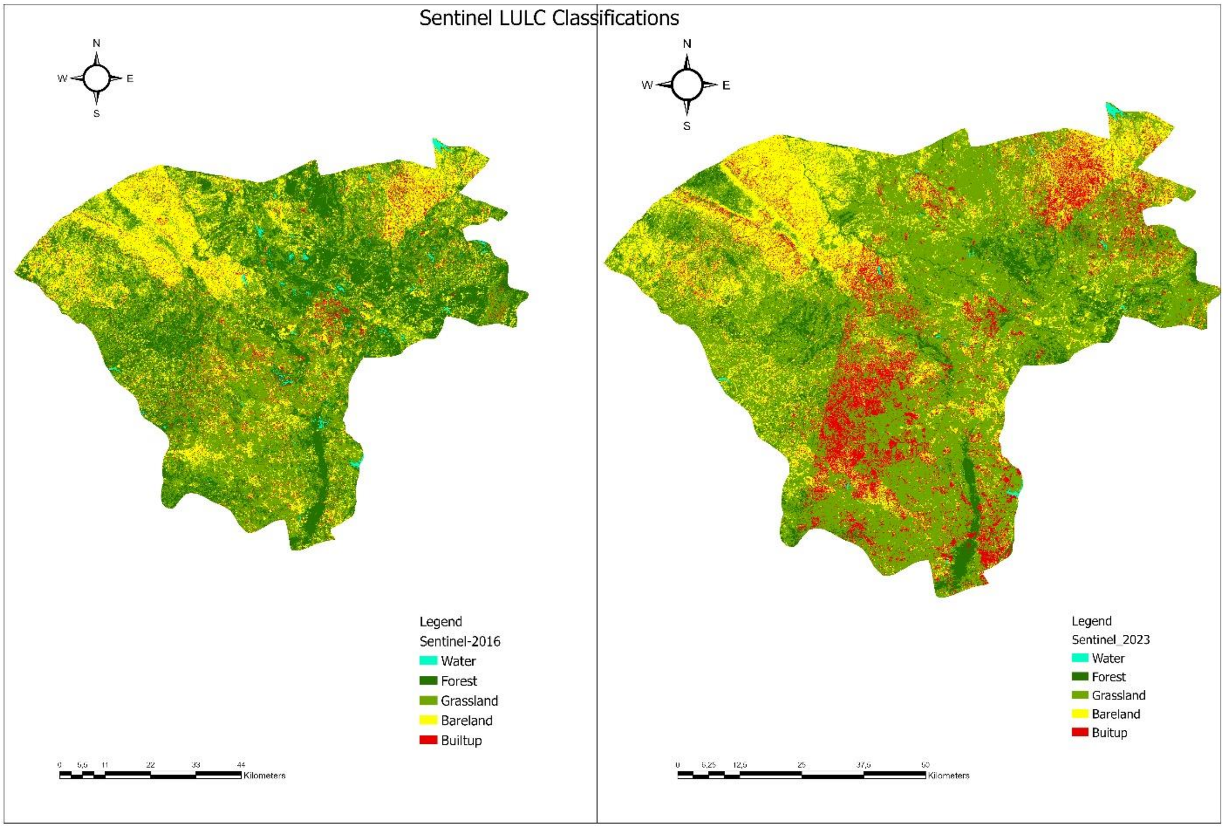

Figure 4.3: showing sentinel classifications of LULC.

Table 4.1 below shows the LULC classes trend in percentages the classes show a decrease in forested and grassland whilst an increase in bareland and built-up areas.

Table 4.1: Percentage trend analysis of LULC classification

Percentage trend analysis of LULC classification					
Year	Built-up	Water	Forest	Bareland	Grassland
1985	0,14	0,68	59,99	10	29,19
1995	0,43	0,65	54,74	15	29,18
2005	102	0,05	55	15,74	28,19
2015	5	0,64	53	15,17	26,19
2023	8,39	0,62	39,98	26,01	25

Table 4.2 below shows that between 1985 and 2023 bareland had the highest gain of 15.01% followed by grassland with 11%. This gain by bare land suggests that most of the forest land is being affected by activities such as land clearing for agriculture, mining activities and over grazing. The built-up areas increased by 7.99% between 1985 and 2023. The 11% gain by grassland suggests that most of the forest might be affected by activities such as overgrazing. Slight decrease of water (-0.05) suggests siltation of water due to soil erosion resulting from removal of soil cover. A sharp decline is noticed for forest, this could be due to deforestation.

Table 4.2: shows change percentage trend analysis for LULC between 1985-2023

Percentage of change	
LULC	1985-2023
Built-up	7,99
water	-0,05
Forest	-25,02
Bareland	15,01
Grassland	11

4.4 Accuracy Assessment

Table 4.3 shows the Landsat classification results for 1985 reveal high accuracy in land cover classification, with an overall accuracy of 94.19% and a kappa coefficient of 0.92. Notably, water bodies were accurately classified with 100% user accuracy and 96.7% producer accuracy. Forest and grassland classifications also yielded high accuracies of 94.44% and 96.3% respectively, while bare land and built-up areas demonstrated slightly lower accuracies but still maintained considerable precision, with producer accuracies of 100% and 75% respectively.

Table 4.3 Accuracy assessment for classification 1985

		1985			
		Predicted Classes			
	Water	Forest	Bareland	Grassland	Built-up
Water	29	1	0	0	0
Forest	0	34	0	0	0
Bareland	0	0	33	1	0
Grassland	0	0	0	26	0
Built-up	0	1	6	1	24
Colum total	29	36	39	27	24
User accuracy	100	94,44	84,62	96,3	100
Producer accuracy	96,7	100	100	100	75
Overall accuracy 94,19%					
kappa 0.92					

Table 4.4 below shows the Landsat classification results for 1995 exhibit high accuracy with an overall accuracy of 93.66% and a kappa coefficient of 0.92, indicating excellent agreement. Water and grassland classes demonstrate particularly high user and producer accuracies, both achieving 100% accuracy. Forest and built-up areas also show strong classification performance, with user accuracies of 87.09% and 96.15% respectively. Bareland exhibits slightly lower accuracy but remains robust at 92.3%.

Table 4.4 Accuracy assessment for classification 1995

		1995			
		Predicted Classes			
	Water	Forest	Bareland	Grassland	Built-up
Water	27	2	1	0	1
Forest	0	27	0	1	0
Bareland	0	2	24	0	0
Grassland	0	0	0	48	0
Built-up	2	0	1	0	25
Colum total	29	29	25	49	26
User accuracy	93,1	87,09	92,3	100	96,15
Producer accuracy	87,09	100	92,3	100	89,23
Overall accuracy 93,66%					
kappa 0.92					

Table 4.5 below shows Landsat classification results for 2005 reveal high accuracies across land cover categories. Water and Built-up areas achieved perfect user and producer accuracies, indicating precise classification. Forest and Grassland show high user and producer accuracies, with slight discrepancies in the latter. Bareland demonstrates a slightly lower user accuracy but maintains high producer accuracy. Overall accuracy stands at 97.08%, indicating robust classification performance, further supported by a kappa coefficient of 0.96.

