Understanding bush encroachment in Bisley Valley Nature Reserve: the use of intensity analysis and cellular automata model on RapidEye and PlanetScope image data

By

Ntuthuko Prosperous Mncwabe

218003689

A thesis submitted, in the fulfilment for the degree of Master of Science in Environmental Sciences, in the College of Agriculture Engineering, and Science, University of KwaZulu-Natal

Pietermaritzburg, South Africa

November 2024

Abstract

The encroachment of woody vegetation into grasslands is a worldwide phenomenon that progressively causes serious disturbances to plant and animal biodiversity, ecosystem function, and recreational activities. This phenomenon has become a major concern in nature reserves due to its adverse impact on woody vegetation and grass ratio causing various disturbances such as decline of palatable grasslands and effects on soil properties. Hence, a comprehensive analysis of bush encroachment is paramount for understanding the past, present and future distribution of the encroachment and to inform effective management schemes. This study assessed and predicted bush encroachment dynamics in Bisley Valley Nature Reserve using high spatial resolution remotely sensed multi-temporal image data. The first objective focused on monitoring bush encroachment and associated land use-land cover types in the nature reserve using RapidEye and PlanetScope data within the Google Earth Engine (GEE) platform. Using RapidEye and PlanetScope image data spanning the period from 2009 to 2023, the study estimated the changing extent of woody vegetation, grassland cover and bare areas, providing a comprehensive analysis of their dynamics over the 14-year study period. Over the study period, results show that approximately 130.69 ha (ha) of grassland was converted to woody vegetation, while approximately 2.78 ha of woody vegetation was transformed into grassland. Moreover, the study established a net increase of 127.91 ha in the total area covered by woody vegetation. The second objective sought to compute and analyze past, current, and future (2009-2033) bush encroachment trends and intensity of land cover transitions using intensity analysis and the Cellular Automata (CA) models. The findings revealed a steady increase in woody encroachment on other land cover types. Moreover, there was an intensive change of land cover in the first period (2009-2014) compared to the other periods. Additionally, the prediction of future bush encroachment demonstrated an increasing trend of woody vegetation in the next decade. This study provides valuable insights on the threat of bush encroachment in the study area and demonstrates the value of various approaches such as change detection, intensity analysis and prediction of future encroachment for spatially explicit and detailed analysis of bush encroachment. The study also revealed that there is a pressing need for evaluation and improvement of management schemes in the study area and other encroached landscapes.

Key words: Bush encroachment, RapidEye, PlanetScope, Intensity analysis, Cellular Automata model, Nature reserve.

Preface

This research was conducted in the School of Agricultural, Earth and Environmental Sciences at the University of KwaZulu-Natal, Pietermaritzburg Campus, from February 2023 to October 2024. The research was supervised by Prof O. Mutanga, Prof J. Odindi, and Dr T.N Matongera.

I declare that this work represents the author's original work and has never been submitted in any form of qualification accomplishment to any institution. In addition, I certify that a reference has been made in the text where there are contributions of others.

Supervisors Signature: Prof O. Mutanga [redacted] Date: 09/11/2024

Prof J. Odindi [redacted] Date: 09/11/2024

Dr T.N Matongera [redacted] Date: 09/11/2024

Plagiarism Declaration

I Ntuthuko Prosperous Mncwabe, declare that:

1. The research reported in this thesis, except where otherwise indicated, is my original research.

2. This thesis has not been submitted for any degree or examination at any other institution.

3. This thesis does not contain other person's data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

4. This thesis does not contain other persons writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted:

   a. Their words have been re-written, and the general information attributed to them has been referenced.

   b. Where their exact words have been used, their writing has been placed in italics inside quotation marks and referenced

5. This thesis does not contain text, graphics or tables copied and pasted from the internet, unless specifically acknowledged, and the source being detailed in the thesis and in the references section.

Signed: [redacted] Date: 09/11/2024

Dedication

I dedicate this dissertation to my beloved family who has continuously supported and inspired me to spread my wings and fly.

Acknowledgements

First and foremost, I would like to convey my gratitude to the Almighty God for his endless blessings. A big thank you to the University of KwaZulu-Natal for giving me the opportunity to pursue my studies. To Dr Trylee Matongera thank you for believing in me, your mentorship and continued support immensely contributed to this research.

My profound gratitude also goes to my supervisors Professor Onisimo Mutanga, Professor John Odindi, and Dr Trylee Matongera, thank you for the opportunity, unwavering support, and guidance. Your positive insights, knowledge, patience, and commitment were key throughout this research.

I would also like to pass my gratitude to Celuxolo Dlamini, Sfundo Mthiyane, Bheka Mlambo, Wandile Khumalo, and Sibusisekile Mabaso for assistance with field data collection. My gratitude also goes to Dr Colins Matiza, Bongokuhle Sibiya, Snethemba Ndlovu, and Anita Masenyama, your support and encouragement is immensely appreciated. I would also like to convey special thanks to my family, particularly my mother and little brother, your support and encouragement has provided the foundation for my academic journey. Lastly, I would like to extend my sincere gratitude to the National Research Foundation for funding this research.

Table of Contents

List of Tables

List of Figures

Acronyms

ANN - Artificial Neural Network

CBD - Central Business District

CO_2 - Carbon dioxide

DEM - Digital Elevation Model

GEE - Google Earth Engine

GDP - Gross Domestic Product

GPS - Global Positioning System

ha - Hectares

KZN - KwaZulu-Natal

LR - Logistic Regression

LULC - Land Use Land Cover

MLP - Multilayer Perception

MODIS - Moderate Resolution Imaging Spectroradiometer

MOLUSCE - Modules for Land-Use Change Simulation

NIR - Near Infrared

QADI - Quantity and Allocation Disagreement index

QGIS - Quantum Geographic Information System

RF - Random Forest

TM - Thematic Mapper

TWI - Topographic wetness index

WGS - World Geodetic System

Chapter One: General Introduction

1.1 Introduction

Over 62% of global land area has significantly experienced landcover transformations, particularly due to the proliferating demand for natural resources and landscape disturbances (Afuye et al., 2024). One of the detrimental landscape disturbances in natural grasslands is bush encroachment, which is the overgrowth and spread of woody plants such as shrubs and trees in a grassland or savanna ecosystem (Cao et al., 2019, Khazieva et al., 2022, Yassin, 2019). Bush encroachment affects more than 7.5 million km^2 (55%) of grassland landscapes in the sub-Saharan Africa and 73 thousand km^2 of the entire land area in South Africa (Belayneh and Tessema, 2017). Studies also highlight that the encroachment of woody vegetation is anticipated to increase in various landscapes globally due to among others over-grazing, rainfall variability, fire intensity and frequency, increase in atmospheric Carbon dioxide (CO_2) concentrations, soil nutrients availability, and woody vegetation seed dispersal by herbivores (Luvuno et al., 2022, Van Auken, 2009, Venter et al., 2018).

Generally, rangelands in Savanna and grassland landscapes are prone to bush encroachment (Gxasheka et al., 2023, Maphanga et al., 2022, Yassin, 2019). However, the adverse impacts of bush encroachment are usually severe in protected areas, particularly in nature reserves (Abdulahi and Yonus, 2020, O'Connor et al., 2014, Shikangalah and Mapani, 2020, Wedel et al., 2024). Such landscapes are crucially important for preservation of endangered, endemic, keystone and flagship species (Khazieva et al., 2022, Kimaro et al., 2019). They maintain plants and animal's biodiversity, provide essential ecosystem services and recreational value to humans and protect natural habitats (Chen et al., 2023, Liu et al., 2023). Nature reserves also contribute to overall planet health by limiting human threats to biodiversity and landscape, consequently reducing anthropogenic induced climate and environmental effects (Gambo et al., 2018, Liu et al., 2017). However, due to encroachment of woody vegetation, the majority of nature reserves largely experience a constant reduction of grasslands (Hudak and Wessman, 2001a, Stewart et al., 2022).

Such landscape changes threaten the future of nature reserves and instigate a wide range of environmental, socio-economic, and ecological costs (Ayelew and Mulualem, 2018, Sebitloane et al., 2020). In nature reserves, bush encroachment reduce grazing pastures for wild herbivores, and influence overgrazing in other parts of the reserve (Kavwele et al., 2017). An earlier study by Ben-Shahar (1992) for instance reported that due to bush encroachment, herbivores such as wildebeest and zebra mainly occupy and increase grazing intensity in less disturbed and bush cleared areas of the Sabi Sand Nature Reserve. Bush encroachment also increases susceptibility of the landscape to land degradation and soil erosion (Yassin, 2019). Additionally, bush encroachment reduces carrying capacity of nature reserve, limiting its conservation and recreational value and contribute approximately 17% loss of biodiversity and the annual Gross Domestic Product (GDP) (Belayneh and Tessema, 2017). Encroachment of woody vegetation also increase management costs and in severe circumstances, can lead to reserve disrepair and abandonment of management schemes (Sebitloane et al., 2020). For instance, private game reserves and state run reserves such as Hluhluwe Game Reserve spend approximately R293,751 and R163,000 ($16,864.36 and $9,357.89) annually on managing bush encroachment, respectively (Luvuno et al., 2022). Due to the persistent threat of bush encroachment in nature reserves, there is a pressing need for monitoring and mapping the dynamics and future trends of the phenomenon.

Various studies on encroachment of woody vegetation have underlined the significance of monitoring the phenomenon to establish an understanding of its severity in the landscape and for devising effective management schemes (Cao et al., 2019, De Klerk, 2004, Symeonakis and Higginbottom, 2014a). Unlike the expensive and labor intensive in-field assessment of woody vegetation densities, Remote Sensing (RS) technology provide economical and reliable monitoring of bush encroachment (Gan et al., 2022, Kopeć and Sławik, 2020, Soubry and Guo, 2022). RS data and approaches provide high spatial and temporal resolution datasets that are critical for providing comprehensive insights on bush encroachment (Schwieder et al., 2014). Such insights are key to landscape management, restoration and improvement of ecosystem services and recreational value (Belayneh and Tessema, 2017, Russell and Ward, 2014).

RS data and approaches have been used in various bush encroachment research, particularly due to its ability to effectively map bush encroachment over vast spatial extents (Banskota et al., 2014, Oldeland et al., 2010, Qabaqaba et al., 2023). For instance, a study by Symeonakis and Higginbottom (2014a) employed Landsat multi temporal remotely sensed data to analyze the progression of bush encroachment in the savanna environment of the Dr Ruth Segomotsi Mompati District Municipality, Northwest Province of South Africa over the 20 year study period. The study found a continuous increase of woody vegetation in the research area, from 58% in 1989 to 67% in 2009. Another study by, Shanungu et al. (2013) mapped and established a 19% expansion of woody vegetation and 17% shrinkage of grasslands in Lochinvar National Park in Zambia between 1986 and 2010 using Landsat Thematic Mapper (Landsat TM) data. Despite the magnitude of research, the mitigation of this complex phenomenon remains a challenge in protected areas particularly due to improper management schemes.

Evidence from literature shows that the current bush encroachment monitoring techniques such as land cover classification and change detection are fundamentally important for understanding the trends and severity of bush encroachment (Liao et al., 2018, Ludwig et al., 2016, Maphanga et al., 2022). Bush encroachment change detection is critical for monitoring the progression of the phenomenon in the landscape, providing essential insights for enhancing landscape management (Graw et al., 2016, Gan et al., 2022). Moreover, bush encroachment change detection allows for temporal analysis of other land cover classes, revealing key information on the land cover transitions such as the shift between grasslands, bare areas and woody vegetation (Cao et al., 2019). However, supplementing insights from general change detection technique is sometimes necessary for explicit assessment of bush encroachment (Bravo-García et al., 2024, Xie et al., 2020).

The use of advanced Land Use Land Cover (LULC) change monitoring methods such as the intensity analysis could be key for acquiring additional insights such as understanding land cover change processes associated with bush encroachment and essential insights on the dynamics, drivers, and impacts of landcover changes (Ekumah et al., 2020, Ouedraogo et al., 2023). Intensity analysis is particularly essential for assessing the rate of transitions across different periods and intensity of class gains and losses from other land cover classes (Aldwaik and Pontius Jr, 2012, Pontius Jr et al., 2013). For instance, the method was key to comprehending change in land cover intensities in Ethiopia’s Northwestern highlands revealing a consistent increase of land cover intensities from the first period (1990-2000) to the subsequent periods (2000-2010, and 2010-2020) (Bogale et al., 2024). Such explicit analysis of landcover changes is necessary for identifying key land cover change policy and beneficial to land managers and conservationists for developing effective management and rehabilitation strategies (Huang et al., 2012). According to Briassoulis (2020) other valuable insights on land cover changes and severity of bush encroachment could be acquired using predictive models.

Predictive models are useful for simulation of bush encroachment and other land cover transitions and immensely contribute to reducing the rate and probability of future encroachment (Cao et al., 2019, Ludwig et al., 2016). The most used predictive models for LULC analysis include Markov chains, Land Change Modeler and Cellular Automata model (Devi et al., 2022, Hamad et al., 2018, Kamaraj and Rangarajan, 2022). These models are particularly essential for analysis of past trends of land cover transitions, construction of future trends, validation, and decision support for landscape management (Gao et al., 2020, Tong and Feng, 2020). The conclusions of this research will equip conservationist and land managers with viable insights on the dynamics of bush encroachment and need for employing other useful, more advanced monitoring techniques to enhance understanding of the phenomenon and facilitate management initiatives.

1.2 Aims and objectives

The overall purpose of this study was to assess and predict bush encroachment dynamics in Bisley Valley Nature Reserve using high spatial resolution multi-temporal data. To accomplish this, the following objectives were established:

1.2.1 Specific objectives

- To monitor bush encroachment and associated LULC types in Bisley Valley Nature Reserve using RapidEye and PlanetScope data within the Google Earth Engine (GEE) platform.
- To assess the past, current, and future (2009-2033) bush encroachment trends in Bisley Valley Nature Reserve using the intensity analysis and Cellular Automata (CA) model.

1.3 Significance of the study

Monitoring and prediction of woody vegetation in protected areas is critically important for the management of grasslands, hence ensuring preservation of landscape's biodiversity and recreational value. In this regard, utilizing robust monitoring techniques such as change detection and intensity analysis can effectively contribute to explicit understanding of spatiotemporal changes of grass and woody vegetation and aid implementation of effective grassland management schemes. Advanced monitoring techniques such as intensity analysis are particularly essential for understanding land cover change intensities, hence providing additional insights on landscape changes and further facilitate decision making for landscape management. Furthermore, employing LULC predictive models is a key approach for understanding severity of encroachment. Through LULC predictive models, environmental managers and conservationists can acquire indispensable insights on future encroachment, allowing for devising and implementation of effective management schemes and rehabilitation of grasslands.

1.4 Study area

The study was caried out in Bisley Valley Nature Reserve located at Lat - 29.6566, Long 30.3956, 7 km from Pietermaritzburg Central Business District (CBD) in the KwaZulu-Natal (KZN) Province of South Africa (Figure 1.1). The study site is situated between 720 and 840 m above sea level and occupies approximately 350 ha. Bisley has humid subtropical climate, receives warm and humid summers, cool and dry winters, and mean rainfall of 694 mm per year (Kraai et al., 2023). The area experiences average annual temperatures of around 26 ºC in summer and appoximately 9 ºC in the winter (Kraai et al., 2023). Shale and dolerite dominate the geological type, and the area has diverse soil types namely, clay loam, silt loam, sand and sandy loam. The nature reserve was established to safeguard and preserve biodiversity and to promote recreational opportunities to local residents and the city of Pietermaritzburg. Bisley Valley Nature Reserve has a range of birds and mammals such as giraffes (*Giraffa camelopardalis*), impala (*Aepyceros melampus*), zebra (*Equus quagga*), wildebeest (*Connochaetes taurinus*), and vervet monkey (*Chlorocebus pygerythrus*). The area is dominated by grasses such as *Eragrostis curvula*, *Panicum maximum*, and *Paspalum dilatatum*, shrubs, thornvelds, *Acacia spp* and other woody vegetation. It is heavily encroached by woody vegetation and different management strategies such as controlled burns and bush clearing have been used to manage the grasslands. However, the application of such control measures has been inconsistent.

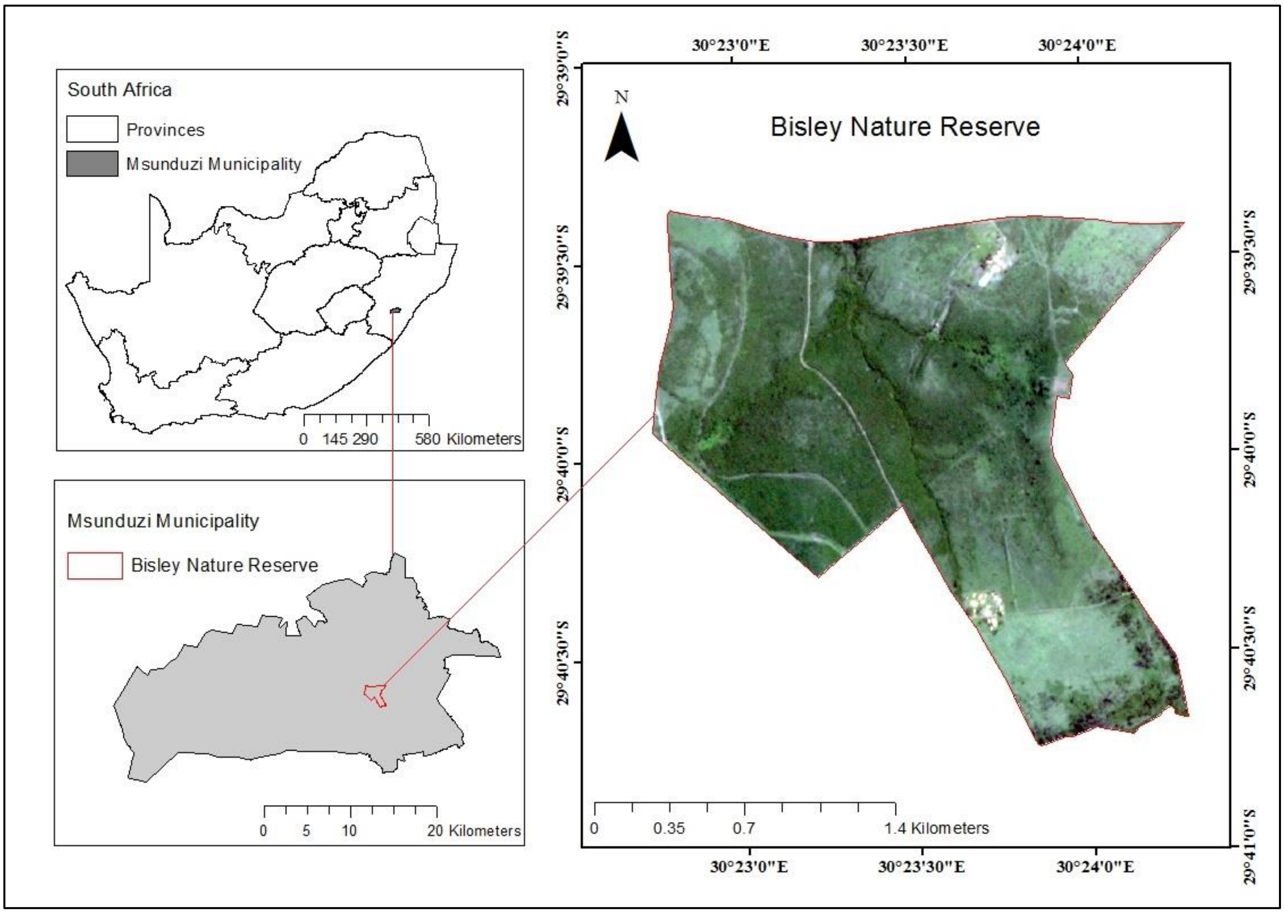

Figure 1.1: Geographic position of the experimental site in the KZN province, South Africa

1.5 General structure of the thesis

This thesis consists of Four chapters. Chapter One is the introduction that provides the aim and objectives and conveys the significance of the study. Chapter Two and Three are two research papers that address research objectives. Specifically, Chapter Two focusses on monitoring spatiotemporal changes of bush encroachment and associated LULC types in a Nature Reserve using RapidEye and PlanetScope data. This chapter provides insights into the extent to which woody vegetation has replaced grasslands over the 14-year study period. Chapter Three provides the critical analysis of bush encroachment based on the intensity analyses and CA model prediction of future bush encroachment dynamics. This chapter provides more in-depth insights into transitions and rate of LULC change in the landscape. Chapter Four is the synthesis of the whole thesis, it highlights the key issues, arguments, findings, and research gaps. The chapter further provides implications and recommendations for future research on bush encroachment.

Chapter Two: Monitoring bush encroachment in Bisley Valley Nature Reserve using RapidEye and PlanetScope data

This chapter is based on a research paper:

Mncwabe, N.P., Mutanga, O., Matongera, T.N., and Odindi, J. (Under review). Monitoring bush encroachment in Bisley Valley Nature Reserve using RapidEye and PlanetScope data. *Landscape Ecology*, Manuscript ID: 012091be-d608-41e3-9966-a7e0902fb5f1.

Abstract

Woody vegetation encroachment into natural grasslands is a significant global concern in nature reserves and other protected and conserved landscapes. Bush encroachment remains one of the major contributors of land degradation and landscape alterations. The phenomenon adversely causes threat to biodiversity, conservation efforts, landscape productivity and recreational value. To understand the progression and threat of woody vegetation invasion into nature reserves, this study aimed to monitor bush encroachment and associated Land Use Land Cover (LULC) types in a nature reserve using high spatial resolution multi-temporal data within the Google Earth Engine (GEE) platform. The study employed RapidEye and PlanetScope data spanning the period from 2009 to 2023 to estimate the changing extent of woody vegetation, grassland cover and bare areas, providing a comprehensive analysis of their dynamics over the 14-year study period. The results indicated that over the study period, approximately 130.69 ha of grassland underwent a transition to woody vegetation, while approximately 2.78 ha of woody vegetation was converted to grassland. The study revealed a net increase of 127.91 ha in the total area covered by woody vegetation. The analysis demonstrated a notable upward trend in woody vegetation expansion during the 14 years of study, with percentage coverage of 37.69%, 51.18%, 64.52% and 74.02% in 2009, 2014, 2019 and 2023, respectively. Considering the outcomes of this study, improvement of management schemes in Bisley is critical for management and restoration of grasslands. Overall, the study provides valuable insights into the threat of bush encroachment in nature reserves and aids decision making for management of these landscapes.

Key words: Bush encroachment, Remote sensing, RapidEye, PlanetScope, Nature reserve

2.1 Introduction

Nature reserves are one of the key ecosystems for biodiversity conservation, delivery of critical ecosystem and recreational services, and mitigation of climate change and environmental catastrophes (Gambo et al., 2018, Yang et al., 2019). These landscapes also contribute to sustainable land management and prevention of human wildlife conflicts (Schmitt et al., 2022). However, the majority of nature reserves, other protected areas, and various landscapes such as grasslands, rangelands and savannas are currently threatened by encroachment of woody vegetation (Fogarty et al., 2022, Li et al., 2022, O'Connor et al., 2014). In nature reserves, the encroachment of woody vegetation threatens the delicate balance of ecosystems and instigate severe environmental, socioeconomic, and ecological impacts (Kraaij and Ward, 2006, Mokgotsi, 2018). In these landscapes, bush encroachment restrains the growth of natural grasslands and other herbaceous vegetation and consequently promotes the growth of unpalatable plants to herbivores species (Oosthuysen and Strauss, 2023). Bush encroachment also reduces the size of pastures for wild herbivores and increase the susceptibility of the area to unsustainable grazing, which may expedite land degradation in the reserve (Graw et al., 2016). Studies have also demonstrated that bush encroachment negatively impacts ecosystem services particularly biodiversity conservation, tourism and employment to reserve workers (Luvuno et al., 2022, Sebitloane et al., 2020). Furthermore, bush encroachment poses challenges to management, and economic aspects of nature reserves (Fisher et al., 2014, Gordijn, 2010, Shekede et al., 2015). For instance, as the encroachment of woody vegetation intensifies, additional financial resources are required for effective reserve management that include curtailing the proliferation of woody vegetation (Borgström et al., 2013). To enhance conservation efforts and address the threats posed by bush encroachment on biodiversity, it is paramount to comprehensively understand the trends of bush encroachment over time (Borkowski, 2002).

Monitoring of bush encroachment in nature reserves plays a vital role in understanding the nature and severity of the phenomenon, and useful to conservationists in developing targeted strategies for mitigation and landscape restoration (Gómez-García et al., 2023, Hudak and Wessman, 2001b). Through the implementation of precise monitoring techniques, conservationists can obtain valuable insights into the causes of bush encroachment, and effectively evaluates land-use practices (Koch et al., 2023, Lewis et al., 2021). Furthermore, with robust monitoring in place, timely interventions can be implemented to prevent further encroachment of woody vegetation and its negative consequences (Li et al., 2022). Advanced monitoring of bush encroachment in nature reserves is also essential for devising strategies for maintaining optimal resources for wildlife and for improving biodiversity, ecosystem services and recreational value (Cao et al., 2019, Symeonakis and Higginbottom, 2014b). However, identifying cost-effective and minimally labour-intensive methodologies for regular monitoring of shifts within grasslands and woody vegetation consistently presents a formidable challenge (Zhao et al., 2021). Over the previous three decades, the availability of new technologies such as Remote Sensing (RS) has played a pivotal role in overcoming this challenge and revolutionized monitoring of bush encroachment (Dong et al., 2019, Kabeta et al., 2020).

