The use of Earth Observation Multi-sensor Systems to Monitor and Model Pastures: A Case of Savannah Grasslands in Hluvukani Village, Bushbuckridge Local Municipality, Mpumalanga Province, South Africa

by

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Declaration of Originality and Dissertation Submission by the Candidate

This is to declare that the research reported in this dissertation is my original work, except where otherwise acknowledged by citation of published sources. This dissertation has not been submitted for any degree, certificate or examination at any other university or institution of higher learning except only at the University of Fort Hare as the Degree awarding institution.

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Signature:

Dedication

To my special mother, Miss Lekani Mashabana Nduku, sisters, brothers and my late father whom God called before I started attending primary school. I am, therefore, thankful to you all for your support, constant love and prayers. Despite my mother not attending any form of schooling in her life, she never denied my enthusiasm towards education. I know and believe that I have made all of you proud.

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The use of Earth Observation multi-sensor systems to monitor and model pastures: A Case of savannah grassland in Hluvukani Village, Bushbuckridge Local Municipality, Mpumalanga Province, South Africa

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Abstract

Grassland degradation associated with climate change and inappropriate grassland management has been characterized as a global environmental concern driving decreased grassland ecosystem's ecological functioning. More than 60% of South African grassland is degraded or permanently transformed to other land uses and nearly 2% properly conserved. Yet, grasslands are a major source of food for livestock grazing and provide material and non-material benefits to many livelihoods. Therefore, grassland above-ground biomass (AGB) estimation is crucial in planning and managing pastoral agriculture and the benefits derived from it. However, current grassland monitoring techniques used in rural smallholder livestock farms rely on conventional methods, which are destructive, labour-intensive, costly, and restricted to small areas. This study investigated the monitoring and modelling of protected grasslands biomass using current Earth observation systems (EOS), an approach, which is non-destructive, cost-effective, cover larger areas and is a time-saving alternative to conventional methods. Hence, the research objectives were: (i) to map the trends and advances in data and models used in the monitoring of grassland (pastures) with Earth observation systems, and (ii) to assess above-ground biomass estimation in semi-arid savannah grassland integrating Sentinel-1 and Sentinel-2 data with Machine-Learning. This goal was to assess if this approach could provide the requisite information, which could contribute to the long-term goal of developing a semi-automated system for data processing, and mapping grassland biomass to benefit local communities. For this investigation, it was crucial to understanding what research had achieved so far in this area of pasture management. An assessment of the Scopus database showed the recent developments in European Union (EU) programs and Sentinel missions, including statistical models and machine learning for monitoring grassland changes at multiple scales. However, Sentinel-1 and Sentinel-2 data, machine learning models, and variable importance techniques were applied for grassland AGB estimation. These techniques have been used in similar studies to determine optimum machine learning models, influential variables, and the capability of integrated Sentinel datasets for mapping grassland AGB, spatial distribution, and abundance. Results showed improved performance with the Random forest regression (RFR) model (R^2 of 34.7%, RMSE of 9.47 Mg ha^{-1} and MAE of 7.68 Mg ha^{-1}). The study also observed optimum sensitivity of Difference Vegetation Index (DVI) and Enhanced Vegetation Index (EVI) in all three machine learning models for modelling grassland AGB estimation in the study area. A further, statistical comparison of all three machine learning models showed an insignificant difference in the predictive capacity for AGB in the study area with Gradient Boosting regression (GBR) model (R^2 of 27.7, RMSE of 9.97 Mg ha^{-1} and MAE of 8.03 Mg ha^{-1}) and Extreme Gradient Boost Regression (XGBR) model (R^2 of 17.3%, RMSE of 10.66 Mg ha^{-1} and MAE of 8.83 Mg ha^{-1}). The study revealed that an integration of Sentinel-1 and Sentinel-2 has improved capabilities for monitoring grassland AGB estimation. This research sheds light on the timely and cost-effective techniques for grassland management strategies to enhance or restore the ecological functioning of grassland ecosystems and promote community sustainability.

Keywords: grasslands, climate change, earth observation systems, monitoring.

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List of Abbreviations

AAC	Average article citations
AGB	Above-ground biomass
ASST	Alternative stable state theory
ATC	Average total citations
AVHRR	Advanced Very High-Resolution Radiometer
BLM	Bushbuckridge Local Municipality
COAPA	Copernicus Open Access Hub
DVI	Difference Vegetation Index
EOS	Earth observation systems
EVI	Enhanced Vegetation Index
GBR	Gradient boosting regression
LAI	Leaf area index
LIDAR	Light Detection and Ranging
MAE	Mean Absolute Error
MCP	Multiple country publications
ML	Machine learning
MODIS	Moderate Resolution Imaging Spectroradiometer
n	Number

NDVI	Normalized difference vegetation index
PGA	Protected grazing areas
PM	Pasture modeling
RFR	Random forest regression
RMSE	Root Mean Square Error
S-1	Sentinel-1
S-2	Sentinel-2
SCP	Single country publications
SNAP	Sentinel application platform
TC	Total citations
USA	United States of America
UAV	unmanned aerial vehicle
VV	Vertical transmit, vertical receive
VH	Vertical transmit, horizontal receive
VIs	Vegetation indices
XGBR	Extreme gradient boosting regression

CHAPTER 1

Highlights

Grasslands provide essential ecosystems benefits and vary from local to large scale. However, these grasslands are vulnerable to multiple threats that accelerate degradation. Therefore, it is crucial to understand effective methods that can minimise degradation pressure and restore the ecological status of grasslands in grazing areas. This chapter provides the extent of grassland cover and recent global degradation statistics revealed in the literature. The goal of this chapter is to provide the purpose of the current study in the form of research questions, objectives, and a problem statement to achieve the overall aim. This chapter has an introduction and significance of the study that explains the need to protect these grasslands for their valuable contribution to ecosystems.

1.1 Introduction

Grasslands are one of the widespread terrestrial ecosystems and cover about 40 % of the global land area (Ali et al., 2016; Liu et al., 2019a; Bardgett et al., 2021). As such, grasslands are categorised into open grassland, grassy shrublands, and savannahs (Wilsey, 2018; Bardgett et al., 2021), and are widely known for their important ecosystems functions. For instance, carbon sequestration and cheap natural feed for livestock production particularly to smallholder animal farmers in developing countries (Franzluebbers, 2010; Kwon et al., 2016; Punalekar et al., 2018; Oduniyi et al., 2020). Furthermore, grasslands support plant growth, are important water-producing landscapes, ecological infrastructure, and animal biodiversity among others (Bergman et al., 2008; Yang et al., 2012; Cadman et al., 2013; Ali et al., 2016; Hardy et al., 2020).

Despite the associated benefits from grasslands, they are vulnerable to degradation triggered by extreme climate change and anthropogenic activities (Xu et al., 2016; Zhang et al., 2018; Liu et al., 2019a; Zhou et al., 2020; Bardgett et al., 2021). Studies have revealed that grasslands are experiencing deterioration as a result of overgrazing, land-use conversion, shrub encroachment, climate change, and urbanization among others (Li et al., 2013; Xu et al., 2015; Weber et al., 2018; Lugassi et al., 2019). Nearly 40% of the degradation of the global grasslands was experienced between 1982 and 2006 (Le et al., 2014). However, the constant pressure on the global grasslands has accelerated degradation to 49% up to date (Lark et al., 2020; Bardgett et al., 2021). Other studies have revealed that most degradation for global grasslands occurs in drylands (Steinfield et al., 2006; Kwon et al., 2016). Yet, it is still complicated to identify the main driving mechanism of grassland degradation in drylands. Zhou et al. (2020) suggest that overgrazing is among the leading mechanism to the degradation of grassland aboveground biomass (AGB). Essentially, poor management of grazing land translates into grassland degradation, slow forage recovery, reduced grassland AGB productivity, and associated benefits among others.

The AGB is described as the mass of plant organic matter per unit area, which is an indicator for plant health and terrestrial grassland ecosystem functioning (Pang et al., 2020). The grasslands AGB are mostly threatened in semi-arid and arid environments by climate phenomena such as increasing temperatures, reduced precipitation and droughts (Matsika, 2007; Bardgett et al., 2021). Grassland threats limit AGB accumulation, abundance, forage yields, and other associated benefits. Hence, restoration, protection, and conservation initiatives are necessary for sustainable terrestrial ecosystem structure, function, and the balanced global carbon cycle. The conservation of grassland AGB needs optimal techniques to monitor changes on a time series scale. There are different approaches for monitoring grassland changes, which include conventional and Earth observation systems-based methods. The study investigates Earth observation based approaches to aid in achieving the Sustainable Development Goals (SDGs) such as climate action (13), and life on land (15). The use of earth observation technology offers cost-effective, reliable data, high resolution, and temporal resolution compared to site-based observation techniques on monitoring grassland and classifying degradation (Lu et al., 2007; Zhou et al., 2020).

Accordingly, similar studies have revealed the efficiency of Earth observation technology with machine learning techniques to monitor and estimate AGB in grassland ecosystems (Ding et al., 2017; Gao et al., 2019; Xu et al., 2020). Which provide the baseline for the current study to investigate the trend and advances in EOS and pasture modelling towards achieving optimum grassland modelling techniques. Moreover, the applicable techniques were used for the mapping of the grassland distribution pattern of AGB in savannah grassland. The study was implemented through mining the literature in this niche area and selecting Earth observation based approaches compatible with selected machine learning algorithms.

1.2 Problem Statement

The inevitable climate change and human activities have placed constant pressure and increased grasslands degradation across the world (Ellis et al., 2010; Cherlet et al., 2018; De la Fuente et al., 2020). Although grassland degradation is a natural process, it is exacerbated by inappropriate management of land-uses across global regions**.** Grassland conservation is a global concern with only less than 10% under protected areas (PAs) (Jenkins & Joppa, 2009; Amara et al., 2020). South Africa is one of the countries faced with a lack of grasslands conservation with only 2% falling under PAs (Reyers et al., 2003; O'Connor et al., 2010). These PAs are found in the Maloti Drakensberg Transfrontier Park, which occupies the smallest part of the South African grasslands (O'Connor et al., 2010). Most importantly, grasslands are the primary economic heartland to South Africans and make a considerable contribution to food security (Palmer et al., 2006; Saforestry, 2011; O'Mara, 2012). In addition, the PAs are fundamental to biodiversity conservation ecosystems services and globally recognized to have a significant role in livelihoods sustainability (Watson et al., 2014; UNEP-WCMC et al., 2018; De la Fuente et al., 2020).

More than 70% of the land surface is covered with grasslands in South Africa and is primarily used for livestock farming or grazing (Mansour et al., 2013). These grasslands support the majority of low-income people for sustaining their livelihoods with food, goods and other services (Boval & Dixon, 2012; Singh et al., 2017). However, these grasslands are declared to be under pressure and threatened by invasive plant species, overgrazing and droughts (Saforestry, 2011, Wang et al., 2019a), and compounded by inefficient grassland management (Punalekar et al., 2018). These threats affect the production of forage, AGB abundance and grazing areas, which could result in the loss of ecosystem benefits and related local livelihood formations. For instance, the majority of the threatened grassland ecosystems occur in Mpumalanga and are characterized by endangered plant species (Lotter et al., 2014; Lotter et al., 2015) posing a risk of increasing livestock pressure on the rangelands (Palmer et al., 2006) and livelihood loss for these communities.

Moreover, in Hluvukani village despite being a protected grassland area, shrub encroachment and overstocking have been reported (Shackleton, 2000; Manyetu, 2016; Masocha et al., 2017). This could be attributed to the continuous grazing system and overgrazing with resultant effects on both the grassland quality and existing livestock. For instance, the estimated loss in pastoral livestock and wildlife found in these protected grassland areas is increasing as a result of the long-term effects of overgrazing (Ibrahim & Usman, 2021). The lack of grassland biomass for livestock grazing cause insufficient nutrients for livestock survival and die due to starvation. However, there was little or no known information documented about the spatial pattern of grassland abundance, especially with regards to smallholder livestock farming communities in PAs like in the Hluvukani protected area. Yet, this information could aid to reduce the current practice of continuous grazing and overstocking that is detrimental to the grassland ecosystem.

In addition, conventional methods are commonly used in rural areas to identify grazing grassland biomass for livestock and feeding grounds. However, these methods are limited to small scale and labour-intensive (Ali et al., 2016; Punalekar et al., 2018) which in turn render them ineffective. Consequently, studies have suggested that Earth observation based systems in conjunction with machine learning algorithms could solve such complex data structures (Kuemmerle et al., 2013). These methods enable the AGB estimation and grassland management with fewer limitations regarding spatial and temporal scales (Estel et al., 2020). This is fundamental in redressing the lack of grassland management and implementation of conservation strategies due to having limited or no knowledge on the current grassland status (Letsaolo, 2019). Agricultural extension practitioners are lacking grassland management frameworks, technical support and models for encouraging sustainable agriculture practice and better natural resource management (Khwidzhili et al., 2020). More importantly, in a changing climate, accurate spatial and temporal analysis is critical in providing the information needed to design sustainable grassland conservation strategies.

Interestingly, current Unmanned Aerial Vehicles (UAV) approaches to estimate AGB have higher spatial resolution than satellite data, but with lower spatial coverage (Colomina & Molina, 2014; Messina et al., 2020; Morais et al., 2021). Also, previous studies have used satellite-based techniques with only Normalized difference vegetation index (NDVI) for indicating the condition of aboveground grassland estimation (Liu et al., 2017a; Dingaan & Tsubo, 2019; Yu et al., 2021a). The current study appraises Sentinel data with multiple vegetation indices (VIs) to identify their optimum performance in grassland AGB estimation.

In general, all the above warrant continuous exploration and hence the current study. To this end, the current study sought to provide the spatial pattern of grassland AGB estimation using the recent EOS and the trends thereof. Accordingly, data mining of published studies from the Scopus database was explored to identify recent EOS with optimal resolution applied for grassland biomass estimation and modelling. This enabled the current study to establish EOS suitable for grassland biomass estimation and contribute towards exploring alternatives to cost-effective methods for grassland biomass estimation. Essentially, this benefits grassland management and the implementation of conservation strategies.

Accordingly, there has been ongoing research on grassland management, therefore, an in-depth understanding of the trends about monitoring grassland approaches was crucial in establishing the research gaps and advancing the existing body of knowledge. In addition, Mpumalanga covers more than half of the grassland biome and has numerous nature reserves with livestock farmers that could impede grassland growth and eventual degradation. These factors warrant the suitability of the study in Mpumalanga to contribute to grassland ecosystem restoration of the region and as such two research questions are were explored.

1.3 Research Questions

1.3.1 What are the trends and advances in data and models used in the monitoring of grassland (pastures) with Earth observation systems?

1.3.2 How to integrate Sentinel-1 and Sentinel-2 Data with Machine-Learning in above-ground biomass estimation and assessment for semi-arid savannah grassland protected grazing areas?

1.4 Research Aim

This study aimed to investigate the usage of the recent Earth observation (EO) multi-sensor satellite to monitor and model grassland (pastures) and contribute towards the development of a semi-automated system to automate data processing, and mapping grassland biomass to benefit local communities in Hluvukani village, at Bushbuckridge Local Municipality.

1.5 Research Objectives

The specific objectives that support and enable the realisation of the overarching research aim were considered:

1.5.1 To map the trends and advances in data and models used in the monitoring of grassland (pastures) with Earth observation systems.

1.5.2 To investigate the ability to assess above-ground biomass estimation in semi-arid savannah grassland of Hluvukani protected grazing areas by integrating Sentinel-1 and Sentinel-2 Data with Machine-Learning.

1.6 Significance of the Study

Grasslands are the primary feed for livestock in rural communities and contribute to sustainable livelihoods. It is crucial to ensure food security in rural communities through better management and early warning systems for grasslands. Mpumalanga covers the South part of the well-known Kruger National Park and surrounding areas that need utmost conservation (Data World, 2018). Development of a system that integrates the satellite-derived information from Sentinel- 1 and Sentinel-2 dataset using field-measured data (grass samples) ensure food security in rural communities through better management and early warning systems for grasslands. This study shed some light on using EOS to safeguard, harness nature for economic value, social, green patches, and conservation reasons. This study aids in contributing to the realization of sustainable development goals (SDGs) such as Climate Action (13) and Life on Land (15). Study outcomes aid decision-makers, conservation agencies and environmental managers to review policies for effective grassland management practice and grazing management policies.

The current study explores capabilities of Sentinel-1 and Sentinel-2 data fusion with machine learning models towards grassland AGB estimation, which contributes, to establishing cost-effective methods for grassland management and conservation strategies. There is still a need for a technical expert in this field of study, particularly for smallholder animal farmers in developing countries. Thus, this study explores possible solutions to the estimation of grassland AGB for determining better grazing patches in livestock production areas. The findings of this application minimise the problem of overstocking that accelerates degradation and overgrazing. Inevitable technology development reduces EOS limitations to monitor and model grassland biomass production. The contribution of performed trend analysis enables the delineation of the current EOS in grassland modelling. Moreover, aid in planning and managing pastoral rangelands through earth observations systems that monitor natural ecosystem vulnerability from climate change impacts, grazing, degradation and guide adaptation strategies that are needed. The suggestions from the current study contribute towards the positive attribute of improving large areas of grass quality that would benefit livestock production and wildlife. This could help livelihoods to maximise profits in livestock trading. Consequently, this necessitated the study to adopt an appropriate conceptual framework (i.e., Alternative stable state theory) to guide both data analysis and interpretation.

1.7 Alternative Stable State Theory (ASST) Conceptual Framework

Alternative stable state theory (ASST) is grounded in adaptive cycles and resilience (Levin et al., 2012; Bowman et al., 2015). ASST has been used to describe differences in rates and vulnerability of changes in ecosystem structure and function for both managed and wildland (Standish et al., 2014; Wilcox et al., 2018). The adoption of ASST in this study is fundamental in explaining why the savannah landscape can abruptly change in response to external disturbances outside its historical range (Ratajczak et al., 2014; Bowman et al., 2015; Wilcox et al., 2018). Recently, ASST has been explored to understand the transition in savannah landscapes across the global to regional scales (Staver et al., 2011; Murphy, 2012; Wilcox et al., 2018). Accordingly, the ASST has three key concepts. Murphy et al. (2012) explain the first key concept as alternative states controlled by strong stabilizing feedbacks that exist under the same exogenous environmental conditions. The second key concept describes if stabilizing feedbacks are weakened enable abrupt state shift to occur. Finally, the third concept describes a change in the state that represents a critical transition or catastrophic shift. For instance, hysteresis and reversing the environmental conditions to pre-transition levels will not result in restoration of the previous state (Scheffer et al., 2001; Wilcox et al., 2018).

About the study, grazing can represent negative or positive feedback associated with the maintenance of the grassland state. Grazing has positive feedback in the rotational grazing system or patch grazing (Schmitz & Isselstein, 2020). This allows restoration of overgrazed paddocks to re-grass. However, long-term grazing or excessive grazing has negative stabilizing feedback to maintain the grassland state, which alters the ecosystem stability (Kleinhesselink, 2020). This may move the ecosystem into an alternative shrub invaded state (Kleinhesselink, 2020). Each livestock paddock can naturally move back toward a predominant grassland state if grazing is stopped (Mata-González et al., 2007). The increasing density and cover of native shrub encroachment on grassland have negative stabilizing feedbacks for Hluvukani protected grazing areas (PGA). Accordingly, it represents a critical shift in the paddocks and restoration of the previous state be impossible, instead shrub encroachment in PGA shift to an alternative stable state.

Therefore, ASST plays a pivotal role in the development of strategies for grassland and savannah restoration and management (Bestelmeyer & Briske, 2012; Wilcox et al., 2018; Hao et al., 2021). The concept of helpful and unhelpful resilience offers options of recovery and impedes recovery through the hysteresis effect (Standish et al., 2014), and allows to explore conditions challenging to conservation managers (Wilcox et al., 2018). Resilience is a common term that has been used in various contexts. However, in ecology, resilience has been defined as “the inherent ability of ecosystems to absorb disturbances and reorganize, while undergoing state changes to maintain critical functions” (Holling, 1973; Connell & Ghedini, 2015). Other studies refer to the broader concept of ecological resilience as adaptive capacity (Smit & Pilifosova, 2003; Dardonville et al., 2021). Ecosystems lose resilience due to external disturbances and get vulnerable to the risk of shifting from ecosystem stability to an alternative stable state (Fan et al., 2021).

However, the ecosystem-management literature describes resilience as the ability for ecosystems to resist the transition to alternative states and has both positive and negative effects on ecosystem structure depending on the degree of degradation (Fan et al., 2021). Therefore, helpful and unhelpful resilience is crucial in ecosystem management. In the current study, helpful resilience, refer to the higher AGB estimation. However, unhelpful resilience refers to a low concentration of grassland biomass that requires utmost management strategies to recover.

Few approaches provide novel lenses like ASST theoretical framework offers for savannah grassland exploration and analysis (Wilcox et al., 2018) and hence its adoption in the current study. In addition, the theoretical framework offered the avenue to deploy the machine learning algorithms to offer robust analysis. These algorithms formed the crux in the grassland ecosystem AGB estimation using a semi-arid case thus contributing to grassland ecological literature and boosting ecological resilience in Hluvukani PGA.

1.8 Organization of the Dissertation

This dissertation is organized into six chapters and the references are provided at the end to avoid duplication of information. The goal of chapter 1 was to provide brief information about the grasslands changes as a result of multiple effects which provide the need for the current study. Chapter 1 sets the tone for this dissertation by providing information that pertains to the state of the grasslands coverage statistics, benefits, impacts that contribute to its degradation and possible methods for monitoring grassland condition. Chapter 1 is presented in form of an introduction, problem statement, research questions, aim and objectives of the study, significance, applicable theoretical framework to the study, and summary of the chapter. Chapter 2 continues with detailed information on grassland definition, classification, threats such as grazing impacts, climate change, woody or shrub encroachment and nitrogen eutrophication. Furthermore, it explains the theoretical perspective of grassland monitoring and modelling including conventional and EOS methods. The aforementioned themes provide a literature review for the current study, anticipated gaps to be addressed in the dissertation with specific objectives, and a summary of key highlights of chapter 2.

Moreover, chapter 3 relates the study area and methodology for addressing identified gaps in previous chapters. This includes a description of the study area, socioeconomic status, population, climate and landscapes characteristics with predominant livestock production in protected grazing areas. More so, the quantitative research method is selected for the current study. Other sections include sampling, ethical consideration, a flowchart of the adopted approach and a summary. Chapter 4 presents the trends of EOS and pasture modelling in a paper format and it has been published. This chapter uses quantitative methods and is structured in form of title, abstracts, introduction, methods, results, discussion and conclusion.

The findings in chapter 4 suggest recent EOS methods for chapter 5 ABG estimation within semi-arid savannah grassland. Sentinel-1, Sentinel-2 and machine learning integration were used to generate grassland AGB estimation maps in chapter 5. Chapter 5 is presented in a paper format. It is structured in a form of title, abstract, introduction, materials and methods, discussion, and conclusion. The title of chapters 4 and 5 might not exactly appear as written on paper publication. Finally, chapter 6 provides the summary, conclusion and recommendations of the dissertation execution. This chapter is structured in a form of an introduction, summary of the key results, recommendations, limitations and future research agenda. The adopted logical flow shape overview of the dissertation and this structure provide both traditional and paper format included in the dissertation.

1.9 Summary

Chapter one provides the terrestrial grasslands cover statistics, benefits and degradation impacts. However, degradation impacts vary across the country. In addition, this chapter provides the importance of constant monitoring and modelling grassland conditions to provide optimal grassland management strategies. Currently, the United Nations has set Sustainable Development Goals (SDGs) to be achieved in 2030. These goals include life on land and climate action that need utmost conservation and the current study contributes to the achievement of these goals. Several theoretical frameworks such as ASST have been developed to manage natural resources including grasslands. However, identifying criteria for increasing ecological resilience in grasslands remains a challenge for the ecological science community. Therefore, this study adopted ASST to identify the urgent areas for restoration and ecosystems resilience. In addition, through the outlined research objectives, the study aims to contribute towards the development of a semi-automated system using EOS to monitor and model grasslands. Therefore, a literature review was required for understanding grassland classification types, threats and optimal methods for monitoring its condition, which is provided in the following chapter 2.