Table 4.5 Accuracy assessment for classification 2005

		2005			
		Predicted Classes			
	Water	Forest	Bareland	Grassland	Built-up
Water	23	0	0	0	0
Forest	0	35	2	0	0
Bareland	0	0	29	0	0
Grassland	0	0	0	35	0
Built-up	0	0	0	4	21
Colum Total	23	35	31	39	21
User accuracy %	100	100	93,54	89,74	100
Producer accuracy%	100	94,56	100	100	84
Overall accuracy 97.08%					
kappa 0.96					

Table 4.6 below shows, the Landsat 5 classification results for 2015 depict high accuracy in categorizing water and forest regions, achieving 94.12% and 100% producer accuracy, respectively. However, built-up areas exhibit a relatively lower accuracy of 80%. Notably, user accuracy remains consistently high across most categories, indicating the reliability of the classification results. These findings underscore the efficacy of Landsat 5 imagery in discerning land cover dynamics, with potential areas for refinement in classification techniques identified for future investigations.

Table 4.6 Accuracy assessment for classification 2015

		2015			
		Predicted Classes			
	Water	Forest	Bareland	Grassland	Built-up
Water	32	2	0	0	0
Forest	0	29	0	0	0
Bareland	0	0	26	0	0
Grassland	0	0	0	23	2
Built-up	0	0	4	2	24
Total Column	32	31	30	25	26
Producer Accuracy	94,12	100	100	92	80
User Accuracy	100	93,55	86,67	92	92,31
Overall accuracy 93,06%					
kappa 0.913					

Table 4.7 below shows the Sentinel 2 classification results for 2023 demonstrate high accuracy across various land cover types. Water bodies were accurately classified with 100% user and producer accuracy, followed by forests with 100% user accuracy and 90% producer accuracy. Bareland and built-up areas were classified with 92.31% and 100% user accuracy respectively. Grasslands showed perfect classification with 100% accuracy. Overall accuracy for the classification stands at an impressive 97.99%.

4.7 Accuracy assessment for classification for 2023

		2023			
		Predicted Classes			
	Water	Forest	Bareland	Grassland	Built-up
Water	29	0	0	0	0
Forest	0	29	0	0	1
Bareland	0	0	22	0	0
Grassland	0	0	0	21	0
Built-up	0	0	1	1	26
Total Column	29	29	23	22	27
User accuracy	100	100	96,65	95,45	80
Producer accuracy	100	96,67	100	100	92,86
Overall accuracy 97,69%					
kappa 0.97					

Table 4.8 below shows the Sentinel 2 classification results for 2016 indicate high accuracy across various land cover types. Notably, water and forest classes achieved perfect user and producer accuracies, while bareland and grassland showed high accuracies of 97.06% and 94.29% respectively. However, grassland and built-up areas exhibited slightly lower user accuracies at

1.43% each, despite satisfactory producer accuracies. Overall accuracy stood at an impressive 97.99%, affirming the reliability of the classification model.

Table 4. 8 Accuracy assessment for classification for 2016 and 2023 for sentinel

									SENTINEL				
		2023							2016				
							Predicted Classes						
	Water	Forest	Grassland	Bareland	Built-up				Water	Forest	Bareland	Grassland	Built-up
Water	29	0	0	0	0				27	0	0	0	0
Forest	0	27	0	0	0				0	33	0	0	0
Grassland	0	0	36	0	0				0	0	39	0	1
Bareland	0	3	0	25	0				0	0	1	33	0
Built-up	0	0	0	0	29				0	0	8	2	25
Colum Total	29	30	36	25	29		Colum Total		27	33	40	35	26
Producer accuracy	100	100	92,31	100	100		Producer Accuracy		100	97,5	97,06	71,43	71,43
Usser accuracy	100	90	100	100	100		User Accuracy		100	100	81,25	94,29	96,15
Overall accuracy 97,99%							Overall accuracy 92.9%						
kappa 0.98							kappa 0.91						

4.5 Rainfall Distribution Analysis

Fig 4.5 below shows the annual spatial distribution of rainfall. The northern area receives an average amount of rainfall, ranging from 695.25 - 731.99 mm and 732 - 779.04 mm). The central-eastern receives the highest amount of rainfall, ranging from 779.05 - 864.58 mm. The west and south are characterized by moderate to low rainfall, ranging from 637.05 - 695.24 mm.

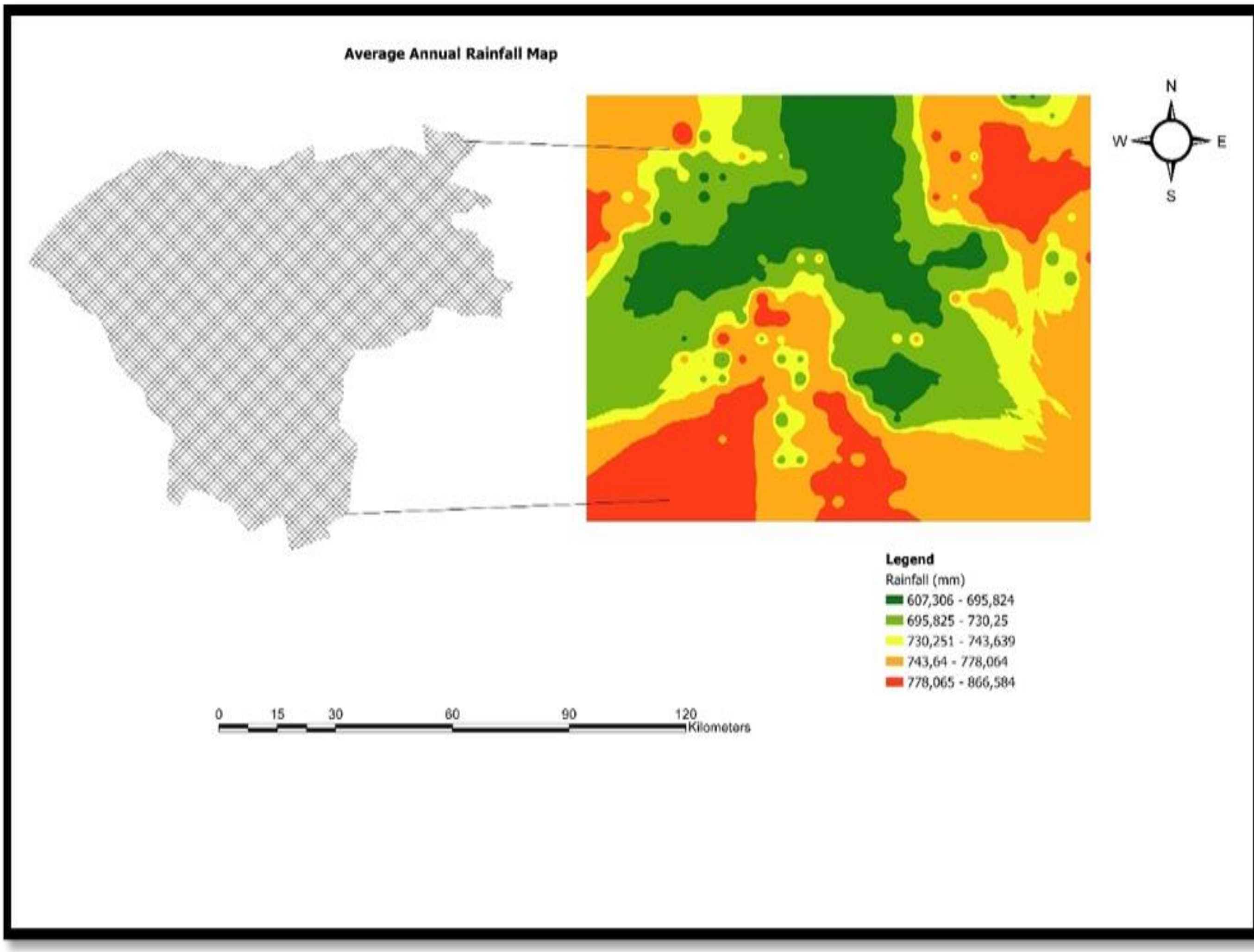

Figure 4.4: shows the distribution of the annual rainfall for the study area.