The RS technology provides efficient methodologies for continuously assessing landscape changes such as the shift from grasslands to woody vegetation and improve temporal analysis of such trends at various spatial extents (Maphanga et al., 2022, Shikangalah and Mapani, 2020). RS technology has become increasingly prominent in the field of geospatial data acquisition and storage, owing to its remarkable ability to collect, archive, and manage vast amounts of spatial data (Fogarty et al., 2022). This offers a potential avenue to enhance comprehension of bush encroachment dynamics and facilitate informed conservation decision-making (Cao et al., 2019, Hamylton et al., 2020, Kopeć and Sławik, 2020). Moreover, RS provides real-time data that is valuable for the bush encroachment change detection analysis (Mpati, 2015). It allows for an easy access to moderate and high spatial resolution datasets, making it feasible to apply robust change monitoring strategies with high accuracy at a reduced labour and financial cost (Graw et al., 2016). Consequently, various studies have utilized RS data to assess bush encroachment. For instance, Shanungu et al. (2013) conducted a change detection and temporal analysis of bush encroachment using the Landsat Thematic Mapper (TM) data in Lochinvar National Park in Zambia and reported a 16% augmentation of woody vegetation and 17% decrease of open areas. Another study by Graw et al. (2016) utilized Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) data and conducted a comprehensive assessment of bush encroachment at a continental scale. Through their research, they successfully created a susceptibility map showing areas that are vulnerable to bush encroachment and determined the associated risk factors. Recently, Gan et al. (2022) used Sentinel-2 data to determine and map the total area of Xilin Gol grasslands encroached by shrubs. Their study produced a regional shrub coverage map with over 80% overall accuracy.

However, RS datasets with moderate and low spatial resolutions, such as MODIS and Landsat, may not be well-suited for vegetation monitoring and mapping of vegetation disturbances in smaller geographic areas like small nature reserves. For instance, a research by Hansen et al. (2016) noted that about 50% of forest disturbances can be missed out when using coarse resolution remotely sensed data. This underscores the critical importance of employing high-resolution data for effective monitoring of vegetation disturbances, such as bush encroachment.

Lately, the availability of high spatial resolution sensors such as RapidEye have opened new opportunities in the assessment of bush encroachment at a fine scale (Cao et al., 2019, Gan et al., 2022). With its high spatial resolution of 5m and additional attributes such as Near Infrared (NIR) and red-edge bands, RapidEye has advanced vegetation discrimination potential and usually yields good accuracy output maps (Kim and Yeom, 2014, Schuster et al., 2015). The daily revisit time of RapidEye allows for in-depth analysis of vegetation providing critical spatiotemporal information and aid decision making (Roessler et al., 2013). Nevertheless, the availability of the datasets may limit its utility, particularly for change detection analysis. For instance, RapidEye constellation was decommissioned in December 2019, posing significant challenges in acquiring current year data needed for change detection analysis (Coffer et al., 2020). Nevertheless, the launch of the PlanetScope sensor, with spectral and spatial characteristics comparable to RapidEye, offers an opportunity for continuity in providing remotely sensed data at a fine scale. PlanetScope offers daily monitoring of vegetation and environmental changes with a high spatial resolution of 3m and has been utilized for various applications including monitoring global deforestation (Acharki, 2022, Shumilo et al., 2020). For example, Francini et al. (2020) used PlanetScope data for forest disturbance alert system and created a forest change map with over 80% overall accuracy. Just like RapidEye, PlanetScope has RedEdge bands which are efficient and highly sensitive to vegetation reflectance and is considered suitable for vegetation analysis (Cornejo-Denman et al., 2020, Mudereri et al., 2019).

In addition to the importance of using high spatial resolution for detailed spatiotemporal analyses and accurate mapping of bush encroachment in nature reserves, there is a need for selection of an accurate classification algorithms (Symeonakis and Higginbottom, 2014b). Random Forest (RF) is one of the robust classification algorithms that has been extensively used for bush encroachment monitoring (Graw et al., 2016, Liao et al., 2018, Zhao et al., 2021). RF is a non-parametric machine learning algorithm that is suitable for classifying multi-temporal data, and often provides reliable results (Naidoo et al., 2012). The RF algorithm with its capabilities to efficiently handle data with noise, reduces multicollinearity and provides robust predictive abilities that can effectively facilitate monitoring of complex phenomenon such as bush encroachment in small landscapes like nature reserves (Rodriguez-Galiano et al., 2012). The utility of RF algorithm and high spatial resolution sensors can provide important insights on progression of bush encroachment and aid decision making for the management of nature reserves.

Surprisingly, with all the benefits provided by RF algorithm, high spatial resolution data, and other remote sensing technologies, globally there is still fewer research studies that has been conducted in nature reserves to provide insights on dynamics of bush encroachment. The Bisley Valley Nature Reserve has recently experienced significant encroachment of woody vegetation, as a result, there are increasing concerns about biodiversity, conservation, and the future of the reserves. Understanding of the magnitude of encroachment and the state of the reserve plays a pivotal role in improving management schemes and prevention of further encroachment of woody vegetation. Therefore, this study aims to utilize high spatial resolution RapidEye and PlanetScope datasets and RF algorithm to present a remote sensing-based monitoring of bush encroachment in a nature reserve. The objectives of the study were to determine the historical trends of bush encroachment trends for measuring the extent to which woody species have replaced grasslands. This research is the initial step towards mitigation of bush encroachment in the Bisley Valley Nature Reserve and its contribution may promote sustainable management and conservation of various animal species within the reserve.

2.2 Materials and Methods

2.2.1 Field data collection

Field data was collected in June 2023 using a handheld sub meter accuracy Trimble Global Positioning System (GPS). The study used purposive sampling to collect samples for woody vegetation (trees and shrubs), grasslands (open area covered with grass species), and bare areas (open area consisting of exposed soil, with no vegetation cover). The purposive sampling method allows for precise acquisition of the best suited elements of the necessary data. Thirty line transects were purposively laid based on the presence of natural vegetation and using visualization, the transects were distributed according to encroachment categories (heavily encroached, medium encroachment and no encroachment) to capture variability across study site. A distance of 70 m was measured for each transect and a total of five sample plots were established along each transect. For each sample plot, an area of 25 m^2 (5 by 5 m plot) was measured and sample plots established at 10 m apart to avoid autocorrelation. A single GPS location was recorded per plot for each of the land cover class. A total of 150 GPS locations were collected for each land cover class.

In change detection, employing the same training samples across different time periods can potentially undermine classification accuracy. Consequently, Google Earth Engine was employed to augment the ground truth data from previous years and to generate new training samples specifically tailored to the years 2009, 2014, and 2019. Using a point format, three land cover classes were collected, namely woody vegetation, grasslands, and bare areas. Point format was preferred over polygons as the method is less susceptible to the influence of spatial autocorrelation. The pre-collected samples of the land cover classes from the field were imported to Google Earth Engine platform. The field samples were used to guide the sampling of land cover classes. In Google Earth Engine platform, samples were collected using visual interpretation, which is the commonly utilized strategy for land cover classification. For each time interval, a cumulative set of 450 sample points was gathered, specifically comprising 150 points dedicated to each distinct land cover class. The classification of images involved dividing the data into training and testing sets, with 70% allocated for training the classification models and the remaining 30% reserved for model testing.

2.2.2 Remotely sensed data acquisition and pre-processing

The satellite images utilized in this research were obtained at a five-year interval spanning from 2009 to 2023. Specifically, three RapidEye images and one PlanetScope image for the year 2023 were used. Both RapidEye and PlanetScope data were acquired from the Planet Education and Research online platform (https://www.planet.com/) and imported into Google Earth Engine (GEE) platform for analysis. These datasets were already pre-processed and atmospherically corrected. RapidEye collects data in different frequencies ranges along the electromagnetic spectrum and provides images with five spectral bands namely, the red (0.63-0.68 µm), green (0.52-0.59 µm), blue (0.44-0.51 µm), near-infrared (0.76-0.85 µm) and red-edge band (0.69-0.73 µm). It has 5 m spatial resolution and additional red-edge and NIR bands considered important for applications related to vegetation mapping and monitoring of plant invasion. On the other hand, PlanetScope provides high temporal resolution (daily) and spatial resolution of 3 m. PlanetScope provides images with an orthorectified pixel size of 3.125 m in the red (59-670 nm), green (500-590 nm), blue (455-515 nm), and near infrared (780-860 nm) wavelengths. PlanetScope satellite constellation also acquire images with the red-edge band which is pivotal for remote sensing of vegetation. PlanetScope and RapidEye sensors operate at distinct spatial resolutions. Consequently, to align their data, bilinear interpolation was employed to resample the PlanetScope imagery, adjusting its spatial resolution to match the 5m resolution characteristic of RapidEye.

2.2.3 Random Forest classification algorithm

Random Forest algorithm was adopted for classification of woody vegetation, grasslands, and bare areas. The RF is a frequently utilized machine learning algorithms for land cover classification and many other applications including mapping of invasive species (Gong et al., 2021, Rusňák et al., 2022), and bush encroachment mapping (Khazieva et al., 2022). The algorithm uses bootstrapping and combine datasets from different classes to classify landscapes (Abdi, 2020). The algorithm generates a set of decision trees and choose their majority vote and is usually reliable to minimize overfitting (Matongera, 2022, Phan et al., 2020). RF algorithm is robust, capable to handle intricate datasets and can manage data that has a lot of noise and outliers (Ustebay et al., 2018). The algorithm is suited for remote sensing of complex phenomena such as bush encroachment as it can facilitate processing, simple to use but still reliable to provide high accuracy. It provides robust predictive capabilities and efficiently deals with multicollinearity (Liao et al., 2018).

2.2.4 Change detection

Four classification maps were generated, depicting the progression of bush encroachment over different time intervals. The initial three maps, representing the years 2009, 2014, and 2019, illustrate the evolution of encroachment in five-year intervals. However, the map for 2023 captures the advancement over a four-year period. The four classification maps were used for change detection. The change detection analysis was conducted by developing a code in the GEE platform to create the final change maps showing progression of bush encroachment over time. Comparisons were made between the classified images of the study area of different time intervals to discriminate the change in total area of woody vegetation and grasslands at Bisley Valley Nature Reserve. To produce the first change detection map, classified 2009 image was compared with the classified 2014 image, 2014 with 2019 and 2019 with 2023 for second and third change detection maps, respectively. Within the GEE, a code was generated using the area function and was utilized for calculation of transitions and area change between woody vegetation and grasslands. To calculate the net increase of woody vegetation, the total area of grasslands replaced by woody vegetation during the 14-year study period was subtracted by the total area of woody vegetation replaced by grasslands.

2.2.5 Accuracy assessment

To evaluate the classification accuracy results, we performed an accuracy assessment within the GEE platform, utilizing the confusion matrix. This widely recognized evaluation approach provides valuable insights into the performance of the classification process. Specifically, three commonly employed measures were employed from the confusion matrix, namely the overall accuracy, producer's accuracy, and user's accuracy. These measures offer comprehensive and quantitative assessments of the classification's reliability and effectiveness in correctly identifying land cover categories (Foody, 2002). The producer's and the user's accuracy are pivotal in evaluating the capability and efficiency of remotely sensed data in evaluating bush encroachment.

Furthermore, the Kappa statistics for each of the classifications were calculated to measure the agreement between the expected accuracies and accuracies that are correctly classified. The Kappa analysis compares the observed accuracy and predictable accuracy (Freeman and Freeland, 2015). The values of Kappa span from -1 to +1 where the Kappa value of one or approximate to one indicates a strong agreement between the accuracies and a Kappa value of zero represent a week agreement (Zhang et al., 2017). Kappa is however, reported to have various constrains such as inaptitude to provide the level of agreement between the classification and the reference data (Feizizadeh et al., 2022). Kappa index measures the degree of agreement based on level of chance and is often misleading for practical applications (Kganyago et al., 2018, Pontius Jr and Millones, 2011). The kappa index is also sensitive to asymmetric distributions.

In addition to Kappa statistics, the current study used the Quantity and Allocation Disagreement Index (QADI) to evaluate the level of agreement between the reference and classification map (Pontius Jr and Santacruz, 2014). QADI utilizes two different kinds of errors derived from the confusion matrix, namely quantity and allocation disagreement. QADI index counts pixels that were incorrectly identified (Allocation disagreement) and compute the difference in count of pixel for each class between the reference and classification map (Quantity disagreement). The QADI value spans from 0 to 1 where the value of zero or close to zero represent a low disagreement between training data and classification results and value close or equal to one representing a high disagreement (Pontius Jr and Millones, 2011). Benchmark for accuracy values and explanation of QADI values are shown in Table 2.1. In the QADI graph, quantity and allocation disagreements are determined based on the position of the black dot where the location of the dot above the diagonal line represent the allocation error and quantity error below the line. QADI index is computed using the equation: $QADI = \sqrt{\left(\frac{A}{N}\right)2 + \left(\frac{Q}{N}\right)2}$

Where A is Allocation disagreement/wrongly placed pixels and Q is Quantity disagreement/ value of disagreement in pixel for each class between classification result and training data, and N is the number of classes. Using the confusion matrix, the QADI index was computed in ArcMap 10.8 through a toolbox that was created by Feizizadeh et al. (2022). The toolbox can be accessed via the link: (https://drive.google.com/file/d/1lMDVknlfFFWDC5k1F0GVQpcb7vJfRwEK/view).

Table 2.1: Benchmark for accuracy values and explanation of QADI values

QADI scale and colour scheme	Description of accuracy
0.00 - 0.07	Very low disagreement
0.08 - 0.12	Low disagreement
0.13 - 0.20	Moderate disagreement
0.21 - 0.30	High level of disagreement
0.30 – 1.00	Lack of accuracy

2.3. Results

2.3.1 Classification accuracy during the study period

The study attained over 85% overall accuracy for every classification period. Overall accuracies of 92.5%, 89.4%, 97.4% and 96.9% were achieved in 2009, 2014, 2019 and 2023, respectively. The study also yielded good kappa values with high kappa values of 95.0% and 94.0% achieved in 2019 and 2023 respectively and the low kappa values of 86.5% and 80.0%, respectively, attained in 2009 and 2014. Additionally, the QADI index indicated good accuracy results (Figure 2.1). For instance, for all classifications, the QADI values are close to zero indicating a low disagreement between training data and classification results. The QADI values of 0.075, 0.088, 0.026 and 0.031 were attained during 2009, 2014, 2019 and 2022, respectively, indicating good classification accuracies. During 2009 and 2023, the main reason for the observed minimal disagreement is the quantity error and during 2014 and 2019, the root cause for the disagreement was allocation error. Overall, the accuracy results achieved in this study shows that the classification outputs are reliable and can be used for deriving valuable insights on bush encroachment trends and progression.

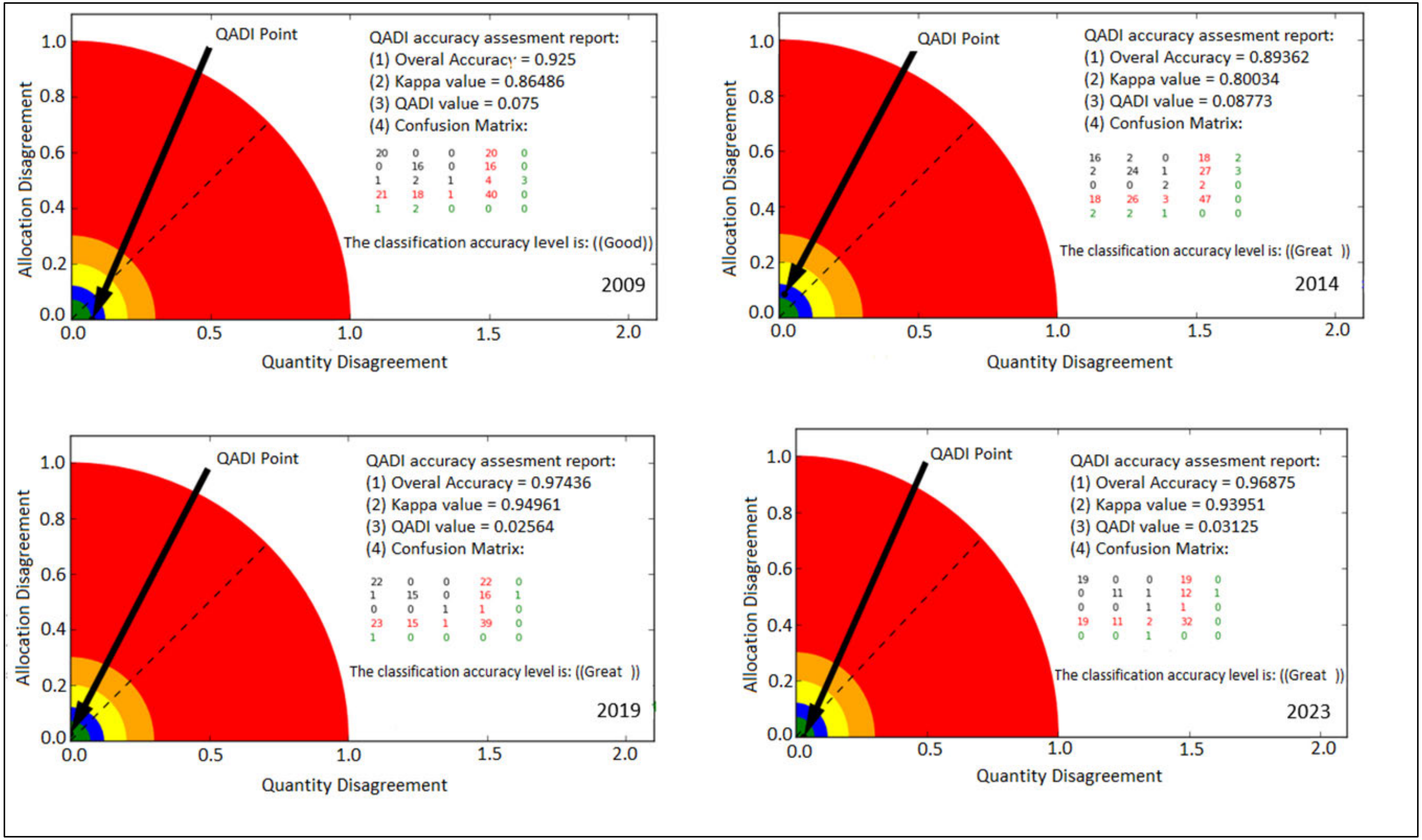

Figure 2.1: QADI graph showing the classification accuracy as a black dot.

2.3.2 Bush encroachment

Table 2.2 shows the area in ha and percentage of the area covered by woody vegetation and grasslands at Bisley Valley Nature Reserve. Woody vegetation increased significantly over the 14 years, causing a shrinkage in grasslands. During the study period, a shrinkage of approximately 123.36 ha (34.87%) of grasslands was recorded, whilst woody vegetation was found to have expanded by approximately 128.54 ha (36.33%). The findings also indicate a 13.49% augmentation in bush encroachment between 2009 and 2014, and 13.34% over the subsequent five-year span (2014 to 2019). During the period 2019 to 2023, the increase was moderate at 9.50%. Additionally, in the year 2009, grasslands exhibited dominance in land cover, encompassing an estimated 213.15 ha, which accounted for 60.25% of the Bisley Valley Nature Reserve. After a five-year period, and during 2019 and 2023, woody vegetation was the dominant land cover class (Table 2.2).

Table 2.2: Area (ha) and percentage cover of woody vegetation, grasslands, and bare areas in Bisley Valley Nature Reserve.

	2009		**2014**		**2019**		**2023**	
Classes	**Area**	**%cover**	**Area**	**%cover**	**Area**	**%cover**	**Area**	**%cover**
Woody vegetation	133.32	37.69	181.05	51.18	224.55	64.52	261.86	74.02
Grasslands	213.15	60.25	153.79	43.47	124.93	35.32	89.79	25.38
Bare areas	7.28	2.06	18.96	5.35	4.28	0.16	2.00	0.60

2.3.3 Spatial distribution of woody vegetation in Bisley Valley Nature Reserve

Figure 2.2 illustrates the multi-temporal evolution of woody vegetation within Bisley Valley Nature Reserve. The areas in brown represent woody vegetation, green representing grasslands and bare areas shown in light green colour. These maps demonstrate a prevailing pattern of dispersion of bush encroachment from the north-western perimeter towards the reserve's central expanse. The study's outcomes underscore that, in the year 2009, only a modest portion along the eastern fringe of Bisley exhibited woody encroachment. Across all four classifications spanning different years, substantial encroachment was concentrated in the north-western and central areas of Bisley, culminating in the near depletion of central grasslands by 2023. Throughout the study's duration, the north-eastern and southern regions were the least encroached portions of the reserve, characterized by ample open grasslands. Nevertheless, a subtle encroachment trend is apparent when advancing toward the southern periphery of the reserve.

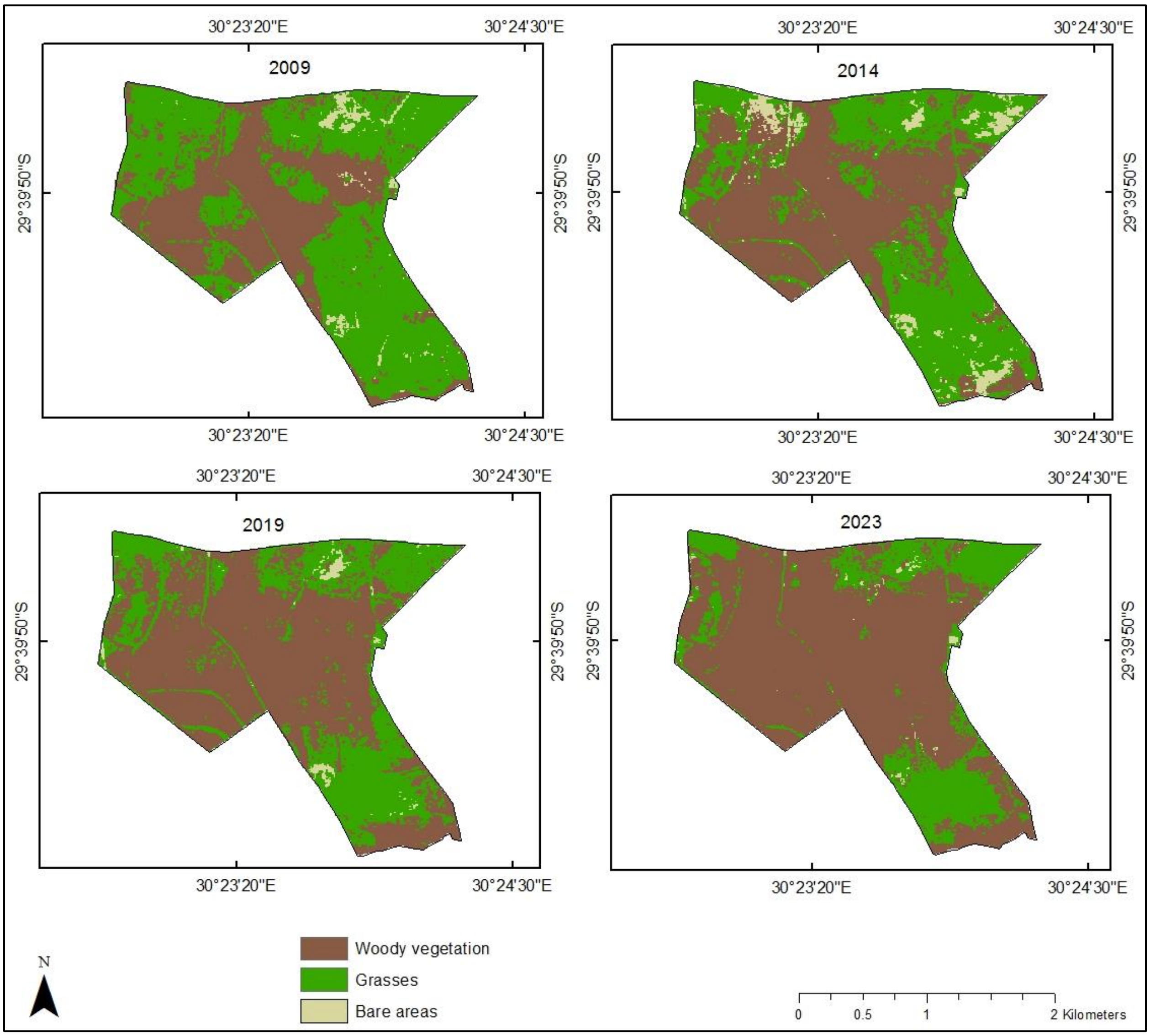

Figure 2.2: Classification map showing progression of woody vegetation in Bisley Valley Nature Reserve during the four different time periods.

2.3.4 Change detection results

Change detection was performed as the difference between every two time-intervals to illustrate the alterations at the study site during each period (Figure 2.3 and Table 2.3). The study's findings demonstrated that there was a reduction in grasslands area of the Bisley Valley Nature Reserve (Table 2.2), with both depletion and expansion of grassland being observed. During the study period, approximately 130.69 ha of grasslands were replaced by woody vegetation. Conversely, approximately 2.78 ha of woody vegetation transitioned to grasslands, as depicted in Table 2.3. The net increase in the total area of woody vegetation was approximately 127.91 ha. A moderate proportion of Bisley grasslands was also lost to bare areas. During the period 2009-2014, a significant 16.07 ha of Bisley grasslands transitioned to bare areas, whereas for the other periods, the transition from grasslands to bare areas was moderate to less than 2 ha. The results also show that large proportion of Bisley grasslands were lost during the period 2009-2014, when 58.63 ha of grasslands transitioned to woody vegetation and 16.07 ha of these grasslands also converted to bare areas. Nevertheless, a moderate proportion of Bisley grasslands was rehabilitated. For instance, 10.18 ha of woody vegetation transitioned to grasslands during the period 2009-2014. However, for the subsequent periods, the rate of grasslands rehabilitation decreased as shown in Table 2.3.