Chapter 2

Literature Review

Highlights

Grassland is classified into different classes and seriously threatened by multiple effects including climate change, shrub encroachment, nitrogen eutrophication and human activity. These multiple effects contribute to the accelerating degradation of the grassland ecosystem. However, different conventional and remote sensing techniques have been used to understand the changes in grasslands. EOS has shown optimum techniques for monitoring grasslands. The assessment of grassland degradation effects has been explored in different studies, which revealed the statistics for degraded lands. This study explores the threats and methods for grassland monitoring, which is necessary for grassland management.

2.1 Introduction

This chapter provides an overview of the grassland ecosystem with a focus on the characterization of grasslands, threats, their significance, their relevance to the ecosystem, and their contribution to food security. Further, cover measurement to reduce grassland degradation vulnerability, both conventional and remote sensing or EOS techniques for pasture modelling are also explored and presented below. This introduction briefly explains the details of the following themes to offer insight into the chapter.

2.2 Overview of Grassland, their Significance and Degradation

Generally, grasslands are characterized into several classes such as Eurasian steppes, entire herbaceous vegetation, North American prairies, South American pampas, African savannah and veldts, woody shrub-based deserts and tundra, artificial grasslands, and pastureland (White et al., 2000; Nunez, 2020; Zhao et al., 2020). However, Coupland (1979) revealed five types of grasslands such as natural temperate grasslands, semi-natural temperate meadows and pastures, tropical grasslands, arable grassland, and cropland. Grassland grows in an enough humid environment (Allaby, 1998). Food and Agriculture Organization (2020) describes grassland as extensive grazing or utilization of maintained natural habitat. For instance, anthropogenic impacts have affected the entire surface cover through land-use change, and livestock production has been identified as one of the major factors of grassland degradation through grazing.

Moreover, globally grassland ecosystems are predominant in all landmasses, yet are still less protected for conservation purposes (White et al., 2000; Sperry et al., 2019; Griffiths et al., 2020). Globally, grasslands account for close to one–third of all land (Suttie et al., 2005; Lemaire et al., 2011) and contributes to livelihood formations. For instance, over the last decades, European farmers had a significant revenue source on bioenergy production from grassland biomass (Rösch et al., 2009). Moreover, other grassland benefits include serving as habitats, reducing atmospheric carbon concentrations, supporting pollinators, absorbing water in less saturated zones, and maintaining soil fertility (Sperry et al., 2019). Grassland normally provides an essential resource, non-physical services for livelihood and well-being. Grassland non-physical services include erosion regulation, climate balance, tourism, recreation, fibres and medicine (Havastad et al., 2007; Sala et al., 2017).

Grassland degradation is a major global concern due to excessive grazing intensity, especially dry climate has resulted in many degraded lands (Kwon et al., 2016; Liu et al., 2019a; Bardgett et al., 2021). An estimated 73% of the grasslands are degraded in drylands (Steinfield et al., 2006; Kwon et al., 2016). Over livestock production (Dingaan et al., 2019), has led to about 37% degraded rangeland in South Africa (Bai et al., 2007). European grasslands experienced a reduction due to severe grazing and livestock production in the previous years (Dabrowska-Zielinsk et al., 2017). Half of Africa is covered with grassland that enables ecosystems services (UCMP, 2020) but is also threatened by multiple stressors. For instance, the grassland continues threatened by the growing human-induced climate change worldwide, encompassing local and regional changes in temperatures (global warming), precipitation (frequent drought, involving extreme weather intensification), and snow cover (Gibson & Newman, 2019).

2.3 Threats to Grasslands

Grasslands are threatened by several factors such as climate change, overgrazing, conversion of native grassland area to crops lands, clearing of native grassland for urban sprawl, poor management of remnant grassland areas, nitrogen eutrophication among others (Török et al., 2018; Gibson & Newman, 2019; Varga et al., 2021). The impacts of these factors are detailed below:

2.3.1 Grazing Impacts

The uncontrolled grazing intensity threatens the grassland ecosystem. Livestock grazing is part of land use worldwide that is dominant in open grassland (Robinson et al., 2011; Pica-Ciamarra et al., 2011; Rojas-Downing et al., 2017; Biglari et al., 2019). Minimal grazing intensity of livestock is encouraged for maintaining grassland biodiversity (Fleurance et al., 2016; Schmitz et al., 2020). Grazing intensification governs grassland biomass and hay quality for a certain grazing season. Establishing and encouraging grazing regulations that prioritize biodiversity integrity or livestock production is essential (Fleurance et al., 2016). Grazing is one of the major drivers of biological diversity reduction (Bösing et al., 2014). However, spatial heterogeneity of grassland composition and sward structure is improved and maintained by the preferred selection of grazing livestock (Schmitz et al., 2020). The variation in grazing species steers to different effects on rangeland vegetation because of specific nutritional demands, feeding behaviour, and jaw anatomy (Olff et al., 1998, Rook et al., 2004; McDonald et al., 2019; Schmitz et al., 2020).

The European agriculturally managed grassland is dominated by grazing cattle and has received scientific attention with respect to cattle or sheep grazing intensity (Schmitz et al., 2020). For South Africa, cattle grazing dominates the eastern part, sheep are predominant in the southeast and western, while goats are scattered all over the country (Palmer et al., 2006). Previously, to protect and conserve grassland ecosystems several studies focused on management strategies and effects of biodiversity (Rook et al., 2004; Wrage et al., 2011; Dumont et al., 2012; Jerrentrup et al., 2015). The studies found out that grazing impacts on grassland could be modified by continuous or rotational grazing. Continuous grazing enables unlimited access to pastures during long grazing seasons (Singer et al., 2001; Rook et al., 2004, Jerrentrup et al., 2015; Fleurance et al., 2016). Rotational grazing provides limited access to grazing areas in a specified time and demarcated space that results in controlled grazing (Bott et al., 2013; Kenny, 2016; Williams et al., 2017).

Selective grazing has proven to modify species composition and the grasslands structure (Owen-Smith, 1999; Little et al., 2015). While more livestock (stocking rate) reaches the required capacity in a selected field result in extensive grazing. South African grasslands are primarily used for grazing and lack policies to guide minimum livestock for the protection of grazing fields (Dingaan et al., 2019). As a result, grassland degradation continues to increase because of overgrazing.

2.3.2 Climate Change

Temperatures are set to rise worldwide from 1 to 6 degrees Celsius depending on the situation and climate model used (Stocker, 2014; Chang et al., 2017; Török et al., 2018). For the past 100 years, 0.7 degrees have warmed the earth through naturogenic and anthropogenic emissions (Canadell et al., 2007; Heijmans et al., 2009). Africa is predicted to experience climate change impacts, global warming, and heavy rainfalls (Parry et al., 2007). Climate change differs and many international initiatives have been established to lessen carbon emissions that continue to increase even more rapidly in the atmosphere (Heijmans et al., 2009). For instance, South Africa has experienced climate change shifts in the North-eastern part with an increase in average temperatures between 1995-2006 (Davis, 2010, Lotter et al., 2014). As result, grassland temperature is set to increase by 1-1.25 degrees Celsius considering variation in each region (Stocker, 2014; Gibson et al., 2019; Dolezal et al., 2021). The rising temperatures impede grassland growth and abundance through droughts (Stanik et al., 2021).

However, previous studies have reported that cattle production systems contribute to the high temperatures through rising carbon dioxide, methane emissions and overgrazing grasslands that contribute to regulating atmospheric emissions (Asem-Hiablie et al., 2019; Oduniyi et al., 2020). These temperature projections lead to surface water loss, heat stress, and prolonged growing season up to 24 days for grassland growth (Gibson et al., 2019). Grassland experience extreme deterioration changes as a result of the shift in weather conditions. Southern Africa has experienced unreliable rainfall, droughts occurrence, and increasing temperatures over the past years (Dzama, 2016). Consequently, climate variability poses a serious threat of minimizing the grassland quality in other regions (Maltou & Bahta, 2019). The livestock producers need to be extremely cautious and innovative with changes demanded by the environment, social, and economic sectors (Oduniyi et al., 2020). The extreme conditions for climate change are projected over many regions, and adequate adjustment may minimize the impacts (Mendelsohn, 2008; WISP, 2010; Dzama, 2016; Mthembu et al., 2017).

Apart from extreme temperatures, rainfall deficits reduce the grassland ecosystems. Rainfall control soil nutrient availability and regulate plant growth by influencing physiological processes related to water absorption (Wu et al., 2013; Gong et al., 2020). Grassland ecosystems are more sensitive and highly responsive to rainfall variability that controls grassland spatial distribution (Zeng et al., 2019; Gong et al., 2020). Studies have revealed that rainfall has a greater influence on grassland AGB compared to temperature (Yang et al., 2009; Cobon et al., 2019; Su et al., 2020). Rainfall is a determining factor for grassland productivity in arid and semi-arid ecosystems where plant growth is limited by water scarcity (Gong et al., 2020). Therefore, understanding both rainfall and temperature impacts are crucial for grasslands management and better predicting their response to climate change. Particularly, climate change has been observed in different parts of the world. This includes the projected increase and extreme rainfall events in the future by climate models (Bao et al., 2017).

2.3.3 Woody or Shrub Encroachment to Grassland

The shrubland encroachment in grassland is a global concern towards the preservation of grassland ecosystems (Ratajczak et al., 2012; Dahl et al., 2020). The transition of grassland to shrubland involves colonization and suppression of the understory to near monocultures of shrubs (Dahl et al., 2020). Studies revealed shrubland encroachment is caused by climate alteration (Archer, 1994; Holechek et al., 2020), industrial nitrogen (Dahl et al., 2020), atmospheric carbon dioxide changes (Daryanto et al., 2019), fire management (D'Odorico et al., 2012) and livestock overgrazing (Marquart et al., 2019). The shrubland species can spread quickly and unevenly through livestock and wildlife consumption and transporting of seeds (Dahl et al., 2020). Water scarcity is the limiting factor for semi-arid grassland growth (Deutsch et al., 2010; Peng et al., 2013), meanwhile, an increase in wetlands may contribute to the shrubland encroachment (Darrouzet-Nardi et al., 2006).

The shrubland encroachment has been documented in many arid and semi-arid grassland (Archer, 2010; Stanton et al., 2018; Cao et al., 2019). For instance, in the semiarid Inner dry grasslands in Central Europe (Elias et al., 2016), Mongolian grasslands of China (Peng et al., 2013), grasslands of northern China (Zhou et al., 2019), savannahs and woodlands in sub-Saharan Africa's (Mitchard & Flintrop, 2013), rangeland in southern Africa (O'connor et al., 2014), and a semi-arid savannah grassland South Africa (Mogashoa et al., 2021). In most of these countries, large hectares of grassland have been affected and altered to bushes. Many grasslands experienced shrubland encroachment across the globe observed with a decrease in grassland cover (D'Odorico et al., 2012).

2.3.4 Nitrogen Eutrophication

Globally, nitrogen deposition is considered an important threat to grassland ecosystems (Sala et al., 2000; Stevens et al., 2010; Basto et al., 2015; Pescott & Jitlal, 2020). Nitrogen has an imperative role in nitrogen-limited environments for plant growth, while excessive concentration destroys plant species such as alpine grass (Chen et al., 2018; Gómez Giménez et al., 2019). A limited nitrogen content reduces grassland AGB productivity and affects distribution (Ding et al., 2021). Studies have revealed that grassland biomass is sensitive to soil nutrients and nitrogen fertilization increase grassland productivity compared to climate change and land conditions (Stevens et al., 2010; Ding et al., 2021). Moreover, excessive nitrogen extracted in manure and animals offers high nutrients to the landmass that increase grassland productivity (FSO, 2015; Gómez Giménez et al., 2019). The grasslands within tropical and temperate regions have low nitrogen content that reduces grassland growth (LeBauer et al., 2008). Other studies have revealed nitrogen fertilizers or atmospheric nitrogen deposition alter grassland diversity either positive or negatively in tropical and temperate regions (Foster & Gross, 1998; Stevens, et al., 2004; Basto et al., 2015; Ding et al., 2021). Negative impacts of nitrogen are triggered by nitrogen loading or nitrogen runoff (Kübert et al., 2019). Nitrogen eutrophication has been observed in different regions as the main driver for degraded grassland productivity. These regions include Midwest in the USA (Foster& Gross, 1998), African grassland (Ward et al., 2017) and Chinas grassland ecosystem (Lü et al., 2020). Savannah grasslands in temperate and tropical regions are nutrient-limited, nitrogen runoff makes them susceptible to degradation and impedes recovery grassland growth (Trisos, 2020). The mapping of nitrogen content in grassland ecosystems has been reported in several studies using different methods (Chen et al., 2018; Fiorentini et al., 2019). These methods include nitrogen nutrition Index (NNI) (Greenwood et al., 1990; Justes et al., 1997), chlorophyll meter (Arregui, 2006; Ali et al., 2015a; Zhao et al., 2016), Chlorophyll content index (Liu et al., 2019b), Soil Plant Analysis Development (SPAD) (Fiorentini et al., 2019), and conventional physicochemical assessment such as Kjeldahl nitrogen detection method, tissue and chemical analysis (Wu et al., 2020). However, traditional methods are time-consuming, destructive, need complex analysis, are limited to sampled areas and are not suitable for continuous monitoring of nitrogen content (Camino et al., 2018). These shortfalls, allow Earth observation based methods with high resolution to be a useful alternative for monitoring the spatial and temporal pattern of nitrogen content in large areas (Quemada et al., 2014). EOS have shown the ability to capture both biochemical and physical impacts on pasture decay (Asener et al., 2004; Numata et al., 2007; Russell & Ward, 2014). Studies have explored nitrogen content using remote sensing and machine learning models in plant species including grasslands (Adjorlolo et al., 2014; Mutanga et al., 2015; Berger et al., 2020).

2.3.5 Theoretical Perspective of Grassland Monitoring and Modelling

Grassland has a key contribution to climate mitigation measures (Gomez-Casanovas et al., 2021). However, grassland threats and other factors may influence the growth distribution pattern and abundance. These threats including other factors continue to reduce the essential benefits of native grassland. Studies have revealed the need to improve and continuously monitor grassland ecosystems for understanding the rate of changes (Alldredge et al., 2013; Gomez-Casanovas et al., 2021). The assessment of grassland intensification and productivity aid to improve the implementation of grassland management to secure valuable grassland benefits (Cadman et al., 2013; Dabrowska-Zielinska et al., 2017). The process of monitoring and modelling rangeland status has been the focal point in many research papers worldwide (Thornley et al., 1997; Yang et al., 2012; Ali et al., 2016; Dabrowska-Zielinska et al., 2017).

Also, several studies have contributed to monitoring and management of grassland in South Africa (Tueller 1991; Palmer and Fortescue 2004; Vanderpost et al., 2011; Bastin et al., 2012; Palmer et al., 2013). These studies have provided a contribution towards baseline literature on grassland monitoring using different techniques which reveals the need for current and future studies in the validation of models and addressing their limitations. The present study utilizes the capabilities of the recent technological advancements to explore and improve methods on grassland management in Hluvukani protected grassland situated in Mpumalanga. Mpumalanga covers 64% of the grassland biome and monitoring of these native grasslands is an ongoing process for conservation purposes (Lotter et al., 2014).

However, approximately 50.7% of natural grasslands, one quarter (20%) of the vegetation types and 23 vegetation types in Mpumalanga grasslands are nationally gazetted threatened (Lotter et al., 2014). The increasing temperatures, shrub encroachment, livestock and wild animal intensive grazing are major impacts of diminishing grasslands in Mpumalanga grasslands. These have triggered evolving research interest for many studies to provide grassland management within Mpumalanga province (Jansen et al., 1999; Engelbrecht et al., 2004; Lötter, 2013; Lötter et al., 2014; Fourie et al., 2015; Lötter, 2015; Masemola et al., 2016; Data World, 2018). Although, there is still a lack of effective methods related to the prediction of grassland abundance on a large scale. Therefore, EOS have the capabilities for improving grassland estimation and productivity.

2.3.6 Conventional Methods for Monitoring Grasslands

Studies have used conventional methods for monitoring grassland productivity and biomass degradation (Le et al., 2016; Chang et al., 2017, Amara et al., 2020). These studies noted that conventional techniques have limitations. For instance, they are destructive (Andresen et al., 2018; Obermeier et al., 2019), labour- and cost-intensive (Punalekar et al., 2018; Murphy et al., 2021). Although, previous studies have shown the capabilities of conventional methods to monitor grassland characteristics such as AGB at a small scale (Ravindranath & Ostwald, 2008; Pandit et al., 2018; Forkuor et al., 2020; Yu et al., 2021a). These conventional methods include forage clipping surveys, cover surveys, grass stubble height surveys, grazing exclosures, rising plate meter, expert opinions and photo points (Newnham, 2010; Alldredge et al., 2013; Ali et al., 2016; Obermeier et al., 2019). However, other methods used for grassland management include chopping (Rejžek et al., 2017), brush management (Briske, 2017), ring barking (Muvengwi et al., 2018), felling (Mizsei et al., 2020), and slashing (Farrar et al., 2021). These methods are based on the physical condition of grassland management. Consequently, conventional methods are arduous, subjective, programmed to detect ex-situ data, cover and provide detailed information on a small scale (Xu et al., 2008; Ali et al., 2016; Yang et al., 2018). The breakthrough of EOS has surpassed conventional methods to monitor grassland dynamics and provided cost-effective and robust techniques.

The application of small remote devices such as field spectrometry gave good information about grassland dynamics but was still limited to small areas (Ali et al., 2016). The conventional method known as on-site-based techniques projected more limitations for large-scale grassland monitoring. Then, accessibility to advanced space technology products has been a desire for EOS to monitor the earth's surface (Brinkmann et al., 2011; Palmer, 2020). Furthermore, the growing increase in open data sources at a broader scale has noticed the execution of spatial modelling (Zerger et al., 2006). Consequently, these spatial modelling were revealed through grassland management dynamics technology (Newell et al., 2006; Sheffield, 2006; Lawley et al., 2016).

2.3.7 Development of Remote Sensing or Earth Observation System Methods in Monitoring Grasslands

Recently developed space technology with advanced technical orientation support grassland management practice through high-resolution spatial data quality (Franke et al., 2012).

Advanced remote sensing technology enables satellite optical and radar datasets fusion, which improve accuracy for identifying surface features (Raab et al., 2020). In the last 30 years, remote sensing satellite or EOS have demonstrated increasing benefits for monitoring earth surfaces across the globe (Horning et al., 2010; Pettorelli et al., 2014). These EOS offer free landmass data to predict the trends and rates of grassland changes. Studies have revealed the successful application of multi-sensors in monitoring grasslands (Claverie et al., 2012; Yang et al., 2018). However, the improvement of spatial, spectral, and temporal resolution is advancing in space science, which is beneficial to grassland management (Zhou & Kafatos, 2002). With the latest developments in sensors, a bunch of new satellites has enhanced spectral and spatial resolutions (Zaks et al., 2011; Kuemmerle, 2013; Gómez Giménez et al., 2019). Also, data fusion products enable to achieve maximum spatial resolution with less cloud interference or atmospheric (e.g., water vapour density) conditions (Ancin-Murguzur et al., 2019).

The optical and radar Sentinel data has demonstrated better spatial resolution to monitor grassland compared with previous Landsat (Ikeda et al., 1999), Moderate Resolution Imaging Spectroradiometer (MODIS) (Pagano & Durham, 1993), and Advanced Very High-Resolution Radiometer (AVHRR) satellites (Horvath, 1982). For instance, optical (Punalekar et al., 2018) and radar datasets (Abdel-Hamid et al., 2020; De Vroey et al., 2021) have proven to be promising tools for grassland monitoring. However, planet Scope can offer better spatial (3-4 m) and temporal resolutions (daily) data compared to Sentinel data for detailed grassland monitoring processes over small areas (Cheng et al., 2020). Studies have revealed successfully the exploration of Sentinel-2 data to estimate grassland biomass distribution and exclude red-edge bands (Adan, 2017; Punalekar et al., 2018; Li et al., 2021). The study was conducted in Ayer Hitam forest reserve for the AGB estimation using Sentinel-2, VIs, Airborne Laser Scanners (ALS), Terrestrial laser scanners (TLS) and allometric equation (Adan, 2017). It was established that a combination of VIs and TLS improved the accuracy of AGB estimation and depicted a good relationship with total AGB obtained from TLS and ALS achieving R^2 of 74%. However, Adan (2017) noted that the resampled images might have affected the accuracy of VIs in biomass estimation due to the loss of spectral information. Moreover, the manual extraction of AGB from TLS is tedious and hence, some data could not be matched with the field data, which affected the model accuracy estimations (Adan, 2017).

Another study in southern England used a combined proximal hyperspectral and Sentinel-

2A with radiative transfer model (PROSAIL) to estimate leaf Area Index (LAI) and biomass in two dairy farms (Punalekar et al., 2018). The study revealed that high spatio-temporal resolution of Sentinel-2A data with radiative transfer model (PROSAIL) approach can be used for good accuracy pasture estimation (Punalekar et al., 2018). However, the Sentinel-2 PROSAIL technique would require a comprehensive process-based grass growth model, driven by weather estimations for assisting farmers to manage their pastures (Punalekar et al., 2018). Furthermore, Sentinel-2 data, random forest and extreme gradient boosting machine learning algorithms were used for modelling AGB estimation in the grassland of Anhui Shengjin Lake National Nature Reserve (Li et al., 2021). This study revealed that extreme gradient boosting has a higher precision when compared to the random forest model in AGB estimation. The study also revealed that red-edge VIs contribute to the machine learning model perfomances and AGB estimation accuracy (Li et al., 2021).

Also, the Sentinel-1 dataset has the spatial, spectral, and temporal resolution been used for monitoring grassland biomass productivity for livestock grazing and grassland management practice (Tamm et al., 2016; Abdel-Hamid et al., 2020; De Vroey et al., 2021). Accordingly, Tamm et al (2016) used Sentinel-1 to detect grassland after mowing events in Estonia located at Rannu parish. This study revealed that after the mowing event, both VH (vertical transmit, horizontal receive) and VV (vertical transmit, vertical receive) polarization coherence values were statistically higher than those from before the mowing event (Tamm et al., 2016). This was influenced by the shorter time interval of the first interferometric acquisition in Sentinel-1 images (Tamm et al., 2016). In addition, Abdel-Hamid et al (2020) study used Sentinel-1 and Landsat-8 which revealed that climate fluctuations affected Eastern Cape communal and commercial grasslands distribution with a significant correlation between VH backscattering and NDVI with R^2 = 0.89%. Furthermore, the exploration of permanent grasslands in Wallonia, Southern region of Belgium showed that Sentinel-1 can be used for detecting mowing events using coherence jump detection methods which requires more field data to improve accuracy (De Vroey et al., 2021).

The above studies show the possibilities of using Sentinel-1 and Sentinel-2 independently to monitor grassland. However, Sentinel-2 optical data is vulnerable to cloud cover penetration, which can limit data availability for monitoring grassland spatial patterns and productivity during the growing season (Asner, 2001). To compensate for this shortfall from sentinel-2, data fusion with sentinel-1 can improve this dataset for monitoring the abundance and spatial pattern of grassland biomass (De Vroey et al., 2021). Several studies have shown the possible combination of optical and radar data to monitor grassland status (Veloso et al., 2017; Wang et al., 2019a; Forkuor et al., 2020; Nuthammachot et al., 2021). However, future studies have been recommended to use the integration of Sentinel-1 and Sentinel-2 data for modelling grasslands which validate other previous model outcomes conducted in different grassland ecosystems (Dusseux et al., 2014; Wang et al., 2019a). The application of Sentinel-1 and Sentinel-2 data in modelling grassland dynamics contribute to addressing the existing gap of limited literature for validation of machine learning models in grassland restoration research.

Grassland modelling activities have been missing in literature in the past 12 years (Ali et al., 2016). However, the developments of spatially extensive grassland modelling using Earth observation based techniques with machine learning algorithms for grassland AGB estimation are still limited (Ali et al., 2014). This is attributed to the complex varying data structure and machine learning model accuracy variations and applications for grassland biomass estimation. Accurate assessment of grassland AGB is beneficial to ensure sustainable pattern and protection of grass productivity and distribution (Meng et al., 2020), for effective ecological functioning. Thus, it is crucial to assess and understand the present status of the research direction in this field of study through mapping the trends and advances in models used to monitor grassland. Moreover, investigating grassland AGB estimation with recent Earth observation based techniques and identify capabilities of Sentinel data fusion could improve model precision.