4.6 Regression analysis

For both rainfall and temperature, the fit plots below illustrate a relationship with NDVI, using a graphical representation. The shaded area represents the confidence interval. The blue line labelled fit is the line that provides the best fit confidence limits, which for this study is 95%, which are presented by the dashed lines.

Figure 4.6 below shows, the linear regression analysis which was done for Landsat, and a positive correlation was noticed for rainfall, as seen in figure. 4.6. as the NDVI rises the amount of rainfall rises. The R-square value is 0,9748, which shows a high degree of goodness of fit.

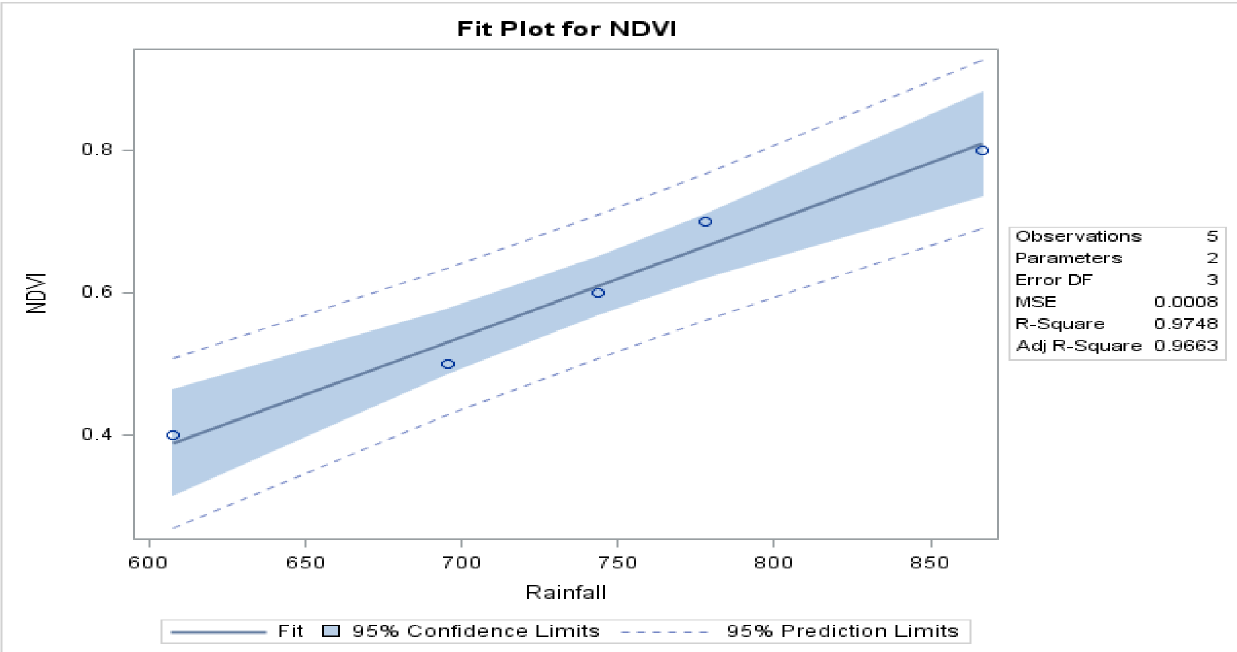

Figure 4.5 shows regression for rainfall and NDVI

The NDVI and temperature show a negative relationship, as seen in figure 4.7 below as the confidence limits show uncertainty around the fit. The R-square is 0,3333, which shows a low degree of goodness of fit.

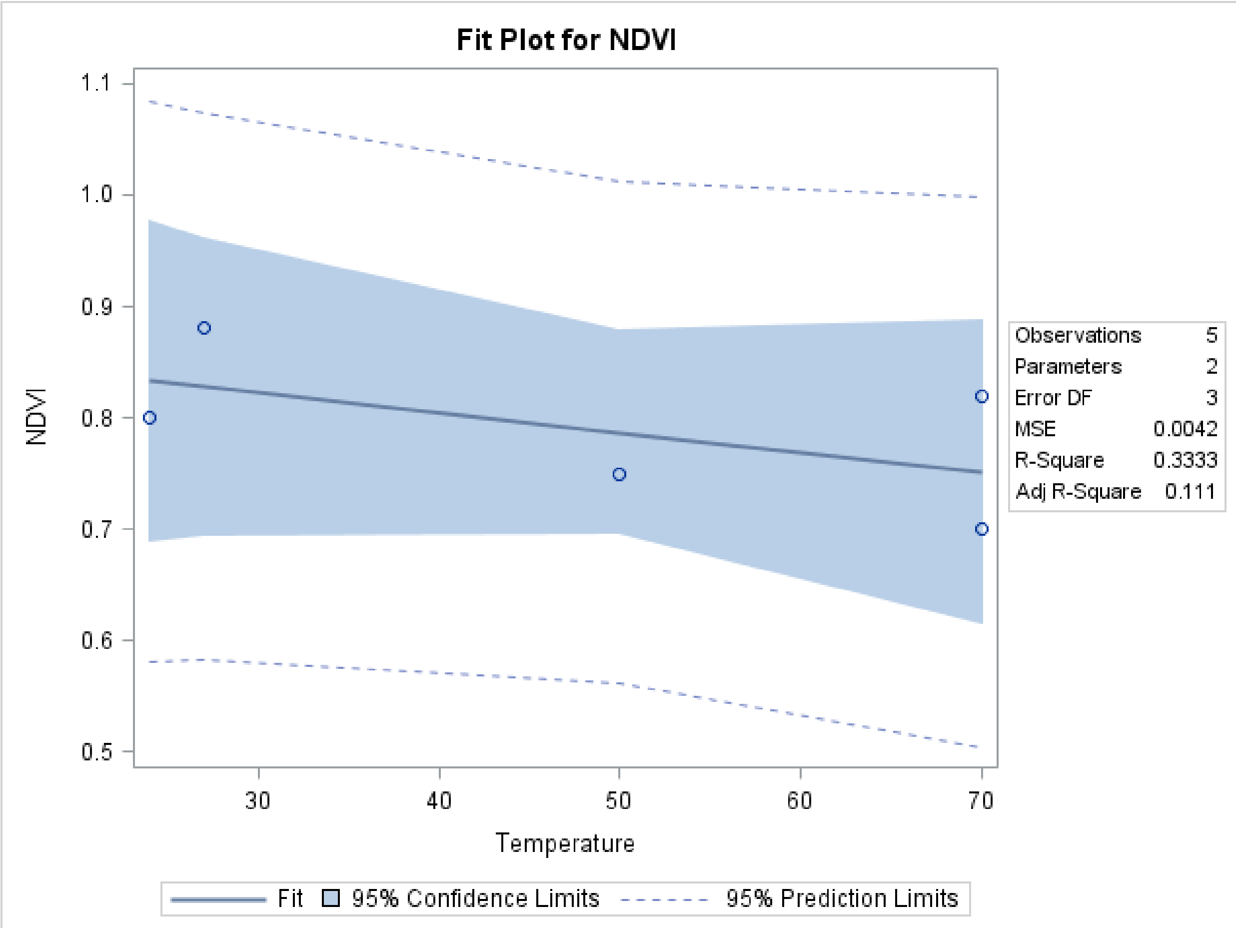

Figure 4.6 shows regression for temperature and NDVI

CHAPTER FIVE: DISCUSSION

5.1 Introduction

This section delves into the insightful discussions arising from a comprehensive analysis of the research objectives, focusing on the assessment of Landsat and Sentinel-2 for mapping rangeland vegetation and detecting temporal changes. By exploring the intricate relationship between NDVI and environmental factors, which are rainfall and temperature. This chapter aims to provide a deeper understanding of rangeland dynamics and ecosystem health. The findings presented in the previous sections serve as a basis for engaging discussions that unravel the implications of these results on sustainable rangeland management practices and environmental conservation efforts.