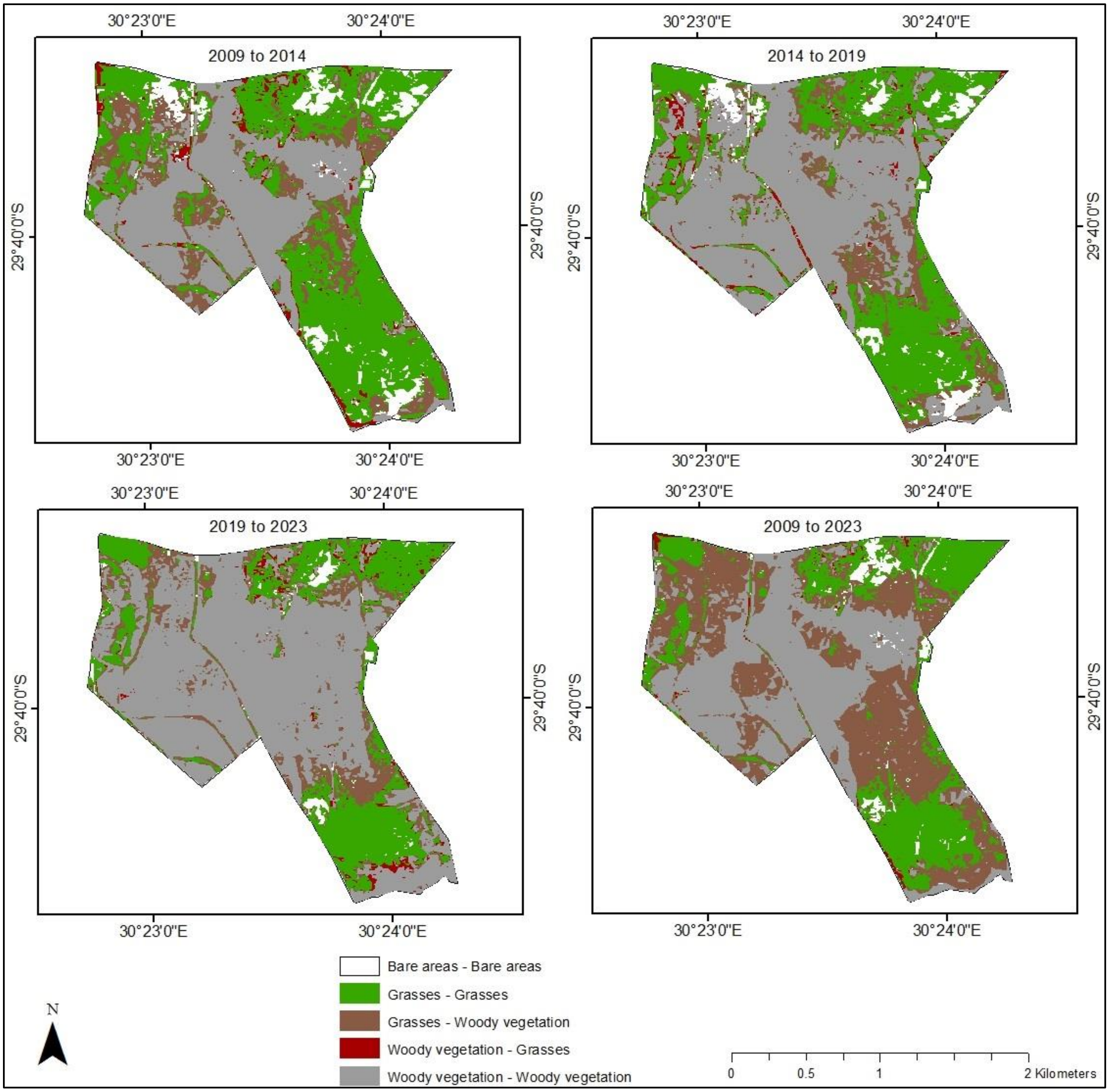

Figure 2.3: Change detection map of Bisley Valley Nature Reserve showing transition of woody vegetation and grasslands for different time periods.

Table 2.3: Transitions and area change in hectares (ha) between woody vegetation, grasslands, and bare areas in Bisley Valley Nature Reserve

	Area Change (ha)			
Classes	**2009-2014**	**2014-2019**	**2019-2023**	**2009-2023**
Grasslands to Grasslands	137.98	104.85	97.19	80.52
Grasslands to woody vegetation	58.63	47.24	44.10	130.69
Woody vegetation to Grasslands	10.18	8.74	6.96	2.78
Woody vegetation to woody vegetation	121.70	172.06	217.23	130.07
Grasslands to Bare areas	16.07	1.41	1.08	0.43
Bare areas to Grasslands	5.21	10.10	3.41	6.21

2.4. Discussion

Monitoring bush encroachment within a nature reserve is essential for preserving the integrity of the ecosystem and safeguarding its unique biodiversity (Lesoli et al., 2013). Regular assessment enables timely intervention to prevent the overgrowth of woody vegetation, ensuring that native plant communities and habitats remain intact and conducive to the survival of diverse flora and fauna. To achieve this, the current study employed a combined approach involving the RapidEye and PlanetScope sensors, in tandem with the Random Forest algorithm to monitor bush encroachment within Bisley Valley Nature Reserve over a 14-year period.

2.4.1 Bush encroachment in Bisley

The findings of this study demonstrated that bush encroachment increased significantly during the study period, causing a reduction in grasslands within the Bisley Valley Nature Reserve. During the study period, approximately 123.36 ha (34.87%) of grasslands was lost, whilst area of woody vegetation expanded by approximately 128.54 ha (36.33%). These findings are in agreement with the literature, for instance, O'Connor et al. (2014) reported that in recent decades, many landscapes in South Africa have seen a rapid expansion of woody vegetation. Skowno et al. (2017) reported similar findings of woody vegetation increase in the last two decades (1990-2013). Their study mapped bush encroachment in grassland biomes of South Africa and found woody vegetation to have increased by 57000 km^2. The phenomenon of bush encroachment is on the increase in Bisley Valley Nature Reserve as during 2009, only 37.69% of the area was encroached whilst for 2014, 2019 and 2023, encroachment increased to 51.18%, 64.52% and 74.02%, respectively.

The results of the current study also demonstrated that large proportions of Bisley grasslands were lost during the period 2009-2014, where majority of grasslands transitioned to woody vegetation and other grasslands also converted to bare areas (Table 2.3). The observed high progression of bush encroachment during 2009-2014 could confirm that during this period, Bisley experienced many disturbances such as rainfall variability and reduced fire intensity which usually supports overgrowth of invasive species. The expansion of woody vegetation during the 14-year study period could be attributed to many other factors including invasion by alien invasive tree species which tend to regenerate and grow fast and progressively dominate the landscape (Cubino et al., 2022, Gazoulis et al., 2022). The other factor that is believed to have a significant contribution to the observed expansion of woody vegetation, at least in recent years is change in climate conditions, particularly rainfall variability.

The connection between woody vegetation encroachment and climate change has been substantially reported in literature (Belayneh and Tessema, 2017, O'Connor et al., 2014, Shen et al., 2022). For instance, recently, a study by Maphanga et al. (2022) highlighted that bush encroachment is perceived to be associated with climate change events such as elevated rainfall variability and increase in concentrations of atmospheric CO_2. Similar to many other places in South Africa, particularly in the KwaZulu-Natal province, during the year 2014 and 2015, the study area experienced rainfall shortages with the annual rainfall ranges between 700 to 780 mm (Ndlovu and Demlie, 2020). The year 2015 was also one of the driest in South Africa, with the country’s annual rainfall declining to 403 mm (Donnenfeld et al., 2018). However, in the past few years, including 2022 and early 2023, the area received heavy rains which could have triggered rapid growth of woody vegetation. Nevertheless, since changes in small geographic extents are usually caused by specific land use activities (Skowno et al., 2017), it cannot be concluded that rainfall variability is the only major driver of change in the study area.

The presence of other factors such as bare areas could also be related to high encroachment in Bisley Valley Nature Reserve. Bare areas may act as niches for encroachment, particularly through reduction of grazing pastures and consequently increasing susceptibility of the remaining grasslands to overgrazing (Hopkinson et al., 2020, Shikangalah and Mapani, 2020). The loss of natural grasslands due to bush encroachment and bare areas was documented by D'Odorico et al. (2012) in arid grasslands and their review paper highlighted that such change could be attributed to disturbances such as overgrazing and climate change.

There is a link between bush encroachment, bare areas, and climate change. For instance, unprecedented climatic conditions cause disturbances in the landscape, particularly through land degradation which exposes more land and reduce cover of herbaceous vegetation (D'Odorico et al., 2012, Maphanga et al., 2022). Therefore, bare areas and bush encroachment both prohibit growth of grasslands and other herbaceous vegetation and could further exacerbates overgrazing and future encroachments (Shen et al., 2022). The correlation between inflated rates of bush encroachment and presence of bare areas was documented in the Maswa Game Reserve, Tanzania (Kimaro et al., 2019). Similarly Manjoro et al. (2012) found a simultaneous increase of woody vegetation and bare areas in the Mgwalwana catchment, Eastern Cape. The expansion of bush encroachment is also triggered by the landscape’s topography (Archer et al., 2017, Gxasheka et al., 2023). Landscapes with steeper slopes are usually most susceptible (Gxasheka et al., 2023). As a result, the expansion of woody vegetation in Bisley Valley Nature reserve could be correlated to the landscape’s topography, particularly steeper slopes which are dominant on the east side of the reserve.

2.4.2 Remote sensing of bush encroachment

Remote sensing approaches offer crucial strengths for robust monitoring of bush encroachment in finer landscapes. The findings of the current study demonstrate the importance of high spatial resolution data such as RapidEye and PlanetScope in acquiring critical spatial information on changes in smaller geographic extents like nature reserves (Pickering et al., 2021, Schuster et al., 2015). RapidEye and PlanetScope datasets allow for accurate delineation of land cover classes and ability to capture detailed information such as transitions between grasslands and woodlands (Cornejo-Denman et al., 2020). Moreover, these datasets have red-edge bands which enhance capturing of changes in reflectance of vegetation (Gašparović et al., 2018). The capabilities of RapidEye and PlanetScope demonstrate their importance for disturbance mapping, particularly in low-income countries as these datasets are now provided at no cost on platforms like Planet Education and Research program.

In the current study, the application of RapidEye and PlanetScope datasets demonstrated good classification results. For instance, the study yielded an overall accuracy of over 85% for all classifications with a high overall accuracy of 97.4% attained for 2019. The observed results denote strengths of remote sensing that concur with the literature. For instance, Khazieva et al. (2022) mapped patterns and drivers of bush encroachment in Kyrgyzstan grasslands using three sets of remotely sensed data (MODIS, Landsat and Sentinel-2) with overall classification accuracies of over 90%. The importance of remote sensing for analysis of land cover changes and landscape disturbances was also observed in a study by Gašparović et al. (2018) who conducted accuracy comparison of the land cover classifications using RapidEye, PlanetScope and WorldView-2. Their study yielded good classification accuracy of over 80% for all datasets.

Analysis of bush encroachment trends is also facilitated by the utility of machine learning algorithms. The performance of Random Forest algorithm proved to be good and reliable for monitoring bush encroachment as the study successfully mapped the progression of woody vegetation in Bisley with good overall accuracies. The strength of Random Forest algorithm in providing robust analysis of bush encroachment has also been previously documented in the literature (Ludwig et al., 2016, Qabaqaba et al., 2023). Using Random Forest, these studies reported high performance models for understanding dynamics of bush encroachment in grasslands of the KwaZulu-Natal province. Additionally, Random Forest algorithm is known to reduce the commission and omission errors (Symeonakis and Higginbottom, 2014b).

2.4.3 The role of management approaches in controlling bush encroachment

Disturbances in nature reserves transform grasslands to woody dominated landscapes (Ben-Shahar, 1992, Borgström et al., 2013, Yang et al., 2019). For instance, poor land use practices and burning as a management tool in grasslands support growth of woody vegetation at the expense of grasslands (Kgosikoma and Mogotsi, 2013). Consequently, the observed progression of woody vegetation in Bisley Valley Nature Reserve could be linked to management practices in the area. According to Kraai (2021), for over two decades, Bisley has been less prioritized by the UMsunduzi Municipality and as a result, the management of the reserve was very poor. During 2019, proper management of the Bisley came into action after recognition of falling of the reserve into disrepair, degradation of grasslands and related threats to wild herbivore, *Friends of Bisley Nature Reserve* Available at: https://www.fobnr.co.za/ (Accessed: 17 May 2023). The grasslands at Bisley are managed using controlled seasonal fires, manual clearance of alien invasive species and application of herbicides. However, due to negligence of management of the reserve before 2019, application of management schemes have not mitigated the encroachment of woody vegetation in the study area (Kraai et al., 2023). Bisley grasslands are considered vulnerable, but minimal role of control methods is also observed in the study area. For example, the results of the current study demonstrate that the rate of bush encroachment has been decreasing for every successive period and there was a reduction of bare areas after 2019 (Table 2.3).

In various landscapes, browsing contributes to controlling and reduction of competitive plant species such as alien invasive plants and improve landscape restoration through establishment of less competitive vegetation (Kraai et al., 2023). Mega browsers such as giraffe and elephant are known to contribute to controlling of bush encroachment through high browsing intensity (Kimaro et al., 2019). For instance, a study by Skowno et al. (2017) found that bush encroachment decreases substantially in protected areas with browser megafauna compared to those areas without mega browsers. The link between reduction or minimal expansion of woody vegetation and mega browsers was also reported in protected areas such as the Kruger National Park (Levick et al., 2009, Scholtz et al., 2018). The Bisley Valley Nature Reserve has a high giraffe population; five times more than the recommended number. However, the high population of giraffe seems to be less effective in controlling bush encroachment in the area as it is still prevalent and invade more grasslands every five-year period as observed in Table 2.2.

2.4.4 Implications and recommendations for future research

Based on the results of the current study, various implications were drawn to highlight the importance of critical analysis of bush encroachment dynamics for better management of nature reserves and safeguarding of biodiversity and conservation goals. The use of classification and change detection techniques provides valuable insights on progression of bush encroachment and can be considered an initial step towards understanding the magnitude of change in the landscape (Vivekananda et al., 2021). However, the process of decision making and devising of targeted management strategies could require more detailed information on change patterns across the periods (Feng et al., 2020, Huang et al., 2012). As a result, it is recommended that future research should analyze bush encroachment using intensity analysis which is the approach that has been extensively used particularly in land cover classification to provide more in-depth insights on transitions and rate of change in the landscape. Intensity analysis could enhance understanding of bush encroachment dynamics in nature reserves and provide conservationists with critical information on the extent and intensity of change from grasslands to woody vegetation, woody vegetation to grasslands and transition to other categories. Additionally, future research should conduct predictions of future encroachment outlooks. Such information may also provide important insights and contributes to restoration and management of grasslands at Bisley.

2.5. Conclusion

The analysis of historical bush encroachment trends and measurements of the extent to which woody vegetation has replaced grasslands is pivotal for management of the Bisley Valley Nature Reserve. This study utilized RapidEye and PlanetScope datasets to perform a change detection analysis. Results revealed that despite management practices, Bisley grasslands are continuously threatened by bush encroachment. The study's findings lead to the conclusion that:

(i) The application of RS technology such as high spatial resolution datasets facilitate monitoring of bush encroachment.

(ii) RapidEye and PlanetScope datasets are efficient and reliable for acquiring detailed spatial data showing trends and patterns of bush encroachment in Bisley Valley Nature Reserve.

(iii) Bush encroachment significantly reduced the area of grasslands of the Bisley Valley Nature Reserve with over 70% of grasslands encroached.

High spatial resolution datasets used in this study were valuable for understanding trends and patterns of bush encroachment and hence the utility of these tools can help in devising effective grasslands management strategies. Consequently, RapidEye and PlanetScope could contribute to prevention of further encroachment and rehabilitation of grasslands. Future studies should also use the freely available RapidEye and PlanetScope datasets to understand potential drivers of change in protected areas and safeguard biodiversity of such areas.

Chapter Three: Bush Encroachment: modelling transformation using Intensity Analysis and Cellular Automata Model

This chapter is based on a research paper:

Mncwabe, N.P., Odindi, J., Matongera, T.N., and Mutanga, O. (Under review). Bush Encroachment: modelling transformation using Intensity Analysis and Cellular Automata Model. *Environmental Monitoring and Assessment*, Manuscript ID: d3e80a49-db63-45e4-941e-016cc9f1df8a.

Abstract

Grassland intrusion by woody species is a globally recognized phenomenon associated with adverse impacts that include degradation and loss in biodiversity, thereby challenging conservation of keystone and flagship species, landscapes' recreational value and people's livelihoods. Hence, a comprehensive analysis of bush encroachment is necessary to provide insights on the past, present and future encroachment, and the severity of transitions. Using the RapidEye and PlanetScope satellite imagery, this study adopted the intensity analysis and the Cellular Automata (CA) models to understand past, current, and future (2009-2033) bush encroachment trends in a protected area. The results demonstrated a steady increase in woody encroachment on other land cover types. Analysis of land cover intensities shows an intensive change in the study area's land cover in the first period (2009-2014) compared to the other periods. During the first two periods (2009-2014 and 2014-2019), woody vegetation gains were at the expense of grassland but partially avoided gaining from grassland during the period 2019-2023. The majority of grassland gains in the area were derived from bare areas and its losses mainly from woody vegetation. The prediction of future encroachment outlooks demonstrated an increasing trend of woody vegetation in the next decade. The results also show that bush encroachment area will expand by 5.50% in 2028 and by 6.67% in 2033. The outcomes of this study demonstrated that there is a pressing need for evaluation and improvement of management schemes in the area, and indeed similar landscapes threatened by woody encroachment. Critical insights on bush encroachment progression trends and intensities of transitions contribute to prioritizing landscape management and aid decision making for restoration of grasslands.

Key words: Bush encroachment, Intensity analysis, Prediction, Cellular Automata model, Nature reserve.

3.1 Introduction

Bush encroachment is a global concern that occurs when a grass dominated landscape is encroached by woody vegetation and result in the suppression of palatable grasslands (Belayneh and Tessema, 2017, Yassin, 2019). The phenomenon has gained great interest due to its impact on various landscapes such as grasslands, savannas, and protected areas (Atkinson et al., 2022, Borges et al., 2022, Stephen et al., 2023). In Southern Africa for instance, bush encroachment is considered a prevalent occurrence that affects approximately 0.131 to 1.275 percent of the landscape per year (O'Connor et al., 2014). Stafford et al. (2017) also reported that bush encroachment occupies about 10-20 million ha of South African grasslands and savannas. Recently, Mndela (2020) highlighted that bush encroachment threatens approximately 7.3 million ha of the entire South Africa's land area. Woody vegetation encroachment is also common in countries like Namibia, affecting an estimated 26-30 ha of the country's grasslands (Stafford et al., 2017).

Bush encroachment phenomenon is commonly more dire in protected areas such as nature reserves (Hudak and Wessman, 2001a). These landscapes hold significant conservation and recreational value due to their rich diversity of animal and plant species (Xu et al., 2020). However, due to injudicious management practices, majority of nature reserves are commonly susceptible to bush encroachment (Shekede et al., 2015). In such landscapes, bush encroachment threatens various ecosystem functions, biodiversity of flora and fauna, recreational opportunities, and people's livelihoods (Mogashoa et al., 2021, Nakanyala and Hipondoka, 2020, Wiegand et al., 2006). The intrusion of woody vegetation in nature reserves also modifies the landscape, increasing its susceptibility to soil erosion and affects nutrient cycling and landscape productivity (Hudak and Wessman, 2001a, Stewart et al., 2022). Moreover, bush encroachment restrains the diversity of habitat structure and impact the quantity and quality of land suitable for grazing hence exacerbates the susceptibility of the reserve to grazing intensities (De Klerk, 2004). Bush encroachment also interferes with densities of wild herbivores and carrying capacity of the reserve and increase management costs (Ayelew and Mulualem, 2018, O'Connor et al., 2014, Stafford et al., 2017). Given these threats, it is indispensable to understand the progression, trends, and spatio-temporal patterns of this phenomenon.

Monitoring and understanding bush encroachment is vital for the protection and management of nature reserves (Ben-Shahar, 1992). In this regard, the availability of innovative technologies such as Remote Sensing (RS) allows for precise analysis of bush encroachment at various spatial extents (Maphanga et al., 2022, Oldeland et al., 2010). RS technologies facilitate the process of acquiring explicit information on spatio-temporal changes of bush encroachment, contributing to decision making for management of nature reserves (Graw et al., 2016, Ludwig et al., 2016). Specifically, the availability of high spatial resolution sensors opens new research opportunities for improved local-scale landscape delineation and assessment of land cover transitions, necessary for improved evaluation of landscape vulnerability to bush encroachment. For instance, datasets such as RapidEye and PlanetScope provide detailed spatial and spectral information valuable for assessment and mapping of vegetation health and environmental changes (Gašparović et al., 2018, Roessler et al., 2013). The inclusion of RapidEye's additional red-edge band for instance, enhances sensitivity to chlorophyll content changes, facilitating improved mapping and discrimination of vegetation types (Kim and Yeom, 2015, Marx and Tetteh, 2017, Zhang et al., 2021).

The value of high spatial resolution image datasets has been shown in various vegetation mapping and modelling applications (Adam et al., 2014, Balha et al., 2021, Khare et al., 2018, Neyns and Canters, 2022). However, for a detailed understanding of bush encroachment, effort beyond transition mapping is critically important (Akinyemi et al., 2017, Xie et al., 2020). Hence, methods such as the intensity analysis can be utilized for a comprehensive understanding of the change processes associated with encroachment of woody vegetation and to quantify the dynamics of transitions in the landscape (Osman et al., 2023). Intensity analyses is the mathematical framework that has been extensively utilized for Land Use Land Cover (LULC) analyses at three hierarchies namely, interval, categorical, and transition levels (Pontius Jr et al., 2013). The method has been adopted in among others China (Zhou et al., 2014), Ghana (Ekumah et al., 2020), Iran (Kourosh Niya et al., 2019) and Kenya (Osman et al., 2023) to provide insights into the dynamics, drivers, and impacts of land cover changes.

Intensity analyses is particularly important in assessing annual change area and change intensity of landcover transitions over different periods by comparing the observed change with the uniform landcover changes (Aldwaik and Pontius Jr, 2012, Xie et al., 2020). The method is also useful for comprehending gains and losses to a specific land cover class (Feng et al., 2020). For instance, it can be used to evaluate why the area transition from land cover class A to class B is greater than the transition from other land cover classes (Quan et al., 2020). Moreover, intensity analysis has the potential to establish the extent of bush encroachment and provide invaluable information on active and dormant categories, revealing the stationarity of processes and pattens of change (Huang et al., 2012). Generally, this method presents an opportunity for in-depth analysis of bush encroachment and can substantially enhance our understanding of the phenomenon at various spatial extents. Its invaluable insights can also support land management strategies, conservation efforts, and sustainable development in nature reserves and indeed other protected areas (John et al., 2013).

Reliable assessment of bush encroachment and optimal management of protected areas could also be facilitated by prediction of future encroachment and a landscape change (Liao et al., 2018, Taylor et al., 2018). Based on accurately classified landcover change maps, studies have simulated future bush encroachment patterns for understanding the dynamics and severity of the phenomenon in grasslands and other landscapes (Cao et al., 2019, Caracciolo et al., 2014). Prediction of future encroachments is particularly useful for analyses of ecosystem vulnerability to bush encroachment and to various other related phenomena such as overgrazing, land degradation and effects of climate change (Liao et al., 2018). Furthermore, land cover simulation models are essential for providing valuable information for long-term management planning (Munthali et al., 2020, Verburg et al., 2019). They contribute to understanding the spatiotemporal patterns of bush encroachment helping managers to develop adaptive management strategies that account for future changes in vegetation dynamics and ecosystem structure (Osman et al., 2023). Moreover, predictive models can serve as early warning systems, allowing managers to anticipate and mitigate the severity of bush encroachment (Briassoulis, 2020, Melesse et al., 2007). In protected areas, prediction of future encroachment can also help optimize resource allocation by identifying priority areas for intervention through targeted efforts on areas most susceptible to encroachment (Wang et al., 2018, Gao et al., 2020). In protected areas, land cover simulation models can also be used to inform policy development and land use planning.

Among the often utilized simulation models for land cover changes is the Cellular Automata (CA) Model (Qiang and Lam, 2015, Saputra and Lee, 2019, Xing et al., 2020). The CA, a spatially dynamic model utilizes remotely sensed data and environmental variables to facilitate land cover simulation and provide detailed insights on land cover transitions (Behera et al., 2012, Yagoub and Al Bizreh, 2014). The model uses artificial intelligence algorithms such as Artificial Neural Network (ANN) and employs multilayer perception (MLP)-ANN learning process to replicate land cover processes and provide reliable prediction of landscape's changes (Tong and Feng, 2020). Moreover, the CA model is robust, simple to calibrate and well adapted for spatial and temporal modelling land cover changes in complex landscapes (Sajan et al., 2022). The CA model is popular for its reliability in modelling land cover changes (Ghalehteimouri et al., 2022, Khan et al., 2022, Koko et al., 2020). Mahamud et al. (2019) for instance, employed the CA model to examine future land use land cover outlooks in Kelantan, Malaysia, and attained an overall accuracy of 78.57%. Saputra and Lee (2019) also used the model to simulate future land cover changes for the years 2050 and 2070 in North Sumatra, Indonesia and attained 87.28% accuracy and kappa value of 83%. The CA model was also employed to determine future landcover prediction in Dhaka, Bangladesh with 96.62% accuracy and kappa value of 95% (Kafy et al., 2021).

The application of land cover simulation models, in tandem with the intensity analysis can be valuable to understanding the dynamics and trends of bush encroachment in protected areas. Consequently, studies are necessary for effective management strategies to rehabilitate grasslands and prevent further encroachment. Therefore, this study sought to compute and analyze spatiotemporal changes of bush encroachment from 2009 to 2023 in the Bisley Valley Nature Reserve using the intensity analysis and to predict future bush encroachment in Bisley utilizing the Cellular Automata (CA) Model.