For the past 40 years, several methods have been developed for grassland biomass estimation using Earth observation based methods (Ali et al., 2016). These methodologies include three categories such as VIs, biophysical simulation models and machine learning algorithms (Ali et al., 2015b). The biophysical simulation models such as LINGRA model that is designed for grassland estimation productivity has not been fully explored for grasslands biomass (Ali et al., 2016), instead frequently used for crops (Jongschaap et al., 2006; Mittenzwei et al., 2017). However, the use of VIs, Earth observation based methods and in situ measurements for the development of regression models in grassland AGB estimation is the most common approach (Shen et al., 2008; Jin et al., 2014; Dusseux et al., 2015). These VIs have higher precision based on regression models for grassland biomass estimation (Bella et al., 2004; Xu et al., 2008). However, machine learning models' performance is limited to the specific site and lack capabilities to learn non-linear complex data patterns (Ali et al., 2016) but it's application in grassland monitoring has been steadily increasing (Morais et al., 2021). It is therefore, important to understand the principles of different machine learning algorithm's applicability in various fields and enough training data to attain higher model accuracy performance.

The information in Table 1 below shows the summary of selected studies with different machine learning methods appraised on the grassland ecosystem. However, several data sources and the varied number of samples collected for these machine learning methods demonstrate the wide range of results in terms of r-squared (R^2) and root mean square error (RMSE) accuracy results. The use of Spectrophotometry, unmanned aerial vehicle (UAV) Partial least squares regression, and Multiple linear regression machine learning was observed as the best performing techniques with significant statistics of (R^2 = 0.86 - 0.94), respectively (Askari et al., 2019; Obermeier et al., 2019). Table 1, also show that Random Forest achieved the highest precision of (R^2 = 0.85) using MODIS data and 256 sampling points for estimating grassland AGB (Zeng et al., 2019). Although, the performance of Random Forest was witnessed inconsistent in other data sources such as Spectrophotometry, Quickbird, RapidEye, WorldView-2 (Meyer et al., 2017), AVHRR (Xia et al., 2018a), Light Detection and Ranging (LiDAR) (Anderson et al., 2018; Jensen et al., 2019), Landsat 8 (Otgonbayar et al., 2019), UAVs (Borra-Serrano et al., 2019), and Sentinel-1 and Sentinel-2 (Wang et al., 2019a) with (R^2 = 0.7 – 0.76). In general, the performance of machine learning methods is not consistent in all ecosystem but depend on the type of data source with the number of samples for training and evaluation of the model.

Table 1: Summary of studies used different machine learning methods, data sources, number of samples, R^2 and RMSE results in grassland ecosystem

Machine learning method	**Data source**	**Number of samples**	**R^2**	**%RMSE**	**Reference**
Linear regression	UAVs	1350	0.67	-	Borra-Serrano et al., 2019
Multiple linear regression			0.81	-	
Principle components analysis			-	-	
Partial least squares regression			0.58	-	
Random Forest			0.7	-	
Random Forest	Landsat 8	553	0.76	-	Otgonbayar et al., 2019
Partial least square regression			0.75		
Random Forest	MODIS	256	0.85	-	Zeng et al., 2019
Partial least squares regression	UAVs	64	0.78	-	Askari et al., 2019
Multiple linear regression			0.76	-	
Partial least squares regression	Spectrophotometry		0.88	-	
Multiple linear regression			0.86	-	
Partial least squares regression	Sentinel-2		0.82	-	
Multiple linear regression			0.81	-	

Multiple linear regression Support vector machine Random Forest Multiple linear regression Support vector machine Random Forest Multiple linear regression Support vector machine Random Forest	Sentinel-1 Landsat-8 and Sentinel-2 Landsat-8, Sentinel-1 and Sentinel-2	24	0.53 0.69 0.78 0.39 0.65 0.47 0.49 0.49 0.49	- - - - - - - - -	Wang et al., 2019
Partial least squares regression	Spectrophotometry	46	0.94	7.00	Obermeier et al.., 2019
Random Forest	LiDAR	65	0.59	-	Jensen et al., 2019
Random Forest	LiDAR	206	0.61	-	Anderson et al., 2018
Random Forest	NOAA/AVHRR	1689	0.76	-	Xia et al., 2018a
Artificial Neural Network	MODIS	1433	0.66	-	Yang et al., 2018
Multiple linear regression Random Forest	UAVs	25	0.42 0.28	12.94 14.06	Viljanen et al., 2018
Random Forest	MODIS	1188	0.62	-	John et al., 2018

Partial least Squares regression	UAVs	56	0.72	-	Van der Meij et al., 2017
Random Forest	Spectrophotometry	325	0.32	-	Meyer et al., 2017
	Quickbird		0.32		
	RapidEye		0.31		
	WorldView-2		0.35		
Multiple Linear Regression	MODIS	311	0.29	-	Ali et al., 2017
Artificial Neural Network			0.63		
Adaptive Neuro fuzzy inference system			0.85		
Multiple Linear Regression		625	0.38		
Artificial Neural Network			0.59		
Adaptive Neuro fuzzy inference system			0.76		
Stepwise multiple regression	LiDAR	46	0.79	-	Li et al., 2017
Linear regression	Landsat 5	68	0.79	34.60	Zhang et al., 2016
Power regression			0.84	38.00	
Exponential regression			0.84	38.80	
Support vector machine			0.83	31.30	
Linear regression	MODIS		0.64	42.1	
Power regression			0.69	40.9	
Exponential regression			0.69	41.1	
Support vector machine			0.72	37.1	

The current and future studies need to explore the gaps identified above including integration of machine learning algorithms, in situ measurements and VIs for grassland AGB estimation. This study attempts to contribute to increasing the application of machine learning with Earth observation based data in the grassland AGB estimation and monitoring. The findings will offer insights on the current state of affairs in the study area, and also contribute to addressing the problem of grassland degradation to boost restoration and developing sustainable grazing management policies.

2.3.8 Summary

Chapter 2 presents different grasslands classifications available in the literature. Grasslands grow in a humid environment other categories are common in drylands. All these grassland categories have a significant contribution to the agriculture sector particularly the livestock industry for grazing and other livelihoods. Yet, much of it is still not protected. Also, grassland degradation vulnerability has increased. This is caused by climate change and overgrazing which are part one of the drivers for grassland degradation. The rainfall has more control over grassland AGB distribution compared to temperature. However, arid and semi-arid ecosystems and drought-prone areas with water scarcity limit grasslands growth. Further, shrub encroachment and nitrogen deposition threaten grassland distribution. Therefore, proper methods are needed for monitoring and modelling grassland growth conditions to support grassland management strategies. Studies have revealed that EOS offer optimal techniques for monitoring grassland ecosystems compared to conventional methods. In general, grasslands experience multiple threats and vary in all grassland ecosystems. For instance, Hluvukani protected grazing areas are drought-prone and experience multiple threats that increase grassland degradation. The next chapter provides insights about the study area in Hluvukani and the methods adopted for addressing identified gaps in the existing literature.

Chapter 3

Study Area and Methodology

Highlights

The Hluvukani village in Mpumalanga was used as the case study for grassland AGB estimation, which was influenced by the predominant Smallholder livestock farming. This livestock farming provides a source of income for many livelihoods in the area. However, protected grazing areas experience grassland degradation as a result of overgrazing, and grazing competition of livestock and wildlife. This area is dominated by Savannah grassland with sub-tropical climatic conditions. The geology type and soil formation of these protected grazing areas contribute to limited grassland growth and distribution. More so, quantitative research techniques were adopted in addressing the current study objectives. Accordingly, the study was approved by the University of Fort Hare Research Ethics Committee (UREC).

3.1 Introduction

This chapter provides brief information about the socio-economic status, population, geographical coordinates and geology of the study area, and a summary of the methods adopted with a justification. However, another information about the study area is available in Chapter 5 under materials and methods. Furthermore, Chapter 4 and chapter 5 provide detailed information on the methods including data acquisition.

3.1.1 Study Area

The study was conducted in Hluvukani village protected grazing areas within savannah grasslands. The village population is estimated to be 9632, meanwhile, the majority of the people are unemployed (Mogakane, 2018). The few individuals employed are found within Nature reserves and Smallholder animal farms. Hluvukani village is commonly known for contact with livestock and wildlife in communal grazing lands due to opposite ends of the rickety fence (De Bruin, 2017). The study area is situated at 24° 39’ S and 31° 20’E of global positioning geographical coordinates and covers about 7.67 km^2 area (Figure 1). The climate is characterised by sub-tropical climatic conditions with rainfall ranging from 450 to 600 mm per annum and summer average maximum temperature is 29°C and winter minimum average of 12°C (Kolo, 2016; Pretorius, 2019).

Savannah, mixed Lowveld, bushveld, sour Lowveld bushveld, Afromontane forest and montane grasslands are dominant vegetation species (Lötter et al., 2014; Fourie et al., 2015; Data World, 2018). Hluvukani is characterised by a varied topography, which comprises of the high lying (Highveld) and the low lying (Lowveld) areas (Data World, 2018). The Lowveld region is mostly flat with some rocky outcrops and interspersed grassland (Data World, 2018). The protected grasslands in Hluvukani are found within the flat landscape in low lying areas surrounded by rivers, wetlands and forests (Data World, 2018). The Khokhovela perennial River provides water for grassland growth, particularly in the dry season.

3.2 Geology and Soil

The classification of geology and soil in Hluvukani is under Bushbuckridge Local Municipality (Table 2) and categories as follows: Red soil (18.7%) yellow soil (0.9%), vertic and melanic cover (17.7%), young soil (22.0%), exposed rock (6.9%), Loam soil (65%), sandy (21.4%) and clay soils (12.8%), respectively (Data World, 2018).

Table 2: Geology of Hluvukani in Bushbuckridge Local Municipal classification (BLM SDF, 2017).

Lithology Class	Area (Km2)	% LM
Amphibolite, Serpentine (met. Mafic and ultramafic rock)	0.55	0.0%
Felsic, intermediate rocks	1050.66	40.55%
Fine-grained felsic rock	30.89	1.2%
Granite Gneiss	1290.02	49.7%
Mafic and Ultramafic volcanic rocks	158.70	6.1%
Siliciclastic rocks	6.99	2.4%
Total	2593.81	100%

The slope, climate and rock properties have a significant influence on soil formation that determines grassland growth (Fernandes et al., 2016a). For instance, soil nutrients, temperature, and water are key elements for ecological grassland status. Low porosity rocks and low nitrogen content characterize the geology for the current study area, which hinders the grassland growth and distribution (Batten et al., 2005). Interestingly, the predominant granites geology in the study area provides a certain geomorphological and pedological condition that is associated with the formation of rupestrian grasslands (*Campos rupestres*) (Fernandes, 2016a). Other studies refer to rupestrian grasslands as savannah grassland (Souza et al., 2010; Fernandes, 2016b; Fernandes et al., 2020). Therefore, the grassland growth and distribution within protected grazing areas of Hluvukani are attributed to the geology and soil of the area. The rock outcrops contribute to the limited grassland distribution while enabling shrubs growth that threaten savannah grassland growth (Conceição et al., 2016).

Further, savannah grasslands are highly deficient in multiple nutrients because of the geology (Gneiss, Granites) that is strongly leached and weathered under well-drained tropical conditions (Schaefer et al., 2016). These nutrients have a significant influence on the distribution of the savannah grassland (Pellegrini, 2016). Therefore, nutrient deficiency in savannah grassland could reduce distribution and abundance in Hluvukani protected grazing areas. Moreover, soils within savannah grasslands are characterized by poor nutrients, low organic carbon content and high sand content that reduce grassland health (Schaefer et al., 2016).

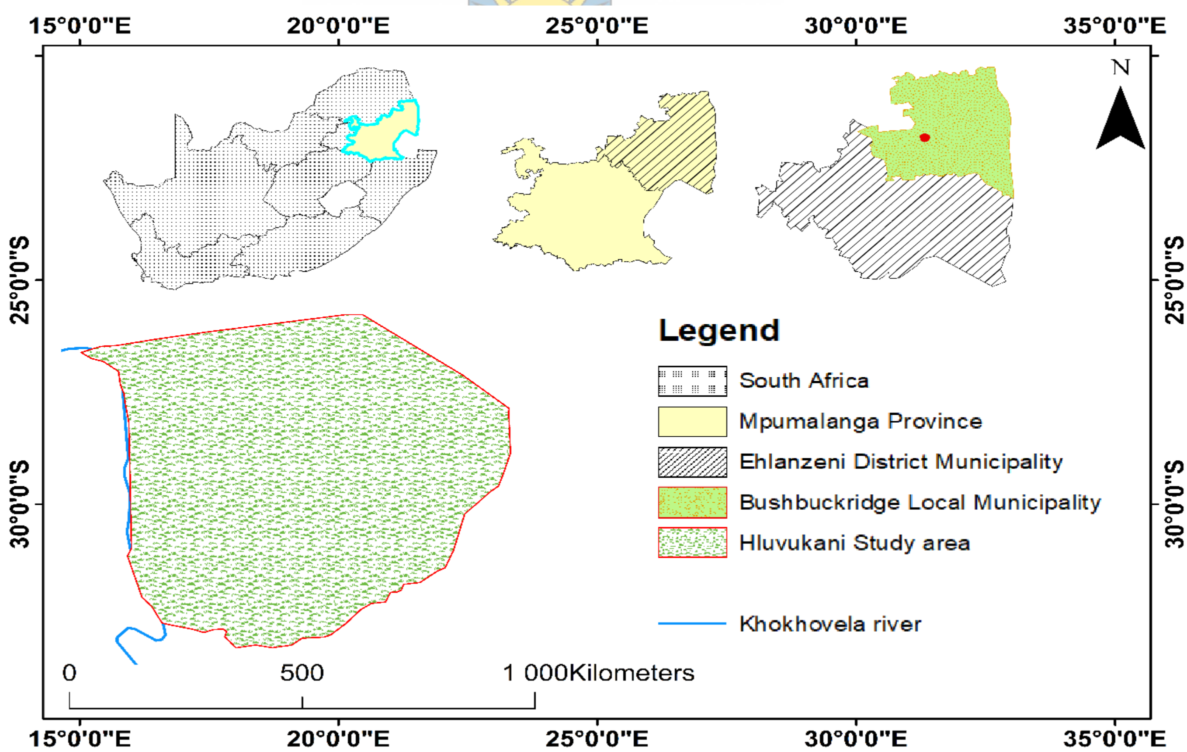

Figure 1: Location of the Hluvukani village Protected grazing grasslands study area situated in Bushbuckridge Local Municipality, Ehlanzeni District and Mpumalanga Province, South Africa

3.3 Research Methodology

3.3.1 Research Design

The study has used quantitative research methods. The quantitative research method is a phenomenon by collecting numerical data that are analyzed using mathematically based methods including statistical representation of data (Creswell, 1994; Creswell et al., 2017). The current study adopted bibliometrics quantitative methods for mapping the trends and advances in data models used in monitoring grasslands with Earth observation systems. Thus, similar studies have revealed that bibliometrics is effective for mapping trends in a particular field of study (Cobo et al., 2011; Okumus et al., 2018). Moreover, the quantitative measures were used during field survey for grass sampling, data pre-processing, and analysis for assessing above-ground biomass estimation in semi-arid savannah grassland integrating Sentinel-1 and Sentinel-2 Data with Machine-Learning. This quantitative approach has been adopted in similar studies for grassland modelling (Cheng et al., 2007; Wang et al., 2017; Reinermann et al., 2020).

3.3.2 Sampling

Random sampling is the best way to reduce the influence of uncontrolled factors, in which samples are randomly identified from the entire field that meets the criteria for inclusion in the study (Emerson, 2015; Larson et al., 2020). However, random sampling has limitations that affect sampling process during data collection. These limitations include costly arrangements during data collection, difficult to implement in widely dispersed fields and designing equal differences between sampling points (Emerson, 2015; Baron et al., 2020). The current study has utilized random sampling across the patches of protected grazing grasslands in Hluvukani, which provided the same probability for each sample to be selected. Other, similar studies have explored this technique for grassland AGB estimation with machine learning algorithms (Yang et al., 2018; Li et al., 2021). In overcoming the limitations of random sampling technique, the handheld Garmin Montana 680 Global Positioning System (GPS) was used for identifying representative points across the study area to reduce biased sampled area distribution. These points were distributed across patches of grassland. The total number of sampling points (90) was guided by previous studies that sampled at least 12 points and more for training models in grassland AGB estimation (Shen et al., 2008; Jiang et al., 2015).

3.3.3 Ethical Consideration

The ethical clearance application for the current study was approved and obtained from the University of Fort Hare Research Ethics Committee (UREC) with reference number KAL031SNDU01 (REC-270710-028-RA Level 01). To this end, all the conditions stipulated were adhered to. In addition, the authors of all published materials were fully acknowledged, and analysis followed already tested techniques, which give credence to the findings of this study.

3.3.4 Flowchart of the Adopted Analytical Approach

Figure 2 below show methodological flow chat for the current study. This flowchart was suitable for the quantitative techniques applied for data collection of the specific objectives. The Scopus databases that were utilized to retrieve published studies for mapping trends are freely available online. However, the main challenge is search terms that need to be streamlined and focus on research interest. Moreover, timespan and language are key factors to retrieve results using search terms. The database can provide a large number of results that require screening, refinement and tedious data cleaning. Therefore, analyses for trends in the current study niche area were done after data cleaning.

On the other hand, the Sentinel dataset was downloaded for the study area AGB estimation and is freely available on Copernicus Open Access Hub. Pre-processing was done using Sentinel Application Platform (SNAP) to correct atmospheric effects and both Sentinel-1 and Sentinel-2 images were resampled to 10 m spatial resolution. Sentinel-1 synthetic-aperture radar (SAR) transformation of VV, HV and vertical transmit were done through SNAP for spectral bands needed for models. The raw bands of Sentinel-1 and Sentinel-2, VIs were used during training data process and experiment of RFR, GBR and XGBR machine learning models with field data. Then, 20% of the filed data was used for model evaluation. This enabled for calculating the variable importance (VIs and spectral bands) and produced the grassland AGB models regression estimation statistics. The grassland AGB estimation maps showing machine learning model performance were generated in a Geographic Information platform using ArcGIS 10.8 tool. This study also generated Scatter plots showing the estimated versus the measured grassland AGB in the three ML models using R-package tools (v4.0).

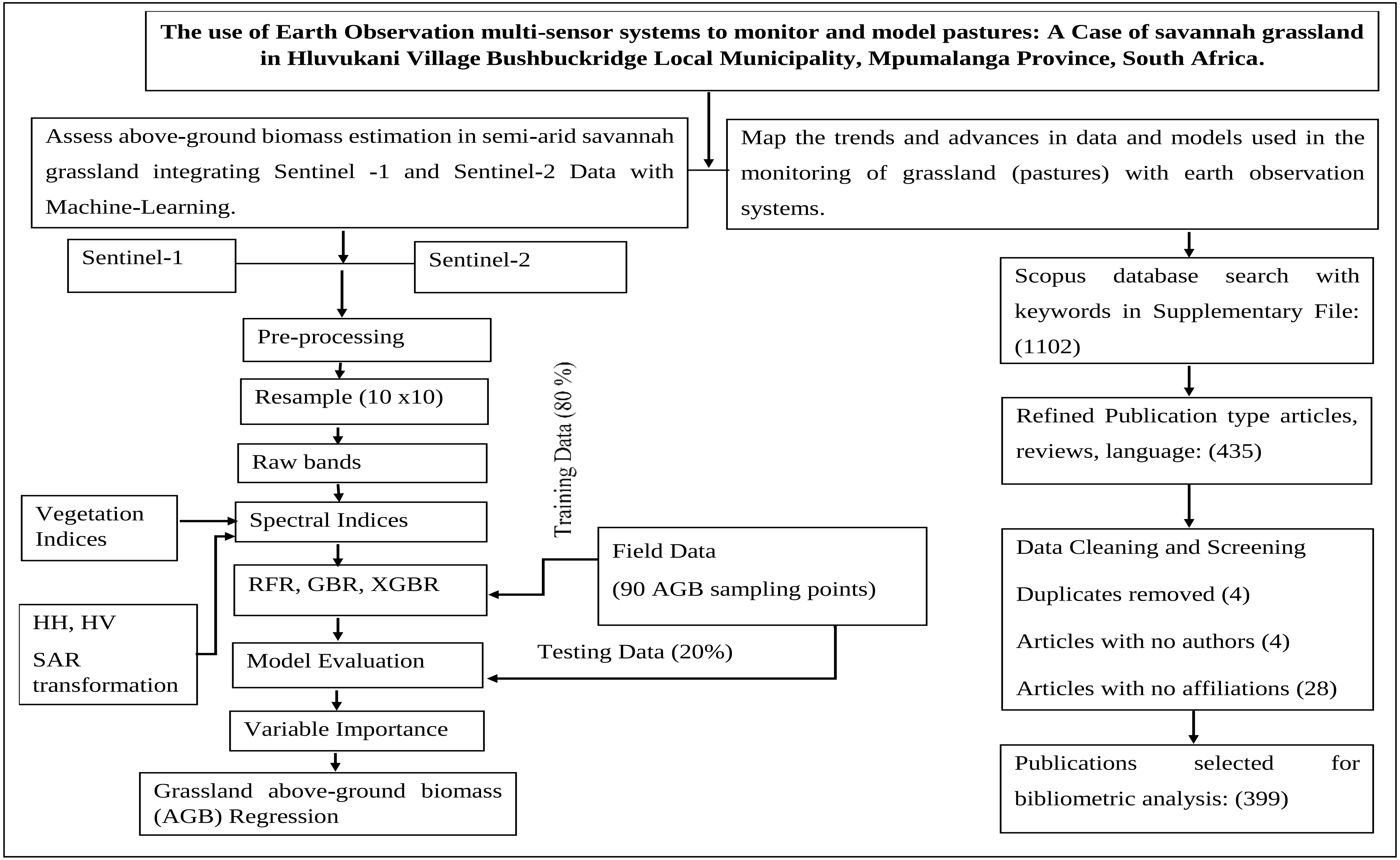

Figure 2: Flow chart of the methodology

3.3.5 Summary

Chapter 3 has highlighted the nature of the study area including the climate, geology and soil characteristics. The study area is situated in a Hluvukani rural setting that is dominated by unemployment and many people making living through livestock farming in protected grazing areas. This rural area is found within a semi-arid and drought-prone region. The vegetation within the study area is good for livestock but is currently degrading because of the geology of the area, overstocking and drying rivers within the protected grazing sites. The current study used quantitative methods to estimate grassland AGB distribution in the protected grazing areas. This application aided the understanding of the current conditions of grassland, which is crucial in developing grassland management strategies. Therefore, understanding the trends of EOS and pasture modelling to identify recent methods for grassland management was very critical in this study (next chapter). To this end, the findings provide new insights about the methodological advancement, developments and solutions to offer possible alternatives to conventional methods that are destructive and labour-intensive used in rural areas for grassland monitoring.

Chapter 4

Mapping the Trends of Earth Observation Systems and Pasture Modeling*

Highlights

An Earth observation system (EOS) is essential in monitoring and improving our understanding of how natural and managed agricultural landscapes change over time or respond to climate change and overgrazing. Such changes can be quantified using a pasture model (PM), a critical tool for monitoring changes in pastures and thus ensuring a sustainable food production system. This study used the bibliometric method to assess global scientific research trends in EOS and PM studies from 1979 to 2019. This study analysed 399 published articles from the Scopus indexed database with the search term "Earth observation systems OR pasture model". The annual growth rate of 19.76% suggests that the global research on EOS and PM has increased over time during the survey period. The average growth per article is n = 74, average total citations (ATC) = 2949 in the USA, is n = 37, ATC = 488, in China and is n = 22, ATC = 544 in Italy). These results show that this field of study was inconsistent in terms of ATC per article during the study period. Furthermore, these results show that three countries (USA, China, and Italy) ranked as the most productive countries by article publications. The Netherlands had the highest average total citations. This may suggest that these countries have strengthened research development on EOS and PM studies. However, developing counties such as Mexico, Thailand, Sri Lanka, and other African countries had a lower number of publications during the study period. Moreover, the results showed that Earth observation is fundamental in understanding PM dynamics to design targeted interventions and ensure food security. In general, the paper highlights various advances in EOS and PM studies and suggests the direction of future studies.