5.2 To identify trends and changes in rangeland vegetation dynamics over time

The temporal trends identified in the analysis, particularly the notable rise in bareland with a percentage increase of 15.01% and grassland with an increase of 11%, signify substantial changes in land use patterns that are exerting significant impacts on the rangeland ecosystem. These changes, characterized by the expansion of bareland and grassland areas coupled with the encroachment of bare land, underscore the dynamic nature of human-induced alterations in the landscape. Activities such as land clearing for agriculture, mining activities, and overgrazing are possibly the primary driving forces behind these transformations, indicative of the pressures exerted on rangeland environments by human activities. Studies have shown that such land use changes can lead to habitat fragmentation and loss, soil erosion, and reduced water quality, further exacerbating the ecological stress on rangeland ecosystems (Reynolds et al., 2007; Wang et al., 2019).The observed trends emphasize the urgent need for targeted conservation strategies that focus on mitigating the adverse effects of unsustainable land practices to safeguard the ecological balance and resilience of the rangeland ecosystem (Weltz et al., 2003).

Addressing the implications of these temporal trends is paramount for ensuring the long-term sustainability and health of rangeland ecosystems. The discernible gains in bareland and grassland areas, alongside the concerning increase in bare land, underscore the necessity of proactive conservation measures to counteract the detrimental impacts of land use changes on biodiversity and ecosystem health. By targeting interventions aimed at promoting sustainable land management practices, reducing land degradation, and enhancing vegetation cover, stakeholders can mitigate the threats posed by activities such as land clearing and overgrazing. For instance, implementing rotational grazing systems, reforestation, and soil conservation techniques have been shown to enhance ecosystem resilience (Baumber et al., 2020). These conservation strategies play a pivotal role in preserving the ecological integrity of rangeland environments, fostering biodiversity conservation, and promoting the long-term health and resilience of these vital ecosystems in the face of evolving environmental (Cowie et al., 2011).

5.3 Assessing the Landsat and Sentinel 2's potential for identifying and mapping rangeland vegetation composition.

An increase in studies on the classification of tree species has been propelled by developments in remote sensing technology during the last forty years. These studies have predominantly utilized multispectral, hyperspectral imaging techniques and very high-resolution satellite sensors (Ma et al., 2021). Expanding upon this groundwork, this study investigated the potential of multispectral images obtained from Landsat and Sentinel-2 to classify unique species of trees and grass occupying the Gweru region of Zimbabwe. Although the study highlights the significant potential of Landsat and Sentinel-2 imagery in improving the classification of tree species, it is important to acknowledge that the results highlight the vital significance of ground-truth species data. Regardless of the practicality of remote sensing technology, the incorporation of field data continues to be critical to attaining precise classification results. The study's comparatively high accuracy was probably due to the extensive gathering of the tree and grass species locations in the field, which enabled the improvement of image classification and validation procedures.

5.4 To evaluate the relationship between rangeland and vegetation dynamics using NDVI and environmental factors.

The research employed a linear regression analysis to examine the correlation between NDVI and climatic variables, namely precipitation and temperature. The results demonstrate that there is an exceptionally strong relationship between NDVI and rainfall, as evidenced by the R-square value of 0.9748 for NDVI and rainfall. This finding is in accordance with the results presented by Shi et al. (2023), in which they documented a noteworthy correlation coefficient of 0.687 between the

Mu Us arid region's precipitation and NDVI. The significant correlation between NDVI and precipitation highlights the crucial function of precipitation in regulating vegetation dynamics, especially in regions where water availability has a substantial impact on plant productivity and development.

In contrast, the R-square value of 0.3333 for the relationship between NDVI and temperature indicates a comparatively lesser association in comparison to the relationship between NDVI and rainfall. The finding aligns with the conclusions drawn by Shi et al. (2023), who documented a weaker correlation coefficient of 0.264 between the NDVI and temperature in the region of Mu Us. Furthermore, the findings of this research are corroborated by Sanz's (2021) investigation, which emphasizes the inverse relationship between NDVI and temperature in situations characterized by insufficient precipitation. Collectively, these results highlight the susceptibility of vegetation dynamics to water availability; in arid and semi-arid rangeland ecosystems, NDVI values demonstrate a more robust correlation with rainfall rather than temperature.

5.5 Conclusion

Precise data regarding the composition of vegetation species is critical for the efficient assessment of rangelands, especially in ecologically vulnerable areas such as Gweru due due to human activities such as mining and deforestation. By implementing the Support Vector Machine (SVM) algorithm in conjunction with Landsat and Sentinel-2 imagery featuring spatial resolutions of 10m and 30m, respectively, this study successfully identified and classified significant tree species and varieties in the Gweru region, including Rhodes grass, Rufa grass, Miombo, and Terminalia. This enhanced classification provides a strong basis for a thorough evaluation of rangelands and initiatives aimed at conserving forests.

Moreover, the significant gains observed in bareland, and grassland highlight the pressing need for sustainable land use practices to mitigate adverse impacts such as land clearing, mining, and overgrazing. These trends underscore the importance of proactive conservation measures to safeguard rangeland biodiversity and ecosystem health. The regression analysis results further emphasize the intricate relationship between vegetation dynamics and environmental factors, emphasizing the critical role of rainfall in shaping rangeland vegetation health. These trends underscore the importance of proactive conservation measures to safeguard rangeland biodiversity and ecosystem health. The regression analysis results further emphasize the intricate relationship between vegetation dynamics and environmental factors, emphasizing the critical role of rainfall in shaping rangeland vegetation health.

The LULC time series analysis shows the significant rise observed in bareland and grassland, it is imperative to implement targeted conservation efforts aimed at protecting vulnerable vegetation types and mitigating the impacts of land use changes on rangeland ecosystems. Sustainable land management practices, coupled with ongoing monitoring using remote sensing data, are essential to ensure the long-term health and resilience of rangeland environments. Additionally, continued research into the relationships between NDVI, environmental factors, and vegetation dynamics will provide valuable insights for informed decision-making in rangeland management. By incorporating these recommendations into future conservation strategies, this strives towards a more sustainable and balanced approach to preserving rangeland ecosystems for generations to come.

Overall, Landsat and Sentinel-2 images demonstrate significant potential for the assessment and identification of vegetation. Their integration into classification methodologies offers valuable insights for rangeland assessment and forest management practices, ultimately aiding in automatic forest inventory and informing government decision-making processes. By harnessing the capabilities of remote sensing technologies, this enhances understanding of ecosystem dynamics leading to the sustainable management and conservation of rangelands.

REFERENCES

Abdullah, M., Al-Ali, Z., Abulibdeh, A., Mohan, M., Srinivasan, S., & Al-Awadhi, T. (2023). Investigating the succession process of native desert plants over hydrocarbon-contaminated soils using remote sensing techniques. *Environmental Research, 219*, 114955.

Abedi, R. (2020). Comparison of parametric and non-parametric techniques to accurate classification of forest attributes on satellite image data. *Journal of Environmental Science Studies, 5*(4), 3229-3235.