3.2 Materials and Methods

3.2.1 Data description

The study utilized two distinct datasets; environmental variables, and land cover change maps. The latter encompassed classification for the years 2009, 2014, 2019, and 2023. Land cover change maps were created using RapidEye and PlanetScope images that were acquired from Planet Education and Research (https://www.planet.com/). The platform provides datasets that are already atmospherically corrected to surface reflectance.

The data on environmental variables included the Digital Elevation Model (DEM), slope, aspect, distance from the road and Topographic wetness index (TWI), (Figure 3.1). Environmental variables are spatial references that are critically important in identifying the driving factors for the landscape design and significantly influence encroachment of woody vegetation. The DEM is among the popularly utilized datasets for analysis of land cover change and vegetation prediction, particularly due to its value in deriving other key datasets such as slope, aspect, and vegetation indices (Hansen and Loveland, 2012, Singh et al., 2018). DEM offers valuable information on the terrain and is critically important for the analysis of spatiotemporal changes in relation to elevation (Mishra et al., 2020). Slope and aspect are other fundamentally important variables in LULC predictive models (Birhanu et al., 2019, Iqbal and Khan, 2014). These variables create spatial variation and influence growth and distribution of vegetation (Hao et al., 2021). The distance from the road is also a key parameter in the analysis of vegetation dynamics. For instance, disturbance from road significantly impacts soil characteristics and vegetation composition, and usually reduces plant diversity (Deljouei et al., 2018). Additionally, the Topographic Wetness Index is frequently utilized in vegetation analysis, particularly due to its strength in determining soil moisture and influence in vegetation pattens (Hojati and Mokarram, 2016, Slezák et al., 2022). The 10m spatial resolution DEM was acquired from the Alaska Satellite Facility data search vertex (https://search.asf.alaska.edu/#/) and used to derive slope and aspect. The shapefile for Bisley roads was acquired from the OpenStreetMap platform (https://www.openstreetmap.org) and used to derive data for distance from the road using the Euclidean distance tool in ArcMap 10.4 software.

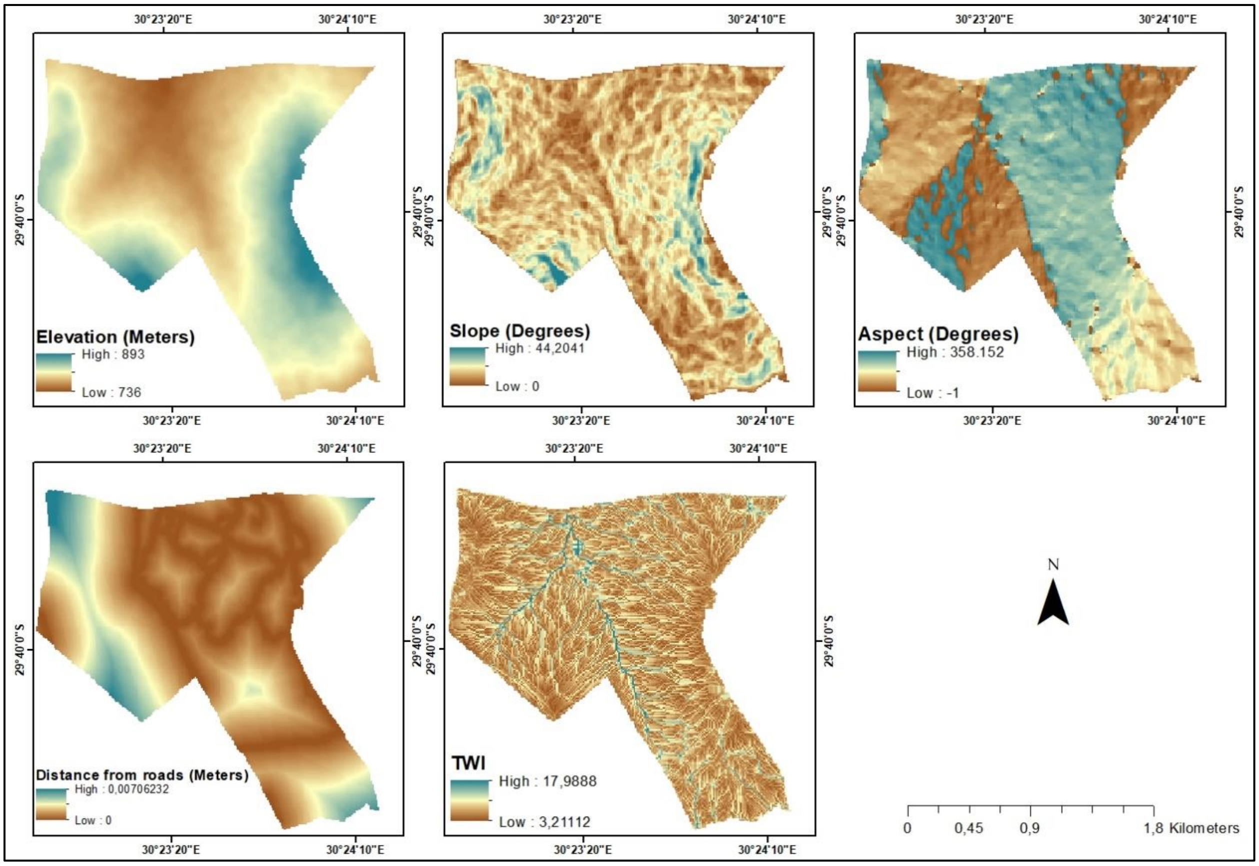

Figure 3.1: Environmental variables used for bush encroachment future prediction.

3.2.2 Image Classification

The RapidEye and PlanetScope data obtained at five-year intervals were used for creation of land cover change maps spanning from 2009 to 2023. Specifically, the study used three RapidEye images tailored for the years 2009, 2014, and 2019 and one PlanetScope image for the year 2023. A total of three land cover classes were selected namely, woody vegetation, grasslands, and bare areas and the maps were classified inside the Google Earth Engine (GEE) platform using Random Forest (RF) algorithm. The RF algorithm is the popularly used machine learning algorithm for classification of land cover (Adam et al., 2014, Symeonakis and Higginbottom, 2014a). The algorithm is capable of managing and performing well with large and noisy data, reduce overfitting, and provides good classification accuracy in comparison to other machine learning algorithms (Phan et al., 2020, Qabaqaba et al., 2023, Zhang et al., 2017).

3.2.3 Change detection

Four bush encroachment classification maps were produced during the different periods. The first three classification maps for the years 2009, 2014, and 2019 are depicting changes in a five-year interval and the fourth map is showing changes in a four-year interval. The transition maps and their corresponding transition matrices were created by developing a code in the GEE platform and using the four classification maps. For instance, to compute the first transition map showing the change in total area of woody vegetation and grasslands, the 2009 and 2014 classification maps were used, and 2014 and 2019, 2019 and 2023 and 2009 and 2023 used to create the remaining three transition maps.

3.2.4 Accuracy assessment

Assessment of the reliability of classification results was conducted using the confusion matrix. The method utilizes popular metrics, namely the overall accuracy, producer's accuracy, and user's accuracy, to assess the classified maps and provide insights on the model performance. Additionally, the Kappa index was used to calculate the proportion of pixels that were accurately classified and evaluate the observed accuracy and predictable accuracy. However, there are concerns regarding the use of Kappa as it has been noted to be misleading for practical applications and computes agreement based on level of chance. Due to this limitation, the study also used Quantity and Allocation Disagreement Index (QADI) to assess the level of agreement between the reference and classification map (Pontius Jr and Santacruz, 2014). The QADI index evaluates accuracy using two types of errors, namely the quantity disagreement and allocation disagreement. Quantity disagreement is the disparity in each class's pixel count between the reference and classification map whereas allocation disagreement is the counts of pixels that were incorrectly identified. The QADI index values range between 0 and 1, where the value close or equal to zero represent a low disagreement between training data and classification results and the value of one or close to one represents a high disagreement (Pontius Jr and Millones, 2011). The confusion matrix was used to compute the QADI index in ArcMap 10.8 using the Feizizadeh et al. (2022) toolbox that can be accessed via the link: (https://drive.google.com/file/d/1lMDVknlfFFWDC5k1F0GVQpcb7vJfRwEK/view).

3.2.5 Intensity analysis

Intensity analysis was utilized to analyze transition maps and determine the variations of land cover change patterns across the periods. The method provides a more detailed analysis of landscape changes and links change patterns across classes with their associated processes. Intensity analysis use transition matrices to quantify the annual change intensity in each period at three levels, namely time interval, category, and transition (Pontius Jr et al., 2013). The assessment of time interval level calculates the size and rate of change over a certain period. Time interval level is important for determining which period has fast and slow annual rate of overall change. For every time interval, the category level computes variations in the size and intensity of change (total losses and total gains) amongst land cover classes. Category level asses which land cover classes are active, and which are dormant in a particular period. The transition level on the other hand is based on the time interval and category level. Transition level deals with the amount and direction of transitions across land cover classes at each period. Moreover, the transition level evaluates if transitions are intensive or not and if they are targeted or avoided by specific land cover class.

The intensity analysis across various periods of the study was conducted using an open-source Microsoft Excel programme from the Intensity Analysis website (https://sites.google.com/site/intensityanalysis/). The programme computes intensities using equations (1) - (6) below (Aldwaik and Pontius Jr, 2012).

$$S_t = \frac{\text{Area of change during interval } [Y_t, Y_{t+1}]}{(\text{Duration of interval } [Y_t, Y_{t+1}]) * (\text{Area of study region})} 100\% \quad (1)$$

$$U = \frac{\text{area of change during all intervals}}{\text{Duration of all intervals} * (\text{Area of study region})} 100\% \quad (2)$$

$$G_{tj} = \frac{\text{Area of annual gain of category j during interval } [Y_t, Y_{t+1}]}{\text{Area of category j at } Y_{t+1}} 100\% \quad (3)$$

$$L_{ti} = \frac{\text{Area of annual loss of category i during interval } [Y_t, Y_{t+1}]}{\text{Area of category i at } Y_t} 100\% \quad (4)$$

$$R_{tin} = \frac{\text{Area of annual transition from i to n during interval } [Y_t, Y_{t+1}]}{\text{Area of i at } Y_t} 100\% \quad (5)$$

$$W_{tn} = \frac{\text{Area of annual gain of category n during interval } [Y_t, Y_{t+1}]}{\text{Area of not category n at } Y_t} 100\% \quad (6)$$

Table 3.1. Mathematical symbols used for calculation of intensities as described by Aldwaik and Pontius Jr (2012).

Symbol	Description
Y_t	year at time point t
t	index for the initial time point of an interval $[Y_t, Y_{t+1}]$, where t ranges from 1 to T−1
J	number of categories
i	index for a category at the initial time point of an interval
j	index for a category at the latter time point of an interval
n	index of the gaining category for the selected transition
S_t	annual change during interval $[Y_t, Y_{t+1}]$
U	uniform annual change during extent $[Y_t, Y_t]$
G_{tj}	intensity of annual gain of category j during interval $[Y_t, Y_{t+1}]$ relative to size of category j at time t+1
L_{ti}	intensity of annual loss of category i during interval $[Y_t, Y_{t+1}]$ relative to size of category i at time t
R_{tin}	intensity of annual transition from category i to category n during interval $[Y_t, Y_{t+1}]$ relative to size of category i at time t
W_{tn}	uniform intensity of annual transition from all non-n categories to category n during interval [γt−γt+1] relative to size of all non-n categories at time t

At interval level analysis, the assessment includes evaluating the total change in every time interval, as well as examining both the observed change and the uniform rate of change. At this level, equation 1 was used to calculate each interval's annual rate of total change by dividing transition size by the time interval to acquire a spatial extent percentage. Equation 2 was used to calculate the uniform rate, specifically the change that would happen if the annual changes were distributed uniformly over the study period. Each interval's annual change intensity is then compared to a uniform annual change rate. For category level of intensity analysis, equation 3 was utilized to calculate intensity of annual total gains for each land cover class. This is the percentage of additional surface area covered by the land cover class. On the other hand, equation 4 was used to calculate intensity of annual gross loss. This is the percentage of surface area that is no longer occupied by the land cover class compared to total surface area previously covered by that land cover class. Acquired annual gross gains and losses were then compared with the uniform intensity of change. Furthermore, the study evaluated variations of the intensity of transitions from one land cover class to the other during each time interval. This stage involves evaluating transition's intensity towards a particular land cover class (gain) using equation 5 and assessing transition's intensity from a specific land cover class (loss) using equation 6. Transitions were evaluated in terms of whether they intensively prefer to gain from certain land cover class or avoid gaining from that land cover class.

3.2.6 Cellular Automata (CA) Model

The CA model was utilized for prediction of future land cover changes in the study area using the Modules for Land-Use Change Simulation (MOLUSCE) plugin in QGIS version 2.18.24. The MOLUSCE plugin was created to assess, model, and simulate future Land Use Land Cover (LULC) change (Aneesha Satya et al., 2020, Kamaraj and Rangarajan, 2022, Muhammad et al., 2022). MOLUSCE plugin is also suitable for analysis of past LULC changes (Al-Rubkhi et al., 2017). It uses popular algorithms such as cellular automata (CA), Logistic Regression (LR) and Artificial Neural Network (ANN) (Değermenci, 2023, Guidigan et al., 2019). The ANN algorithm and Multilayer Perception (MLP)-ANN learning process were employed for this study to model future land cover changes using six prediction phases namely, inputs, evaluation correlation, area change, transition potential modeling, MLP-ANN, and validation.

During the input phase, the classified maps for land cover change and environmental variables were inserted into the MOLUSCE plugin. All datasets were prepared and set to the same spatial resolution of 10 m and WGS 84 geographical coordinate system. For the first stage of the model, the 2014 classification map was used as the initial classified raster image and 2019 utilized as the final raster image. The initial and final raster images were then added to the model together with the environmental variables (DEM, slope, aspect, distance from road, and Topographic Wetness Index) to prepare for the other stages of prediction of future bush encroachment trends. During the evaluation correlation phase, the model evaluates the correlation between two raster images or environmental variables using the Pearson's correlation, Cramer's V coefficient or Joint information uncertainty (Hakim et al., 2019). This research utilized the Pearsons correlation to test the correlation between driving factors. Then, the model computed the area change in ha from one land cover class to another between the initial (2014) and final year (2019). For the transition potential modeling stage, the model used the MLP-ANN learning process to simulate land cover transition potential (Hyandye and Martz, 2017, Kamaraj and Rangarajan, 2022). The method uses land cover change information and geographic factors as input to predict future trends of the investigated categories (Rahman et al., 2017). Next, the Cellular Automator Simulation phase was utilized for prediction and creation of future land cover map using the MLP-ANN learning process. The study simulated 2023 map using 2014 and 2019 classification maps and the selected environmental variables presented in figure 3.1. The accuracy of the model was assessed using the model's validation process which includes the comparison of the overall percent of correctness and Kappa value of the reference (Classified 2023) and simulation (simulated 2023) maps. After completing all six stages of the simulation process using the CA Model, raster maps for 2028 and 2033 depicting simulated bush encroachment pattens were generated.

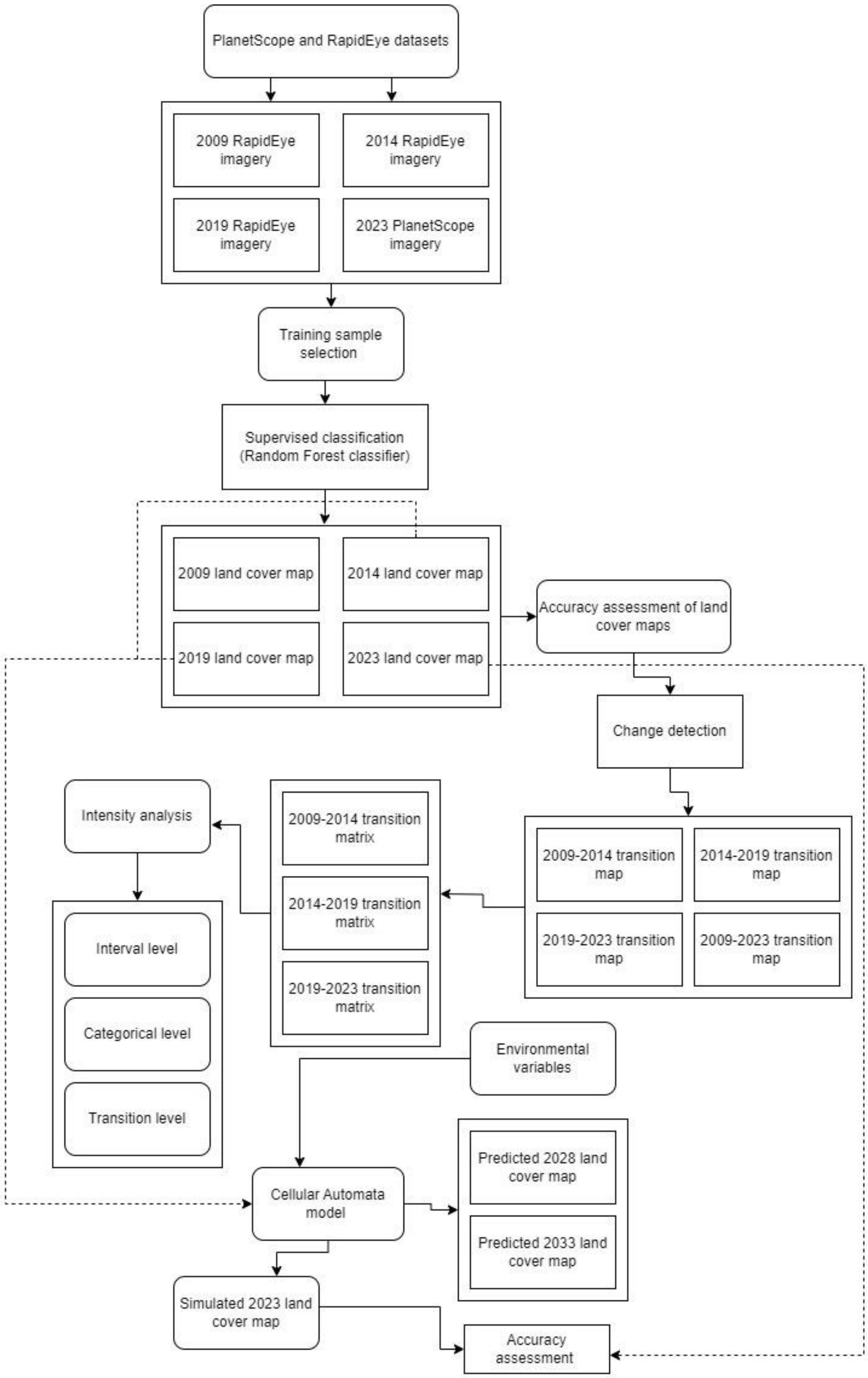

Figure 3.2: Methodology flowchart for land cover intensity analysis and simulation of future bush encroachment.

3.3 Results

3.3.1 Bush encroachment between 2009 and 2023

The results from the classification maps and change matrix show increasing bush encroachment over the study period as illustrated in Figure 3.3 and Table 3.2. Over the 14-year study period, woodlands increased by approximately 128.54 ha (36.33%), while grasslands decreased by approximately 123.36 ha (34.87%). The percentage of the area that is covered by woody vegetation, grasslands and bare areas varied across the periods. Initially, of the three landcover classes, grasslands were the dominant landcover class, occupying an estimated 213.15 ha (60.25%) of the study area. However, over the subsequent years, woody vegetation was dominant, covering 51.18%, 64.52%, and 74.02% in 2014, 2019, and 2023, respectively.

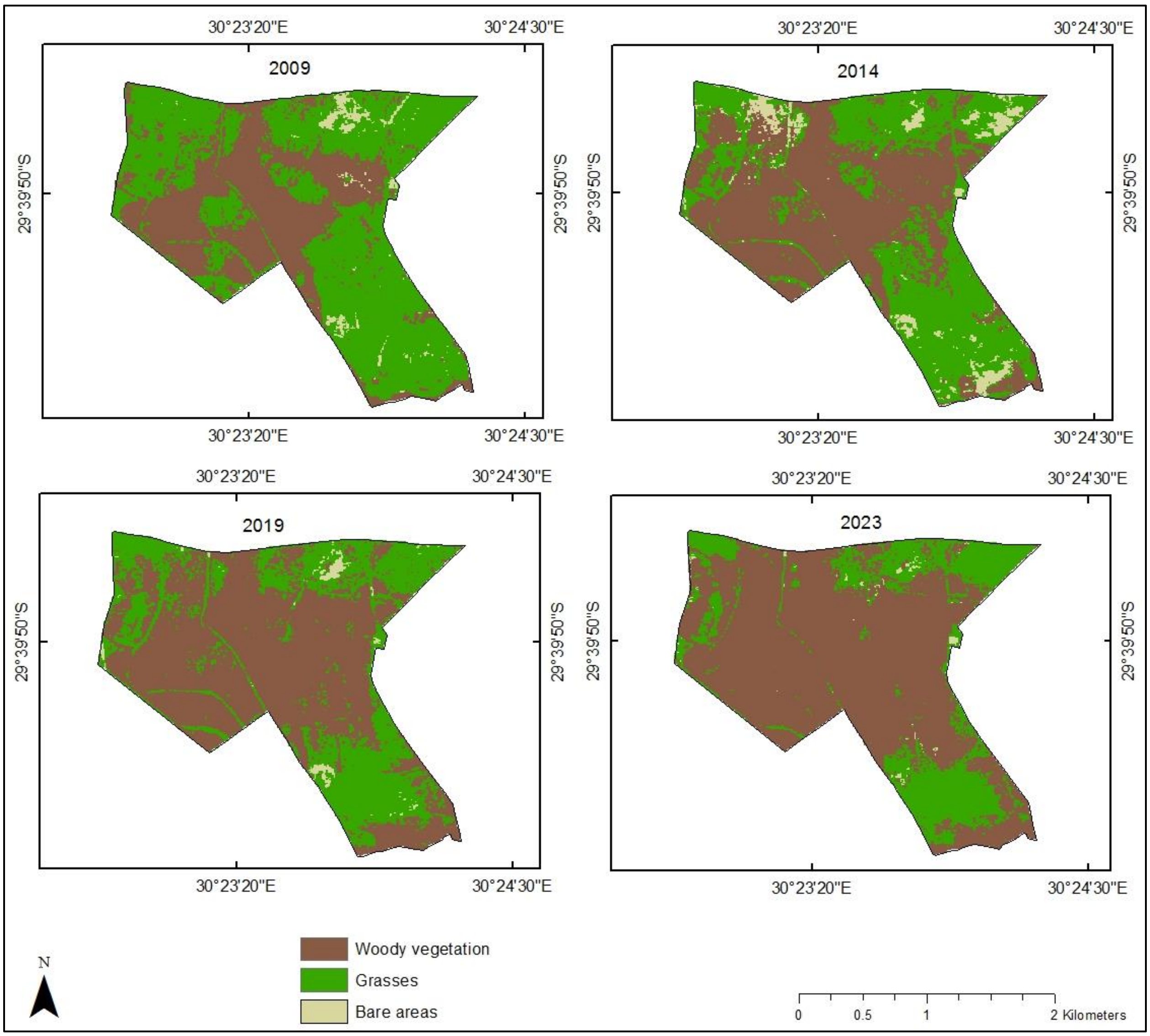

Figure 3.3: Classification map showing progression of woody vegetation in Bisley Valley Nature Reserve during the study period.

Table 3.2: Area (ha) and percentage cover of woody vegetation, grasslands, and bare areas in Bisley Valley Nature reserve.

	2009		**2014**		**2019**		**2023**	
Classes	**Area**	**%cover**	**Area**	**%cover**	**Area**	**%cover**	**Area**	**%cover**
Woody vegetation	133.32	37.69	181.05	51.18	224.55	64.52	261.86	74.02
Grasslands	213.15	60.25	153.79	43.47	124.93	35.32	89.79	25.38
Bare areas	7.28	2.06	18.96	5.35	4.28	0.16	2.00	0.60

3.3.2 Change statistics

The land cover transitions were computed to show gains and losses in landcover classes between the different periods (Figure 3.4 and Table 3.3). The findings of the study demonstrate that the nature reserve is progressively threatened by bush encroachment. However, there was a general shrinkage in area encroached during the study period. For instance, a decrease of 19.43% in transition from grasslands to woody vegetation was recorded from the period 2009-2014 to the period 2014-2019, and a minimal decrease of 6.65% from the period 2014-2019 to the next period (2019-2023). During the study period, about 36.94 percentage area of grasslands transitioned to woody vegetation, whereas approximately 0.78 percentage area of woody vegetation was converted to grasslands. Another portion of the study area was lost to bare areas, with a noticeable 4.54% area of the class lost in 2009-2014.