Keywords: bibliometrics; climate change; EOS; PM; remote sensing

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4.1. Introduction

Pastures are one of the most widespread terrestrial plant systems (Latham et al., 2014). Pastures cover about 31.5% of the global land area and other land cover types such as farmland and managed grazing lands, thus making pastures predominant among nature's services (Latham et al., 2014; Ali et al., 2016). Pastures are the second-largest coverage of the Earth's surface and are also second in carbon dioxide sequestration from the atmosphere after forests (Franzluebbers, 2010; Ali et al., 2016, Afuye et al., 2017). Pastures are an important natural resource that supports plant growth and provides a cheap feed source for livestock production (Letsoalo, 2019). Consequently, the functions and benefits of pastures are associated with soil erosion protection, nutrient persistence, and are a habitat for animal biodiversity, among others (Yang et al., 2012; Cadman et al., 2013). Global studies suggested different trends in pastures dynamics (Eriksen et al., 2010; Clementini et al., 2020; de la Fuente et al., 2020). Such studies estimate 40% of pasture degradation globally between 1982 and 2006 (Le et al., 2016; Wang et al., 2019a). In Europe, pastures have undergone reductions in quality and quantity through the intensification of animal production over the past decades (Dabrowska-Zielinska et al., 2017). Eastern Spain, western Mediterranean Badlands, Loess Plateau of China, eastern Himalayas of India, Western Brazilian Amazon, and Slovakia have been affected by high soil erosion rates leading to the degradation of pastures and rangeland ecosystems (Symeonakis et al., 2007; Xu et al., 2014; Galdino et al., 2016). Large areas in Australia, South America, India, and half of the pasture surface in Africa have experienced varying degrees of deterioration from grazing pressure and soil erosion (Truter et al., 2015; Mirzabaev et al., 2016; Nkonya et al., 2016; Letsoalo, 2019). Meanwhile, pastures suffer from poor farming methods and long-term grazing and unsustainable stocking levels in sub-Saharan Africa (Kwon et al., 2016; Sevov et al., 2018). In southern Africa, pastures have been over-utilized for livestock production and are often associated with intensive agricultural production systems (Dingaan et al., 2019). Consequently, the increasing rate of overgrazing is one of the leading factors in the degradation of pastures globally (Kwon et al., 2016; Dabrowska-Zielinska et al., 2017). Therefore, continuous monitoring of pastures is crucial to track changes in grazing capacity and intensity in any given region.

Studies show that pastures are affected by different factors such as climate change, overgrazing, soil erosion, urbanization, mining, and land-use change (Numata et al., 2007; Weber et al., 2018; Lugassi et al., 2019). These factors present multiple threats to livestock production, human society, vegetated ecosystem, and natural resource conservation (Weber et al., 2018; Letsoalo, 2019, Afuye et al., 2021a). Climate change projections indicate that pastures will experience extreme water shortage, heat stress, and prolonged growing seasons (Gibson & Newman, 2019). Global climate models (GCM) have predicted that the temperature is expected to increase from 1 to 1.25 °C in 2006 and may impede pasture growth across regions. Consequently, areas with rainfall deficits could experience a reduction in pasture productivity (Cobon et al., 2019). Weather parameters such as temperature and rainfall have significantly influenced pasture dynamics over the past decades (Afuye et al., 2018). Many studies have reported that overgrazing has threatened native vegetation and reduced soil infiltration thereby inhibiting pasture growth (Eriksen et al., 2010; Lai et al., 2020). Soil erosion is one of the factors that reduces soil fertility, which facilitates pasture growth and development (Galdino et al., 2016). The expansion of built-up areas leads to the total loss of pasture areas (Calotă et al., 2019). A study reported that pollution from industrial, mining, and agricultural activities poses a significant impact on pasture conditions (Gankhuyag, 2013). Meanwhile, intensive land-use change can also improve or degrade pasture areas (Guo et al., 2019). Therefore, it is important to explore the existing literature and identify other influential factors that can contribute to pasture loss or degradation in a given region. On the other hand, pasture modelling based on the experimentation of monitoring the condition is short-lived and expensive. The breakthrough of EOS to monitor the Earth's surface provides optimal, timely, and cost-effective techniques for pasture modelling on large scales. The pasture model (PM) refers to an incremental change in time to monitor and assess pasture conditions in response to climate, urbanization, soil evaporation, overgrazing, runoff, and land-use change (Thornley et al., 1997; Johnson et al., 2008). In general, pastures are monitored with the aid of conventional and remotely sensed techniques. Conventional techniques are used to determine pasture quality and require detailed sampling. However, this presents limited information about the spatial pattern of pasture dynamics. Limitations of conventional methods also include the high cost of laboratory analysis and are prone to human errors (Stolter et al., 2018; Dos Reis et al., 2020). Remote sensing techniques are superior to conventional methods, as they provided robust and time-effective solutions. These remote sensing techniques were applied on data acquired from different satellite sensors. Notable limitations of remote sensing techniques are associated with big data assimilation in managing spectral and spatial resolutions over time. However, current advances in cloud computing and the launch of improved satellite sensors address these limitations. For instance, the recent advancements in EOS such as synthetic aperture radar (SAR) Sentinel-1 and optical imagery of Sentinel-2 are associated with improved spectral and spatial resolutions to monitor pasture change dynamics (Segarra et al., 2020; Mashaba-Munghemezulu et al., 2021a). Remote sensing data have been efficiently used to predict pasture yields, herbage quality, productivity, and pasture quality parameters (Abdel-Hamid et al., 2021; Chen et al., 2021). Therefore, it is important to appraise the evolutionary trends and identify current research hotspots to better understand the dominant themes by using the bibliometric method of published literature on EOS and PM studies.

Bibliometrics is a comprehensive statistical method used in evaluating published literature (Khiste et al., 2017; Mair et al., 2018; Jiang et al., 2019; Gao et al., 2020; Mishra et al., 2021). Generally, the bibliometric analysis provides a clear understanding of published research articles on informative and objective scientific studies within a specified field of study (Mongeon et al., 2016; Radhakrishnan et al., 2017; Aria & Cuccurull, 2017; Linnenluecke et al., 2020; Vieira et al., 2021; Orimoloye et al., 2021). Most studies used bibliometric analysis to identify gaps and advance the literature review in a specific niche area (Chen et al., 2015; Zhou et al., 2016; Yang et al., 2017; Yu et al., 2018; Busayo et al., 2020; Tang et al., 2020; Singh et al., 2021; Afuye et al., 2021b). This study assessed global scientific research history on EOS and PM studies from 1979 to 2019. The study appraised published articles by assessing the annual scientific production, author's global citation, decadal trending topics, keywords co-occurrence network, journal analysis, institutions, and countries' collaboration on EOS and PM studies. The outcome of this study is fundamental in EOS by providing important information on pasture model dynamics for designing targeted interventions and ensuring food security.

4.2 Data Collection, Preparation and Methods

The Scopus indexed database provided adequate data to perform a bibliometric analysis on EOS and PM studies and to determine specific trends and identify knowledge gaps. The Scopus database was used to mine the data for this study on 2 October 2020, as presented in Table 1. The bibliometric analysis was carried out using bibliometric R-package (RStudio v4.0), biblioshiny (Cuccurullo et al., 2017; Zhang et al., 2017; Chen et al., 2021) and VOSviewer software (v1.6.16) (Van Eck & Waltman, 2010; Van Eck & Waltman, 2013; Moral Muñoz et al., 2020). The application of these software provides a web interface for bibliometrix (Cobo et al., 2011; Perianes-Rodriguez et al., 2016; Leung, et al., 2017; Muritala et al., 2020). These are available open-source software. All publications related to EOS and PM research were searched using the search term ("Earth observation systems OR pasture model"), which include an article title, abstract, and keywords from 1979 to 2019. The Boolean operation OR was used to combine the search terms. Therefore, the search terms generated a total of 1,102 articles, including conference papers, articles, reviews, book chapters, conference reviews, short surveys, books, editorial, notes, and erratum, from the Scopus database. The search term was refined to 435 articles written in the English language and of the review document type. The retrieved 435 articles were processed for data cleaning to identify duplications of articles without authors and affiliations using the Citation Analysis Package (CITAN) in the R repository (Gagolewski et al., 2011; Aria & Cuccurullo, 2017). Data cleaning is one of the basic steps in bibliometric analysis but is time-consuming. CITAN and biblioshiny packages were performed for the disambiguation process of identifying articles without authors and affiliation institutions (Gagolewski et al., 2011). Therefore, the study used a total of 399 articles for bibliometric analysis and interpretation. Consequently, the bibliometric method utilized for this study cannot generalize studies on EOS and PM using one database. The analyses were carried out based on published research articles to streamline and focus on published studies that explored EOS and PM to accommodate the niche area. To this end, the highlighted factors shaped the research direction of materials and methods explored and adopted in data collection and analysis. Figure 3 presents the graphical representation of data processing as shown below.

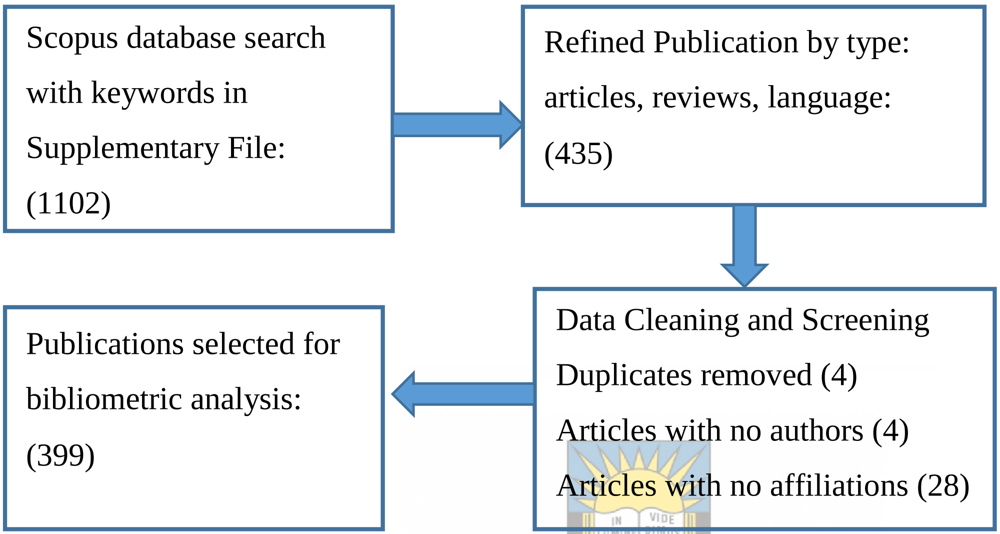

Figure 3. Graphical representation of data processing.

4.3. Results

4.3.1. Characteristics of Scopus Indexed Database

The analysis includes 399 articles published and retrieved from the Scopus database with a focus on EOS and PM during the survey period. Accordingly, Table 3 summarizes the information retrieved from the Scopus database. For example, a collaborative index of 4.42 for 1682 authors have been revealed, with 1622 authors contributing to multi-authored documents and 68 authors of single-authored published documents, as shown in Table 3. The evaluation of journals, books, etc., includes 229 sources with 2018 author's appearances with 0.259 documents per author (3.78 authors per document) and 4.64 co-authors per document. The average annual percentage growth rate was 19.76% of citations per article recorded during the survey period.

Table 3: Main summary information retrieved on EOS and PM studies (1979-2019)

Description	Results
Time span	1979-2019
Documents	435
Sources (Journals, Books, etc.)	229
Keywords Plus (ID)	3279
Author's Keywords (DE)	1257
Average citations per document	19.76
Authors	1682
Author Appearances	2018
Authors of multi-authored documents	1622
Single-authored documents	68
Documents per Author	0.259
Authors per Document	3.78
Co-Authors per Documents	4.64
Collaboration index	4.42
Article	402
Review	33

4.3.2. Temporal Scientific Contribution per Article

The information in Figure 4 shows a relatively low annual production rate on the number of articles recorded from 1979 to 1993. The notable decreasing trend in articles production rate started in 1980 and continued from 1984, 1990, 1992, 1994, 1997, 1999, 2001, 2006, 2009, 2010, 2013, and 2014, and a steady decrease was observed from 2018 and 2019, respectively. Furthermore, it is worth noting that the trend of publication peaked in some years and significantly decreased in some other years, particularly in 1981, 1990, 1997, and 2014, respectively, while the highest number of publications was observed in 2017. The study observed inconsistency in the publication trend rather than maintaining the same growth rate. During the survey period, an increased average citation per article was observed in 2019, reaching a maximum of 19.76%. Consequently, the average citations per article declined, which connotes that the field of research was unstable in terms of average total citation per document (Ellegaard et al., 2015).

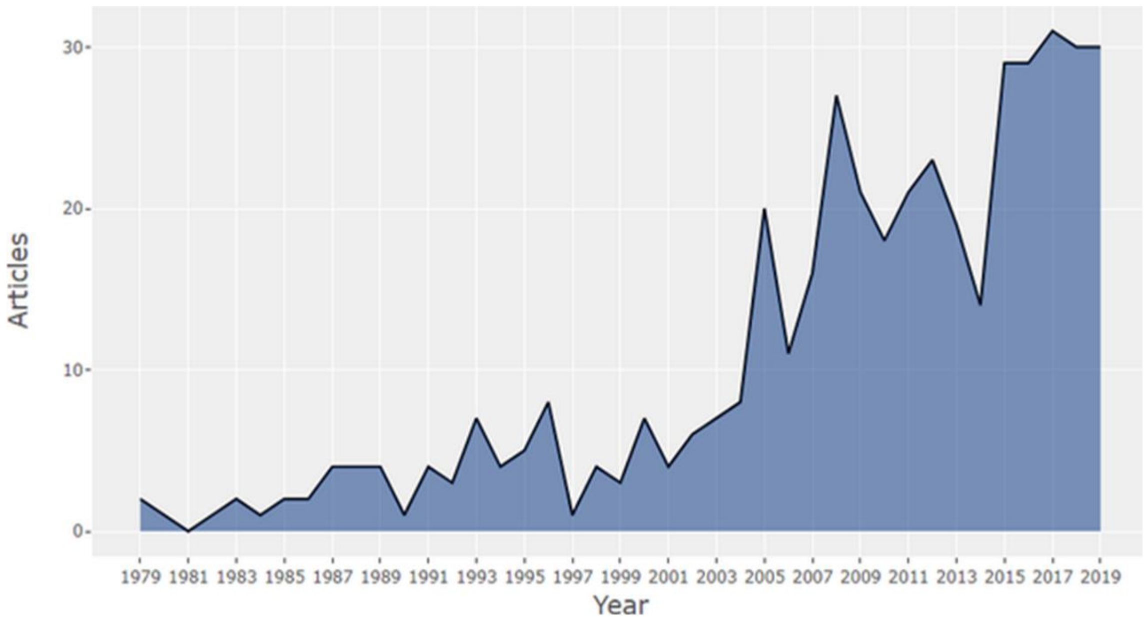

Figure 4. Annual scientific production on EOS and PM from 1979–2019.

4.3.3. Scopus Global EOS and PM Most Cited and Spatial Distribution

The information summarized in Table 4 shows the top 20 most cited countries on EOS and PM studies. The number of average article citations (AAC) and published articles varied across EOS and PM studies. However, 61 single-authored articles came from single country publications (SCP), while 13 joint authored articles came from multiple country publications (MCP). The USA ranked first among the top 20 countries based on published articles and total citations during the survey period. The USA accounts for 74 articles in terms of countries' contributions. It is worth noting that, among the most-cited countries, the USA had a total citation accounting for (TC = 2949) and of (AAC = 39.85), followed by the Netherlands (TC=1097 and AAC = 219.40) and France (TC = 640 and AAC = 45.71), respectively. Results show that most of the cited studies came from developed countries, while a small number of cited studies came from developing countries such as Mexico, Thailand, Sri Lanka, and Brazil, among others. Consequently, there was a low research output from developing countries, which are characterized by a high level of self-funded or autonomous research and a language barrier (Huang et al., 2016). The developed country's performance is measured in terms of most article citations, the highest number of publications, and their influence in the field among other developing countries. This implies that the publications of developed countries and the availability of research grants contributed to the increase in research productivity in the EOS and PM studies during the survey period (Barnett et al.,2015; Saygitov, 2018).

Table 4. Top 20 countries most cited per average article citation on EOS and PM from 1979–2019.

Country	Articles	TC	AAC	SCP	MCP	A/MP
USA	74	2949	39.85	61	13	0.176
Netherlands	5	1097	219.40	0	5	1.000
France	14	640	45.71	8	6	0.429
Italy	22	544	24.733	10	12	0.545
China	37	488	12.11	30	7	0.189
Germany	14	281	20.07	10	4	0.286
Brazil	2	192	96.00	1	1	0.500
Switzerland	6	151	25.17	3	3	0.500
Canada	5	149	29.80	3	2	0.400
United Kingdom	5	118	23.60	2	3	0.600
Spain	4	111	27.75	1	3	0.750
Japan	14	83	5.93	11	3	0.214
Austria	2	70	11.67	1	5	0.833
Mexico	2	43	21.50	0	2	1.000
New Zealand	2	41	20.50	2	0	0.000
Greece	3	40	13.33	1	2	0.667
Thailand	1	37	37.00	1	0	0.000
India	8	36	4.50	8	0	0.000
Sri Lanka	1	31	31.00	1	0	0.000
Poland	4	23	5.75	4	0	0.000

Note: Total citations (TC); average article citations (AAC); single country publications (SCP); multiple country publications (MCP); articles per million publications (A/MP)

4.3.4. Scientific Collaboration Analysis per Countries

Figure 5 shows the top 20 collaborations between countries that contributed to the EOS and PM studies. The bigger the node, the greater the country's dominance per article publication and the number of its associated links between different countries. The most dominant country was the USA, followed by China, France, Italy, Germany, and Japan, respectively. The country's influence in terms of its dominance may suggest the importance of strengthening research needs and collaboration networks to advance EOS and PM studies.

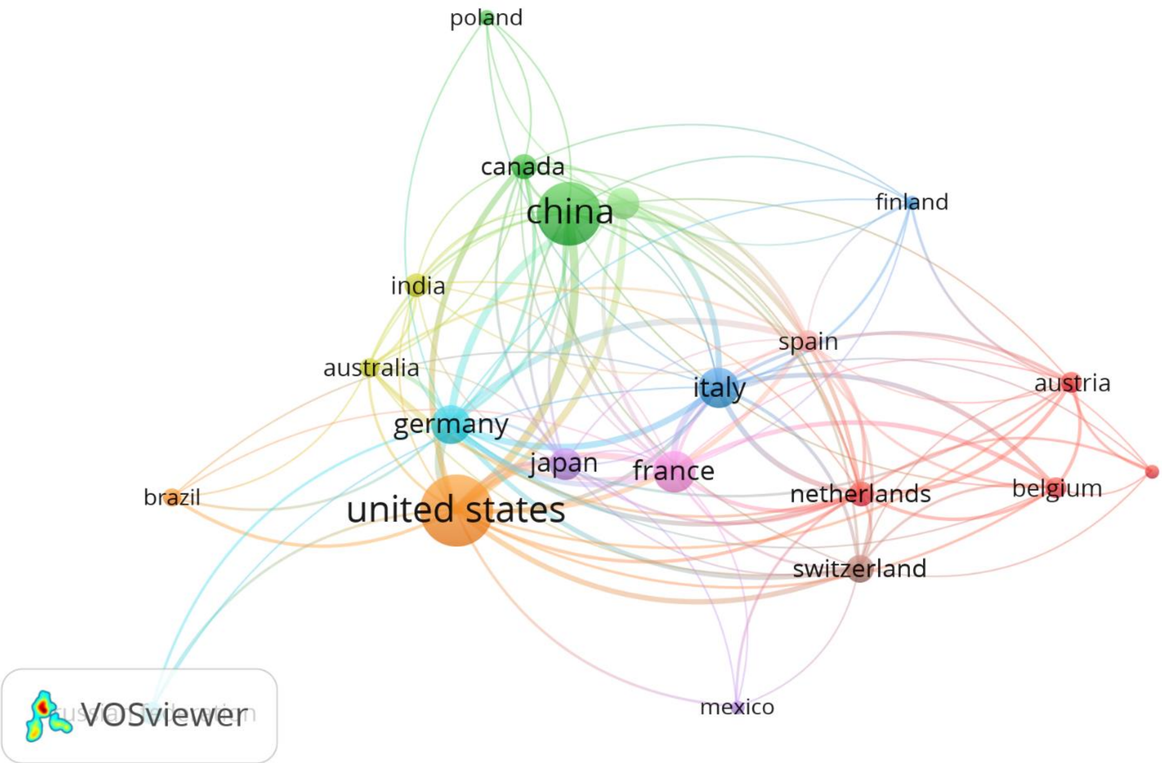

Figure 5. Top 20 Collaboration between Countries Network on EOS and PM Studies.

4.3.5. Collaboration Analysis between Institutions.

Figure 6 shows the top 20 collaborations between various institutions that contributed to EOS and PM studies. Institutions with larger boxes and thicker connectors represent the strength of dominance in the field per article publication. Wuhan University, followed by the University of Chinese academy of sciences, University of Maryland, Institute of Remote Sensing and Digital Earth in China, California Institute of Technology, and NASA Goddard Spaceflight Center in the USA were amongst the most influential institutions on EOS and PM research. This suggests that scientific collaboration occurs mostly within national borders. The University of Geneva, University of Tokyo, Mississippi State University, Space Research Institute, and the University of Defense Technology witnessed little or no publication on EOS and PM studies during the survey period.

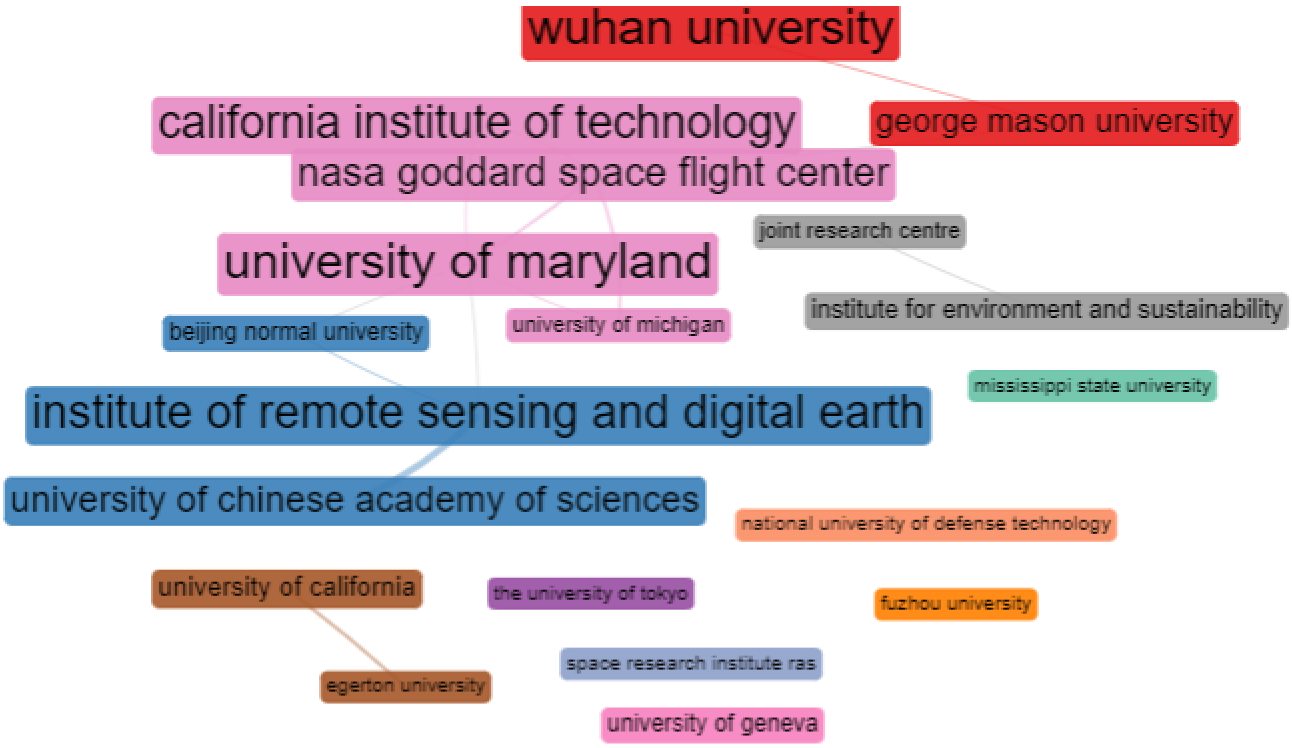

Figure 6. Top 20 Collaboration between institutions network on EOS and PM studies.