Adepoju, K. A., & Adelabu, S. A. (2020). Improving accuracy of Landsat-8 OLI classification using image composite and multisource data with Google Earth Engine. *Remote Sensing Letters, 11*(2), 107-116.

Al-Najjar, H. A., Kalantar, B., Pradhan, B., Saeidi, V., Halin, A. A., Ueda, N., & Mansor, S. (2019). Land cover classification from fused DSM and UAV images using convolutional neural networks. *Remote Sensing, 11*(12), 1461.

Amede, T., Descheemaeker, K., Peden, D., & van Rooyen, A. (2009). Harnessing benefits from improved livestock water productivity in crop–livestock systems of sub-Saharan Africa: synthesis. *The Rangeland Journal, 31*(2), 169-178.

Archer, E. R. (2004). Beyond the “climate versus grazing” impasse: using remote sensing to investigate the effects of grazing system choice on vegetation cover in the eastern Karoo. *Journal of Arid Environments, 57*(3), 381-408.

Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). Segnet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE transactions on pattern analysis and machine intelligence, 39*(12), 2481-2495.

Baumber, A., Waters, C., Cross, R., Metternicht, G., & Simpson, M. (2020). Carbon farming for resilient rangelands: people, paddocks and policy. *The Rangeland Journal, 42*(5), 293-307.

Bekunda, M., Sanginga, N., & Woomer, P. L. (2010). Restoring soil fertility in sub-Sahara Africa. *Advances in agronomy, 108*, 183-236.

Bhaga, T. D., Dube, T., Shekede, M. D., & Shoko, C. (2020). Impacts of climate variability and drought on surface water resources in Sub-Saharan Africa using remote sensing: A review. *Remote Sensing, 12*(24), 4184.

Binot, A., Hanon, L., Joiris, D. V., & Dulieu, D. (2009). The challenge of participatory natural resource management with mobile herders at the scale of a Sub-Saharan African protected area. *Biodiversity and conservation, 18*, 2645-2662.

Bioucas-Dias, J. M., Plaza, A., Camps-Valls, G., Scheunders, P., Nasrabadi, N., & Chanussot, J. (2013). Hyperspectral remote sensing data analysis and future challenges. *IEEE Geoscience and remote sensing magazine, 1*(2), 6-36.

Birhane, E., Treydte, A. C., Eshete, A., Solomon, N., & Hailemariam, M. (2017). Can rangelands gain from bush encroachment? Carbon stocks of communal grazing lands invaded by Prosopis juliflora. *Journal of Arid Environments, 141*, 60-67.

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing, 65*(1), 2-16.

Booth, D. T., & Tueller, P. T. (2003). Rangeland monitoring using remote sensing. *Arid Land Research and Management, 17*(4), 455-467.

Breiman, L. (2001). Random forests. *Machine learning, 45*, 5-32.

Brink, A. B., & Eva, H. D. (2011). The potential use of high-resolution Landsat satellite data for detecting land-cover change in the Greater Horn of Africa. *International journal of Remote sensing, 32*(21), 5981-5995.

Brinkmann, K., Schwieger, D. A. M., Grieger, L., Heshmati, S., & Rauchecker, M. (2023). How and why do rangeland changes and their underlying drivers differ across Namibia's two major land-tenure systems? *The Rangeland Journal, 45*(3), 123-139.

Bruzzone, L., Cossu, R., & Vernazza, G. (2002). Combining parametric and non-parametric algorithms for a partially unsupervised classification of multitemporal remote-sensing images. *Information Fusion, 3*(4), 289-297.

Chang, L., Wang, J., & Woodgate, W. (2021). Analysing spectroscopy data using two-step group penalized partial least squares regression. *Environmental and Ecological Statistics, 28*, 445-467.

Cowie, A., Penman, T., Gorissen, L., Winslow, M., Lehmann, J., Tyrrell, T., Twomlow, S., Wilkes, A., Lal, R., & Jones, J. (2011). Towards sustainable land management in the drylands:

scientific connections in monitoring and assessing dryland degradation, climate change and biodiversity. *Land Degradation & Development, 22*(2), 248-260.

David, R. M., Rosser, N. J., & Donoghue, D. N. (2022). Remote sensing for monitoring tropical dryland forests: A review of current research, knowledge gaps and future directions for Southern Africa. *Environmental Research Communications, 4*(4), 042001.

De Lange, W. J., & van Wilgen, B. W. (2010). An economic assessment of the contribution of biological control to the management of invasive alien plants and to the protection of ecosystem services in South Africa. *Biological invasions, 12*(12), 4113-4124.

DiTomaso, J. M. (2000). Invasive weeds in rangelands: species, impacts, and management. *Weed science, 48*(2), 255-265.

Dodd, J. L. (1994). Desertification and degradation in sub-Saharan Africa. *Bioscience, 44*(1), 28-34.

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., & Martimort, P. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment, 120*, 25-36.

Du Preez, C., & Van Huyssteen, C. (2020). Threats to soil and water resources in South Africa. *Environmental Research, 183*, 109015.

Du, Z., Yang, J., Huang, W., & Ou, C. (2018). Training SegNet for cropland classification of high resolution remote sensing images. AGILE Conference,

Dube, O. P., & Pickup, G. (2001). Effects of rainfall variability and communal and semi-commercial grazing on land cover in southern African rangelands. *Climate Research, 17*(2), 195-208.

Dube, T., Pandit, S., Shoko, C., Ramoelo, A., Mazvimavi, D., & Dalu, T. (2019). Numerical assessments of leaf area index in tropical savanna rangelands, South Africa using Landsat 8 OLI derived metrics and in-situ measurements. *Remote Sensing, 11*(7), 829.

Eddy, I. M., Gergel, S. E., Coops, N. C., Henebry, G. M., Levine, J., Zerriffi, H., & Shibkov, E. (2017). Integrating remote sensing and local ecological knowledge to monitor rangeland dynamics. *Ecological Indicators, 82*, 106-116.

Ediz, Ü., MERMER, A., & YILDIZ, H. (2014). Assessment of rangeland vegetation condition from time series NDVI data. *Tarla Bitkileri Merkez Araştırma Enstitüsü Dergisi, 23*(1), 14-22.

Ehrenfeld, J. G. (2010). Ecosystem consequences of biological invasions. *Annual review of ecology, evolution, and systematics, 41*(1), 59-80.

Ekblom, A., Shoemaker, A., Gillson, L., Lane, P., & Lindholm, K.-J. (2019). Conservation through biocultural heritage—Examples from sub-Saharan Africa. *Land, 8*(1), 5.

Ergon, R., Granato, D., & Ares, G. (2014). Principal component regression (PCR) and partial least squares regression (PLSR). *Mathematical and statistical methods in food science and technology Wiley Blackwell, Chichester*, 121-142.

Eriksen, S. E., & Watson, H. K. (2009). The dynamic context of southern African savannas: investigating emerging threats and opportunities to sustainability. *Environmental Science & Policy, 12*(1), 5-22.

Faramarzi, M., Kesting, S., Isselstein, J., & Wrage, N. (2010). Rangeland condition in relation to environmental variables, grazing intensity and livestock owners' perceptions in semi-arid rangeland in western Iran. *The Rangeland Journal, 32*(4), 367-377.

Fava, F., & Vrieling, A. (2021). Earth observation for drought risk financing in pastoral systems of sub-Saharan Africa. *Current opinion in environmental sustainability, 48*, 44-52.