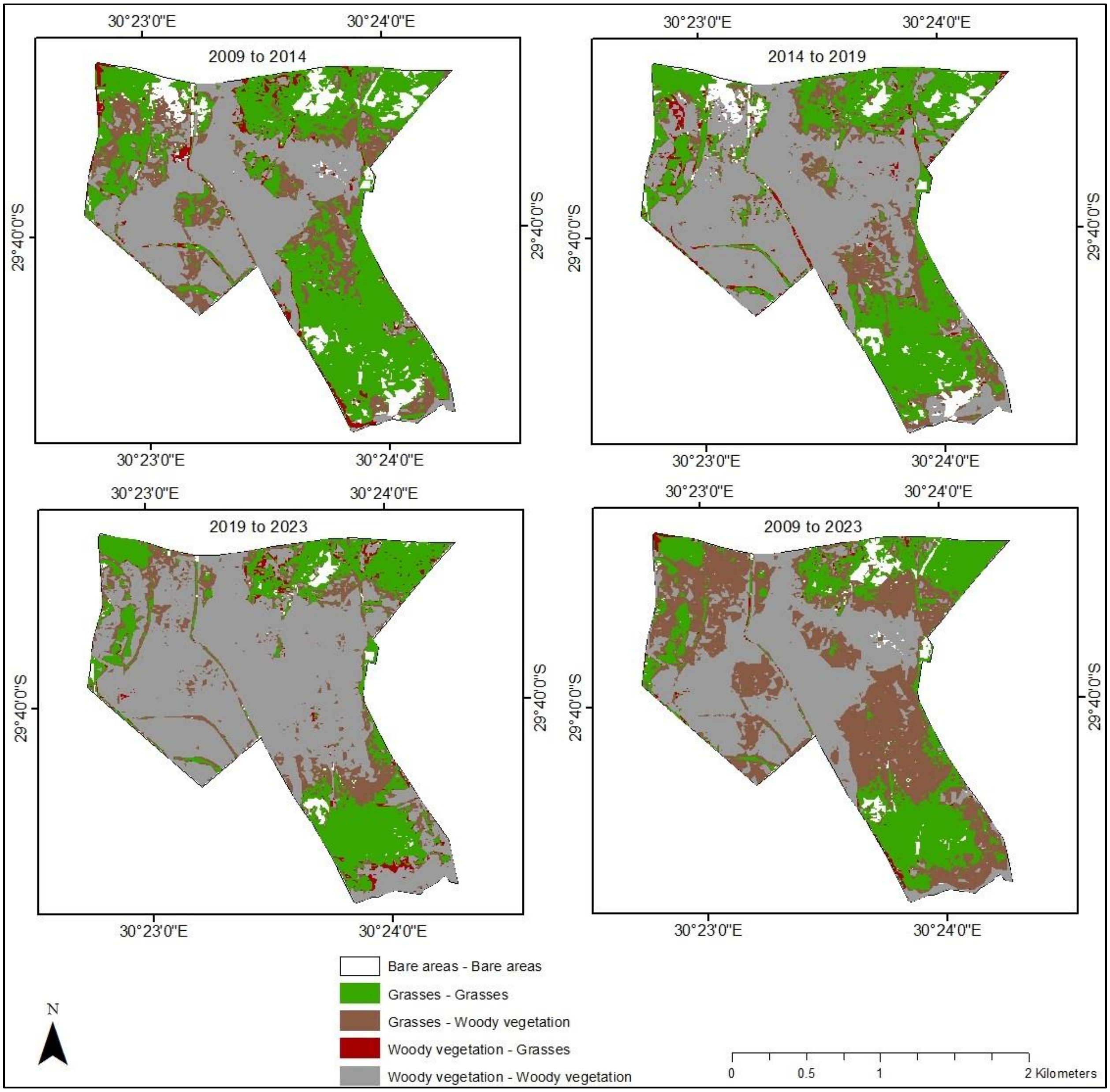

Figure 3.4: Change detection map of Bisley Valley Nature Reserve showing transition of woody vegetation and grasslands for different time periods.

Table 3.3: Transitions and area change in hectares (ha) between woody vegetation, grasslands, and bare areas in Bisley Valley Nature Reserve.

	Area Change (ha)			
Classes	**2009-2014**	**2014-2019**	**2019-2023**	**2009-2023**
Grasslands to Grasslands	137.98	104.85	97.19	80.52
Grasslands to woody vegetation	58.63	47.24	44.10	130.69
Woody vegetation to Grasslands	10.18	8.74	6.96	2.78
Woody vegetation to woody vegetation	121.70	172.06	217.23	130.07
Grasslands to Bare areas	16.07	1.41	1.08	0.43
Bare areas to Grasslands	5.21	10.10	3.41	6.2

3.3.3 Intensity analysis

Figure 3.5 indicates findings of the interval level intensity. Figure 3.5a represents the observed change intensity over different time periods and Figure 3.5b shows the annual change in area between different periods. The terminologies, fast and slow are used to indicate the intensity of land cover changes and particularly define whether the landscape changes were fast or slow. The event where changes exceed the uniform intensity line indicates the fast intensity of landcover transitions and falling below the line for the slow intensity of transitions. The research findings revealed that the period 2009-2014 exhibited a fast annual change intensity (5.20% per year against a uniform intensity of 4.45%) and fast change intensity/transition rate (25.98% per year against a uniform intensity of 22.26%). During the other time intervals, 2014-2019, and 2019-2023 both the annual change and transition rates fall below the uniform line, indicating a slow annual change intensities and transition rates during the periods.

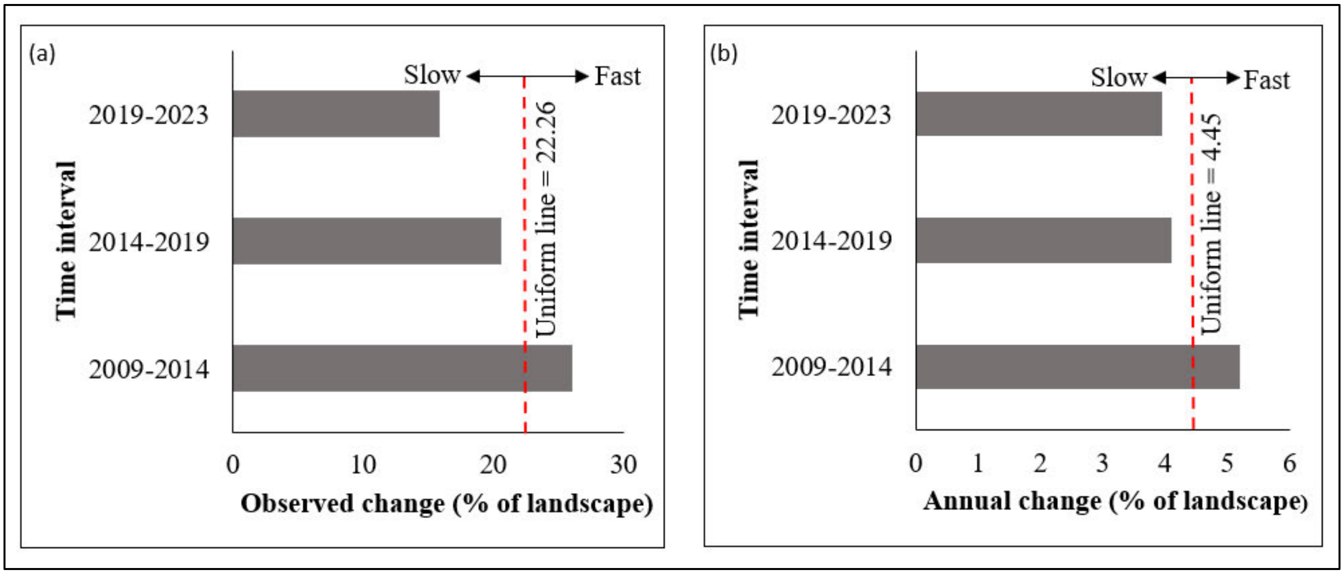

Figure 3.5: Interval level intensity of land cover class changes for three periods. (a) the percentage area that changed in each period and (b) the percentage annual area change in each period.

The category level analysis (Figure 3.6) indicate the gross loss and gross gain amongst land cover classes and show active or dormant landcover classes in a particular period. The active landcover category have their gains or losses exceeding the uniform intensity line and falling lower than this line in the dormant category. For all periods, the class bare areas and woody vegetation were active gainers and grasslands were the dormant gainer. The bare area class saw the biggest gross gains during all the periods, however, the class gains fluctuated, decreasing from the initial period to the second and increased again during the third period. Woody vegetation gains slightly decreased for successive periods, with the high class gain observed during the first period.

Bare areas and grasslands consistently experienced net losses throughout the three-time intervals. Consequently, bare areas represent the sole category that exhibited both gains and losses across all three periods. The bare areas class had high losses during the periods 2014-2019 and 2019-2023, respectively. Grassland losses decreased from the first period to the next and increased the following period. The findings of the category level analysis demonstrate that woody vegetation was the dormant loser during all three periods.

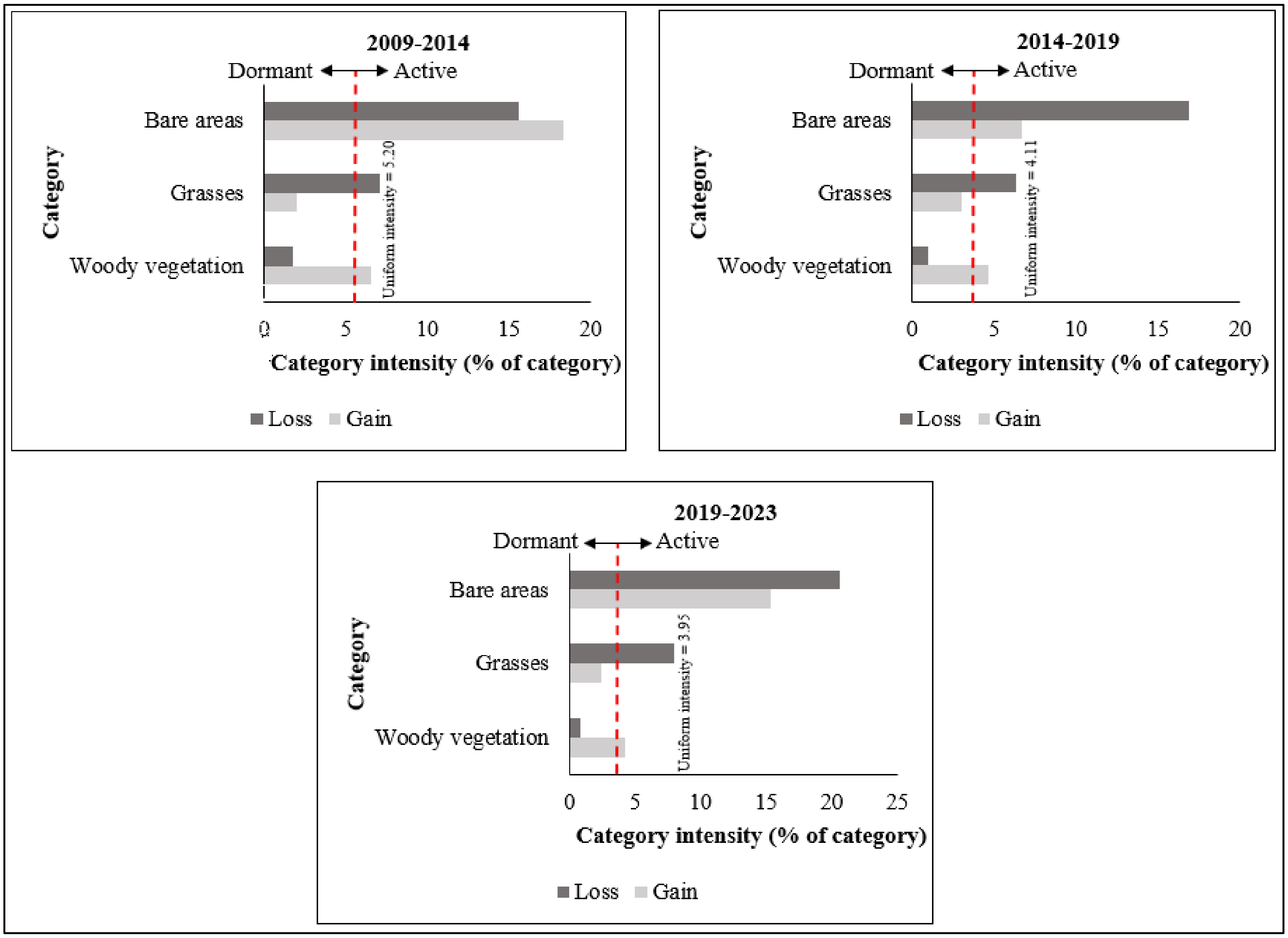

Figure 3.6: Category level intensity of land cover for three different periods.

Figures 3.7-3.9 illustrates results of the transition level intensity analysis results for the three land cover classes. The gains and losses of the category are explained based on the uniform intensity lines, which are indicators of the transitions' uniform intensity values. The line's left side shows loss in a particular landcover class, and the right side represents class gains. The transition intensity analysis shows that during the first two periods (2009-2014 and 2014-2019), gains for the woody vegetation class were prevalent on grasslands. However, during the period 2019-2023, woody vegetation gained less intensively from grasslands. The gains for woody vegetation from grasslands were slightly lower than the uniform intensity value. The results also show that during the period 2009-2014, woody vegetation was also less intensively gaining from and losing to bare areas. Consequently, during this period 2009-2014, losses for bare areas were much more intensive from grasslands, at the same time grasslands gains were also intensive from bare areas and less prevalent on woody vegetation. The results also show that during the periods 2014-2019 and 2019-2023, the gains and losses for bare areas were intensive from grasslands while at the same time, gains for grassland were intensive from bare areas.

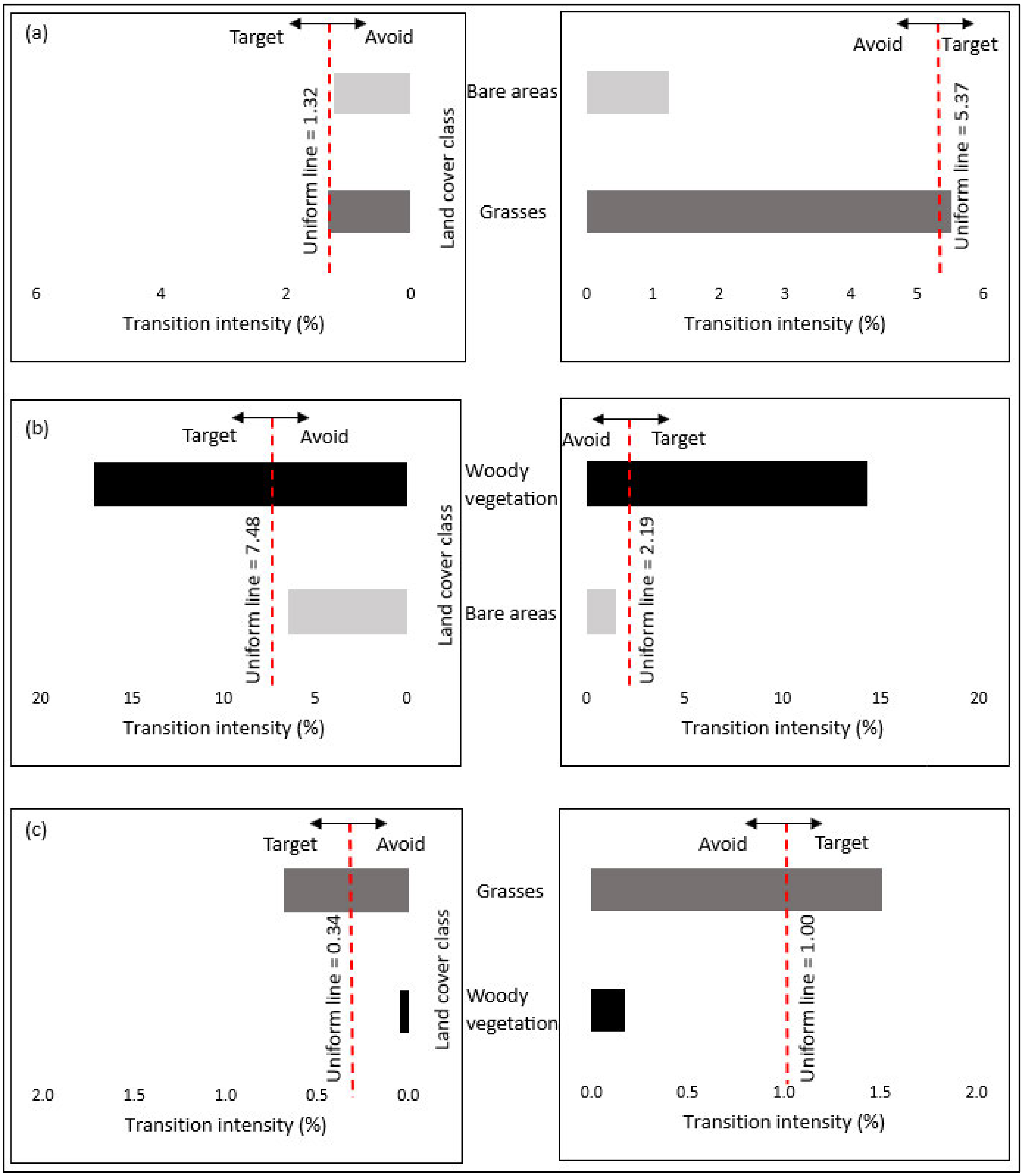

Figure 3.7: Transition level intensity analysis for the period 2009-2014. (a) transition intensity for woody vegetation, (b) grasslands, and (c) bare areas (gains on the right and losses on the left)

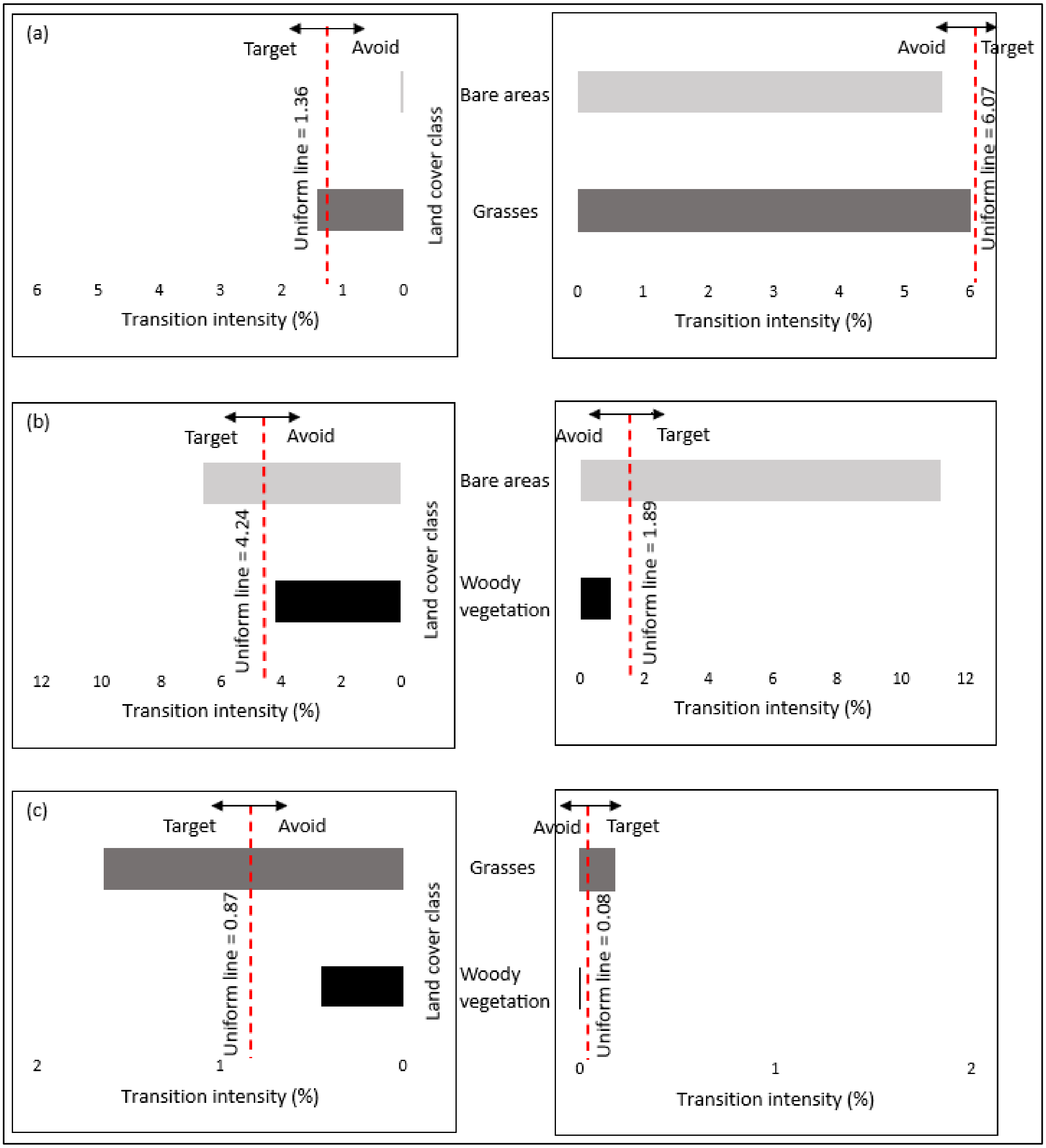

Figure 3.8: Transition level intensity analysis for the period 2014-2019. (a) transition intensity for woody vegetation, (b) grasslands, and (c) bare areas (gains on the right and losses on the left)

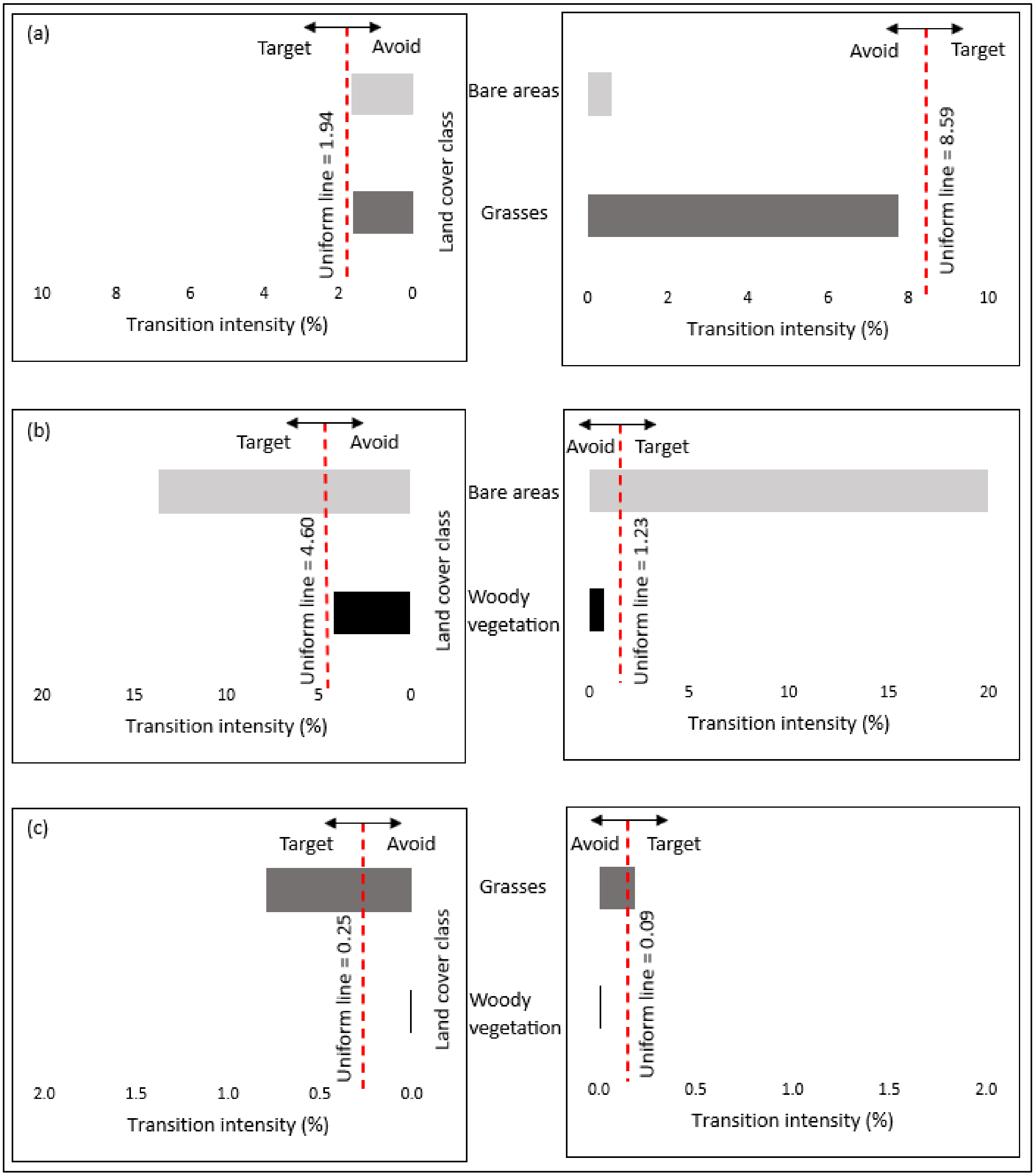

Figure 3.9: Transition level intensity analysis for the period 2019-2023. (a) transition intensity for woody vegetation, (b) grasslands, and (c) bare areas (gains on the right and losses on the left)

3.3.4 Prediction of future bush encroachment

The current study simulated the percentage cover for woody vegetation, grasslands, and bare areas in Bisley Valley Nature Reserve for the years 2028 and 2033. The Cellular Automata (CA) Model predicted a minimal expansion of woody vegetation from the current year (2023) to 2028 and 2033. Specifically, woody vegetation increased from 261.86 ha (74.02%) during 2023 to 281.31 ha (79.52%) and 304.91 ha (86.19%) in 2028 and 2033, respectively. During the first five-year period (2023-2028), only 5.50% of land transitioned to woody vegetation. However, for the next five years (2028-2033), the percentage area covered by woody vegetation is anticipated to increase by 6.67%. The model also shows that Bisley grasslands will shrink from 89.79 ha (25.38%) in 2023 to 66.89 ha (18.91%) in 2028 and further decrease to only 46.10 ha (13.03%) in the subsequent five years (2033). The results also show that bare areas will increase from 2.00 ha (0.60%) in 2023 to 5.55 ha (1.57%), in 2028 and decrease to 2.75 ha (0.78%) 2033.