4.3.6. Author's Contribution

Figure 7 shows the top 20 global citations of authors' articles in EOS and PM studies. The results show that Drusch M., ranked the most cited author in the field, with the total number of articles accounting for TC = 1030, followed Kaufman Y. J., accounting for TC = 467, and Duchemin B., accounting for TC = 262, respectively. Drusch M. focused on the global monitoring environment, security for the European Commission, and European space agency on EOS and PM studies. Duchemin B, investigated the feasibility of using the NDVI derived from remote sensing data to provide indirect estimates of the LAI, a vital pasture parameter for the crop process model among others. Accordingly, the author's influence in terms of their productivity and the average total citation was centered on EOS and PM studies to measure the author's contribution in a specific field (Xie et al., 2020).

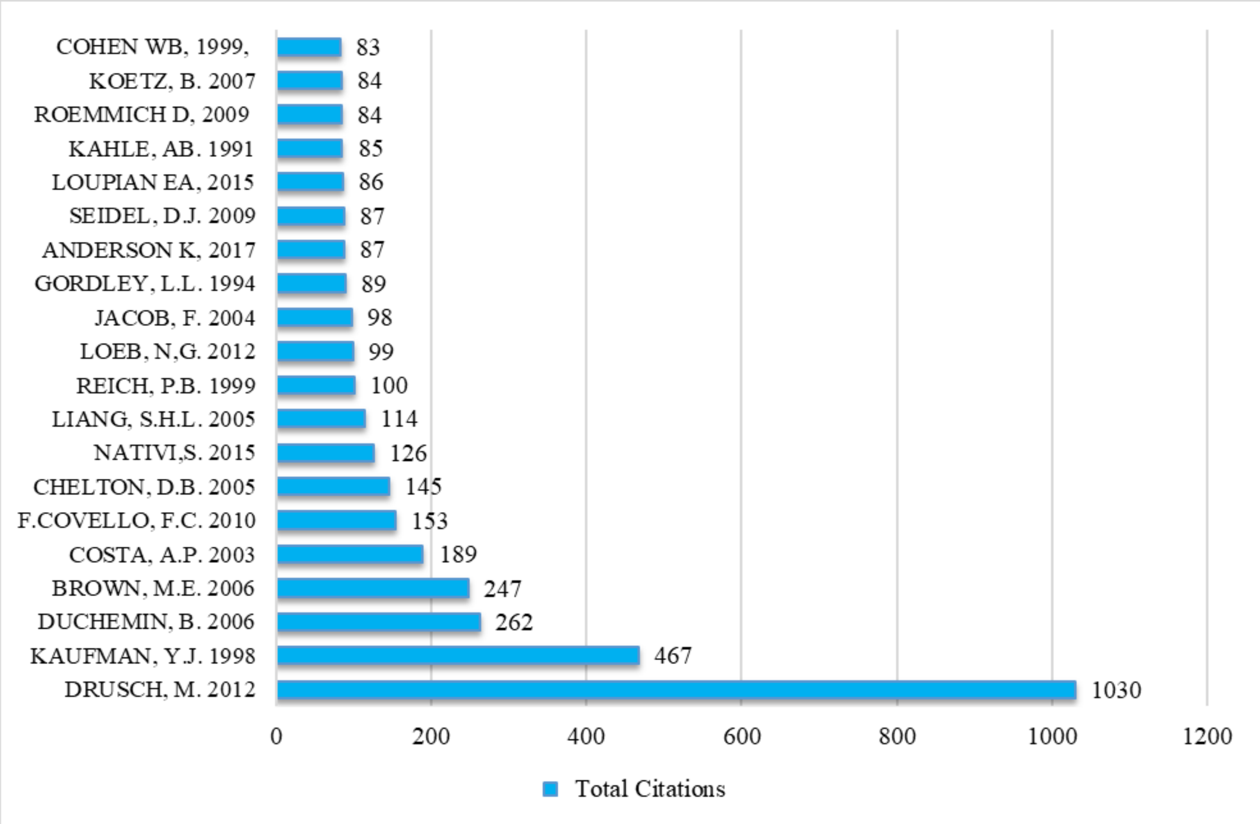

Figure 7. Top 20 global citations of authors on EOS and PM from 1979–2019.

4.3.7. Journal Analysis

Information in Table 5 shows the top 20 Journals on EOS and PM studies. A total of 229 journals were published on EOS and PM during the survey period. The journal sources were ranked based on the number of most cited articles and each journal start year of publication on EOS and PM studies. IEEE Transaction on Geoscience and Remote Sensing, accounting for (n = 23) in 1987, followed by the Remote Sensing journal accounting for (n = 14) in 1999, and Remote Sensing of Environment accounting for (n = 13) in 2010 had the highest number of articles, with 3.49% of the total. This may suggest that this field is relatively distributed through large journals and covers research erudition across many fields of study (Mishra et al., 2021).

Table 5. Top 20 journals on EOS and PM studies from 1979–2019.

Source	NP	TC	Start year
IEEE transaction on geoscience and remote sensing.	23	682	1987
Remote sensing.	14	205	2010
Remote sensing of environment	13	1688	1999
IEEE Journal of selected topics in applied earth observation and remote sensing.	12	159	2008
IEEE systems journal.	11	195	2008
Journal of remote sensing.	11	93	2016
ACTA astronautic.	10	106	1987
Advances in space research	10	87	1994
International journal of remote sensing.	8	316	2000
Proceedings of SPIE- the international society for optical engineering.	7	27	1979
Space policy	7	120	1995
Computers and Geosciences	6	176	2005
International journal of applied earth observation and geoinformation.	6	139	2009
Canadian journal of remote sensing.	5	103	1997
Journal of geophysical research atmospheres.	5	607	1998
Sovrmennye problem distantsinnogo zondirovaniya zemli iz kosmosa	5	109	2015
Environmental modelling and software.	4	188	2013
IEEE Geoscience and remote sensing letters.	4	69	2005
Journal of atmospheric science	4	109	2000
Sensors (Switzerland)	4	29	2017

Note: Number of articles (n); total citations (TC).

4.3.8. Top Global Cited Published Articles on EOS and PM studies

The information in Table 6 presents global top-cited articles on EOS and PM studies and summarizes findings explored using different satellites/EOS and models. The studies revealed synergy between EOS and PM through change detection, satellite type, and algorithms trained and validated for PM. Most studies revealed positive outcomes for pasture models with high-resolution satellite imagery such as Sentinel-2, Gaofen (GF)-1 and others (Jacob et al., 2004; Drusch et al., 2012; Jia et al., 2016). Some studies on pasture models showed negative results on EOS such as the

Advanced Very High-Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS). The multisensor data fusion process in EOS may improve the pasture model accuracy, which counters the low-resolution satellite sensors (Duchemin et al., 2006; Jia et al., 2016). The constant development of EOS over the years has been inevitable in EOS and PM studies, such that EOS data utilized the NDVI, enhanced vegetation index (EVI), and LAI for calibration and validation of different models (Koetz et al., 2007; De Rosa et al., 2021). Most studies have used remote sensing data, algorithms, and in situ sampling methods to generate data for pasture models (Kaufman et al., 1998; Chen et al., 2021).

Table 6**.** Top 15 globally cited articles on EOS and PM studies from 1979–2019.

Satellite/EOS/Model	**Findings/Gaps**	**Total Citation**	**Reference**
Sentinel-2	The findings reveal the effectiveness of using sentinel-2 in a global monitoring environment but unable to retrieve data from previous decades' data for a long time series.	1030	Drusch, 2012
MODIS	The results show that MODIS products work better than AVHRR in the monitoring of global fire detection changes in the location and rate of biomass consumption by fires.	467	Kaufman et al., 1998
Landsat7-ETM+ images, NDVI, LAI, AET, ET_o	Findings demonstrate exponential relationships between LAI and NDVI, as well in LAI and plant transpiration coefficient (K_{cb}); good accuracy linear relationship on NDVI and K_{cb} to wheat phenology in the seasonal land cover using Landsat data. Such analysis approaches on a regional scale are limited by high resolution and re-visit time.	262	Duchenim et al., 2006
AVHRR, SPOT-Vegetation, SeaWiFS, MODIS, Landsat ETM+. NDVI	Findings reveal consistency on NDVI records derived in different satellites through statistical and correlation analyses for monitoring the surface vegetation.	247	Brown, 2006
COSMO-SkyMed	Findings show COSMO-SkyMed constellation contribution of the X-band SAR, fast response, and short revisit time for various agriculture monitoring applications.	153	Covello et al., 2010
Global Earth Observation System of Systems	The findings reveal the importance of knowledge and semantic formalization to address multidisciplinary applications (i.e., pasture change detection over time).	126	Nativi et al., 2015.
NASA Sensor Web	The findings showed the development of GeoSWIFT for the integration of remote	114	Liang et al., 2005

	sensing imagery and real-time in situ sensing observations of crop yielding.		
Earth Observation System, MODIS, Land Science Team model, LAI	The results show the combination of remote sensing data with process-based and spatially distributed and process-based biogeochemistry models to examine variation in ecosystem processes. However, these process models can be validated against direct measurements made with eddy covariance flux towers and ground-based NPP sampling.	100	Reich et al., 1999
ASTER and MODIS. TES algorithm, TISIE algorithm	The results reveal the feasibility of merging ASTER and MODIS data for emissivity and radiometric temperature in semi-arid rangelands and agricultural areas.	98	Jacob et al., 2004
Earth Observations	The findings show the significant role of Earth Observations systems in supporting the 2030 Agenda directly addressing the Sustainable Development Goals (SDGs).	87	Anderson et al., 2017
Advanced Spaceborne Thermal Emission Reflectance Radiometer	Findings demonstrate the ability of ASTER to provide science objectives identified by the EOS global change program such as surface reflected radiances and the application of digital elevation models for vegetation conditions.	85	Kahle et al., 1991
LiDAR, Imaging spectrometer, Radiative transfer models, LAI	The findings specified robust estimates of the characteristics of the forest canopy characteristics that were achieved, ranging from maximal tree height, fractional cover (Fcover), LAI to the foliage chlorophyll and water content of the foliage for a wide range of pastures.	84	Koetz et al., 2007
MODIS, LAI	The findings validate land cover and land use change models using MODIS data based on the MODIS Land Discipline Group (MODLAND).	83	Cohen et al., 1999
Environmental Mapping and Analysis Program (EnMAP) mission	Findings revealed the simulated tool of remote sensing images for Hyperspectral and multispectral data called EnMAP to applications such as pasture monitoring.	77	Guanter et al., 2009
Widefield view (WFV for GF-1), Prospect + Sail radiative transfer model	Findings show a high-quality frictional Vegetation cover estimation algorithm using a physical model and neural networks through the first high-resolution EOS Chinese satellite (GF-1 data).	74	Jia et al., 2016

4.3.9. Top 20 Authors Keywords and Co-occurrence Network

The information in Table 7 shows the top 20 authors' keywords on EOS and PM during the survey period. The author keywords were classified according to the author keyword (DE) and keyword Plus (ID). Remote sensing was ranked first and appeared most as a keyword term of the author (DE), accounting for n=34, followed by Earth observation (n=20) and global Earth observation systems (GEOSS) (n= 18), respectively. Remote sensing had the highest appearance in author keyword Plus (ID), accounting for n=171, Earth observation accounting for n=98, and EOS accounting for (n=76), respectively. Accordingly, Earth observation and remote sensing revealed dominance in authors' keywords (DE) and keyword Plus (ID). However, these keyword terms indicate that Earth observation applications have been central in remote sensing and global change detection. In addition, remote sensing, Earth observation, climate change, and MODIS appeared more between the author's keyword (DE) and keyword Plus (ID). This may suggest that these variables highlight the relationship between remote sensing and Earth observation system in monitoring and modelling pasture dynamics under global change (Mineart & Crout, 2005). However, Sentinel-2, agriculture, big data, and mathematical model were rarely used in authors' keywords in EOS and PM research, which may suggest more studies for future development.

Table 7. Top authors keywords used on EOS and PM studies from 1979–2019.

Rank	Author Keywords (DE)	Articles	Author Keywords (ID)	Articles
1	Remote sensing	34	Remote sensing	171
2	Earth observation	20	Earth observation	98
3	Geoss	18	EOS	76
4	NDVI	9	Observations	71
5	Climate change	8	Satellite imagery	62
6	Interoperability	8	Satellites	54
7	Satellite	7	Earth (planet)	42
8	Geoss	6	Geoss	40
9	MODIS	6	Earth observations	31
10	Data sharing	5	Radiometers	31
11	Monitoring	5	Satellite data	31
12	Sentinel-2	5	MODIS	28
13	Agriculture	4	Calibration	27
14	AMSR-E	4	Climate change	27
15	Aster	4	Decision Making	24

16	Big data	4	Spatial resolution	24
17	Biodiversity	4	Environmental monitoring	23
18	Calibration	4	Orbit	21
19	Classification	4	Weather forecasting	21
20	Data management	4	Mathematical model	20

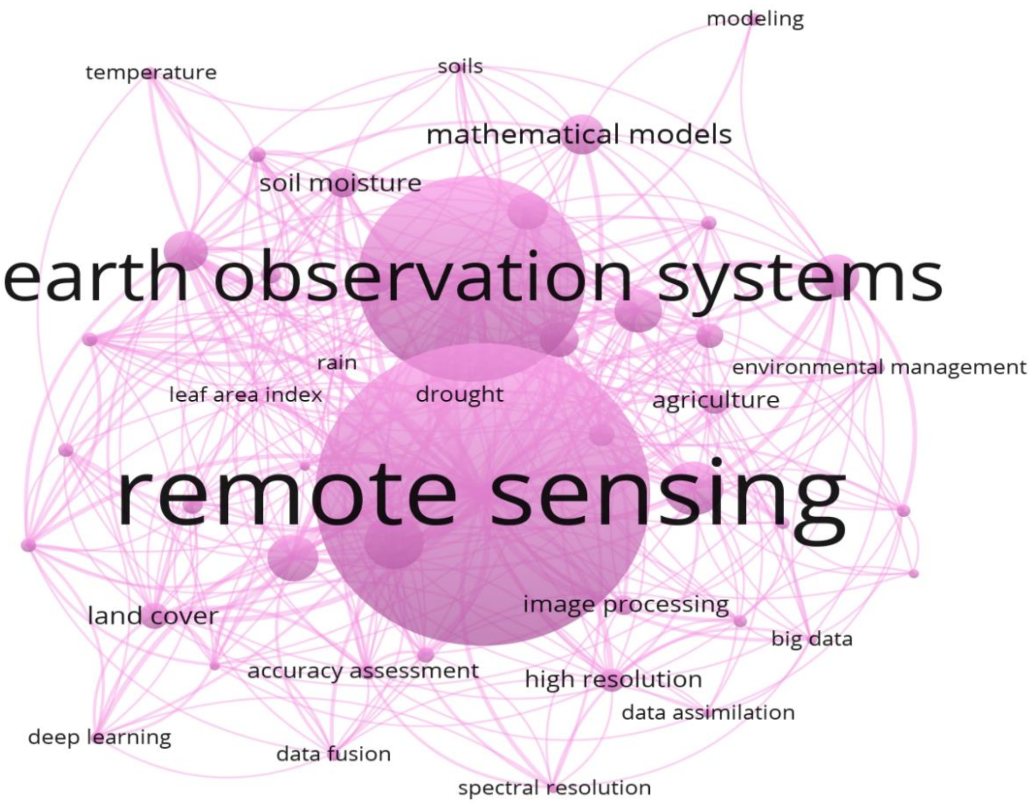

Figure 8. Top 20 keywords' co-occurrence network on EOS and PM studies.

Figure 8 shows the top 20 keywords' co-occurrence in EOS and PM studies. The size of nodes depicts the frequency of keywords. The larger the size of the node, such as remote sensing and Earth observation, the higher the frequency of keywords. Soil moisture, agriculture, land cover, environmental management, and rain (precipitation) are the most common factors used as keywords and are influential in the field of EOS and PM studies. Other important variables, such as soil, LAI, drought, and temperature, among others, had a low frequency of keywords, suggesting more research for future development in EOS and PM studies.

4.3.10. Decadal Trending Topics of High-frequency Keywords

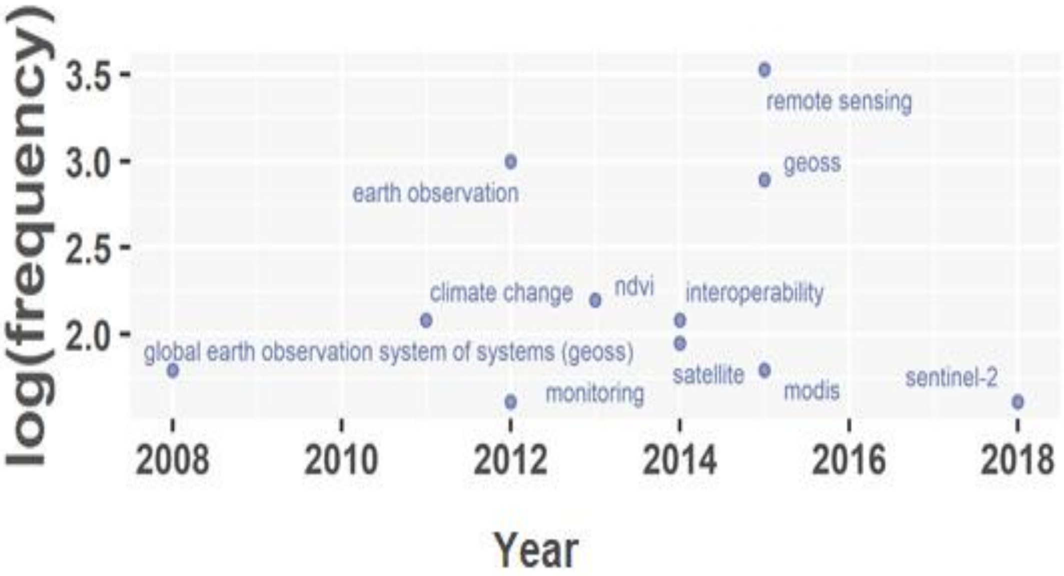

Figure 9. Decadal trending topics on EOS and PM studies.

Figure 9 shows the trending topics over the last decade in the EOS and PM studies. The decadal trending topics were generated based on the trending topics associated with the high frequency of the author's keyword in the field during the survey period. The frequency of authors' keywords on EOS and PM was summarized within the period of the analysis by a structured scheme to classify the core high-frequency keywords with a word frequency greater than or equal to 10 being selected. Therefore, 12 high keywords were obtained in terms of their occurrence in the field and drawn as decadal trending topics, as shown in Figure 9. This depicts the keywords and areas to identify in EOS and PM studies. It is worth noting that trending topics such as climate change, Earth observation, NDVI, remote sensing, MODIS, and Sentinel-2, among others, have been included under EOS and PM studies. Accordingly, remote sensing was observed at the highest peak in terms of its frequent applications in EOS and PM studies during the survey period. In addition, it was observed that, between the years 2008 and 2018, EOS and PM studies gained increased global attention and significance in space-based technology and development in modelling pasture dynamics.

4.4 Discussion

This study assessed a total of 399 published articles on EOS and PM studies, using the bibliometric method. A detailed analysis was carried out to evaluate the annual scientific production, author's contribution, top global cited published articles, author's keyword, trending topics, and co-occurrence of keywords in EOS and PM studies. The average growth per article of EOS and PM research showed inconsistency during the survey period, which suggests that the field was unstable in terms of average total citations per article. The observed decline in publication of EOS and PM studies between 1980 and 2019 cannot be generalized in terms of countries' publications. This may be linked with complex data structures, limited large-scale high-resolution sensors, and the lack of EOS designed for PM studies (Abdel-Hamid et al., 2020). The highest average citation per article was 19.76%, suggesting that global research on EOS and PM has been increasing over the last decade, particularly between 2008 and 2018. The gradual increase in annual scientific production rate and average total citations on EOS and PM research resulted in increased production in terms of the number of publications and total citations per year over time. Progress in EOS and PM studies was at its highest peak in 2017 in terms of the number of publications, thus revealing the impact of recent EOS with an improved resolution for pasture modelling (Pandit et al., 2018; Reida et al., 2020; Chen et al., 2021). The results show that the USA, China, and Italy ranked the most cited and most productive authors in terms of average total citations and multiple country publications, which strengthened the research development in EOS and PM studies. Mexico, Thailand, Sri Lanka, Brazil, and other African nations had a low research output and single country publications on EOS and PM studies during the survey period. This reveals the need for these nations with low engagement to collaborate with nations in the global north to boost their research in EOS and PM to bolster the current food security initiatives. Furthermore, it is revealed that the USA developed the environment vulnerability decision technology (EVDT) to support environmental management decision-making and reduce the dual needs of processing data for monitoring surface changes on pasture dynamics (Xia et al., 2018a; Susanty et al., 2021). Therefore, this justifies the USA's advance in EOS and PM, which depicts the country's advancement in space-based technology. Additionally, the USA has been at the center in recent spatiotemporal index developments for accelerating access to EOS big data assimilation to better understand the Earth system and PM research (Bovée, 2019). This development may suggest that the author's keywords and the leading country's contribution to EOS and PM studies are an eye-opener to make room for other developing nations. Studies revealed that the Earth observation system race often varies between the USA, Europe, Asia, and North America in terms of advances in Earth observation and geoinformation science and technology (Cracknell, 2018; Woldai, 2020). The lack of investment in EOS for environmental monitoring decision-making could suggest the low publication rate for other developing countries on EOS and PM studies (Cracknell, 2018). Remote sensing was observed to be the most appeared keyword in the field of EOS and PM studies. This is a demonstration that the contribution of remote sensing applications since 1978 in ecological research advances the synergy between EOS and PM studies (Amedjar, 2020; Crabbe et al., 2020). This may have also contributed to the development of space-based technology and data assimilation techniques suitable for pasture modelling (Crabbe et al., 2020; Chen et al., 2021). Furthermore, free access to EOS, such as Sentinel, Landsat, and MODIS, among others, contributed to pasture model research in terms of their applications to pasture management (Duchemin et al., 2006). The use of remote sensing has the potential to influence policy makers to incorporate the use of remote sensing for strategic planning and minimize the impact of pasture degradation. The results of this study revealed the limitations of low-resolution satellite sensors such as AVHRR, Landsat, and MODIS, among others. However, these limitations might have affected the monitoring assessment of pasture modelling research on EOS and PM. Results further revealed that a series of authors' keyword terms and keywords' co-occurrence network help to identify factors such as soil moisture, climate change, and precipitation, among others affecting pasture dynamics in EOS and PM studies. However, the use of the author's keyword terms such as monitoring, Sentinel-2, agriculture, big data, and mathematical model has been scantly explored in EOS and PM studies. This may also suggest the recent development in European Union (EU) programs and sentinel missions, including statistical models and machine learning to monitor pasture dynamics at multiple scales (Clementini et al., 2020; Chen et al., 2021).

4.5. Conclusion

This study evaluated studies on EOS and PM to reveal the evolution and current research hotspot and better understand the dominant themes by using the bibliometric method to analyze published articles from l979 to 2019. The findings in this study would help to advance the understanding of evolutionary trends of these studies by assessing the intellectual domain and identifying the history of global scientific research history in EOS and PM studies. Furthermore, the study appraised published articles by assessing the annual scientific production, author's global citation, decadal trending topics, keywords' co-occurrence network, journal analysis, and institutions' and countries' collaboration associated with EOS and PM studies. Therefore, using these available articles on EOS and PM helps to identify the research gap. The reviewed studies were used to evaluate and determine the current research hotspots and dominant themes, considering the information from time-varying trends observed in EOS and PM during the study period. The important scientific findings from these studies show that EOS and remote sensing are in the central position in all keywords with the largest significant appearance in the field. This connotes that future studies must appraise how far the EOS has been able to contribute to the advancements of modelling pasture dynamics. EOS play an important role in pasture monitoring and development using remote sensing techniques for mapping and assessing degraded land. Advances in artificial intelligence, deep and machine learning may compensate for the assessment of big ensemble data assimilation using mathematical algorithms for future EOS and PM studies. The key findings are associated with the application of pasture modelling, as EOS provided important information of time-series satellite imagery associated with change detection of terrain characteristics of pastoral rangelands. This information may help to spatially delineate anomalies in pastoral conditions, as well as growth and development in both length and intensity at different temporal and spatial scales. Therefore, bibliometrics has been widely utilized as a methodological approach to evaluate various research niche areas over time. Consequently, the study provided information for individuals, institutions, and governments in understanding the current state of research on EOS and PM. The results of this study are crucial in planning and managing pastoral rangelands and forest ecosystems. This also serves as an eye-opener for those developing countries, especially African nations, who had little or no research on EOS and PM studies and to provide hints for future research. This article suggests that various research databases should be incorporated to identify other possible research developments within the area of focus. This chapter suggests the necessity for modelling and managing pastoral rangelands using EOS and machine learning algorithms, which is the focus of the next chapter.