Finca, A., Linnane, S., Slinger, J., Getty, D., & Igshaan Samuels, M. (2023). Implications of the breakdown in the indigenous knowledge system for rangeland management and policy: a case study from the Eastern Cape in South Africa. *African journal of range & forage science, 40*(1), 47-61.

Friedl, M. A., & Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment, 61*(3), 399-409.

Gaffney, R., Augustine, D. J., Kearney, S. P., & Porensky, L. M. (2021). Using hyperspectral imagery to characterize rangeland vegetation composition at process-relevant scales. *Remote Sensing, 13*(22), 4603.

Galloway, F., Wynberg, R., & Nott, K. (2016). Commercialising a perfume plant, Commiphora wildii: livelihood implications for indigenous Himba in north-west Namibia. *International Forestry Review, 18*(4), 429-443.

Garai, S., Khatun, M., Singh, R., Sharma, J., Pradhan, M., Ranjan, A., Rahaman, S. M., Khan, M. L., & Tiwari, S. (2022). Assessing correlation between Rainfall, normalized difference Vegetation Index (NDVI) and land surface temperature (LST) in Eastern India. *Safety in Extreme Environments, 4*(2), 119-127.

Gascon, F., Bouzinac, C., Thépaut, O., Jung, M., Francesconi, B., Louis, J., Lonjou, V., Lafrance, B., Massera, S., & Gaudel-Vacaresse, A. (2017). Copernicus Sentinel-2A calibration and products validation status. *Remote Sensing, 9*(6), 584.

Geerken, R., & Ilaiwi, M. (2004). Assessment of rangeland degradation and development of a strategy for rehabilitation. *Remote Sensing of Environment, 90*(4), 490-504.

Getabalew, M., & Alemneh, T. (2019). Factors affecting the productivity of rangelands. *MedPub Journals, 3*(1), 19.

Gororo, E. (2013). *Land Management and Improvement Techniques in Zimbabwe*. Department of Research and Specialist Services. Retrieved 17 January 2024 from https://www.slideshare.net/gororoeddington/rangeland-management-and-improvement-in-zimbabwe

Group, W. B. (2019). *Sustainable Rangeland Management in Sub-Saharan Africa : Guidelines to Good Practice* World Bank Group. Retrieved 23 March 2024 from http://documents.worldbank.org/curated/en/237401561982571988/Sustainable-Rangeland-Management-in-Sub-Saharan-Africa-Guidelines-to-Good-Practic

Habiboullah, A., & Louly, M. A. (2023). Soil Moisture Prediction Using NDVI and NSMI Satellite Data: ViT-Based Models and ConvLSTM-Based Model. *SN Computer Science, 4*(2), 140.

Hoffman, T., & Vogel, C. (2008). Climate change impacts on African rangelands. *Rangelands, 30*(3), 12-17.

Holou, R. A., Achigan-Dako, E., & Sinsin, B. (2013). Ecology and management of invasive plants in Africa. *Invasive plant ecology*, 161-174.

Honda, E. A., & Durigan, G. (2016). Woody encroachment and its consequences on hydrological processes in the savannah. *Philosophical Transactions of the Royal Society B: Biological Sciences, 371*(1703), 20150313.

Hubert-Moy, L., Cotonnec, A., Le Du, L., Chardin, A., & Pérez, P. (2001). A comparison of parametric classification procedures of remotely sensed data applied on different landscape units. *Remote Sensing of Environment, 75*(2), 174-187.

Hunt Jr, E. R., Everitt, J. H., Ritchie, J. C., Moran, M. S., Booth, D. T., Anderson, G. L., Clark, P. E., & Seyfried, M. S. (2003). Applications and research using remote sensing for rangeland management. *Photogrammetric Engineering & Remote Sensing, 69*(6), 675-693.

Ienco, D., Gaetano, R., Dupaquier, C., & Maurel, P. (2017). Land cover classification via multitemporal spatial data by deep recurrent neural networks. *IEEE Geoscience and Remote Sensing Letters, 14*(10), 1685-1689.

Jiao, J., Zou, H., Jia, Y., & Wang, N. (2009). Research progress on the effects of soil erosion on vegetation. *Acta Ecologica Sinica, 29*(2), 85-91.

Joelsson, S. R., Benediktsson, J. A., & Sveinsson, J. R. (2006). Random forest classification of remote sensing data. In *Signal and Image Processing for Remote Sensing* (pp. 344-361). CRC Press.

Kakinuma, K., Sasaki, T., Jamsran, U., Okuro, T., & Takeuchi, K. (2014). Relationship between pastoralists' evaluation of rangeland state and vegetation threshold changes in Mongolian rangelands. *Environmental management, 54*, 888-896.

Kariuki, R., Willcock, S., & Marchant, R. (2018). Rangeland livelihood strategies under varying climate Regimes: Model insights from Southern Kenya. *Land, 7*(2), 47.

Karl, J. W. (2010). Spatial predictions of cover attributes of rangeland ecosystems using regression kriging and remote sensing. *Rangeland Ecology & Management, 63*(3), 335-349.

Kattenborn, T., Leitloff, J., Schiefer, F., & Hinz, S. (2021). Review on Convolutional Neural Networks (CNN) in vegetation remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing, 173*, 24-49.

Khatami, R., Mountrakis, G., & Stehman, S. V. (2016). A meta-analysis of remote sensing research on supervised pixel-based land-cover image classification processes: General guidelines for practitioners and future research. *Remote Sensing of Environment, 177*, 89-100.

Kiage, L. M. (2013). Perspectives on the assumed causes of land degradation in the rangelands of Sub-Saharan Africa. *Progress in Physical Geography, 37*(5), 664-684.

Kiala, Z., Odindi, J., Mutanga, O., & Peerbhay, K. (2016). Comparison of partial least squares and support vector regressions for predicting leaf area index on a tropical grassland using hyperspectral data. *Journal of Applied Remote Sensing, 10*(3), 036015-036015.

Kimambo, N. E., & Radeloff, V. C. (2023). Using Landsat and Sentinel-2 spectral time series to detect East African small woodlots. *Science of Remote Sensing, 8*, 100096.

Kotsiantis, S. B. (2013). Decision trees: a recent overview. *Artificial Intelligence Review, 39*, 261-283.

Lake, E. C., & Minteer, C. R. (2018). A review of the integration of classical biological control with other techniques to manage invasive weeds in natural areas and rangelands. *BioControl, 63*, 71-86.

Lakhankar, T., Ghedira, H., Temimi, M., Sengupta, M., Khanbilvardi, R., & Blake, R. (2009). Non-parametric methods for soil moisture retrieval from satellite remote sensing data. *Remote Sensing, 1*(1), 3-21.

Li, J., Hong, D., Gao, L., Yao, J., Zheng, K., Zhang, B., & Chanussot, J. (2022). Deep learning in multimodal remote sensing data fusion: A comprehensive review. *International journal of applied earth observation and geoinformation, 112*, 102926.

Liniger, H. a. M. S., R. (2021). *Why are rangelands in SSA important*. World Bank Group. Retrieved 23 March 2024 from https://1library.net/article/rangelands-ssa-important-sustainable-rangeland-management-saharan-africa.zxxd4lvz

Lu, X., Zheng, X., & Yuan, Y. (2017). Remote sensing scene classification by unsupervised representation learning. *IEEE Transactions on Geoscience and Remote Sensing, 55*(9), 5148-5157.

Maabreh, H. G., Waheeb, K., Ryadh, A., Abdulghani, S. B., Hamoodah, Z. J., Jasim, N. Y., Alajeeli, F., Al Mansor, A. H., & Andreevich, M. (2023). Application of M5 algorithm of decision tree in simulation and investigation of effective factors of erosion in rangelands and forests. *Caspian Journal of Environmental Sciences, 21*(3), 533-541.