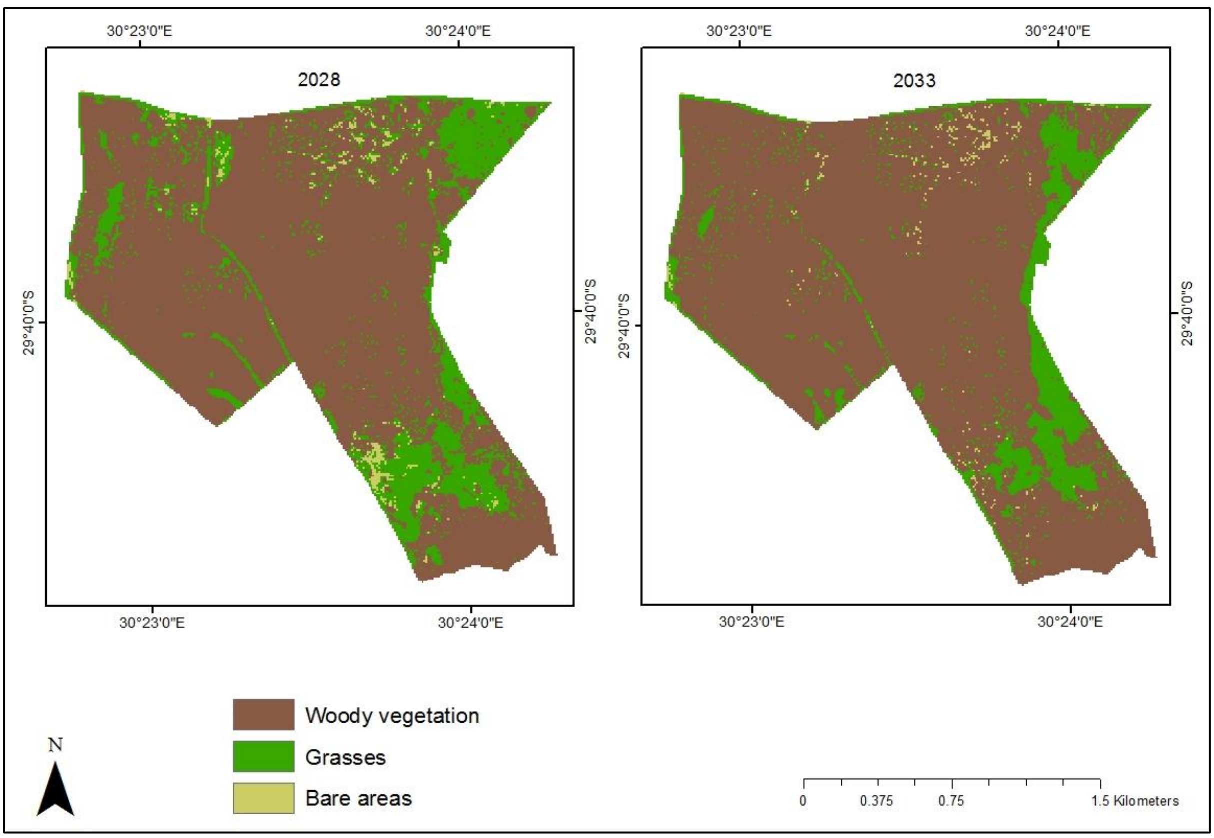

Figure 3.10: Simulation map showing future progression of woody vegetation in Bisley Valley Nature Reserve for 2028 and 2033.

Table 3.4: Transitions and area change in hectares (ha) between woody vegetation, grasslands, and bare areas in Bisley Valley Nature Reserve.

	Area Change (ha)	
Classes	**2023-2028**	**2028-2033**
Grasslands to Grasslands	44.84	37.07
Grasslands to woody vegetation	40.68	28.97
Woody vegetation to Grasslands	20.87	8.41
Woody vegetation to woody vegetation	239.39	272.55
Grasslands to Bare areas	3.99	0.86
Bare areas to Grasslands	0.64	0.61

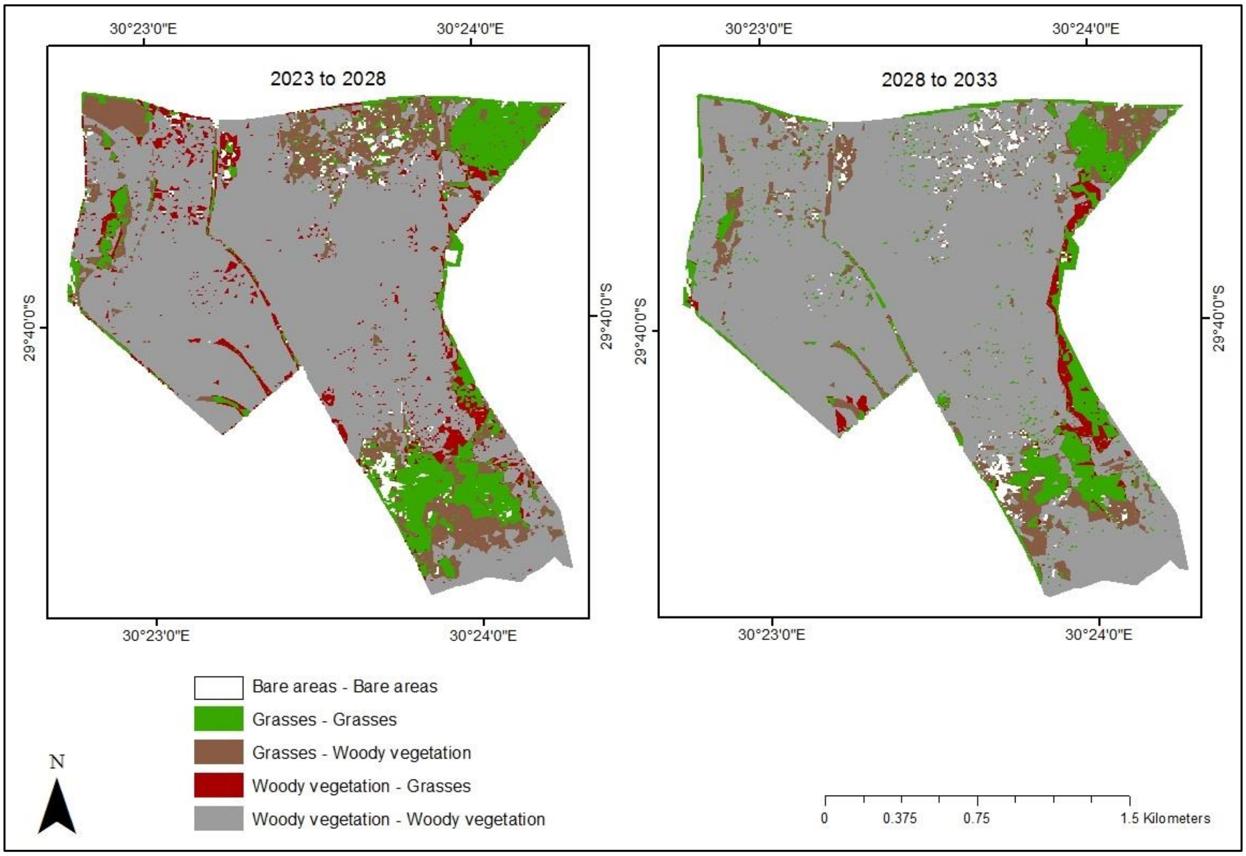

Figure 3.11: Predicted transition map of Bisley Valley Nature Reserve showing transition of woody vegetation and grasslands for different time periods.

3.3.5 Accuracy of bush encroachment predictions

The model accuracy was assessed using the comparison of the reference (Classified 2023) and simulation (simulated 2023) maps. The accuracy results demonstrated that the model adequately predicted the future encroachment trends in Bisley Valley Nature Reserve. The model simulated landcover transitions with an overall accuracy of 89%. The study also yielded good Kappa value of 80%. Additionally, the QADI index values of 0.08 indicated good accuracy results (Figure 3.12). The black dot is situated above the doted diagonal line and is near the allocation disagreement axis, showing that the main factor responsible for the observed minimal disagreement is the allocation error. Overall, the achieved accuracy results in this study demonstrate that the model prediction is reliable and that the reference and prediction maps are comparable.

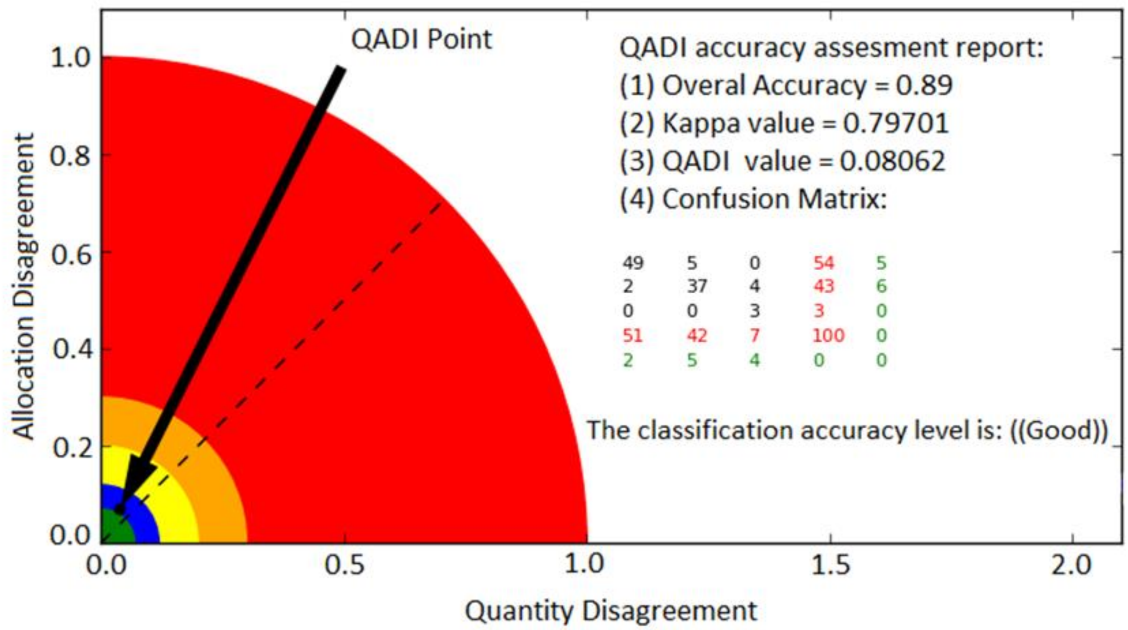

Figure 3.12: QADI graph showing model simulation accuracy for 2023 as a black dot.

3.4 Discussion

The analysis of landscape changes, particularly invasion of woody vegetation into protected areas is crucial for effective management of the area in ensuring preservation of natural ecosystems, biodiversity, and recreational activities. Hence, this study sought to provide a comprehensive analysis of bush encroachment in Bisley Valley Nature Reserve through mapping the progression of the phenomenon in the landscape, assessing the rate of change and intensity of transitions and predict the future bush encroachment changes.

3.4.1 Bush encroachment in the nature reserve

The analysis of bush encroachment trends showed that over the past 14 years, Bisley Valley Nature Reserve experienced woody vegetation expansion at the expense of grassland. During the course of the study, woody vegetation increased by 36.33%, contributing to approximately 34.87% reduction of grassland. The observed woody vegetation expansion in the area is linked to disturbances such as climate change and rainfall variability, alien invasive species, and use of injudicious land management approaches such as infrequent fires and inconsistency of mechanical control (Kellner et al., 2022, Liao et al., 2018). The study location is also characterised by inconsistent climatic conditions and heavy rains, which may support overgrowth of woody vegetation (Ndlovu and Demlie, 2020). Moreover, the nature reserve is also invaded by invasive plants such as the *Acacia spp, Solanum mauritianum* and *Lantana camara* amongst others (Kraai, 2021). Such species are known to proliferate in their newly established landscapes (Gazoulis et al., 2022).

3.4.2 Bush encroachment Intensity Analysis

The results from the analysis at the interval level showed an intensive change of Bisley's land cover in the first period (2009-2014) compared to the successive periods (2014-2019 and 2019-2023). However, change during the period 2019-2023 was slower than during 2014-2019. This implies that during the three time periods, the study area has been subjected to transformations at different rates, with a rapid transformation observed during the first five years of the study period. The rapid transformations in Bisley land cover and change in intensity of transitions are influenced by improvements in management of the reserve and increasing concerns about biodiversity conservation. According to Kourosh Niya et al. (2019) for instance, the intensity of land cover changes is associated to developments and advancements of management schemes in a particular landscape. Other studies on intensity analysis of land cover also reported rapid land cover change in the first and second intervals compared to subsequent intervals, indicating that the rate of changes in the area were progressing steadily in the recent periods (Bogale et al., 2024, Feng et al., 2020, Osman et al., 2023, Sang et al., 2019).

The main findings at the categorical level analysis revealed that the class woody vegetation and bare areas were active gainers during the study period. This is influenced by climate change and rainfall variability, which supports growth and dominance of woody vegetation in the landscape, while also degrading some parts of grasslands through erosion (Kraai, 2021). Bare areas are the only category that actively gained and actively lost in all three periods. These findings suggest that gains and losses in bare areas happen at intensities higher than the average intensity of all land cover classes gains and losses (Osman et al., 2023, Ouedraogo et al., 2023). The intensities of active gains in class bare areas are attributed to landscape disturbance, particularly through burrowing by smaller mammals such as porcupines and by heavy rains and floods (Centeri, 2022). On the other hand, the class active losses are linked to management and restoration schemes (D'Odorico et al., 2012, Maphanga et al., 2022). The findings also showed that for all periods, grasslands were the dormant gainer and active loser due to suppression by overgrowth of woody vegetation and influence of heavy rain and soil erosion. Interestingly, the categorical analysis also revealed that woody vegetation gains slightly decreased at every successive period, with the 6.54% class gains during the period 2009-2014, and only 4.66% and 4.23% during the periods 2014-2019 and 2019-2023, respectively. These findings suggest that some of the management schemes are minimally effective and contribute to reduction of woody vegetation overgrowth.

The key findings at the transition level analysis showed that woody vegetation gains from grasslands were higher during the period 2014-2019 compared to the gains in woody vegetation from the same class over the period 2009-2014. The major expansion of woody vegetation at the cost of grasslands during the second period is attributed to inconsistency of bush encroachment control measures at Bisley and rainfall variability, which may trigger rapid overgrowth of woody vegetation in some years (Kraai, 2021, Makin et al., 2012). The findings also demonstrated that during the period 2019-2023, class woody vegetation less intensively gained and lost to grasslands. These results reveal that woody vegetation increase led to a reduction of Bisley grasslands and that woody vegetation gains from grasslands vary for different periods. The observed low intensity gains and losses of woody vegetation on grasslands in the recent period (2019-2023) is linked to advancement of management schemes and increasing interest in conserving biodiversity and recreational value of the Bisley Valley Nature Reserve. The class woody vegetation was also less intensively gaining from and losing to bare areas during all periods. These findings suggest that woody vegetation had a minimal impact in the transformation of land to bare areas and that bare areas are less favorable for establishment, invasion, and dominance of woody vegetation in Bisley. The findings also showed that for all the periods, gains to grasslands were mainly from bare areas. This is because the process of restoration of grasslands from bare areas is less complicated and faster than conversion of woody landscape to grassland area, which might take many years and require more resources (Kellner et al., 2021, Mndela et al., 2022). The interesting key finding of the intensity analysis at transition level is that woody vegetation gains were intensive on grasslands whereas grasslands intensively loosed to bare areas for all the periods.

3.4.3 Bush encroachment future outlooks

The results of the study demonstrated that by 2028, bush encroachment will increase by 5.50% and 6.67% by 2033. The predicted increase of woody vegetation is attributed to the climate change and rainfall variability. For instance, in recent years, including 2023 and 2024, South Africa has been experiencing climate variability and change characterized by heavy rains and storms (Mashao et al., 2023, Sivakumar and Fazel-Rastgar, 2021). There is a possibility of continued rainfall variability that will induce growth and expansion of woody vegetation in Bisley (Brandt et al., 2017, Gillham et al., 2017). The observed trend of protrusion of woody vegetation in the area could also be influenced by adaptation and overgrowth of invasive plant species, particularly the *acacia* species. According to Kaplan et al. (2012), *acacia* species are among the most pernicious and prolific invasive plant species in many regions, including the Southern Africa. The species impact the quality and quantity of grasslands and soil resources and frequently reported as a driver of ecosystem degradation in grasslands of South Africa (Grellier et al., 2012, Jansen and Kumschick, 2022, Yapi et al., 2018). The protrusion of woody vegetation in Bisley is also linked to carbon dioxide (CO_2) concentration increase in the earth's atmosphere. According to Nackley et al. (2018), over the past three decades, the earth's atmosphere is increasingly experiencing elevated CO_2 concentration and the phenomenon has become a major concern to conservationist and environmental managers. The increase of CO_2 concentrations is particularly destructive in grassland landscape as it instigates rapid growth and dominance of woody vegetation at the expense of grasslands (Buitenwerf et al., 2012, Raubenheimer and Ripley, 2022, Raubenheimer et al., 2022). High atmospheric CO_2 concentrations support roots growth and plants water use efficiency, consequently increasing plant's ability to outcompete other coexisting vegetation (Thomas et al., 2018). The model also shows that the trend of grassland loss to woody vegetation in Bisley will continue for the next decade, with approximately 40.68 ha of grasslands lost from 2023-2028 and 28.97 ha lost in the next period as shown in Table 3.4. The research findings reveal that there is a need for evaluation of grass management schemes to acquire proper management of the reserve and achieve conservation goals.

Prediction of future bush encroachment trends could guide landscape management in Bisley Valley Nature Reserve and present viable strategies for effective biodiversity conservation. Prediction results will enhance understanding of bush encroachment implications to various species within the reserve (Gambo et al., 2018, Teferi, 2021). The approach will provide insights on habitat loss and will be critical for comprehending ecological succession and resilience of Bisley ecosystem to shifts in vegetation cover and structure (Liao et al., 2018, Sahara et al., 2015). Consequently, this will further provide comprehension of the possible impacts of bush encroachment on the balance between grazer and browser species within the reserve and implications on ecosystem services particularly carbon sequestration, erosion control, and recreational opportunities for Bisley and the Pietermaritzburg community (Kusiima et al., 2022, O'Connor et al., 2014). Furthermore, understanding of future bush encroachment prospects could facilitate understanding of the impact of the phenomenon and invasive species to local hydrological processes and water availability (Rolo and Moreno, 2019).

3.4.4 Ecological and management implication of the study

Based on the results of the current research, various ecological and management implications are drawn to highlight the importance of spatiotemporal analysis of bush encroachment using various approaches such as change detection, intensity analysis and prediction of future encroachment. Such spatially explicit and detailed analysis of bush encroachment contributes essential insights into the dynamics and major factors influencing the invasion and overgrowth of woody vegetation in landscapes such as nature reserves (Mndela, 2020, Rolo and Moreno, 2019). The findings of the current study are particularly essential for influencing sustainable conservation of biodiversity and recreational activities. They profoundly influence evaluation and improvement of management schemes, contributing to proper management and restoration of nature reserves and other protected landscapes. Analysis of landscape changes is also pivotal for maintaining habitat heterogeneity and healthy ecosystems (Phan et al., 2020). Additionally, it contributes to prevention of natural catastrophes related to bush encroachment (Skowno et al., 2017, Thomas et al., 2018). According to Sobhani et al. (2021) for instance, research on landscape design and land use contributes significantly to sustainable land use and proper management of protected areas, reducing erosion risks and other forms of land degradation.

3.5. Conclusion

Understanding historical and future trends and progression of bush encroachment is critically important for management and restoration of grasslands in protected areas. This study utilized intensity analysis frameworks to develop insights on the size and intensity of bush encroachment transitions in Bisley Valley Nature Reserve. Moreover, the study predicted bush encroachment future outlooks using Cellular Automator model. The results of this research revealed that the Bisley Valley Nature Reserve is undergoing transformation where its grasslands are continuously threatened by bush encroachment. Based on the research findings, it is concluded that:

(i) The use of robust quantitative methods such as Intensity Analysis facilitates understanding of the dynamics of bush encroachment and provides explicit information on changes in the landscape.

(ii) Bush encroachment is on the increase in Bisley Valley Nature Reserve with over 85% of grasslands encroached by 2033.

The use of Intensity Analysis framework provides additional insights on bush encroachment that were not feasible using a general transition matrix and change detection techniques. Specifically, this method is valuable for providing critical information on the intensity of transitions and annual rates of change, which could be beneficial for improvement of management and conservation initiatives. Moreover, the prediction of future bush encroachment using Cellular Automator model further contributes to acquiring explicit understanding of encroachment trends and vulnerability of grasslands. The study is invaluable to conservation initiatives and provides foundation for proper evaluation and implementation of effective management schemes in protected areas and other grassy landscapes.

Chapter Four: The Synthesis

4.1 Introduction

The encroachment of woody vegetation into natural grasslands is one of the major challenges threatening many landscapes globally (Gan et al., 2022, O'Connor et al., 2014). The phenomenon affects approximately 7.5 million km^2 of grassland landscapes in the sub-Saharan Africa and 73 000 km^2 of the entire land area in South Africa (Belayneh and Tessema, 2017). Bush encroachment has been particularly prevalent and severe in protected areas such as nature reserves (Borgström et al., 2012). Considering the critical value of nature reserves in biodiversity conservation and recreational value, comprehending the progression and severity of bush encroachment in these landscapes is therefore paramount (Borgström et al., 2012). In this regard, acquiring insights on spatio-temporal patterns of bush encroachment in nature reserves will immensely contribute to implementing the most effective methods for controlling encroachment of woody vegetation. Remote sensing technologies such as high spatial and temporal long term satellite data is documented as key to accurately and efficiently monitor bush encroachment (Maphanga et al., 2022). Moreover, techniques such as change detection, intensity analysis and bush encroachment future prediction offers a great potential for acquiring explicit insights on bush encroachment and other landcover changes in the landscape (Symeonakis and Higginbottom, 2014b, Zhang et al., 2021). As a result, this study sought to assess and predict bush encroachment dynamics in Bisley Valley Nature Reserve using high spatial resolution multi-temporal data. To achieve this, the following objectives were set:

- To monitor bush encroachment and associated land use-land cover types in Bisley Valley Nature Reserve using RapidEye and PlanetScope data within the Google Earth Engine (GEE) platform.
- To assess the past, current, and future (2009-2033) bush encroachment trends in Bisley Valley Nature Reserve using the intensity analysis and Cellular Automata (CA) model.

4.2 Monitoring bush encroachment in Bisley Valley Nature Reserve using RapidEye and PlanetScope data

PlanetScope and RapidEye remotely sensed data spanning the period from 2009 to 2023 was utilized to estimate the changing extent of woody vegetation, grassland cover and bare areas in Bisley Valley Nature Reserve. Over the 14-year study period, a significant increase of woody vegetation at the expense of grassland was observed. Approximately 130.69 ha of grassland underwent a transition to woody vegetation, while approximately 2.78 ha of woody vegetation was converted to grassland. A net increase of 127.91 ha in the total area covered by woody vegetation was recorded. The analysis demonstrated a notable upward trend in woody vegetation expansion during the 14 years of study, with percentage coverage of 37.69%, 51.18%, 64.52% and 74.02% in 2009, 2014, 2019 and 2023, respectively. The study concluded that improvement of management schemes in Bisley is necessary for management and restoration of grasslands. The study provided critical insights on the threat of bush encroachment in nature reserves and lay a foundation to establish effective landscape management strategies.

4.3 Bush Encroachment: modelling transformation using Intensity Analysis and Cellular Automata Model

Using the RapidEye and PlanetScope satellite imagery, the intensity analysis and the Cellular Automata (CA) models was adopted to understand past, current, and future (2009-2033) bush encroachment trends in Bisley Valley Nature Reserve. A steady woody encroachment increase on other land cover types was observed. Analysis of land cover intensities demonstrated an intensive change in the study area's land cover in the first period (2009-2014) compared to the other periods. During the first two periods (2009-2014 and 2014-2019), woody vegetation gains were at the expense of grassland but partially avoided gaining from grassland during the period 2019-2023. Moreover, during the study period, majority of grassland gains were from the class bare areas and its losses mainly from woody vegetation. The prediction of future bush encroachment showed an increasing trend of woody vegetation in the next decade. The results particularly demonstrated that bush encroachment will expand by 5.50% and 6.67% during 2028 and 2033, respectively. The study demonstrated that there is a pressing need for evaluation and implementation of the most effective grassland management schemes in the study area, and other bush encroached landscapes. Additionally, insights on bush encroachment trends and landcover change intensities contribute to prioritizing landscape management and restoration of grasslands.

4.4 Conclusion

The overall purpose of this research was to assess and predict bush encroachment dynamics in Bisley Valley Nature Reserve using high spatial resolution multi-temporal data. The first objective of the study focused on monitoring bush encroachment and associated LULC types in the study area using RapidEye and PlanetScope datasets within the GEE platform. The findings of the first objective revealed that despite the current management initiatives in the Bisley Valley Nature Reserve, its' grasslands are continuously threatened by encroaching woody vegetation. The study concludes that high spatial resolution datasets such as RapidEye and PlanetScope are efficient and reliable for acquiring detailed spatial data showing trends and patterns of bush encroachment in nature reserves. Additionally, it is concluded that bush encroachment is a continuous threat in Bisley Valley Nature Reserve, encroaching over 70% of grasslands.