Chapter 5

Semi-Arid Savannah Grassland Above-Ground Biomass Estimation: Sentinel-1, Sentinel-2 Data and Machine-Learning Integration

Highlights

The grassland ecosystem is important in carbon sequestration and is a primary feed source for livestock, especially in rural areas. Determining the Above-ground biomass (AGB) is essential for grassland productivity monitoring and management in terrestrial ecosystems. To this end, EOS and machine learning approaches offer an avenue for accurate AGB estimation, which is crucial in designing appropriate strategies to redress grassland degradation. However, limited research has focused on villages with predominant smallholder livestock farming. This study examined the integration of Sentinel-1 and Sentinel-2 satellite data with VIS to map AGB spatial patterns at the protected grassland of Hluvukani village. The experiment was set with spectral bands + VIs for machine learning models to establish their predictive performances using the R^2, mean absolute error (MAE) and RMSE. Model evaluation results show that Random forest regression (RFR), gradient boosting regression (GBR) and extreme gradient boosting regression (XGBR) machine learning models were examined for this purpose. The findings show that RFR (R^2 = 34.7%) machine learning model performed better than GBR (R^2 = 27.7%) and XGBR (R^2 = 17.3%) models. The statistical comparison of these models showed an insignificant predictive capacity for AGB in the study area. Moreover, variable importance measures revealed Sentinel-2 VIs particularly EVI and DVI have superior performance. All three machine learning models showed the improved capability of integrating Sentinel-1 and Sentinel-2 data for grassland AGB estimation. Moreover, increasing the number of collected samples can improve the accuracy of these models and provide a robust estimation of AGB distribution. This serves to contribute to grazing and grassland management practices for rural livestock farmers. These findings support the effort to achieve Sustainable Development Goal number 15, which aims at improving food security and livelihoods in villages for sustainable livelihoods.

Keywords: Machine learning, grassland, above-ground biomass, food security

[*] **This chapter is under Journal Review:**

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5. 1. Introduction

Above-ground biomass (AGB) provides the basis for estimating the net primary productivity of grasslands (Meng et al., 2017; Wang et al., 2019a; Dos Reis et al., 2020). AGB is the weight of dry grass in the above soil per unit area, which varies with climate, topography, edaphic factors and type of land use (Ding e al., 2017; Wilkes et al., 2018; Kuhn et al., 2021). AGB account for 70% - 90% of the terrestrial ecosystem and has a central role in maintaining functions and processes of natural ecosystems (Kumar & Mutanga, 2017; Chen et al., 2018; Zumo et al., 2021). Furthermore, the benefits of AGB include: being a cheap forage for livestock, playing a role in carbon sequestration, providing habitat for animal biodiversity and conserving soil (Deb et al., 2017; Chen et al., 2018a; Wang et al., 2019a; Jiang et al., 2020). Above-ground biomass is important for rural smallholder livestock farmers as they largely depend on agriculture for their livelihoods, especially in Africa (Mutea et al., 2019; Masiza et al., 2019; Mugumaarhahama et al., 2021). Smallholder animal farming has a role in alleviating poverty and household food insecurity in South Africa (Maltou & Bahta, 2019), and other parts of the world (Mmbengwa, 2015; Mutea et al., 2019). Consequently, livestock farming provides incentives and benefits for the rural communities such as consumption, manure, cash income, savings and insurance, social status, and social capital (Morton et al., 2007; Pica-Ciamarra et al., 2011; Mmbengwa, 2015; Biglari et al., 2019).

Despite the benefits of livestock, AGB is sensitive to environmental changes particularly extreme temperatures (Zhang et al., 2018; Zarei et al., 2021) and is susceptible to pasture biomass degradation (Change, 2019). Recent, studies have shown that AGB has been affected by inevitable climate change associated effects such as droughts (Change, 2019), fires and overgrazing (Zarei et al., 2021). Furthermore, rainfall deficit, soil moisture, limited nitrogen, and heat waves have caused AGB stress and changes in forage quality and quantity (Rojas-Downing et al., 2017; Hossain et al., 2018; Biglari et al., 2019). This leads to degraded grazing grounds, loss of livestock from diseases, and starvation on rural smallholder animal farming (Morton et al., 2007; de Meira Junior et al., 2020). This has reduced pasture-based ecosystem benefits and caused food insecurity for many households (Ghosh et al., 2018; Duncanson et al., 2019; Forkuor et al., 2020).

Moreover, the smallholder animal farmers in rural areas, usually use conventional methods to predict grassland AGB for livestock grazing (Ravindranath et al., 2008; Zumo et al., 2021). Conventional measurements are accurate in small areas while also, destructive, costly, time-consuming (Yue et al., 2017; Punalekar et al., 2018; Yu et al., 2021a). However, these conventional methods reveal limitations in terms of temporal scale and spatial extent (Lu, 2006; Yu et al., 2021a). Remote sensing provides optimal, cost-effective, temporally and spatially contiguous data for monitoring grassland AGB estimation (Shoko et al., 2016; Yu et al., 2021a). These methods may help redesign management strategies and policy decision-making for the protection of natural ecosystems. Intensive AGB estimation contributes towards achieving the sustainable development goals (SDGs) such as Life on land goal number 15. Together with climate change programs such as Reducing Emissions from Deforestation and Forest Degradation Plus (REDD+) (Castillo et al., 2017; Chen et al., 2018b; Duncanson et al., 2019).

Recently, earth observation has been used for understanding potential pasture changes in Spatio-temporal patterns to global climate change (Xia et al., 2014; Liu et al., 2017b; Zarei et al., 2021). Studies revealed low spatial resolution imagery affects AGB estimation accuracy meanwhile high-resolution satellite imagery improves AGB estimation precision on terrestrial ecosystem management (Adan, 2017; Ding e al., 2017; Wilkes et al., 2018). EOS such as Sentinel-1 and Sentinel-2 have been investigated as single or multiple datasets for AGB application respectively (Haywood et al., 2018; Wang et al., 2019a; Issa et al., 2020; Nuthammachot et al., 2020). Sentinel-1 and Sentinel-2 have improved spatial resolution of 10-60 m with a shorter revisit time of 10-12 days (Drusch et al., 2012). Studies have explored the possibilities for achieving higher precision on AGB prediction using Sentinel-1 and Sentinel-2 within different geographical zones. EOS are compatible with machine learning (ML) algorithms and spectral indices for AGB estimation (Castillo et al., 2017; Chen et al., 2019a; Forkuor et al., 2020). Notably, the contribution of red-edge derived VIs enhance the performance of the regression models and AGB prediction accuracy than using spectral bands only (Adan, 2017; Pandit et al., 2018). The superior performance of non-parametric machine learning algorithms revealed a significant contribution to AGB estimation (Walinder, 2014; Chen et al., 2018a). For instance, studies show RFR has outperformed support vector machines for regression (SVR) and artificial neural networks (ANN) on AGB estimation observation (Chen et al., 2019; Jiang et al., 2021). In general, most studies revealed the possibility of ML methods with RF having a better ability for identifying complex relationships between predictors and AGB (Liu et al., 2017c; Yue et al., 2017; Gao et al., 2019; Jiang et al., 2021). Other studies revealed the efficient performances of gradient boosting regression (GBR) and extreme gradient boost regression (XGBR) for AGB estimation (Baumann et al., 2018; Forkuor et al., 2020). These ML algorithms use adaptive learning to reduce errors and learn on limited data. ML performance outcomes vary with regions because of climate zones and edaphic factors. The most application of these ML techniques are based on open grasslands, crops, mangroves, forests, and lacking in PAs used for livestock feeding. Hence, this study requires the assessment of different ML techniques to identify a suitable model to model the spatio-temporal distribution of AGB at PAs on a local level.

Studies have revealed diverse outcomes for machine learning algorithms in grassland AGB estimation (Zeng et al., 2019; Forkuor et al., 2020, Jiang et al., 2021). Also, Ali et al (2014) has reported that several studies revealed the lack of machine learning and remote sensing application for grassland AGB estimation. The machine learning model's performance is limited to the specific site (Ali et al., 2016). However, these machine learning outcomes provide a necessity for more studies to investigate other regions and select suitable models for grassland AGB estimation. This will help to identify machine learnings that can be used in similar regions for grassland AGB estimation. The present study uses RFR, GBR, and XGBR machine learning algorithms. The capabilities of these algorithms to deal with noisy, non-linear and high dimensional data enabled their selection for the study. Consequently, these machine learning algorithms were applied to data fusion of Sentinel-l and Sentinel-2 imagery to predict AGB abundance at the selected protected grazing area (PGA) in Hluvukani village, South Africa. The specific questions addressed here are; (1) which of the selected machine learning algorithms has better performance in AGB estimation? (2) Which variables are fundamental in predicting AGB? and (3) what is the spatial distribution of AGB in the selected PGA.

5. 2. Materials and Methods

5.2.1 Study Area

The study was conducted in Hluvukani village, which has protected grazing areas within savannah grasslands. Hluvukani village is situated under Bushbuckridge Local Municipality (BLM) within Ehlanzeni District, in the northeast part of Mpumalanga province in South Africa (Figure 10). Hluvukani rural area is known for smallholder animal farmers with cattle being the most dominant species, wildlife in the nearby Mnyaleti nature reserve, Andover Nature reserve and an animal clinic that serves the surrounding areas in Hluvukani (Conan et al., 2017; De Bruin, 2017). The area was selected because of its rural setting primarily based on smallholder animal farming for a living and partially selling for local markets (Mogakane, 2018). The rate of unemployment is high and dwellers make their primary income from livestock feeding on protected grassland. Hluvukani experience droughts (Integrated development plan, 2017), and have livestock/wildlife interface sharing borders that increase grazing pressure, overgrazing, overstocking that contribute to the degradation of grasslands (Twine et al., 2002; Choopa, 2015). However, there are no known studies that have focused on the mapping of the distribution of grassland AGB for forage availability in a semi-arid especially the South African protected areas. Hence, the need for the current study and aid to identify abundance and distribution of grasslands AGB for livestock grazing and reduce continuous grazing practice.

Hluvukani has sub-tropical climatic conditions with rainfall ranging from 450 to 600 mm per annum, summer average maximum temperature is 29°C and winter minimum average of 12°C (Kolo, 2016; BLM Spatial Development Framework, 2017; Pretorius, 2019). The area has an altitude that stretches to 2000 m above sea level as a consequence the area usually experiences high temperatures. Hluvukani rural area is characterized as a semi-arid region with dominant vegetation species such as savannah, mixed Lowveld, bushveld, sour Lowveld bushveld, Afromontane forest and montane grasslands (BLM Spatial Development Framework, 2017; Mashele et al., 2021). The insufficient rainfall limits above-ground biomass abundance. Hluvukani is part of the Mpumalanga region that has recorded the warmest temperature in 11 years (1995-2006), is prone to droughts and climate change models predict increasing temperatures that will affect livestock forage (Davis, 2010; Lötter et al., 2014).

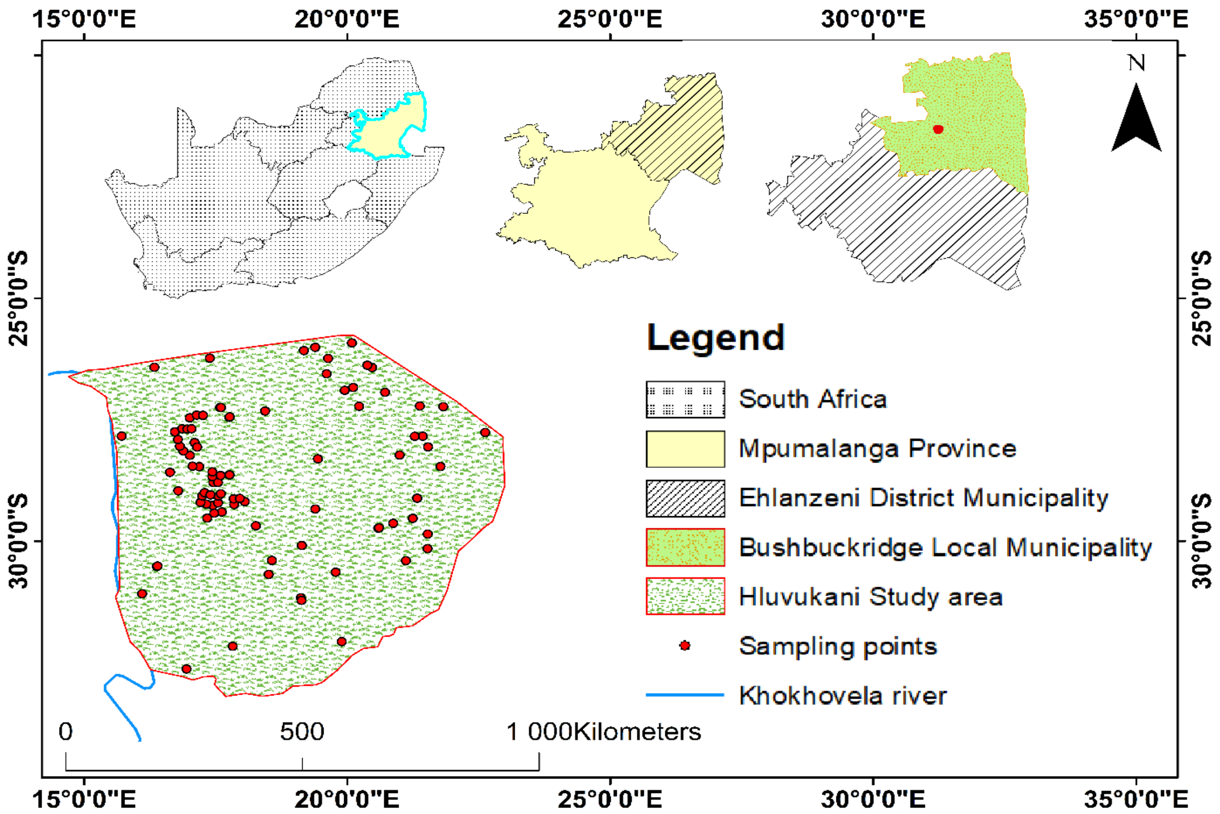


Figure 10. The location of the study area and sampling points for grassland in Hluvukani village protected areas

5.2.2 Data Acquisition and Pre-Processing

The grassland AGB in PGA was estimated with the data fusion of Sentinel-1 and Sentinel-2. The cloud-free satellite images were retrieved from Copernicus Open Access Hub (COAP) from 10 to 15 October 2021 during the late grass growing season. Pre-processing of the imagery was done to correct atmospheric effects and calculate the indices. Both Sentinel-1 and Sentinel-2 images were resampled to 10 m. Consequently, RF, GBR and XGBR machine learning regression algorithms were applied using 80% of the grassland AGB training data to models. Meanwhile, 20% of the data was utilized for model evaluation. Moreover, variable importance was derived from the three machine learning regression models for the spectral and VIs predictors. Lastly, the spatial distribution of grassland AGB was mapped with three ML models. Accordingly, figure 11 highlights adopted procedure in data acquisition, satellite –image processing and generation of AGB models using ML techniques.

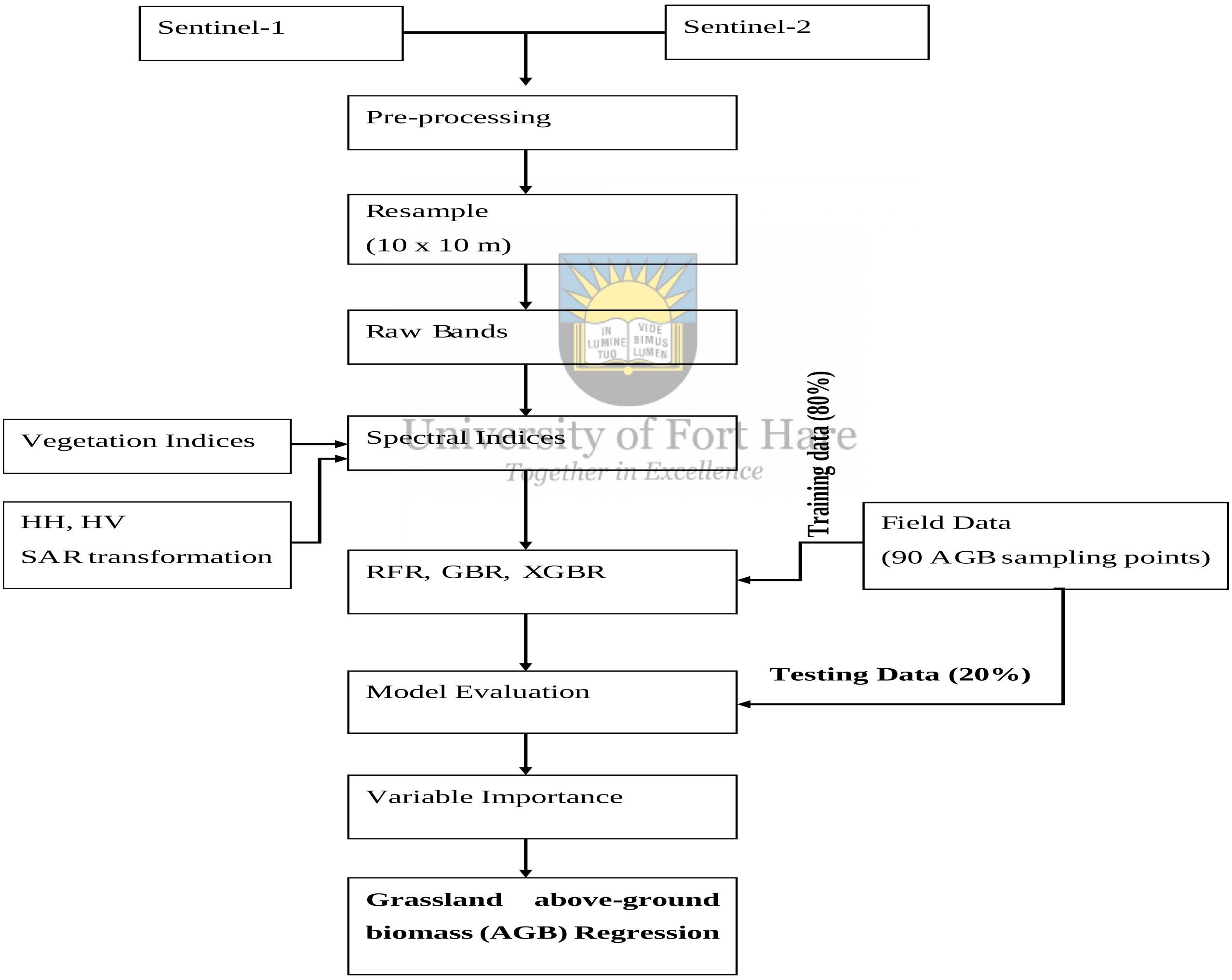


Figure 11: Flowchart of satellite –image processing and generation of AGB models on ML techniques

5.2.3. Field Data Collection

A total of 90 AGB samples were collocated from Hluvukani PGA (0.5m x 0.5m) during 1-7 October 2021 corresponding to a period of late grass growing season (Figure 12). A GPS was used to capture the position of each sample, while an electronic scale weighed the collected AGB samples. Moreover, measuring tape (30m) was used for grassland AGB height as one of the biophysical indicators that provide important information, such as knowing when to move livestock to another pasture or if grass height is sufficient for nesting cover (Wright et al. 2005; Yang et al., 2018; Yu et al., 2021b).

Figure 12: Grassland AGB measurements in the study area, biophysical parameters measurement (Photographs were taken by L. Nduku & Rodney during grazing season during fieldwork).

5.2.4 Sentinel-1 Data Acquisition and Pre-Processing

The Sentinel-1 mission has a constellation of two satellites consisting of Sentinel-1A and Sentinel-1B with a C-band and SAR instrument respectively. The Interferometric Wide (IW) mode was used to retrieve Sentinel-1 Level-1 ground range detected (GRD) from the COAP. The study used both VV and VH polarized backscatter values (in decibels) with a 10 m spatial resolution. The Sentinel application platform (SNAP) has been used for radar image pre-processing (Filipponi et al., 2019;

Mashaba-Munghemezulu et al., 2021a). For instance, Mashaba-Munghemezulu et al. (2021b) used five steps for Sentinel-1 imagery processing using SNAP. Hence, the study adopted the SNAP Version 8.0.0 (https://step.esa.int/main/download/snap-download/) approach for pre-processing. Initially, the orbit file was applied to update the orbit state vectors in the metadata files. The radiometric calibration was done to convert the intensity values into sigma nought values. Then, speckle filtering was applied to eliminate the granular noise produced by many scatters. Shuttle Radar Topography Mission (SRTM) 3-sec Digital Elevation Model (DEM) was used to correct geometric distortions caused by topography such as shadows.

Table 8: Sentinel-1 SAR and Sentinel-2 MSI data characteristics used in this study.

Spectral bands/ polarization	**Central wavelength(nm)**	**Bandwidth (nm)**	**Spatial resolution (m)**
	Sentinel-1		
Vertical transmit and vertical receive (VV)	55,465,763	-	10
Vertical transmit and horizontal receive (VH)	55,465,763	-	10
	Sentinel-2 MSI		
Band 2-Blue	490	65	10
Band 3-Green	560	35	10
Band 4-Red	665	30	10
Band 5–Vegetation Red Edge (RE1)	705	15	20
Band 6–Vegetation Red Edge (RE2)	740	15	20
Band 7–Vegetation Red Edge (RE3)	783	20	20
Band8–Near-Infrared (NIR)	842	115	10
Band 8a–Vegetation Red Edge (RE4)	865	20	20
Band 11–Short-wave Infrared (SWIR1)	1610	90	20
Band 12–Short-wave Infrared (SWIR2)	2190	180	20

*Note: Red Edge (RE), Near-infrared (NIR), Short Wave Infrared (SWIR)

5.2.5 Sentinel-2 Data Acquisition and Pre-Processing

The COAP was used to acquire Sentinel-2 Level-1C imagery (Table 9). Then Sen2Cor version 2.9 (http://step.esa.int/thirdparties/sen2cor/2.9.0/Sen2Cor-02.09.00-win64.zip) plugin in SNAP was applied for pre-processing the Sentinel-2 images, which converted them to the bottom of atmosphere reflectance from the top of atmosphere reflectance units.

Table 9: Sentinel-1 and Sentinel-2 imagery acquisition used in the current study

No.	Acquisition date/Time	Satellite platform	Pass	Product type	Polarisation	Sensor Mode
1	2021/10/10 11:23	S1A	Asc	GRD	VV VH	IW
			Sentinel-2			
2	2021/10/15 13:18	S2A	Asc	S2MSI2A	-	-

*Note Asc = Ascending

Table 10. The list of vegetation indices used in this study from Sentinel-2.