Mancino, G., Falciano, A., Console, R., & Trivigno, M. L. (2023). Comparison between parametric and non-parametric supervised land cover classifications of sentinel-2 msi and landsat-8 oli data. *Geographies, 3*(1), 82-109.

Mapfumo, L., Muchenje, V., Mupangwa, J., Scholtz, M., & Washaya, S. (2021). Dynamics and influence of environmental components on greenhouse gas emissions in sub-Saharan African rangelands: a review. *Animal Production Science, 61*(8), 721-730.

Marchante, H., Palhas, J., Núñez, F. A. L., & Marchante, E. (2021). Invasive species impacts and management. *Life on Land*, 560-571.

Masemola, C., Cho, M. A., & Ramoelo, A. (2016). Comparison of Landsat 8 OLI and Landsat 7 ETM+ for estimating grassland LAI using model inversion and spectral indices: case study of Mpumalanga, South Africa. *International journal of Remote sensing, 37*(18), 4401-4419.

Mccollum, D. W., Tanaka, J. A., Morgan, J. A., Mitchell, J. E., Fox, W. E., Maczko, K. A., Hidinger, L., Duke, C. S., & Kreuter, U. P. (2017). Climate change effects on rangelands and rangeland management: affirming the need for monitoring. *Ecosystem Health and Sustainability, 3*(3), e01264.

McKay, A. (1968). Rangeland productivity in Botswana. *East African Agricultural and Forestry Journal, 34*(2), 178-193.

Micijevic, E., Rengarajan, R., Haque, M. O., Lubke, M., Tuli, F. T. Z., Shaw, J. L., Hasan, N., Denevan, A., Franks, S., & Choate, M. J. (2022). *ECCOE Landsat quarterly Calibration and Validation report—Quarter 3, 2021* (2331-1258).

Miller, B. W., & Doyle, M. W. (2014). Rangeland management and fluvial geomorphology in northern Tanzania. *Geomorphology, 214*, 366-377.

Mngadi, M., Odindi, J., Mutanga, O., & Sibanda, M. (2022). Quantitative remote sensing of forest ecosystem services in sub-Saharan Africa's urban landscapes: A review. *Environmental Monitoring and Assessment, 194*(4), 242.

Mou, L., Ghamisi, P., & Zhu, X. X. (2017). Deep recurrent neural networks for hyperspectral image classification. *IEEE Transactions on Geoscience and Remote Sensing, 55*(7), 3639-3655.

Moustakidis, S., Mallinis, G., Koutsias, N., Theocharis, J. B., & Petridis, V. (2011). SVM-based fuzzy decision trees for classification of high spatial resolution remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing, 50*(1), 149-169.

Muir, K. (1989). The potential role of indigenous resources in the economic development of arid environments in Sub-Saharan Africa: The case of wildlife utilization in Zimbabwe. *Society & Natural Resources, 2*(1), 307-318.

Mujaju, C., Mudada, N., & Chikwenhere, G. P. (2021). Invasive Alien Species in Zimbabwe (Southern Africa). *Invasive Alien Species: Observations and Issues from Around the World, 1*, 330-361.

Muñoz-Marí, J., Bruzzone, L., & Camps-Valls, G. (2007). A support vector domain description approach to supervised classification of remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing, 45*(8), 2683-2692.

Munyati, C. (2022). Detecting the distribution of grass aboveground biomass on a rangeland using Sentinel-2 MSI vegetation indices. *Advances in Space Research, 69*(2), 1130-1145.

Mureithi, S. M., Verdoodt, A., Njoka, J. T., Gachene, C. K., & Van Ranst, E. (2016). Benefits derived from rehabilitating a degraded semi-arid rangeland in communal enclosures, Kenya. *Land Degradation & Development, 27*(8), 1853-1862.

Musekiwa, N. B., Angombe, S. T., Kambatuku, J., Mudereri, B. T., & Chitata, T. (2022). Can encroached rangelands enhance carbon sequestration in the African Savannah? *Trees, Forests and People, 7*, 100192.

Mutuku, E. A., Vanlauwe, B., Roobroeck, D., Boeckx, P., & Cornelis, W. M. (2021). Visual soil examination and evaluation in the sub-humid and semi-arid regions of Kenya. *Soil and Tillage Research, 213*, 105135.

Navulur, K. (2006). *Multispectral image analysis using the object-oriented paradigm*. CRC press.

Nichols, M. H., Ruyle, G. B., & Nourbakhsh, I. R. (2009). Very-high-resolution panoramic photography to improve conventional rangeland monitoring. *Rangeland Ecology & Management, 62*(6), 579-582.

O'Connor, T. G., & van Wilgen, B. W. (2020). The impact of invasive alien plants on rangelands in South Africa. *Biological Invasions in South Africa, 14*, 459-487.

Oba, G., Stenseth, N. C., & Lusigi, W. J. (2000). New perspectives on sustainable grazing management in arid zones of sub-Saharan Africa. *Bioscience, 50*(1), 35-51.

Omondi, S., Kidali, J. A., Ogali, I., Mugambi, J. M., & Letoire, J. (2014). The status of livestock technologies and services in the Southern Maasai rangelands of Kenya. *African Journal of Agricultural Research, 9*(15), 1166-1171.

Onyango, C. M., Nyaga, J. M., Wetterlind, J., Söderström, M., & Piikki, K. (2021). Precision agriculture for resource use efficiency in smallholder farming systems in sub-saharan africa: A systematic review. *Sustainability, 13*(3), 1158.

Oyekola, M. A., & Adewuyi, G. K. (2018). Unsupervised classification in land cover types using remote sensing and GIS techniques. *International Journal of Science and Engineering Investigations, 7*(72), 11-18.

Pavlidis, P., Wapinski, I., & Noble, W. S. (2004). Support vector machine classification on the web. *Bioinformatics, 20*(4), 586-587.

Peel, M., & Stalmans, M. (2018). The effect of Holistic Planned Grazing™ on African rangelands: a case study from Zimbabwe. *African journal of range & forage science, 35*(1), 23-31.

Perumal, K., & Bhaskaran, R. (2010). Supervised classification performance of multispectral images. *arXiv preprint arXiv:1002.4046*.

Pfeiffer, M., Langan, L., Linstädter, A., Martens, C., Gaillard, C., Ruppert, J. C., Higgins, S. I., Mudongo, E. I., & Scheiter, S. (2019). Grazing and aridity reduce perennial grass abundance in semi-arid rangelands–Insights from a trait-based dynamic vegetation model. *Ecological Modelling, 395*, 11-22.

Ramoelo, A., Skidmore, A., Cho, M. A., Mathieu, R., Heitkönig, I., Dudeni-Tlhone, N., Schlerf, M., & Prins, H. (2013). Non-linear partial least square regression increases the estimation accuracy of grass nitrogen and phosphorus using in situ hyperspectral and environmental data. *ISPRS Journal of Photogrammetry and Remote Sensing, 82*, 27-40.

Reed, M. S., Stringer, L., Dougill, A., Perkins, J., Atlhopheng, J., Mulale, K., & Favretto, N. (2015). Reorienting land degradation towards sustainable land management: Linking sustainable livelihoods with ecosystem services in rangeland systems. *Journal of environmental management, 151*, 472-485.

Reynolds, J. F., Smith, D. M. S., Lambin, E. F., Turner, B., Mortimore, M., Batterbury, S. P., Downing, T. E., Dowlatabadi, H., Fernández, R. J., & Herrick, J. E. (2007). Global desertification: building a science for dryland development. *science, 316*(5826), 847-851.