The second objective sought to compute and analyze the past, current, and future (2009-2033) spatiotemporal changes of bush encroachment in Bisley Valley Nature Reserve using the intensity analysis and Cellular Automata (CA) Model. This objective provides a comprehensive analysis of bush encroachment, revealing additional insights such as rate of land cover transitions and prospects of bush encroachment. The study revealed that the Bisley Valley Nature Reserve is undergoing transformation where woody vegetation is continuously threatening grasslands. The study concludes that robust quantitative methods such as Intensity Analysis facilitate understanding of the dynamics of bush encroachment and provides explicit information on transformations in the landscape. Additionally, the study established that bush encroachment is continuously increasing in Bisley Valley Nature Reserve with over an anticipated 85% of grasslands encroached by 2033. Overall, this study provides invaluable insights on bush encroachment severity in nature reserves and contributes to understanding of robust monitoring techniques for prioritizing landscape management.

4.5 Recommendations for future research

The findings of this research provide key insights on the trends and progression of bush encroachment in the study site. The study also underscores the importance of critical analysis of woody vegetation and associated LULC types using robust LULC monitoring approaches and predictive models. However, despite the success of this study, there are still gaps and research areas that require addressing in future. Specifically, future research should consider:

- Predicting and evaluating the drivers of bush encroachment in the encroached landscapes using biophysical and environmental variables.
- Evaluating short-term responses of herbaceous vegetation to fires and bush clearing.
- Assessing the optimal number of browser and grazer herbivores for maintaining a balanced ratio of grass and woody vegetation in nature reserves.

References

ABDI, A. M. 2020. Land cover and land use classification performance of machine learning algorithms in a boreal landscape using Sentinel-2 data. *GIScience & Remote Sensing,* 57**,** 1-20.

ABDULAHI, M. & YONUS, A. 2020. Bush Encroachment Control Impact on Rangeland Vegetation in the Southeast Ethiopian Rangelands. *Livestock Research Results***,** 834.

ACHARKI, S. 2022. PlanetScope contributions compared to Sentinel-2, and Landsat-8 for LULC mapping. *Remote Sensing Applications: Society and Environment,* 27**,** 100774.

ADAM, E., MUTANGA, O., ODINDI, J. & ABDEL-RAHMAN, E. M. 2014. Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. *International Journal of Remote Sensing,* 35**,** 3440-3458.

AFUYE, G. A., NDUKU, L., KALUMBA, A. M., SANTOS, C. A. G., ORIMOLOYE, I. R., OJEH, V. N., THAMAGA, K. H. & SIBANDZE, P. 2024. Global trend assessment of land use and land cover changes: A systematic approach to future research development and planning. *Journal of King Saud University-Science***,** 103262.

AKINYEMI, F. O., PONTIUS JR, R. G. & BRAIMOH, A. K. 2017. Land change dynamics: insights from Intensity Analysis applied to an African emerging city. *Journal of Spatial Science,* 62**,** 69-83.

AL-RUBKHI, A., TALAL, A. & MOHAMMED, A. 2017. Land Use Change Analysis and Modeling Using Open Source (QGis)-Case Study: Boasher Willayat. *Muscat: College of Arts and Social Science, Department of Geography, Sultan Qaboos University*.

ALDWAIK, S. Z. & PONTIUS JR, R. G. 2012. Intensity analysis to unify measurements of size and stationarity of land changes by interval, category, and transition. *Landscape and Urban Planning,* 106**,** 103-114.

ANEESHA SATYA, B., SHASHI, M. & DEVA, P. 2020. Future land use land cover scenario simulation using open source GIS for the city of Warangal, Telangana, India. *Applied Geomatics,* 12**,** 281-290.

ARCHER, S. R., ANDERSEN, E. M., PREDICK, K. I., SCHWINNING, S., STEIDL, R. J. & WOODS, S. R. 2017. Woody plant encroachment: causes and consequences. *Rangeland Systems: Processes, Management and Challenges***,** 25-84.

ATKINSON, H., CRISTESCU, B., MARKER, L. & ROONEY, N. 2022. Bush encroachment and large carnivore predation success in African landscapes: A review. *Earth,* 3**,** 1010-1026.

AYELEW, S. & MULUALEM, G. 2018. A review on bush encroachment effect on cattle rearing in rangelands. *Journal of Rangeland Science,* 8**,** 403-415.

BALHA, A., MALLICK, J., PANDEY, S., GUPTA, S. & SINGH, C. K. 2021. A comparative analysis of different pixel and object-based classification algorithms using multi-source high spatial resolution satellite data for LULC mapping. *Earth Science Informatics,* 14**,** 2231-2247.

BANSKOTA, A., KAYASTHA, N., FALKOWSKI, M. J., WULDER, M. A., FROESE, R. E. & WHITE, J. C. 2014. Forest monitoring using Landsat time series data: A review. *Canadian Journal of Remote Sensing,* 40**,** 362-384.

BEHERA, M. D., BORATE, S. N., PANDA, S. N., BEHERA, P. R. & ROY, P. S. 2012. Modelling and analyzing the watershed dynamics using Cellular Automata (CA)–Markov model–A geo-information based approach. *Journal of Earth System Science,* 121**,** 1011-1024.

BELAYNEH, A. & TESSEMA, Z. K. 2017. Mechanisms of bush encroachment and its inter-connection with rangeland degradation in semi-arid African ecosystems: a review. *Journal of Arid Land,* 9**,** 299-312.

BEN-SHAHAR, R. 1992. The effects of bush clearance on African ungulates in a semi-arid nature reserve. *Ecological Applications,* 2**,** 95-101.

BIRHANU, L., HAILU, B. T., BEKELE, T. & DEMISSEW, S. 2019. Land use/land cover change along elevation and slope gradient in highlands of Ethiopia. *Remote Sensing Applications: Society and Environment,* 16**,** 100260.

BOGALE, T., DAMENE, S., SEYOUM, A. & HAREGEWEYN, N. 2024. Land use land cover change intensity analysis for sustainable natural resources management: The case of northwestern highlands of Ethiopia. *Remote Sensing Applications: Society and Environment,* 34**,** 101170.

BORGES, J., HIGGINBOTTOM, T. P., CAIN, B., GADIYE, D. E., KISINGO, A., JONES, M. & SYMEONAKIS, E. 2022. Landsat time series reveal forest loss and woody encroachment in the Ngorongoro Conservation Area, Tanzania. *Remote Sensing in Ecology and Conservation,* 8**,** 808-826.

BORGSTRÖM, S., COUSINS, S. & LINDBORG, R. 2012. Outside the boundary–Land use changes in the surroundings of urban nature reserves. *Applied Geography,* 32**,** 350-359.

BORGSTRÖM, S., LINDBORG, R. & ELMQVIST, T. 2013. Nature conservation for what? Analyses of urban and rural nature reserves in southern Sweden 1909–2006. *Landscape and Urban Planning,* 117**,** 66-80.

BORKOWSKI, M. 2002. Limiting bush encroachment at Biebrza marsh by Konik/Tarpan grazing. *Grazing as a Conservation Management Tool in Peatland***,** 22-26.

BRANDT, M., TAPPAN, G., DIOUF, A. A., BEYE, G., MBOW, C. & FENSHOLT, R. 2017. Woody vegetation die off and regeneration in response to rainfall variability in the West African Sahel. *Remote Sensing,* 9**,** 39.

BRAVO-GARCÍA, J., CAMARILLO-NARANJO, J., BLANCO-VELÁZQUEZ, F. J., GONZÁLEZ-PEÑALOZA, F. & ANAYA-ROMERO, M. 2024. Mapping the potential habitat suitability and opportunities of bush encroacher species in Southern Africa: a case study of the SteamBioAfrica project. *Frontiers of Biogeography,* 17**,** e136222.

BRIASSOULIS, H. 2020. Analysis of land use change: theoretical and modeling approaches.

BUITENWERF, R., BOND, W., STEVENS, N. & TROLLOPE, W. 2012. Increased tree densities in S outh A frican savannas:> 50 years of data suggests CO 2 as a driver. *Global Change Biology,* 18**,** 675-684.

CAO, X., LIU, Y., CUI, X., CHEN, J. & CHEN, X. 2019. Mechanisms, monitoring and modeling of shrub encroachment into grassland: a review. *International Journal of Digital Earth,* 12**,** 625-641.

CARACCIOLO, D., NOTO, L. & ISTANBULLUOGLU, E. 2014. Modelling the shrub encroachment in a grassland with a Cellular Automata Model. *Proceedings of the International Association of Hydrological Sciences,* 364**,** 20-25.

CENTERI, C. 2022. Effects of grazing on water erosion, compaction and infiltration on grasslands. *Hydrology,* 9**,** 34.

CHEN, W., GU, T., XIANG, J., LUO, T. & ZENG, J. 2023. Assessing the conservation effectiveness of national nature reserves in China. *Applied Geography,* 161**,** 103125.

COFFER, M. M., SCHAEFFER, B. A., ZIMMERMAN, R. C., HILL, V., LI, J., ISLAM, K. A. & WHITMAN, P. J. 2020. Performance across WorldView-2 and RapidEye for reproducible seagrass mapping. *Remote sensing of environment,* 250**,** 112036.

CORNEJO-DENMAN, L., ROMO-LEON, J. R., HARTFIELD, K., VAN LEEUWEN, W. J., PONCE-CAMPOS, G. E. & CASTELLANOS-VILLEGAS, A. 2020. Landscape dynamics in an iconic watershed of northwestern Mexico: vegetation condition insights using landsat and PlanetScope data. *Remote Sensing,* 12**,** 2519.

CUBINO, J. P., TĚŠITEL, J., FIBICH, P., LEPŠ, J. & CHYTRÝ, M. 2022. Alien plants tend to occur in species-poor communities. *NeoBiota,* 73**,** 39-56.

D'ODORICO, P., OKIN, G. S. & BESTELMEYER, B. T. 2012. A synthetic review of feedbacks and drivers of shrub encroachment in arid grasslands. *Ecohydrology,* 5**,** 520-530.

DE KLERK, J. 2004. *Bush encroachment in Namibia: Report on phase 1 of the bush encroachment research, monitoring, and management project*, Ministry of Environment and Tourism, Directorate of Environmental Affairs.

DEĞERMENCI, A. S. 2023. Spatio-temporal change analysis and prediction of land use and land cover changes using CA-ANN model. *Environmental Monitoring and Assessment,* 195**,** 1229.

DELJOUEI, A., SADEGHI, S. M. M., ABDI, E., BERNHARDT-RÖMERMANN, M., PASCOE, E. L. & MARCANTONIO, M. 2018. The impact of road disturbance on vegetation and soil properties in a beech stand, Hyrcanian forest. *European Journal of Forest Research,* 137**,** 759-770.

DEVI, A. B., DEKA, D., ANEESH, T. D., SRINIVAS, R. & NAIR, A. M. 2022. Predictive modelling of land use land cover dynamics for a tropical coastal urban city in Kerala, India. *Arabian Journal of Geosciences,* 15**,** 399.

DONG, Y., YAN, H., WANG, N., HUANG, M. & HU, Y. 2019. Automatic identification of shrub-encroached grassland in the Mongolian plateau based on UAS remote sensing. *Remote Sensing,* 11**,** 1623.

DONNENFELD, Z., HEDDEN, S. & CROOKES, C. 2018. A delicate balance: Water scarcity in South Africa.

EKUMAH, B., ARMAH, F. A., AFRIFA, E. K., AHETO, D. W., ODOI, J. O. & AFITIRI, A.-R. 2020. Assessing land use and land cover change in coastal urban wetlands of international importance in Ghana using Intensity Analysis. *Wetlands Ecology and Management,* 28**,** 271-284.

FEIZIZADEH, B., DARABI, S., BLASCHKE, T. & LAKES, T. 2022. QADI as a new method and alternative to kappa for accuracy assessment of remote sensing-based image classification. *Sensors,* 22**,** 4506.

FENG, Y., LEI, Z., TONG, X., GAO, C., CHEN, S., WANG, J. & WANG, S. 2020. Spatially-explicit modeling and intensity analysis of China's land use change 2000–2050. *Journal of Environmental Management,* 263**,** 110407.

FISHER, J., ERASMUS, B., WITKOWSKI, E., VAN AARDT, J., ASNER, G., WESSELS, K. & MATHIEU, R. 2014. Management approaches of conservation areas: Differences in woody vegetation structure in a private and a national reserve. *South African Journal of Botany,* 90**,** 146-152.

FOGARTY, D. T., PETERSON, R. B. & TWIDWELL, D. 2022. Spatial patterns of woody plant encroachment in a temperate grassland. *Landscape Ecology,* 37**,** 2835-2846.

FOODY, G. M. 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment,* 80**,** 185-201.

FRANCINI, S., MCROBERTS, R. E., GIANNETTI, F., MENCUCCI, M., MARCHETTI, M., SCARASCIA MUGNOZZA, G. & CHIRICI, G. 2020. Near-real time forest change detection using PlanetScope imagery. *European Journal of Remote Sensing,* 53**,** 233-244.

FREEMAN, P. K. & FREELAND, R. S. 2015. Agricultural UAVs in the US: potential, policy, and hype. *Remote Sensing Applications: Society and Environment,* 2**,** 35-43.

GAMBO, J., SHAFRI, H. M., SHAHARUM, N. S. N., ABIDIN, F. A. Z. & RAHMAN, M. T. A. 2018. Monitoring and predicting land use-land cover (LULC) changes within and around krau wildlife reserve (KWR) protected area in Malaysia using multi-temporal landsat data. *Geoplanning: Journal of Geomatics and Planning,* 5**,** 17-34.

GAN, L., CAO, X., CHEN, X., HE, Q., CUI, X. & ZHAO, C. 2022. Mapping shrub coverage in Xilin Gol Grassland with multi-temporal sentinel-2 imagery. *Remote Sensing,* 14**,** 3266.

GAO, C., FENG, Y., TONG, X., JIN, Y., LIU, S., WU, P., YE, Z. & GU, C. 2020. Modeling urban encroachment on ecological land using cellular automata and cross-entropy optimization rules. *Science of the Total Environment,* 744**,** 140996.

GAŠPAROVIĆ, M., DOBRINIĆ, D. & MEDAK, D. Urban vegetation detection based on the land-cover classification of planetscope, rapideye and worldview-2 satellite imagery. Proceedings of the 18th International Multidisciplinary Scientific Geo-Conference SGEM2018, Albena, Bulgaria, 2018. 249-256.

GAZOULIS, I., ANTONOPOULOS, N., KANATAS, P., KARAVAS, N., BERTONCELJ, I. & TRAVLOS, I. 2022. Invasive Alien Plant Species—Raising Awareness of a Threat to Biodiversity and Ecological Connectivity (EC) in the Adriatic-Ionian Region. *Diversity,* 14**,** 387.

GHALEHTEIMOURI, K. J., SHAMSODDINI, A., MOUSAVI, M. N., ROS, F. B. C. & KHEDMATZADEH, A. 2022. Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model based scenarios (2019–2049) Zarriné-Rūd River Basin in Iran. *Environmental Challenges,* 6**,** 100399.

GILLHAM, J., CURRY, C. & BREDIN, I. 2017. WETLAND AND BIODIVERSITY ASSESSMENT FOR THE EXPANSION OF THE PIETERMARITZBURG AIRPORT.

GÓMEZ-GARCÍA, D., AGUIRRE DE JUANA, Á. J., JIMÉNEZ SÁNCHEZ, R. & MANRIQUE MAGALLÓN, C. 2023. Shrub encroachment in Mediterranean mountain grasslands: Rate and consequences on plant diversity and forage availability. *Journal of Vegetation Science,* 34**,** e13174.

GONG, Z., ZHANG, C., ZHANG, L., BAI, J. & ZHOU, D. 2021. Assessing spatiotemporal characteristics of native and invasive species with multi-temporal remote sensing images in the Yellow River Delta, China. *Land Degradation & Development,* 32**,** 1338-1352.

GORDIJN, P. J. 2010. *The role of fire in bush encroachment in Ithala Game Reserve.*

GRAW, V., OLDENBURG, C. & DUBOVYK, O. 2016. Bush Encroachment Mapping for Africa: Multi-scale analysis with remote sensing and GIS. *ZEF-Center for Development Research University of Bonn, Discussion Paper*.

GRELLIER, S., KEMP, J., JANEAU, J.-L., FLORSCH, N., WARD, D., BAROT, S., PODWOJEWSKI, P., LORENTZ, S. & VALENTIN, C. 2012. The indirect impact of encroaching trees on gully extension: A 64 year study in a sub-humid grassland of South Africa. *Catena,* 98**,** 110-119.

GUIDIGAN, M. L. G., SANOU, C. L., RAGATOA, D. S., FAFA, C. O. & MISHRA, V. N. 2019. Assessing land use/land cover dynamic and its impact in Benin Republic using land change model and CCI-LC products. *Earth Systems and Environment,* 3**,** 127-137.

GXASHEKA, M., GAJANA, C. S. & DLAMINI, P. 2023. The role of topographic and soil factors on woody plant encroachment in mountainous rangelands: A mini literature review. *Heliyon*.

HAKIM, A., BAJA, S., RAMPISELA, D. & ARIF, S. Spatial dynamic prediction of landuse/landcover change (case study: tamalanrea sub-district, makassar city). IOP Conference Series: Earth and Environmental Science, 2019. IOP Publishing, 012023.

HAMAD, R., BALZTER, H. & KOLO, K. 2018. Predicting land use/land cover changes using a CA-Markov model under two different scenarios. *Sustainability,* 10**,** 3421.

HAMYLTON, S. M., MORRIS, R. H., CARVALHO, R. C., RODER, N., BARLOW, P., MILLS, K. & WANG, L. 2020. Evaluating techniques for mapping island vegetation from unmanned aerial vehicle (UAV) images: Pixel classification, visual interpretation and machine learning approaches. *International Journal of Applied Earth Observation and Geoinformation,* 89**,** 102085.

HANSEN, M. C., KRYLOV, A., TYUKAVINA, A., POTAPOV, P. V., TURUBANOVA, S., ZUTTA, B., IFO, S., MARGONO, B., STOLLE, F. & MOORE, R. 2016. Humid tropical forest disturbance alerts using Landsat data. *Environmental Research Letters,* 11**,** 034008.

HANSEN, M. C. & LOVELAND, T. R. 2012. A review of large area monitoring of land cover change using Landsat data. *Remote Sensing of Environment,* 122**,** 66-74.

HAO, S., ZHU, F. & CUI, Y. 2021. Land use and land cover change detection and spatial distribution on the Tibetan Plateau. *Scientific Reports,* 11**,** 7531.

HOJATI, M. & MOKARRAM, M. 2016. Determination of a topographic wetness index using high resolution digital elevation models. *European Journal of Geography,* 7**,** 41-52.

HOPKINSON, P., HAMMOND, M., BARTOLOME, J. W. & MACAULAY, L. 2020. Using consecutive prescribed fires to reduce shrub encroachment in grassland by increasing shrub mortality. *Restoration Ecology,* 28**,** 850-858.

HUANG, J., PONTIUS JR, R. G., LI, Q. & ZHANG, Y. 2012. Use of intensity analysis to link patterns with processes of land change from 1986 to 2007 in a coastal watershed of southeast China. *Applied Geography,* 34**,** 371-384.

HUDAK, A. T. & WESSMAN, C. A. 2001a. Textural analysis of high resolution imagery to quantify bush encroachment in Madikwe Game Reserve, South Africa, 1955-1996. *International Journal of Remote Sensing. 22 (14): 2731-2740.***,** 2731-2740.

HUDAK, A. T. & WESSMAN, C. A. 2001b. Textural analysis of high resolution imagery to quantify bush encroachment in Madikwe Game Reserve, South Africa, 1955-1996. *International Journal of Remote Sensing,* 22**,** 2731-2740.

HYANDYE, C. & MARTZ, L. W. 2017. A Markovian and cellular automata land-use change predictive model of the Usangu Catchment. *International Journal of Remote Sensing,* 38**,** 64-81.

IQBAL, M. F. & KHAN, I. A. 2014. Spatiotemporal land use land cover change analysis and erosion risk mapping of Azad Jammu and Kashmir, Pakistan. *the Egyptian journal of remote sensing and space science,* 17**,** 209-229.

JANSEN, C. & KUMSCHICK, S. 2022. A global impact assessment of Acacia species introduced to South Africa. *Biological Invasions,* 24**,** 175-187.

JOHN, L. R., HAMBATI, H. & ARMAH, F. A. 2013. An intensity analysis of land-use and land-cover change in Karatu District, Tanzania: community perceptions and coping strategies.

KABETA, L., DALLE, G., TOLERA, M. & KELBORO, G. 2020. Bush encroachment and impacts on grass biomass in Senkelle Swayne’s Hartebeest Sanctuary, Ethiopia. *Biodiversity,* 21**,** 217-226.

KAFY, A.-A., NAIM, M. N. H., SUBRAMANYAM, G., AHMED, N. U., AL RAKIB, A., KONA, M. A. & SATTAR, G. S. 2021. Cellular Automata approach in dynamic modelling of land cover changes using RapidEye images in Dhaka, Bangladesh. *Environmental Challenges,* 4**,** 100084.

KAMARAJ, M. & RANGARAJAN, S. 2022. Predicting the future land use and land cover changes for Bhavani basin, Tamil Nadu, India, using QGIS MOLUSCE plugin. *Environmental Science and Pollution Research,* 29**,** 86337-86348.

KAPLAN, H., VAN ZYL, H., LE ROUX, J., RICHARDSON, D. & WILSON, J. 2012. Distribution and management of Acacia implexa (Benth.) in South Africa: A suitable target for eradication? *South African Journal of Botany,* 83**,** 23-35.

KAVWELE, C. M., KIMANZI, J. K. & KINYANJUI, M. J. 2017. Impacts of bush encroachment on wildlife species diversity, composition, and habitat preference in Ol Pejeta Conservancy, Laikipia, Kenya. *International Journal of Ecology,* 2017**,** 5620125.

KELLNER, K., FOUCHÉ, J., TONGWAY, D., BONESCHANS, R., VAN COLLER, H. & VAN STADEN, N. 2022. Landscape Function Analysis: Responses to Bush Encroachment in a Semi-Arid Savanna in the Molopo Region, South Africa. *Sustainability,* 14**,** 8616.

KELLNER, K., MANGANI, R. T., SEBITLOANE, T. J., CHIRIMA, J. G., MEYER, N., COETZEE, H. C., MALAN, P. W. & KOCH, J. 2021. Restoration after bush control in selected range-land areas of semi-arid savannas in South Africa. *Bothalia-African Biodiversity & Conservation,* 51**,** 1-13.

KGANYAGO, M., ODINDI, J., ADJORLOLO, C. & MHANGARA, P. 2018. Evaluating the capability of Landsat 8 OLI and SPOT 6 for discriminating invasive alien species in the African Savanna landscape. *International journal of applied earth observation and geoinformation,* 67**,** 10-19.

KGOSIKOMA, O. E. & MOGOTSI, K. 2013. Understanding the causes of bush encroachment in Africa: The key to effective management of savanna grasslands. *Tropical Grasslands-Forrajes Tropicales,* 1**,** 215-219.

KHAN, F., DAS, B. & MOHAMMAD, P. 2022. Urban growth modeling and prediction of land use land cover change over Nagpur City, India using cellular automata approach. *Geospatial Technology for Landscape and Environmental Management: Sustainable Assessment and Planning***,** 261-282.

KHARE, S., LATIFI, H. & GHOSH, S. K. 2018. Multi-scale assessment of invasive plant species diversity using Pléiades 1A, RapidEye and Landsat-8 data. *Geocarto International,* 33**,** 681-698.

KHAZIEVA, E., VERBURG, P. H. & PAZÚR, R. 2022. Grassland degradation by shrub encroachment: Mapping patterns and drivers of encroachment in Kyrgyzstan. *Journal of Arid Environments,* 207**,** 104849.

KIM, H.-O. & YEOM, J.-M. 2014. Effect of red-edge and texture features for object-based paddy rice crop classification using RapidEye multi-spectral satellite image data. *International Journal of Remote Sensing,* 35**,** 7046-7068.

KIM, H.-O. & YEOM, J.-M. 2015. Sensitivity of vegetation indices to spatial degradation of

RapidEye imagery for paddy rice detection: a case study of South Korea. *GIScience & remote sensing,* 52**,** 1-17.

KIMARO, H., ASENGA, A., MUNISHI, L. & TREYDTE, A. 2019. Woody encroachment extent and its associated impacts on plant and herbivore species occurrence in Maswa Game Reserve, Tanzania.

KOCH, F., TIETJEN, B., TIELBÖRGER, K. & ALLHOFF, K. T. 2023. Livestock management promotes bush encroachment in savanna systems by altering plant–herbivore feedback. *Oikos,* 2023**,** e09462.

KOKO, A. F., YUE, W., ABUBAKAR, G. A., HAMED, R. & ALABSI, A. A. N. 2020. Monitoring and predicting spatio-temporal land use/land cover changes in Zaria City, Nigeria, through an integrated cellular automata and markov chain model (CA-Markov). *Sustainability,* 12**,** 10452.

KOPEĆ, D. & SŁAWIK, Ł. 2020. How to effectively use long-term remotely sensed data to analyze the process of tree and shrub encroachment into open protected wetlands. *Applied Geography,* 125**,** 102345.

KOUROSH NIYA, A., HUANG, J., KARIMI, H., KESHTKAR, H. & NAIMI, B. 2019. Use of intensity analysis to characterize land use/cover change in the biggest Island of Persian Gulf, Qeshm Island, Iran. *Sustainability,* 11**,** 4396.

KRAAI, U. M. 2021. *Impacts of foraging behavior [sic] by Cape porcupines and their effects on nutrient cycling in mesic savannas.*

KRAAI, U. M., KRAAI, M., TSVUURA, Z., MKHIZE, N. R. & TJELELE, T. J. 2023. The impacts of Cape porcupines on woody plant mortality. *Austral Ecology*.

KRAAIJ, T. & WARD, D. 2006. Effects of rain, nitrogen, fire and grazing on tree recruitment and early survival in bush-encroached savanna, South Africa. *Plant Ecology,* 186**,** 235-246.