Vegetation index	Acronyms	Equation	References
Chlorophyll indexRedEdege	clRedEdge	$\frac{NIR}{RedEdge} - 1$	Li et al., 2021
Difference Vegetation Index	DVI	$NIR - Red$	Ghatkar et al., 2019
Enhanced Vegetation Index	EVI	$2.5 \times \frac{NIR - Red}{NIR + 6 \times Red - 7.5 \times \text{Blue}) + 1}$	Miura et al., 2000; Huete et al., 2002
Green Normalized Difference Vegetation Index	GNDVI	$\frac{NIR - Green}{NIR + Green}$	Gitelson et al., 1996; Sims et al., 2002.
Modified Simple Ratio RE	MsrRedEdge	$\frac{(NIR/\ RE1) - 1}{(NIR/\ RE1) + 1}$	Pinty et al., 1992; Chen, 1996
Normalized Difference Vegetation Index	NDVI	$\frac{NIR - Red}{NIR - \ Red}$	Tucker, 1979; Pham et al., 2018
Normalized Difference Vegetation Index RE1	NDVIRE1n	$\frac{RE4 - RE1}{RE4 + RE1}$	Fernández-Manso et al., 2016
Normalized Difference Vegetation Index RE2	NDVIRE2n	$\frac{RE4 - RE2}{RE4 + RE2}$	Fernández-Manso et al., 2016
Normalized Difference Vegetation Index RE3	NDVIRE3n	$\frac{RE4 - RE3}{RE4 + RE4}$	Fernández-Manso et al., 2016
Normalized Difference Vegetation Index RedEdge	NDVIRedEdge	$\frac{NIR - Red\text{Edge}}{NIR + \ Red\text{Edge}}$	Gitelson et al., 1997

Optimized soil adjusted vegetation index	OSAVI	$(1+Y)\,\frac{NIR-Red}{NIR-Red+016}$	Rondeaux et al., 1996
Ratio Vegetation Index	RVI	$\frac{NIR}{Red}$	López-Serrano et al., 2016
Soil-Adjusted Vegetation Index	SAVI	$(1+L)(\frac{NIR-Red}{NIR+2.4Red+L})$	Gumus et al., 2017
Transformed vegetation index	TVI	$\sqrt[2]{\frac{NIR-Red}{NIR-Red}}+0.5$	Tesfaye et al., 2021
Red Edge Wide Dynamic Range index	WDRIREdedge	$\frac{0.1\times NIR-Red}{0.1\times NIR+Red}$	Gitelson, 2004; Dang et al., 2019

*Note: Y= 0.16, L= 0.5

The use of VIs for grassland biomass estimation based on regression models has very high accuracies (Bella et al., 2004; Xu et al., 2008). These VIs are frequently used as predictive variable importance to qualify and quantify the grassland biomass (Guerini Filho et al., 2020). Studies showed excellent performance of red edge and infrared regions for analyses of natural grassland biomass estimation accuracy (Guerini Filho et al., 2020; Li et al., 2021). Ultimately the current study explores the selected VIs for identifying the most influential variables in the study area, instead of choosing a few indices.

5.3. Machine Learning Regression Models

The application of machine learning regression models has demonstrated possibilities to achieve better accuracies for AGB prediction. Recently, studies have compared the performances of the machine learning models using single (Pandit et al., 2018; Zeng et al., 2021; De Rosa et al., 2021) and multiple earth observation datasets (Wang et al, 2019a; Pham et al., 2020; Mashaba-Munghemezulu et al., 2021a). The RFR and XGBR models have shown robust and superior performance among other machine learning models for AGB estimation (Pandit et al., 2018; Xu et al., 2020; Zeng et al., 2021). Consequently, RFR, XGBR and GBR were selected for the current study. GBR model has been used in different fields for AGB estimation (Pham et al., 2020; Li et al., 2021), hence it was included.

5.3.1 Random Forest Regression

RFR is described as a bagging ensemble model used to solve classification and regression problems (Breiman, 2001; Pham et al., 2020). The bootstrapping technique enables RFR to estimate a continuous response variable during classification and regression trees, with provided data fit on decision tree models. Consequently, in-bag samples are referred to all different trees trained with bootstrap samples from training data. Meanwhile, samples excluded from bootstrap are known as out-of-bag samples and are used during model evaluation and variable importance (Pal, 2005). Then, the final model is generated by averaging individual tree outputs (Breiman, 2001; Pal, 2005). RFR requires two necessary parameters to be determined for split towards the training model which is the number of trees and the number of features. These parameters were determined through the Gridsearch method in python following similar studies (Lerman, 1980). The superiority and high-performance of RFR enable the model to process non-linear data without overestimation in the training phase. The procedure to extract variable importance of RFR was done using the built-in Python variable importance measure which can be found on statistics for machine learning (Dangeti et al., 2017).

5.3.2 Gradient Boosting Regression

Friedman (2001) developed a gradient-boosting regression model to solve classification and regression problems. The gradient boosting can achieve over random guessing through enhancement of performance on weak learners (Zemel et al., 2001). However, residuals of each tree are determined with each iteration to enhance the loss function determined by the steepest gradient (Mashaba-Munghemezulu et al., 2021c). Finally, the results are retrieved through a combination of all regression trees (Friedman, 2001; Friedman, 2002). The capability of GBR to be robust to outliers aids in handling unstable and mixed data types (Wei et al., 2019). There is are few studies, which have used GBR in grassland AGB estimation hence it was selected for the present study to evaluate its performance among other robust machine learning regression models. The parameters required in GBR include the number of features for the best split, number of trees, minimum number of samples at a leaf node, maximum depth and learning rate (Pham et al., 2020; Mashaba-Munghemezulu et al., 2021c). The Gridsearch method was used for the optimization of parameters. Finally, the procedure to extract the variable importance of GBR was done using the built-in Python variable importance measure (Dangeti et al., 2017).

5.3.3 Extreme Gradient Boost Regression

The Extreme Gradient Boosting machine learning algorithm applies to both classification and regression problems. Chen and Guestrin (2016) recently proposed this ensemble XGB model that uses additive training strategies. Additive learning is divided into two phases. The learning phase is fitted to the entire dataset and the other phase is adjusted to the residuals for improving the performance of weakly supervised learning. The procedure to achieve stopping criteria completely requires repetition of the fitting process multiple times (Chen & Guestrin, 2016). XGB model achieves optimized performance and resolves the overfitting problem (Georganos et al., 2018). However, the XGB algorithm still needs a rigorous number of regularization parameters that were determined using a Grid search. The procedure to extract variable importance of XGBR was done using the built-in Python variable importance measure (Dangeti et al., 2017).

5.4 Experiment

The present study investigated feature variables for modelling AGB estimation in a grassland area. The 90 samples collected were split into 80% training and 20% testing dataset for the input data on training models. The experiment was set with spectral bands + VIs based on three models RFR, GBR and XGBR.

5.5 Model Evaluation

A selection of statistics to evaluate the predictive performances of RF, GBR and XGBR ML models were done. The MAE, RMSE and R^2 were computed for all these models using the equations below (1) − (3):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} | P_i - O_i | \tag{1}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{2}$$

$$R^2 = \frac{\sum_{i=1}^{n}(P_i - \bar{O}_i)^2}{\sum_{i=1}^{n}(P_i - \bar{O}_i)^2} \tag{3}$$

Where n represent sample points, P_i and O_i are representing mean values of the predicted and measured grassland AGBs respectively. However, i represent the standard deviation. These statistics are commonly used in studies for AGB estimation (Vafaei et al., 2018; Wang et al., 2019b; Forkuor et al., 2020). The optimal performing ML model attains high R^2, low RMSE and MAE (Navarro et al., 2019; Wang et al., 2020; Pham et al., 2020).

5.6 Results

5.6.1 Characteristics of Grassland AGB in PGA

The characteristics of PGA are represented in (Table 11) below with the 90 sampling points. The grassland height varied from 1.4 to 67.7 cm. However, AGB ranged from 0.08 to 2.74 (Mgha^{-1}), with a mean of 0.94 (Mg ha^{-1}).

Table 11: Characteristics of the grassland in PGA

Attribute	Minimum	Maximum	Mean	Standard Deviation (SD)
H (cm)	1.4	67.7	17.06	159.69
AGB (Mg ha^{-1})	0.08	2.74	0.94	0.56

5.6.2 ML Modeling Results, Performances and Comparison

The three machine learning performances were derived from Sentinel-1 and Sentinel-2 data fusion for savannah grassland AGB estimation in the study area. Table 12 shows the performance of all RFR, GBR and XGBR observed in the study. The RFR model achieved the highest performances in (Table 12), with an R^2 of 34.7%, RMSE of 9.47 Mg ha^{-1} and an MAE of 7.68 Mg ha^{-1} in the testing dataset. Furthermore, RFR revealed a good fit among other models with more estimates using field-based measurements. The GBR ranked second and XGBR ranked the last in terms of performance among the models. However, all the tested machine learning algorithms were not statistically significant for the savannah grassland AGB at the study site compared to similar studies on AGB estimation (Singh et al., 2018; Li et al., 2021; Yu et al., 2021b).

Table: 12 Comparison of machine learning techniques on grassland AGB estimation.

No	**Machine Learning Model**	**R^2** (%)	**RMSE** (Mg ha^{-1}).	**MAE** (Mg ha^{-1}).
1	RFR	34.7	9.47	7.68
2	GBR	27.7	9.97	8.03
3	XGBR	17.3	10.66	8.83

The scatter plots illustrated in Figure 13 (a-c) below were constructed based on the performance of RFR, GBR and XGBR models to relate the observed and predicted AGB in the study area. The diagonal line with most data points around it shows a better agreement between the measured and predicted values such as the RFR and GBR model. The three machine learning models had different distribution data points on the scatter plots.

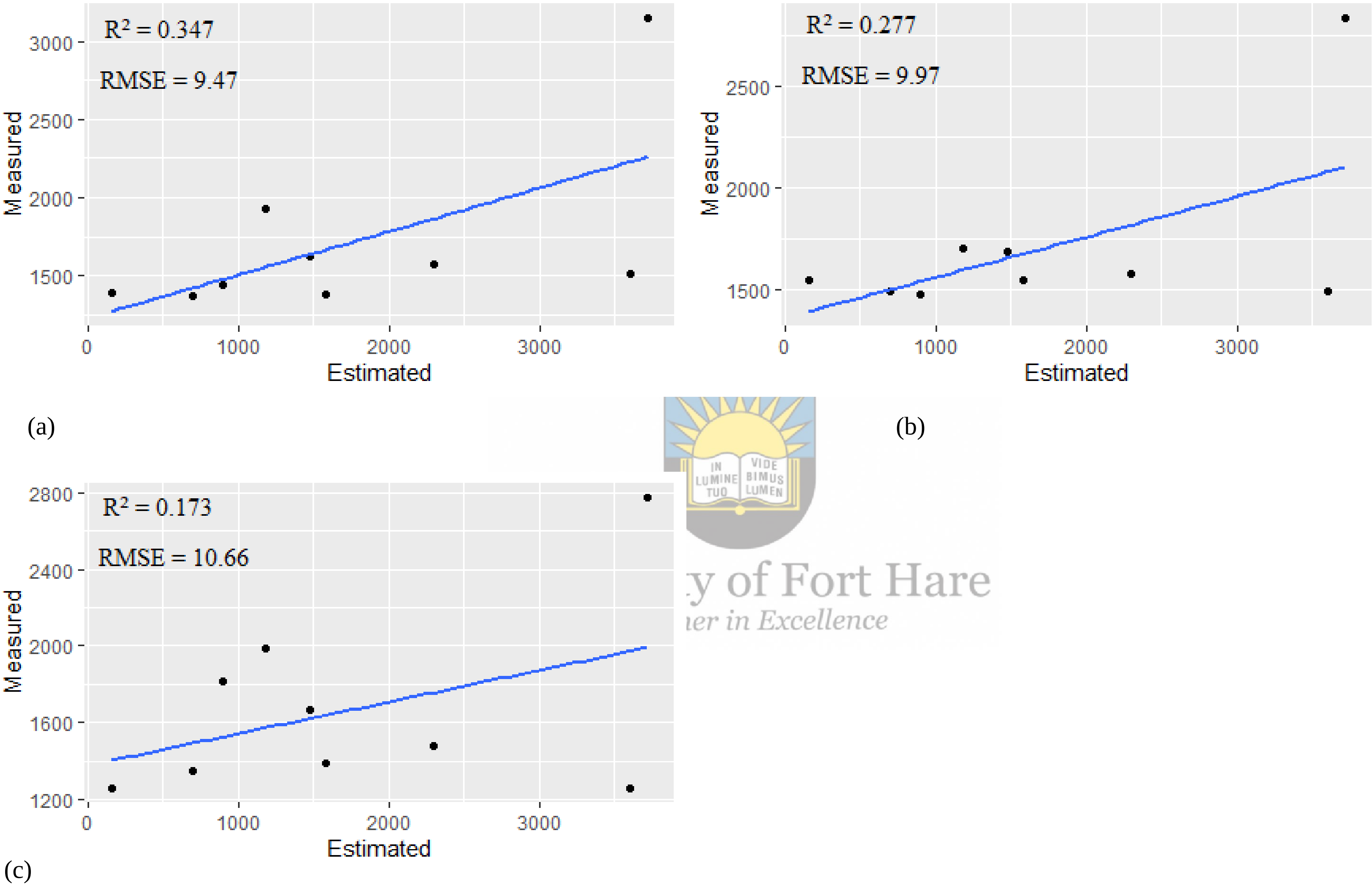
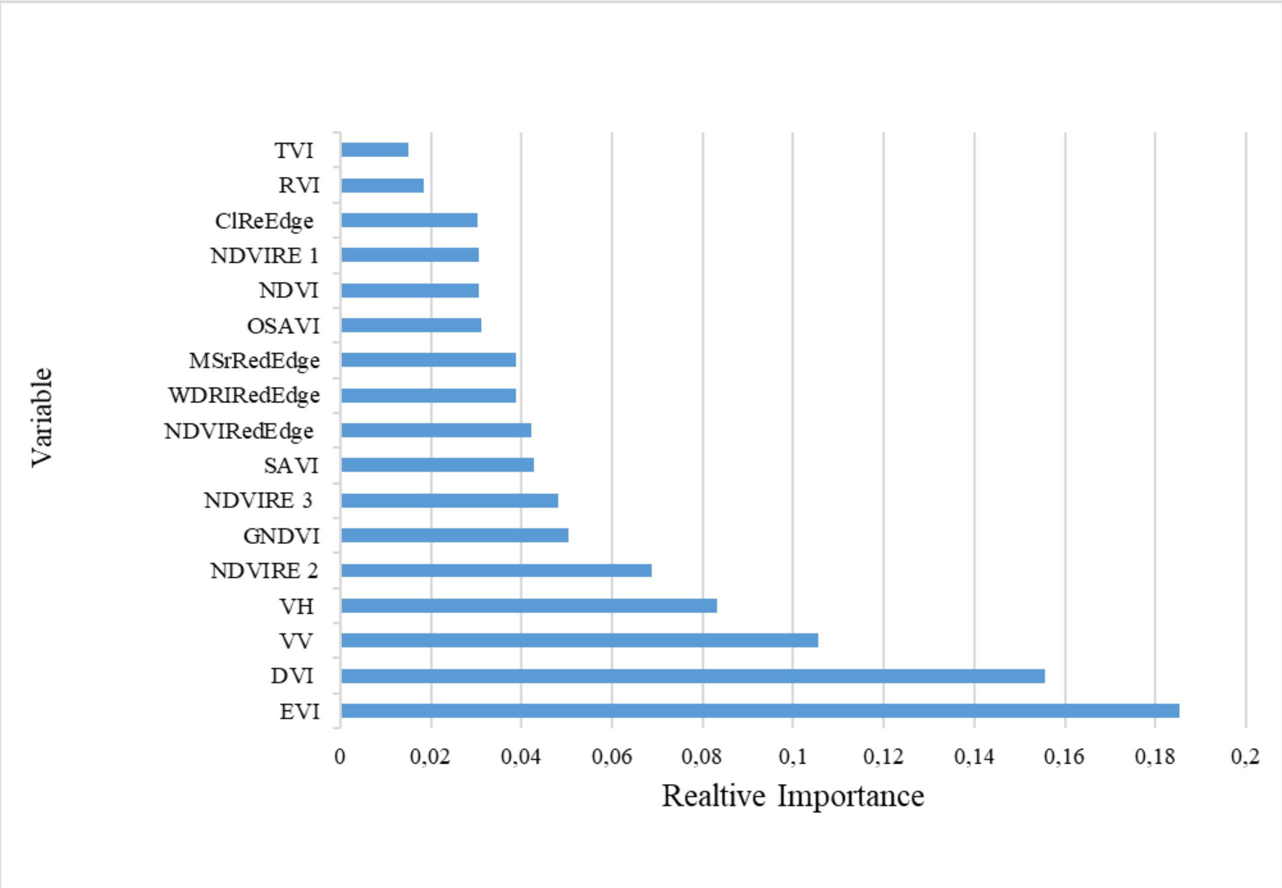


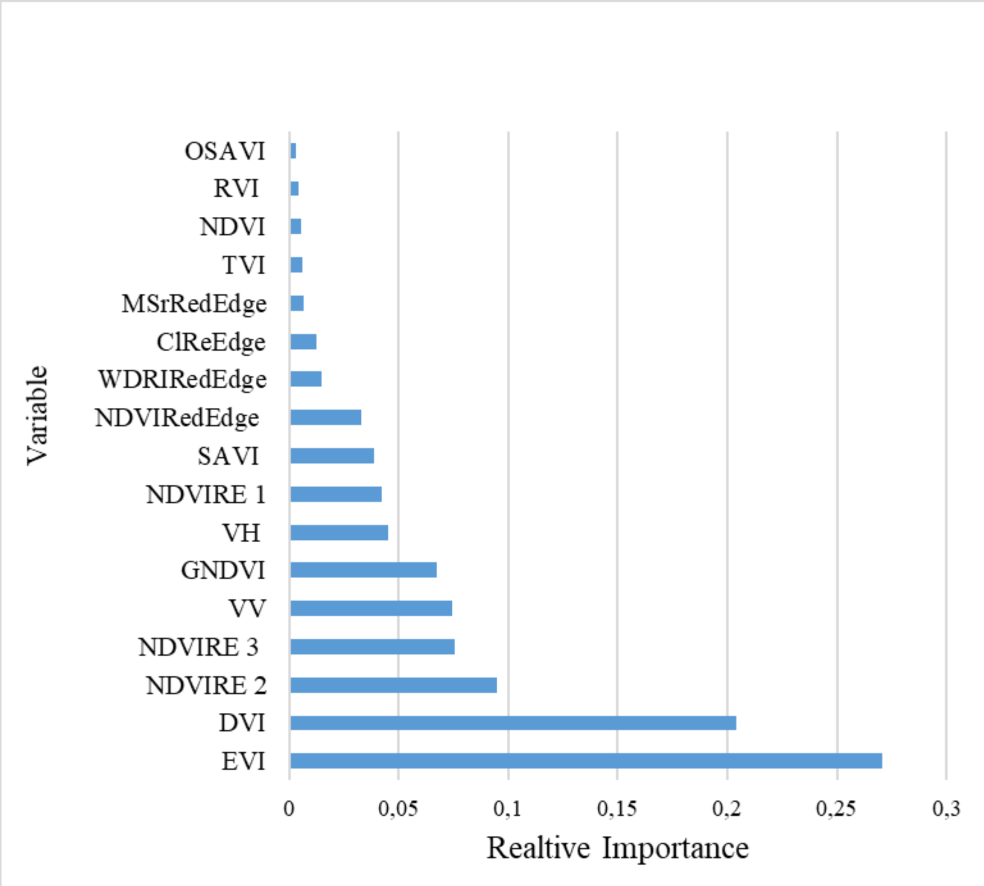
Figure 13. Scatter plots of the estimated (X-axis) versus the measured (Y-axis) grassland AGB in the three ML models, integrating the data of S-1, S-2 and VIs in the experiment. (a) RF, (b) GBR, (c) XGB

5.6.3 Variable Importance

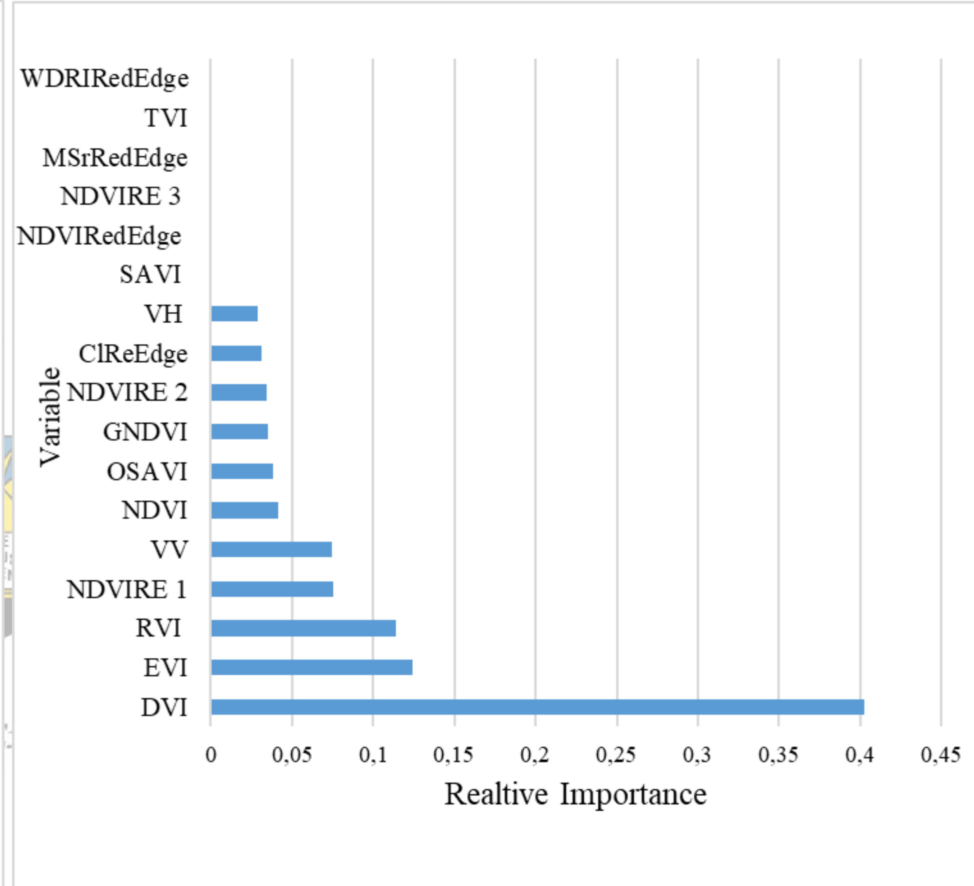
A total of 17 predictor variables including VV, VH polarizations and VIs from Sentinel-1 and Sentinel-2 were determined for the RF, GBR and XGBR respectively. Figure 14 (a-c) below shows the varied predictor performance for all three models. The RFR model had a more even distribution of predictor importance amongst the three models. There is a contrast in the distribution of predictor importance for XGBR in comparison with other models. However, EVI and DVI VIs have the highest performance among other predictor importance for all the models.



(a)



(b)



(c)

Figure 14: Variables comparison for predicting AGB with (a) RFR, (b) GBR, and (c) XGBR algorithms.

5.6.4. Mapping and Analysis of the AGB for grasslands

The spatial distribution of grassland AGB estimation was mapped in Figure 15 (a-c) below for the three machine learning models. The green patches show where there is a low concentration of grassland biomass. The distribution of AGB estimation varied across the three models. The distribution of AGB estimation is low in the central and eastern parts of the Hluvukani PGA. Meanwhile, higher AGB estimation was observed towards the edges of the PGA. The XGBR model achieved the lowest AGB estimation distribution in comparison to RF and GBR.