Roba, H. G., & Oba, G. (2009). Efficacy of integrating herder knowledge and ecological methods for monitoring rangeland degradation in northern Kenya. *Human Ecology, 37*, 589-612.

Rogan, J., & Chen, D. (2004). Remote sensing technology for mapping and monitoring land-cover and land-use change. *Progress in planning, 61*(4), 301-325.

Roy, D. P., Huang, H., Boschetti, L., Giglio, L., Yan, L., Zhang, H. H., & Li, Z. (2019). Landsat-8 and Sentinel-2 burned area mapping-A combined sensor multi-temporal change detection approach. *Remote Sensing of Environment, 231*, 111254.

Salehinejad, H., Sankar, S., Barfett, J., Colak, E., & Valaee, S. (2017). Recent advances in recurrent neural networks. *arXiv preprint arXiv:1801.01078*.

Sangeda, A. Z., & Maleko, D. D. (2018). Rangeland condition and livestock carrying capacity under the traditional rotational grazing system in northern Tanzania. *Livestock Research for Rural Development, 30*(5), 79.

Sannier, C. (2000). *Strategic monitoring of crop yields and rangeland conditions in Southern Africa and remote sensing*. Cranfield University (United Kingdom).

Senda, T. S., Kiker, G. A., Masikati, P., Chirima, A., & van Niekerk, J. (2020). Modeling climate change impacts on rangeland productivity and livestock population dynamics in Nkayi District, Zimbabwe. *Applied sciences, 10*(7), 2330.

Serpico, S. B., Bruzzone, L., & Roli, F. (1996). An experimental comparison of neural and statistical non-parametric algorithms for supervised classification of remote-sensing images. *Pattern recognition letters, 17*(13), 1331-1341.

Shah, A. N., Tanveer, M., Shahzad, B., Yang, G., Fahad, S., Ali, S., Bukhari, M. A., Tung, S. A., Hafeez, A., & Souliyanonh, B. (2017). Soil compaction effects on soil health and cropproductivity: an overview. *Environmental Science and Pollution Research, 24*, 10056-10067.

Shao, Z., Yang, K., & Zhou, W. (2018). Performance evaluation of single-label and multi-label remote sensing image retrieval using a dense labeling dataset. *Remote Sensing, 10*(6), 964.

Shiferaw, B., Tesfaye, K., Kassie, M., Abate, T., Prasanna, B. M., & Menkir, A. (2014). Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. *Weather and climate extremes, 3*, 67-79.

Sibanda, A., Tui, S. H.-K., Van Rooyen, A., Dimes, J., Nkomboni, D., & Sisito, G. (2011). Understanding community perceptions of land use changes in the rangelands, Zimbabwe. *Experimental Agriculture, 47*(S1), 153-168.

Siyabulela, S., Tefera, S., Wakindiki, I., & Keletso, M. (2020). Comparison of grass and soil conditions around water points in different land use systems in semi-arid South African rangelands and implications for management and current rangeland paradigms. *Arid Land Research and Management, 34*(2), 207-230.

Snyman, H. (1998). Dynamics and sustainable utilization of rangeland ecosystems in arid and semi-arid climates of southern Africa. *Journal of Arid Environments, 39*(4), 645-666.

Speiser, J. L., Miller, M. E., Tooze, J., & Ip, E. (2019). A comparison of random forest variable selection methods for classification prediction modeling. *Expert systems with applications, 134*, 93-101.

Stuckens, J., Coppin, P., & Bauer, M. (2000). Integrating contextual information with per-pixel classification for improved land cover classification. *Remote Sensing of Environment, 71*(3), 282-296.

Sumbul, G., & Demİr, B. (2020). A deep multi-attention driven approach for multi-label remote sensing image classification. *IEEE Access, 8*, 95934-95946.

Sweeney, S., Ruseva, T., Estes, L., & Evans, T. (2015). Mapping cropland in smallholder-dominated savannas: integrating remote sensing techniques and probabilistic modeling. *Remote Sensing, 7*(11), 15295-15317.

Tavirimirwa, B., Manzungu, E., Washaya, S., Ncube, S., Ncube, S., Mudzengi, C., & Mwembe, R. (2019). Efforts to improve Zimbabwe communal grazing areas: a review. *African journal of range & forage science, 36*(2), 73-83.

Taylor, S., Ferguson, J., Engelbrecht, F. A., Clark, V., Van Rensburg, S., & Barker, N. (2016). The Drakensberg Escarpment as the great supplier of water to South Africa. In *Developments in Earth Surface Processes* (Vol. 21, pp. 1-46). Elsevier.

Tessema, B., Sommer, R., Piikki, K., Söderström, M., Namirembe, S., Notenbaert, A., Tamene, L., Nyawira, S., & Paul, B. (2020). Potential for soil organic carbon sequestration in grasslands in East African countries: A review. *Grassland Science, 66*(3), 135-144.

Thamaga, K. H., Dube, T., & Shoko, C. (2022). Advances in satellite remote sensing of the wetland ecosystems in Sub-Saharan Africa. *Geocarto International, 37*(20), 5891-5913.

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment, 8*(2), 127-150.

Tully, K., Sullivan, C., Weil, R., & Sanchez, P. (2015). The state of soil degradation in Sub-Saharan Africa: Baselines, trajectories, and solutions. *Sustainability, 7*(6), 6523-6552.

Vågen, T. G., Lal, R., & Singh, B. (2005). Soil carbon sequestration in sub-Saharan Africa: a review. *Land Degradation & Development, 16*(1), 53-71.

Vetter, S. (2009). Drought, change and resilience in South Africa's arid and semi-arid rangelands. *South African Journal of Science, 105*(1), 29-33.

Walter, V. (2004). Object-based classification of remote sensing data for change detection. *ISPRS Journal of Photogrammetry and Remote Sensing, 58*(3-4), 225-238.

Wang, Z., Zhang, B., Zhang, X., & Tian, H. (2019). Using MaxEnt model to guide marsh conservation in the Nenjiang River Basin, Northeast China. *Chinese Geographical Science, 29*, 962-973.

Weltz, M. A., Dunn, G., Reeder, J., & Frasier, G. (2003). Ecological sustainability of rangelands. *Arid Land Research and Management, 17*(4), 369-388.

Winowiecki, L. A., Vågen, T.-G., Kinnaird, M. F., & O'Brien, T. G. (2018). Application of systematic monitoring and mapping techniques: Assessing land restoration potential in semi-arid lands of Kenya. *Geoderma, 327*, 107-118.

Xiaoping, W., Ni, G., Kai, Z., & Jing, W. (2011). Hyperspectral remote sensing estimation models of aboveground biomass in Gannan rangelands. *Procedia Environmental Sciences, 10*, 697-702.

Xu, M., Watanachaturaporn, P., Varshney, P. K., & Arora, M. K. (2005). Decision tree regression for soft classification of remote sensing data. *Remote Sensing of Environment, 97*(3), 322-336.

Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M., & Schirokauer, D. (2006). Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery. *Photogrammetric Engineering & Remote Sensing, 72*(7), 799-811.

Zhao, Q., Yu, L., Li, X., Peng, D., Zhang, Y., & Gong, P. (2021). Progress and trends in the application of Google Earth and Google Earth Engine. *Remote Sensing, 13*(18), 3778.

Zou, K. H., Tuncali, K., & Silverman, S. G. (2003). Correlation and simple linear regression. *Radiology, 227*(3), 617-628.