KUSIIMA, S. K., EGERU, A., NAMAALWA, J., BYAKAGABA, P., MFITUMUKIZA, D., MUKWAYA, P., MENSAH, S. & ASIIMWE, R. 2022. Interconnectedness of Ecosystem Services Potential with Land Use/Land Cover Change Dynamics in Western Uganda. *Land,* 11**,** 2056.

LESOLI, M., GXASHEKA, M., SOLOMON, T. & MOYO, B. 2013. Integrated plant invasion and bush encroachment management on Southern African Rangelands. *Herbicides-Current Research and Case Studies in Use***,** 259-313.

LEVICK, S. R., ASNER, G. P., KENNEDY-BOWDOIN, T. & KNAPP, D. E. 2009. The relative influence of fire and herbivory on savanna three-dimensional vegetation structure.

Biological Conservation, 142**,** 1693-1700.

LEWIS, J. R., VERBOOM, G. A. & FEBRUARY, E. C. 2021. Coexistence and bush encroachment in African savannas: The role of the regeneration niche. *Functional Ecology,* 35**,** 764-773.

LI, J., RAVI, S., WANG, G., VAN PELT, R. S., GILL, T. E. & SANKEY, J. B. 2022. Woody plant encroachment of grassland and the reversibility of shrub dominance: Erosion, fire, and feedback processes. *Ecosphere,* 13**,** e3949.

LIAO, C., CLARK, P. E. & DEGLORIA, S. D. 2018. Bush encroachment dynamics and rangeland management implications in southern Ethiopia. *Ecology and Evolution,* 8**,** 11694-11703.

LIU, P., JIANG, S., ZHAO, L., LI, Y., ZHANG, P. & ZHANG, L. 2017. What are the benefits of strictly protected nature reserves? Rapid assessment of ecosystem service values in Wanglang Nature Reserve, China. *Ecosystem services,* 26**,** 70-78.

LIU, Y., ZHAO, W., ZHANG, Z., HUA, T. & FERREIRA, C. S. S. 2023. The role of nature reserves in conservation effectiveness of ecosystem services in China. *Journal of Environmental Management,* 342**,** 118228.

LUDWIG, A., MEYER, H. & NAUSS, T. 2016. Automatic classification of Google Earth images for a larger scale monitoring of bush encroachment in South Africa. *International Journal of Applied Earth Observation and Geoinformation,* 50**,** 89-94.

LUVUNO, L., BIGGS, R., STEVENS, N. & ESLER, K. 2022. Perceived impacts of woody encroachment on ecosystem services in Hluhluwe, South Africa. *Ecology and Society,* 27.

MAHAMUD, M., SAMAT, N., TAN, M., CHAN, N. & TEW, Y. 2019. Prediction of future land use land cover changes of Kelantan, Malaysia. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* 42**,** 379-384.

MAKIN, D. F., PAYNE, H. F., KERLEY, G. I. & SHRADER, A. M. 2012. Foraging in a 3-D world: how does predation risk affect space use of vervet monkeys? *Journal of Mammalogy,* 93**,** 422-428.

MANJORO, M., KAKEMBO, V. & ROWNTREE, K. M. 2012. Trends in soil erosion and woody shrub encroachment in Ngqushwa District, Eastern Cape Province, South Africa. *Environmental Management,* 49**,** 570-579.

MAPHANGA, T., DUBE, T., SHOKO, C. & SIBANDA, M. 2022. Advancements in the satellite sensing of the impacts of climate and variability on bush encroachment in savannah rangelands. *Remote Sensing Applications: Society and Environment,* 25**,** 100689.

MARX, A. & TETTEH, G. O. 2017. A forest vitality and change monitoring tool based on

RapidEye imagery. *IEEE Geoscience and Remote Sensing Letters,* 14**,** 801-805.

MASHAO, F. M., MOTHAPO, M. C., MUNYAI, R. B., LETSOALO, J. M., MBOKODO, I. L., MUOFHE, T. P., MATSANE, W. & CHIKOORE, H. 2023. Extreme rainfall and flood risk prediction over the East Coast of South Africa. *Water,* 15**,** 50.

MATONGERA, T. N. 2022. *Estimating and monitoring the phenological cycle of bracken fern (Pteridium aquilinum) using remote sensing.*

MELESSE, A. M., WENG, Q., THENKABAIL, P. S. & SENAY, G. B. 2007. Remote sensing sensors and applications in environmental resources mapping and modelling. *Sensors,* 7**,** 3209-3241.

MISHRA, P. K., RAI, A. & RAI, S. C. 2020. Land use and land cover change detection using geospatial techniques in the Sikkim Himalaya, India. *The Egyptian Journal of Remote Sensing and Space Science,* 23**,** 133-143.

MNDELA, M. 2020. *The extent of bush encroachment and its effects on the ecosystem services of a mixed bushveld of Makapanstad rangelands, North-West Province, South Africa.* University of Pretoria Pretoria.

MNDELA, M., MADAKADZE, I. C., NHERERA-CHOKUDA, F. V., DUBE, S., RAMOELO, A., MANGWANE, M. & TJELELE, J. T. 2022. Short-term responses of herbaceous vegetation to bush clearing in semi-arid rangelands of South Africa. *Pastoralism,* 12**,** 17.

MOGASHOA, R., DLAMINI, P. & GXASHEKA, M. 2021. Grass species richness decreases along a woody plant encroachment gradient in a semi-arid savanna grassland, South Africa. *Landscape Ecology,* 36**,** 617-636.

MOKGOTSI, R. 2018. *Effects of bush encroachment control in a communal managed area in the Taung region, North West Province, South Africa.* North-West University.

MPATI, T. M. 2015. *Satellite based long-term evaluation of bush encroachment on sourish-mixed veld at the Towoomba Reseach Station in Bela Bela, Limpopo Province.*

MUDERERI, B., DUBE, T., ADEL-RAHMAN, E., NIASSY, S., KIMATHI, E., KHAN, Z. & LANDMANN, T. 2019. A comparative analysis of PlanetScope and Sentinel-2 space-borne sensors in mapping Striga weed using Guided Regularised Random Forest classification ensemble. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci,* 42**,** 701-708.

MUHAMMAD, R., ZHANG, W., ABBAS, Z., GUO, F. & GWIAZDZINSKI, L. 2022. Spatiotemporal change analysis and prediction of future land use and land cover changes using QGIS MOLUSCE plugin and remote sensing big data: a case study of Linyi, China. *Land,* 11**,** 419.

MUNTHALI, M., MUSTAK, S., ADEOLA, A., BOTAI, J., SINGH, S. & DAVIS, N. 2020.

Modelling land use and land cover dynamics of Dedza district of Malawi using hybrid Cellular Automata and Markov model. *Remote Sensing Applications: Society and Environment,* 17**,** 100276.

NACKLEY, L. L., BETZELBERGER, A., SKOWNO, A., WEST, A. G., RIPLEY, B. S., BOND, W. J. & MIDGLEY, G. F. 2018. CO2 enrichment does not entirely ameliorate Vachellia karroo drought inhibition: A missing mechanism explaining savanna bush encroachment. *Environmental and Experimental Botany,* 155**,** 98-106.

NAIDOO, L., CHO, M. A., MATHIEU, R. & ASNER, G. 2012. Classification of savanna tree species, in the Greater Kruger National Park region, by integrating hyperspectral and LiDAR data in a Random Forest data mining environment. *ISPRS journal of Photogrammetry and Remote Sensing,* 69**,** 167-179.

NAKANYALA, J. & HIPONDOKA, M. 2020. The root structure of Terminalia sericea Burch. ex DC, an encroaching shrub in the Kalahari Basin. *ROOTING STRATEGIES OF SAVANNA SHRUBS IN THE KALAHARI BASIN: IMPLICATIONS FOR THE COEXISTENCE OF WOODY AND HERBACEOUS PLANTS AND SHRUB ENCROACHMENT IN THE AFRICAN SAVANNAS***,** 150.

NDLOVU, M. S. & DEMLIE, M. 2020. Assessment of meteorological drought and wet conditions using two drought indices across KwaZulu-Natal Province, South Africa. *Atmosphere,* 11**,** 623.

NEYNS, R. & CANTERS, F. 2022. Mapping of urban vegetation with high-resolution remote sensing: A review. *Remote sensing,* 14**,** 1031.

O'CONNOR, T. G., PUTTICK, J. R. & HOFFMAN, M. T. 2014. Bush encroachment in southern Africa: changes and causes. *African Journal of Range & Forage Science,* 31**,** 67-88.

OLDELAND, J., DORIGO, W., WESULS, D. & JÜRGENS, N. 2010. Mapping bush encroaching species by seasonal differences in hyperspectral imagery. *Remote Sensing,* 2**,** 1416-1438.

OOSTHUYSEN, M. & STRAUSS, W. 2023. The relationship between mammalian burrow abundance and bankrupt bush (Seriphium plumosum) encroachment.

OSMAN, M. A., ABDEL-RAHMAN, E. M., ONONO, J. O., OLAKA, L. A., ELHAG, M. M., ADAN, M. & TONNANG, H. E. 2023. Mapping, intensities and future prediction of land use/land cover dynamics using google earth engine and CA-artificial neural network model. *PLoS One,* 18**,** e0288694.

OUEDRAOGO, V., HACKMAN, K. O., THIEL, M. & DUKIYA, J. 2023. Intensity Analysis for Urban Land Use/Land Cover Dynamics Characterization of Ouagadougou and Bobo-

Dioulasso in Burkina Faso. *Land,* 12**,** 1063.

PHAN, T. N., KUCH, V. & LEHNERT, L. W. 2020. Land cover classification using Google Earth Engine and random forest classifier—The role of image composition. *Remote Sensing,* 12**,** 2411.

PICKERING, J., TYUKAVINA, A., KHAN, A., POTAPOV, P., ADUSEI, B., HANSEN, M. C. & LIMA, A. 2021. Using multi-resolution satellite data to quantify land dynamics: Applications of PlanetScope imagery for cropland and tree-cover loss area estimation. *Remote Sensing,* 13**,** 2191.

PONTIUS JR, R. G., GAO, Y., GINER, N. M., KOHYAMA, T., OSAKI, M. & HIROSE, K. 2013. Design and interpretation of intensity analysis illustrated by land change in Central Kalimantan, Indonesia. *Land,* 2**,** 351-369.

PONTIUS JR, R. G. & MILLONES, M. 2011. Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing,* 32**,** 4407-4429.

PONTIUS JR, R. G. & SANTACRUZ, A. 2014. Quantity, exchange, and shift components of difference in a square contingency table. *International Journal of Remote Sensing,* 35**,** 7543-7554.

QABAQABA, M., NAIDOO, L., TSELE, P., RAMOELO, A. & CHO, M. A. 2023. Integrating random forest and synthetic aperture radar improves the estimation and monitoring of woody cover in indigenous forests of South Africa. *Applied Geomatics,* 15**,** 209-225.

QIANG, Y. & LAM, N. S. 2015. Modeling land use and land cover changes in a vulnerable coastal region using artificial neural networks and cellular automata. *Environmental Monitoring and Assessment,* 187**,** 1-16.

QUAN, B., PONTIUS JR, R. G. & SONG, H. 2020. Intensity Analysis to communicate land change during three time intervals in two regions of Quanzhou City, China. *GIScience & Remote Sensing,* 57**,** 21-36.

RAHMAN, M. T. U., TABASSUM, F., RASHEDUZZAMAN, M., SABA, H., SARKAR, L., FERDOUS, J., UDDIN, S. Z. & ZAHEDUL ISLAM, A. 2017. Temporal dynamics of land use/land cover change and its prediction using CA-ANN model for southwestern coastal Bangladesh. *Environmental Monitoring and Assessment,* 189**,** 1-18.

RAUBENHEIMER, S. L. & RIPLEY, B. S. 2022. CO2-stimulation of savanna tree seedling growth depends on interactions with local drivers. *Journal of Ecology,* 110**,** 1090-1101.

RAUBENHEIMER, S. L., SIMPSON, K., CARKEEK, R. & RIPLEY, B. 2022. Could CO2-induced changes to C4 grass flammability aggravate savanna woody encroachment?

African Journal of Range & Forage Science, 39**,** 82-95.

RODRIGUEZ-GALIANO, V. F., GHIMIRE, B., ROGAN, J., CHICA-OLMO, M. & RIGOL-SANCHEZ, J. P. 2012. An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing,* 67**,** 93-104.

ROESSLER, S., WOLF, P., SCHNEIDER, T. & MELZER, A. 2013. Multispectral remote sensing of invasive aquatic plants using RapidEye. *Earth Observation of Global Changes (EOGC)***,** 109-123.

ROLO, V. & MORENO, G. 2019. Shrub encroachment and climate change increase the exposure to drought of Mediterranean wood-pastures. *Science of the Total Environment,* 660**,** 550-558.

RUSŇÁK, T., HALABUK, A., HALADA, Ľ., HILBERT, H. & GERHÁTOVÁ, K. 2022. Detection of invasive black locust (Robinia pseudoacacia) in small woody features using spatiotemporal compositing of Sentinel-2 data. *Remote Sensing,* 14**,** 971.

RUSSELL, J. M. & WARD, D. 2014. Remote sensing provides a progressive record of vegetation change in northern KwaZulu-Natal, South Africa, from 1944 to 2005. *International Journal of Remote Sensing,* 35**,** 904-926.

SAHARA, E. A., SARR, D. A., VAN KIRK, R. W. & JULES, E. S. 2015. Quantifying habitat loss: Assessing tree encroachment into a serpentine savanna using dendroecology and remote sensing. *Forest Ecology and Management,* 340**,** 9-21.

SAJAN, B., MISHRA, V. N., KANGA, S., MERAJ, G., SINGH, S. K. & KUMAR, P. 2022. Cellular automata-based artificial neural network model for assessing past, present, and future land use/land cover dynamics. *Agronomy,* 12**,** 2772.

SANG, X., GUO, Q., WU, X., FU, Y., XIE, T., HE, C. & ZANG, J. 2019. Intensity and stationarity analysis of land use change based on CART algorithm. *Scientific Reports,* 9**,** 12279.

SAPUTRA, M. H. & LEE, H. S. 2019. Prediction of land use and land cover changes for North Sumatra, Indonesia, using an artificial-neural-network-based cellular automaton. *Sustainability,* 11**,** 3024.

SCHMITT, M. H., STEARS, K., DONOVAN, M. K., BURKEPILE, D. E. & THOMPSON, D. I. 2022. Integrating herbivore assemblages and woody plant cover in an African savanna to reveal how herbivores respond to ecosystem management. *PloS One,* 17**,** e0273917.

SCHOLTZ, R., POLO, J., TANNER, E. & FUHLENDORF, S. 2018. Grassland fragmentation and its influence on woody plant cover in the southern Great Plains, USA. *Landscape* *ecology,* 33**,** 1785-1797.

SCHUSTER, C., SCHMIDT, T., CONRAD, C., KLEINSCHMIT, B. & FÖRSTER, M. 2015. Grassland habitat mapping by intra-annual time series analysis–Comparison of RapidEye and TerraSAR-X satellite data. *International Journal of Applied Earth Observation and Geoinformation,* 34**,** 25-34.

SCHWIEDER, M., LEITÃO, P. J., SUESS, S., SENF, C. & HOSTERT, P. 2014. Estimating fractional shrub cover using simulated EnMAP data: A comparison of three machine learning regression techniques. *Remote Sensing,* 6**,** 3427-3445.

SEBITLOANE, T. K., COETZEE, H., KELLNER, K. & MALAN, P. 2020. The socio-economic impacts of bush encroachment in Manthestad, Taung, South Africa. *Environmental & socio-economic studies,* 8**,** 1-11.

SHANUNGU, G. K., BLASER, W. J., HARMS, J., CHABWELA, H. N., ELLENBROEK, G. A., SIMUKONDA, C., VAN GILS, H. A., EDWARDS, P. J. & VENTERINK, H. O. 2013. Impact of shrub encroachment on the understory vegetation differs among shrub species in the Kafue Flats, Zambia. *IMPACT OF WOODY ENCROACHMENT ON SOIL-PLANT-HERBIVORE INTERACTIONS IN THE KAFUE FLATS FLOODPLAIN ECOSYSTEM***,** 75.

SHEKEDE, M. D., MURWIRA, A. & MASOCHA, M. 2015. Wavelet-based detection of bush encroachment in a savanna using multi-temporal aerial photographs and satellite imagery. *International Journal of Applied Earth Observation and Geoinformation,* 35**,** 209-216.

SHEN, X., LIU, Y., LIU, B., ZHANG, J., WANG, L., LU, X. & JIANG, M. 2022. Effect of shrub encroachment on land surface temperature in semi-arid areas of temperate regions of the Northern Hemisphere. *Agricultural and Forest Meteorology,* 320**,** 108943.

SHIKANGALAH, R. & MAPANI, B. 2020. A review of bush encroachment in Namibia: from a problem to an opportunity? *Journal of Rangeland Science,* 10**,** 251-266.

SHUMILO, L., YAILYMOV, B., LAVRENIUK, M. & BILOKONSKA, Y. Remote sensing approaches for deforestation identification in Ukraine. 2020 IEEE 5th International Symposium on Smart and Wireless Systems within the Conferences on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS-SWS), 2020. IEEE, 1-4.

SINGH, S. K., LAARI, P. B., MUSTAK, S., SRIVASTAVA, P. K. & SZABÓ, S. 2018. Modelling of land use land cover change using earth observation data-sets of Tons River Basin, Madhya Pradesh, India. *Geocarto International,* 33**,** 1202-1222.

SIVAKUMAR, V. & FAZEL-RASTGAR, F. Heavy rainfall resulting from extreme weather disturbances in eastern coastal parts of South Africa: 11 April 2022. Proceedings of the

Earth and Environmental Sciences International Webinar Conference, 2021. Springer, 161-186.

SKOWNO, A. L., THOMPSON, M. W., HIESTERMANN, J., RIPLEY, B., WEST, A. G. & BOND, W. J. 2017. Woodland expansion in South African grassy biomes based on satellite observations (1990–2013): general patterns and potential drivers. *Global change biology,* 23**,** 2358-2369.

SLEZÁK, M., DOUDA, J., ŠIBÍKOVÁ, M., JAROLÍMEK, I., SENKO, D. & HRIVNÁK, R. 2022. Topographic indices predict the diversity of Red List and non-native plant species in human-altered riparian ecosystems. *Ecological Indicators,* 139**,** 108949.

SOBHANI, P., ESMAEILZADEH, H., BARGHJELVEH, S., SADEGHI, S. M. M. & MARCU, M. V. 2021. Habitat integrity in protected areas threatened by LULC changes and fragmentation: A case study in Tehran province, Iran. *Land,* 11**,** 6.

SOUBRY, I. & GUO, X. 2022. Quantifying woody plant encroachment in grasslands: A review on remote sensing approaches. *Canadian Journal of Remote Sensing,* 48**,** 337-378.

STAFFORD, W., BIRCH, C., ETTER, H., BLANCHARD, R., MUDAVANHU, S., ANGELSTAM, P., BLIGNAUT, J., FERREIRA, L. & MARAIS, C. 2017. The economics of landscape restoration: Benefits of controlling bush encroachment and invasive plant species in South Africa and Namibia. *Ecosystem Services,* 27**,** 193-202.

STEPHEN, R. J., CHATANGA, P., SELETENG-KOSE, L., MAPESHOANE, B. & MARAKE, M. V. 2023. Herbaceous vegetation changes along a bush encroachment intensity gradient in a montane area. *African Journal of Ecology,* 61**,** 907-918.

STEWART, T., SCOGINGS, P. F. & BAIJNATH, H. 2022. Occurrence of Dalbergia obovata in grasslands of urban nature reserves within a metropolitan municipality: Is it an encroaching woody species? *African Journal of Range & Forage Science,* 39**,** 214-221.

SYMEONAKIS, E. & HIGGINBOTTOM, T. 2014a. Bush encroachment monitoring using multi-temporal Landsat data and random forests. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* 40**,** 29-35.

SYMEONAKIS, E. & HIGGINBOTTOM, T. 2014b. BUSH ENCROACHMENT MONITORING USING MULTI-TEMPORAL LANDSAT DATA AND RANDOM FORESTS. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*.

TAYLOR, J., SMIT, N. & JEWITT, D. 2018. Predictive modelling of the potential future distribution of Vachellia nilotica within the KwaZulu-Natal province of South Africa. *African Journal of Range & Forage Science,* 35**,** 73-80.

TEFERI, E. 2021. Detecting Past, Present and Future Land Use Changes and Their Impacts on Ecosystem Services: Remote Sensing, GIS and Modelling Approaches in the Borana Pastoral Areas of Southern Ethiopia. *Ethiopian Journal of Development Research,* 43**,** 51-82.

THOMAS, A. D., ELLIOTT, D. R., DOUGILL, A. J., STRINGER, L. C., HOON, S. R. & SEN, R. 2018. The influence of trees, shrubs, and grasses on microclimate, soil carbon, nitrogen, and CO2 efflux: Potential implications of shrub encroachment for Kalahari rangelands. *Land Degradation & Development,* 29**,** 1306-1316.

TONG, X. & FENG, Y. 2020. A review of assessment methods for cellular automata models of land-use change and urban growth. *International Journal of Geographical Information Science,* 34**,** 866-898.

USTEBAY, S., TURGUT, Z. & AYDIN, M. A. Intrusion detection system with recursive feature elimination by using random forest and deep learning classifier. 2018 international congress on big data, deep learning and fighting cyber terrorism (IBIGDELFT), 2018. IEEE, 71-76.

VAN AUKEN, O. 2009. Causes and consequences of woody plant encroachment into western North American grasslands. *Journal of Environmental Management,* 90**,** 2931-2942.

VENTER, Z., CRAMER, M. & HAWKINS, H. 2018. Drivers of woody plant encroachment over Africa. Nat Commun 9: 2272.

VERBURG, P. H., ALEXANDER, P., EVANS, T., MAGLIOCCA, N. R., MALEK, Z., ROUNSEVELL, M. D. & VAN VLIET, J. 2019. Beyond land cover change: towards a new generation of land use models. *Current Opinion in Environmental Sustainability,* 38**,** 77-85.

VIVEKANANDA, G., SWATHI, R. & SUJITH, A. 2021. Multi-temporal image analysis for LULC classification and change detection. *European journal of remote sensing,* 54**,** 189-199.

WANG, Y., LI, X., ZHANG, Q., LI, J. & ZHOU, X. 2018. Projections of future land use changes: Multiple scenarios-based impacts analysis on ecosystem services for Wuhan city, China. *Ecological Indicators,* 94**,** 430-445.

WEDEL, E. R., NIPPERT, J. B., O'CONNOR, R. C., NKUNA, P. & SWEMMER, A. M. 2024. Repeated clearing as a mechanism for savanna recovery following bush encroachment. *Journal of Applied Ecology*.

WIEGAND, K., SALTZ, D. & WARD, D. 2006. A patch-dynamics approach to savanna dynamics and woody plant encroachment–insights from an arid savanna. *Perspectives in*

Plant Ecology, Evolution and Systematics, 7**,** 229-242.

XIE, Z., PONTIUS JR, R. G., HUANG, J. & NITIVATTANANON, V. 2020. Enhanced intensity analysis to quantify categorical change and to identify suspicious land transitions: A case study of Nanchang, China. *Remote Sensing,* 12**,** 3323.

XING, W., QIAN, Y., GUAN, X., YANG, T. & WU, H. 2020. A novel cellular automata model integrated with deep learning for dynamic spatio-temporal land use change simulation. *Computers & Geosciences,* 137**,** 104430.

XU, L., AO, C., MAO, B., CHENG, Y., SUN, B., WANG, J., LIU, B. & MA, J. 2020. Which is more important, ecological conservation or recreational service? Evidence from a choice experiment in wetland nature reserve management. *Wetlands,* 40**,** 2381-2396.

YAGOUB, M. & AL BIZREH, A. A. 2014. Prediction of land cover change using Markov and cellular automata models: case of Al-Ain, UAE, 1992-2030. *Journal of the Indian Society of Remote Sensing,* 42**,** 665-671.

YANG, J., YANG, J., LUO, X. & HUANG, C. 2019. Impacts by expansion of human settlements on nature reserves in China. *Journal of Environmental Management,* 248**,** 109233.

YAPI, T. S., O'FARRELL, P. J., DZIBA, L. E. & ESLER, K. J. 2018. Alien tree invasion into a South African montane grassland ecosystem: impact of Acacia species on rangeland condition and livestock carrying capacity. *International Journal of Biodiversity Science, Ecosystem Services and Management,* 14**,** 105-116.

YASSIN, I. M. 2019. Bush encroachment in Borana rangeland in the case of Southern Ethiopia: Causes, impacts and management implications. *International Journal of Agriculture Innovations and Research,* 7**,** 420-428.

ZHANG, H., LI, Q., LIU, J., SHANG, J., DU, X., MCNAIRN, H., CHAMPAGNE, C., DONG, T. & LIU, M. 2017. Image classification using rapideye data: Integration of spectral and textual features in a random forest classifier. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* 10**,** 5334-5349.

ZHANG, X., DU, L., TAN, S., WU, F., ZHU, L., ZENG, Y. & WU, B. 2021. Land use and land cover mapping using RapidEye imagery based on a novel band attention deep learning method in the three gorges reservoir area. *Remote Sensing,* 13**,** 1225.

ZHAO, Y., LIU, X., WANG, Y., ZHENG, Z., ZHENG, S., ZHAO, D. & BAI, Y. 2021. UAV-based individual shrub aboveground biomass estimation calibrated against terrestrial LiDAR in a shrub-encroached grassland. *International Journal of Applied Earth Observation and Geoinformation,* 101**,** 102358.

ZHOU, P., HUANG, J., ROBERT GILMORE JR, P. & HONG, H. 2014. Land classification and change intensity analysis in a coastal watershed of Southeast China. *Sensors*, 14**,** 11640-11658.