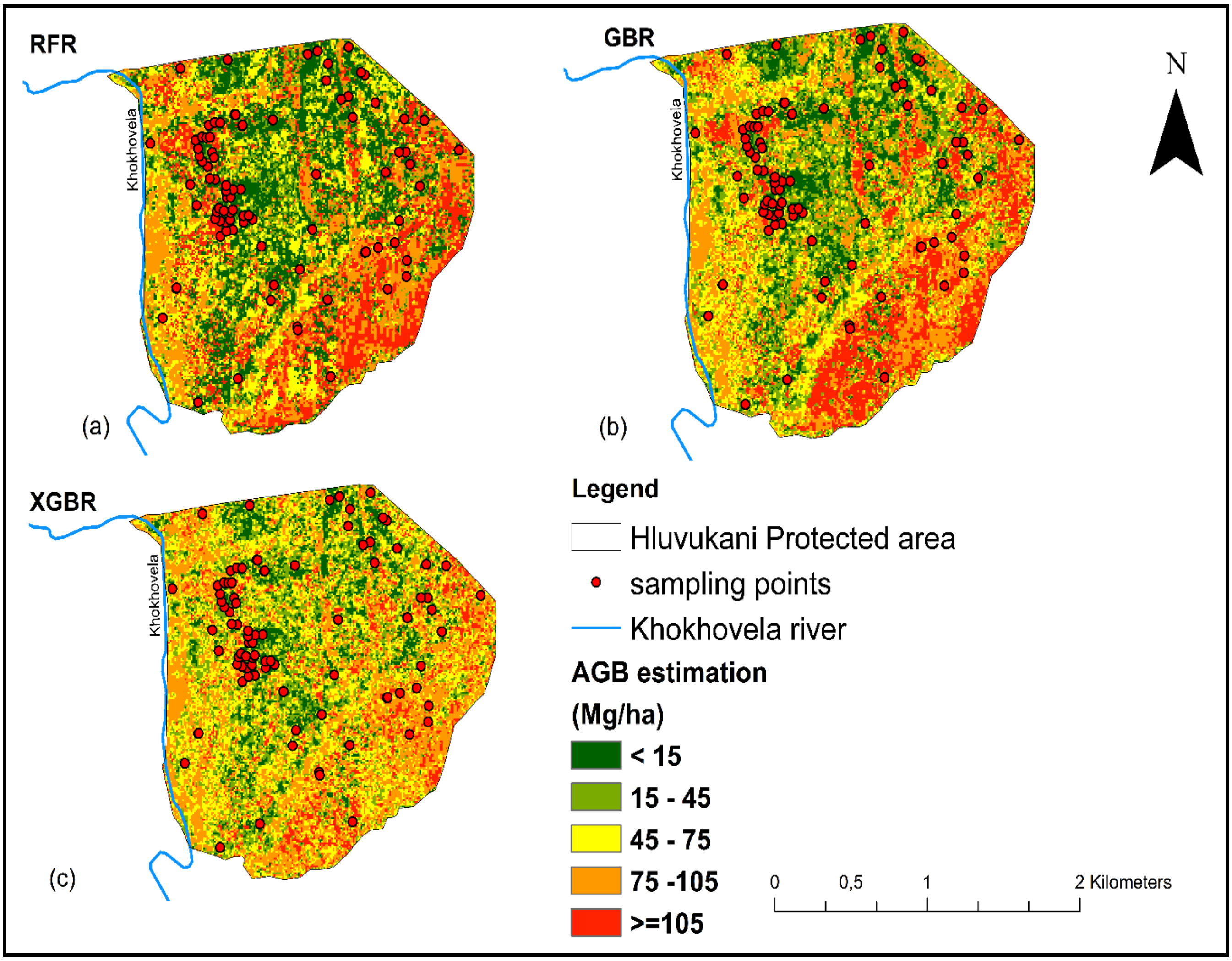


Figure 15: Estimated spatial distribution of savannah grassland AGB in Hluvukani Protected area with (a) RFR, (b) GBR, and (c) XGBR

5.6.5. Discussion

This study assessed different machine learning regression models using integrated Sentinel-1 and Sentinel-2 data and derived VIs for AGB estimation in the protected grassland of Hluvukani village. The designed experiment was able to show the best performing machine learning algorithm among RFR, GBR and XGBR. The collected grassland AGB samples were used to generate statistics to assess the predictive performances of machine learning regression models. All three machine learning algorithms revealed the varied performance of variable importance selected for the present study. The study revealed similar findings for the applicability of Sentinel-1 and Sentinel-2 data fusion on AGB estimation studies in grazing grassland (Wang et al., 2019a; Nuthammachot et al., 2020). RFR, GBR and XGBR machine learning model's performance was not statistically significant for the savannah grassland AGB estimation. The number of sampling has affected the performance of these models. The RFR machine learning had better performance and influence of variable importance for predicting AGB. The distribution of AGB estimation abundance was observed towards the edges of Hluvukani protected grazing areas.

Findings show that RFR yielded the highest performance with an R^2, RMSE and MAE of 34.7%, 9.47 Mg ha^{-1} and 7.68 Mg ha^{-1}, respectively for AGB prediction given in Table 12. The worst performing machine regression model was XGBR, with an R^2, RMSE and MAE of 17.3%, 10.66 Mg ha^{-1} and 8.83 Mg ha^{-1} respectively. Similar studies reported the superior performance of the RF model in grassland AGB estimation amongst other models (Wang et al., 2017; Xia et al, 2018b; Zeng et al., 2019; Xu et al., 2020). However, the weak performance of XGBR contradicts similar studies that assessed the prediction of AGB with other machine learning algorithms (Li et al., 2019; Wieland et al., 2021). Consequently, these studies revealed the high performance of XGBR compared to other machine learning models (Li et al., 2021; Yu et al., 2021a). Which revealed that climate change has effects on the grassland AGB distribution (Zhang et al., 2018; Change, 2019; Zarei et al., 2021). Thus, the varied performance of machine learning algorithms with different regions. The multicollinearity between predictors revealed the effective application of RFR, GBR and XGBR machine learning models and their suitability to the dataset.

The study assessed the most significant predictors among variable importance for grassland AGB prediction and distribution at Hluvukani protected grazing areas. The results showed that Sentinel-1 and Sentinel-2 data fusion have an advantage in predicting grassland AGB, similar findings with previous studies (Ghosh et al., 2018; Nuthammachot et al., 2020). RFR machine learning model was observed with the significant performance of variables, particularly EVI and DVI in all machine algorithms. However, not all variables (WDRIRedEdge, TVI, MSrRedEdge, NDVIRE 3, NDVIRedEdge and SAVI) showed relative importance for the XGBR model observed in the distribution pattern. The RFR has the advantage of variable importance (Li et al., 2021). These findings contrast similar studies that found variable importance was more significant in XGBR than RFR (Li et al., 2019; Li et al., 2021). EVI is sensitive to high vegetation areas (Liu & Huete, 1995). DVI is sensitive to the amount of vegetation and distinguishes between soil and vegetation (Richardson & Wiegand, 1977; Tucker, 1979; Gupta & Pandey, 2018). Which explains the robust performance of all three machine learning algorithms. Both RFR and GBR showed high variable importance of EVI and DVI respectively. A similar, study revealed a higher and more significant performance of EVI in the RFR model (Jacon et al., 2021). Pandit et al (2018) contrast these findings on EVI, showing SAVI with more significance over EVI in the RFR model. However, the DVI did not rank highly for AGB prediction (Dang et al., 2019). Interestingly, the dominant performance of EVI and DVI in the current study contrast with previous studies that revealed red-edge indices have the potential of improving the detection of vegetation (Kim et al., 2014; Forkuor et al., 2018). The variable importance influence varies in machine learning algorithms and regions (Dube et al., 2018; Li et al., 2020). For instance, mountains and hilly landscapes have a wide range of altitude changes, which affect temperature, precipitation and the variety of AGB forms (Li et al., 2020). Random sampling

The resulting spatial distribution of grassland AGB prediction was mapped from three machine algorithms. The findings show the capability of machine learning algorithms for AGB prediction in protected grazing areas. The AGB maps generated in this study can be used to identify grazing patches for livestock and vulnerable degrading. Livestock farmers, extension services can also benefit from the AGB prediction map to revise their policies and grassland management strategies. Moreover, control the maximum number of cattle, sheep and goats per protected grazing site which will aid in reducing overgrazing and associated impacts. The National development plan (NDP) 2030, Department of Agriculture, Land Reform and Rural Development (DALRRD), and other government initiatives programs (SA agriculture, 2021), aimed to provide superior breeding animals to targeted smallholder and substance farmers. The smallholder and substance farmers can benefit from AGB prediction maps for decision-making in getting many livestock supplies based on the grazing land with abundant biomass. The present study provides AGB estimation maps that benefit the Department of Agriculture, Rural Development and Land Administration (DARDLA) Clare livestock project within Hluvukani protected grasslands. Areas with sufficient grassland biomass and the current state of protected grazing areas used for livestock feeding grounds can be identified. The RFR and XGBR model performed poorly, similar results were reported to other regions for both models (Jachowski et al., 2013; Li et al., 2020). However, other studies found the RFR and GBR robust in AGB prediction (Wang et al., 2017; Pandit et al., 2018; Li et al., 2021). The robust estimation of AGB in grasslands will show areas that require an intervention to halt degradation, increase livestock production and improve food security (Kwon et al., 2016; Wang et al., 2019a). This application support achieving SDGs number 15 that protect, restore and promote sustainable use of terrestrial ecosystems. Also, contribute to SDGs number 13 which take urgent action to combat climate change and its impacts.

The limitations of the current study include the small number of samples collected as a result of lockdown restriction that presented limited time for sampling, high fieldwork cost. The collected number of samples usually influence the robust performance and accuracy of the machine learning model (Morais et al., 2021). Studies focusing on monitoring the protected grasslands are still lacking in the literature. The current study presents the utilization integrated Sentinel dataset with machine learning for grassland AGB estimation which is similar to previous studies (Naidoo et al., 2019; Nuthammachot et al., 2020; Reinermann et al., 2020). These studies recommend Sentinel as the highest resolution dataset that is free for research purposes and can be used to monitor grasslands. Degradation is accelerating in the grassland ecosystem and reducing the main source of feed for livestock that support livelihoods (Kwon et al., 2016; Mutea et al., 2019; Mugumaarhahama et al., 2021). Therefore, technical skills and application of remote sensing such as grassland AGB estimation are crucial for decision making in livestock farming (Singh et al., 2004; Twumasi et al., 2021). These skills aid to guide and advising small livestock farmers that operates under limited resources to trade their livestock when they cannot afford to buy extra feed during grassland growing season (Bahta et al., 2021).

5.6.6 Conclusion

This study aimed at assessing data fusion of Sentinel-1 and Sentinel-2 datasets, VIs, and machine learning algorithms to predict AGB abundance distribution at the protected grassland of Hluvukani village. The variable importance was used to identify variables that are important for the prediction of AGB in grasslands. Statistical comparison of the three models (RFR, GBR and XGBR) show that machine learning models achieved insignificant predictive capacity in AGB estimation with R^2 ranging (17.3–.3.47 %) in protected grasslands. The variable importance shows that VIs are fundamental for AGB estimation, particularly EVI and DVI in all three machine learning models. The spatial distribution maps of AGB prediction in this study can be used to inform livestock farmers on areas with abundant grassland biomass for grazing. Different stakeholders such as decision-makers, grassland management, government livestock projects and agricultural extension officers can benefit from using such maps. Consequently, these maps are useful to develop grazing management practices based on the area under investigation which will reduce overgrazing, degradation, improve local livestock production and food security for rural livelihoods. Future studies should maximize the number of samples to calibrate the machine learning models which improves accuracy estimation of AGB. However, more suggestions are detailed in the next chapter for new research opportunities based on the current study limitations.

Chapter 6

Summary, Conclusion and Recommendations

Highlights

This chapter provides a synopsis of the current study and shows the importance of Earth observation-based techniques in monitoring the grassland ecosystem. Findings have revealed that EOS have a potential data source that offers an optimum dataset for grassland biomass estimation and modelling. Hence, spatial distribution maps of grassland biomass estimation can guide the implementation of grassland management policies. The key scientific findings emanate from Sentinel data, VIs, and machine learning integration for grassland AGB estimation, which provide insights for future studies to assess other variables and models in change detection. The study findings and limitations have influenced recommendations and proposed future research agendas provided in this chapter.

6.1 Introduction

This research was complimentary to a bigger research programme aimed at investigating the utility of the recent EOS to develop a semi-automated system that can automate data processing and map the grassland biomass distribution. This study also showed the importance of grassland biomass to the feeding of livestock in developing countries. However, these grasslands are vulnerable to degradation because of multiple effects that include climate change, overgrazing, shrub encroachment and nitrogen eutrophication. Thus, monitoring the grassland ecosystem is necessary to minimize multiple impacts accelerating degradation and restore the ecology status of grasslands. Literature has revealed that conventional techniques are limited to a small spatial extent and labour intensive for monitoring grassland ecosystems. However, EOS presents unlimited spatial extent, cost-effective and timely results for monitoring grasslands. Therefore, the current study was influenced by unlimited spatial extent for using Earth observation based- approach to address the research questions and objectives. This study also used bibliometric quantitative methods to retrieve the Earth observation and pasture modelling studies, which offered insights about trends in this field of research.

6.2 Conclusion

The current study has noted grassland degradation as a global concern that needs to be monitored and reduced through optimum techniques. Hluvukani protected grazing areas is experiencing grassland degradation and were selected as a case study for the current study. This area is characterized by many ranchers that feed their livestock on savannah grasslands in the region.

However, overstocking has resulted in overgrazing and is one of the major drivers for grassland degradation. The literature shows that climate change has caused increasing temperatures over North-Eastern part of South Africa (Davis, 2010; Lotter et al., 2014), where the Hluvukani region is situated in the past years. Shrub encroachment has invaded the grazing areas of the Hluvukani region and together with increased temperatures have contributed to grassland degradation. These degraded grasslands have been linked to the reported deaths of livestock in the Hluvukani region caused by a lack of grazing fields that can supply the present livestock.

The conventional methods were not suitable for this study based on their limitations. Therefore, this study investigated the utility of the recent EO multi-sensor satellite to monitor and model grassland (pastures) and contribute to the development of a semi-automated system to automate data processing, and mapping grassland biomass to benefit local communities in Hluvukani village, at Bushbuckridge Local Municipality. To guide this research, specific research questions for the study were categorized into the following: (i) How to map the trends and advances in data and models used in the monitoring of grassland (pastures) with earth observation systems, and (ii) How to assess above-ground biomass estimation in semi-arid savannah grassland of Hluvukani protected grazing areas integrating Sentinel -1 and Sentinel-2 Data with Machine-Learning? The research questions, key findings and limitations for each objective are summarized below:

Objective one. To map the trends and advances in data and models used in the monitoring of grassland (pastures) with Earth observation systems.

The research questions addressed in this objective, appraised published articles by assessing the annual scientific production, author's global citation, decadal trending topics, keywords co-occurrence network, journal analysis, institutions, and countries' collaboration on EOS and PM studies. This objective used a comprehensive bibliometrics statistical method that analyses and provide a clear understanding of published research articles in scientific studies within a specified field of study (Yu et al., 2018; Jiang et al., 2019; Gao et al., 2020; Mishra et al., 2021). The study assessed global scientific research history on EOS and PM studies from 1979 to 2019 for grassland monitoring on the Scopus database.

This objective has contributed to the new knowledge in literature through showing increasing research trends with 19.76% in this field from 1979 to 2019. Findings revealed that EOS and remote sensing are dominant themes for grassland monitoring in this field. The study also, showed that Earth observation is fundamental in understanding PM dynamics to design management strategies for ensuring food security. Moreover, results revealed the lack of machine learning to monitor grassland biomass estimation, which shows research hotspot for future studies.

Objective two. To investigate the utility to assess above-ground biomass estimation in semi-arid savannah grassland of Hluvukani protected grazing areas through integrating Sentinel -1 and Sentinel-2 Data with Machine-Learning.

The research questions addressed in this objective were: (i) which of the selected machine learning algorithms has better performance in AGB estimation? (ii) Which variables are fundamental in predicting AGB? and (iii) what is the spatial distribution of AGB in the selected PGA? The prospect of using integrated Sentinel data and VIS for above-ground biomass estimation in semi-arid savannah grassland of Hluvukani protected grazing areas was investigated using machine learning regression models. Findings showed statistical comparison of three machine learning used for grassland AGB estimation and RFR (R^2 = 34.7%) outperformed other two GBR (R^2 = 27.7%) and XGBR (R^2 = 17.3%) models. These results were similar to other studies in the literature that show a robust estimation of grassland AGB for RFR (Wang et al., 2019a; Nuthammachot et al., 2020). However, EVI and DVI VIs showed dominance contribution and sensitivity to grassland AGB estimation during the study period. Sentinel-1, Sentinel-2 data, machine learning and spectral indices integration showed utility for mapping spatial distribution of grassland AGB estimation, which is a key focus on future studies to validate these findings. The mapped spatial distribution of grassland AGB estimation contributed to the positive feedback of helpful resilience in the adopted ASST framework. These grassland AGB estimation Maps can be useful to identify the areas that require interventions to restore grassland degradation. The important findings indicate the capabilities of machine learning and EOS to estimate grassland biomass in any region. The study findings are crucial to livestock farmers that use native grasslands as the primary feed to livestock and which aid rehabilitate grassland ecosystem in severely degraded grasslands.

6.3 Summary of key Contributions

The current study showed how the ASST conceptual framework can be used as a lens to interrogate grassland ecosystem change thus contributing to the protection and restoration of grassland ecosystems resilience. The study also reveals that grassland degradation is a result of multiple threats, and therefore, the grassland ecosystem requires robust methods to monitor the spatio-temporal changes and the current status of the available AGB. The study results further affirm the relevance of an Earth observation based approach to address the shortfalls of conventional methods in AGB estimation and provide the information needed for robust model building.

On the methodological front, the study demonstrates the relevance of the adoption of a hybrid methodology estimating the AGB. To this end, the study highlights the benefits of assessing above-ground biomass estimation in semi-arid savannah grassland integrating Sentinel -1 and Sentinel-2

Data with machine learning. Furthermore, the study reveals the need to embrace Earth observation technology in pasture monitoring, to offer just-in-time information needed in pasture modelling dynamics to ensure food security, especially in the semi-arid environment due to the compromised climate. In addition, the study revealed the positive capability to integrate the recent EO multi-sensor satellite and machine learning to monitor and model grasslands underpinned by the ASST framework.

The study further reveals the multicollinearity of the RFR machine learning model to predict grassland AGB that can be explored in another grassland ecosystem for more validation. Interestingly, EVI and DVI showed notable consistency contribution in all three machine learning models for grassland AGB estimation among other selected VIs for the current study. It is also important to note that this study contributes to reducing the existing bias in the literature (i.e., few studies focusing on the African continent, limited adoption of machine learning, and limited focus on semi-arid savannah grassland ecosystem especially in PAs with communities) among others. In general, these new contributions are important to guide future studies in this field of study and pastoralism to ensure grassland ecosystems' sustainability. Finally, these findings contribute to the required understanding towards the goal of developing a semi-automated system that can automate data processing, and map grassland biomass to benefit local communities and large-scale grassland ecosystems.

6.4 Recommendations

Due to the current study having explored a single database and bibliometric quantitative methods for examining research trends and advances in data and models used in the monitoring of grassland with Earth observation systems. It is, therefore, recommended that future studies should explore multiple databases and other analytical techniques such as meta-analysis or systematic review among others. In addition, the results revealed the lack of machine learning application for monitoring grassland estimation and future studies should shift and advance to adopt these optimum quantitative techniques. The bibliometric quantitative methods served as an eye-opener for future bibliometric studies to map research trends in the field of study. Also, the findings showed the potential of using integrated Sentinel data with machine learning and VIs for monitoring grasslands and AGB. To this end, the government should aid and equip smallholder livestock keepers in rural areas with technical skills to maintain the grazing site and minimise the vulnerability of overgrazing using grasslands AGB maps distribution. This study suggests upcoming research opportunities to include the above VIs with other machine learning to validate their robust performance and contribution during grassland biomass estimation in other regions.

Those findings will aid to know important VIs to include for developing a semi-automated system for mapping grassland biomass. Grasslands AGB maps will guide policy formulation and decision-making on grassland management plans.

6.5 Limitations of the Study

The limitations of the study include the exploration of one database for comprehensive trend analysis in EOS and pasture modelling. Secondly, the study was limited to a small number of samples collected and high cost to arrange the fieldwork. Furthermore, the COVID-19 pandemic with lockdown restrictions and regulations made it difficult to conduct fieldwork with limited time provided for accessing protected grazing areas. This contributed to the small sample size that may have effects on the statistical robustness of machine learning model results. It is also important to acknowledge that the poor grazing management practices of smallholder livestock farmers, overgrazing and the increased temperatures also affected the spectral signatures of grassland AGB. This also decreases the precision at which they can be detected by the satellite with resultant effects on the overall results. However, the analysis that was done for the current study is sufficient for AGB estimation. More so, the study results contribute to more objective evidence in support of the necessitate for representative studies to cover unrepresented regions in the literature. In addition, the current study followed the same trend like most bibliometric studies but suggests that multiple research databases should be incorporated in assessing niche area future trends. Also, of importance, the study offers crucial information needed in developing robust AGB estimation models and contributes to closing the identified gaps in the literature. In general, the study findings are very important in sustainable livelihood sustenance, grassland ecosystem restoration and designing of the required policies to promote grassland sustainability and ensure food security. All these are critical in contributing to the attaining of SDGs at different fronts, especially at the community, local and regional levels among others.

6.6 Future Research Agenda

The projected climate change and overgrazing continue to threaten grassland distribution in arid and semi-arid regions which were revealed through AGB estimation in the current study. It is crucial to monitor the ecological status of grasslands AGB, particularly in grazing lands for achieving sustainable grassland management policies. The earth observations systems have shown capabilities of modelling grassland AGB estimation during the study. Therefore, future studies can rely on using EOS with other machine learning models and time-series data for monitoring the grassland ecosystem. This will contribute to extensive livestock production and pastoralism. Other studies can compare the application of Sentinel-1 and Sentinel-2 separately with machine learning models for grassland AGB estimation to identify the optimum dataset. However, the spectral resolution of unmanned aerial vehicles (UAV) can increase the precision and performance of machine learning models in grassland AGB estimation.

The spectral resolution, climate variability and topography vary, which influence the detection of grassland AGB estimation. It is crucial to monitor the ecologically valuable grasslands for the benefit of better livestock production in different regions. The lack of resources and costly laboratory nitrogen analyses for the current study suggests future studies can focus on mapping grassland biomass or soil nitrogen content. This will aid to determine the amount of needed nitrogen fertilizer to improve forage quality and growth in the study area. Future research should increase the number of grassland biomass samples to improve the machine learning models' precision.

6.6 Summary

Grassland AGB is known for its contribution to livestock production, yet degradation is accelerating due to multiple factors. The lack of grassland management strategies, resources and conventional methods in rural livestock farmers affects the sustainable grassland management practice. The current study contributes to the adopted ASST framework with grassland AGB estimation application that helps understand changes within grassland ecosystems that require interventions. However, the application of Earth observations systems and machine learning algorithms are still unlimited to monitor grassland AGB. This study also, suggests more application of Earth observation based techniques in the preservation and restoration of grassland ecosystems in drylands. This is fundamental in designing sustainable policies for grassland management, particularly pastoralism. Therefore, these policies plays a role in determining the number of livestock per paddock during the grazing season. In addition, grassland AGB samples should be maximized based on the grassland ecosystem to increase machine learning model precision. The current study suggests extensive literature review from multiple databases for understanding comprehensive trends in EOS and grassland modelling. While other studies can rely on data fusion of the sentinel dataset or use Sentinel-1 and Sentinel-2 separately for grassland AGB estimation and mapping grassland biomass nitrogen content.

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Appendix: Ethical clearance certificate

University of Fort Hare
Together in Excellence

ETHICS CLEARANCE
REC-270710-028-RA Level 01

Project Number:	KAL031SNDU01
Project title:	**The use of earth observation multi-sensor systems to monitor and model pastures: towards the development of an automated system: A Case of Hluvukani Village in the Mpumalanga Province, South Africa.**
Qualification:	Masters in Geography (Full Dissertation)
Student name:	Lwandile Nduku
Registration number	201609310
Supervisor:	Dr A.M Kalumba
Department:	Geography
Co-supervisor:	Dr C Munghemezulu Dr J.G Chirima

On behalf of the University of Fort Hare's Research Ethics Committee (UREC) I hereby grant ethics approval for KAL031SNDU01. This approval is valid for 12 months from the date of approval. Renewal of approval must be applied for BEFORE termination of this approval period. Renewal is subject to receipt of a satisfactory progress report. The approval covers the undertakings contained in the above-mentioned project and research instrument(s). The research may commence as from the 28/06/21, using the reference number indicated above.

Note that should any other instruments be required or amendments become necessary, these require separate authorisation.
Please note that UREC must be informed immediately of

- Any material changes in the conditions or undertakings mentioned in the document;
- Any material breaches of ethical undertakings or events that impact upon the ethical conduct of the research.

The student must report to the UREC in the prescribed format, where applicable, annually, and at the end of the project, in respect of ethical compliance.

UREC retains the right to

- Withdraw or amend this approval if
    - Any unethical principal or practices are revealed or suspected;
    - Relevant information has been withheld or misrepresented;
    - Regulatory changes of whatsoever nature so require;
    - The conditions contained in the Certificate have not been adhered to.

- Request access to any information or data at any time during the course or after completion of the project.

Your compliance with Department of Health 2015 guidelines and any other applicable regulatory instruments and with UREC ethics requirements as contained in UREC policies and standard operating procedures, is implied.

UREC wishes you well in your research.

Yours sincerely

Dr N Taole-Mjimba
Chairperson: University Research Ethics Committee
13 August 2021