THE USE OF GEOSPATIAL TECHNIQUES IN DETECTING AND MAPPING THE SPATIO-TEMPORAL VARIABILITY OF COMMUNAL RANGELANDS IN SOUTH AFRICA

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Thesis submitted to the College of Agriculture, Engineering, and Science, at the University of KwaZulu-Natal, in fulfilment of the academic requirements of the degree of Master of Science in Environmental Science

(Specialization: GIS and Remote Sensing)

Pietermaritzburg

South Africa

FEBRUARY 2023

Abstract

Rangelands are an important ecosystem service that provides food and supplement income for farmers through livestock production. However, rangelands are deteriorating because of human activities such as settlement development and agriculture. The depletion of rangelands requires an understanding of the drivers of change to implement optimal intervention measures. Hence, understanding changes in the spatial and temporal distribution of rangelands would assist in establishing robust and efficient conservation policies for monitoring and management. In this regard, the aim of this study was to map the spatio-temporal variability of rangelands using geospatial techniques. To achieve this objective, two specific objectives were evaluated. The first was to assess changes in the spatial extent of rangelands from the year 2000, 2010 and 2020 using Landsat remotely sensed data and Random Forest Classifier in Google Earth Engine cloud base platform. The second focussed on predicting the future rangeland spatial distribution (year 2040) using the Cellular Automata and Markov model (CA Markov model) in IDRISI TerrSet. In classifying grasslands from other land cover classes, overall accuracies of 75%, 79% and 83% were obtained in Inhlazuka while accuracies of 89%, 85%, and 89% were obtained in Vulindlela for the years 2000, 2010 and 2020, respectively. It was also observed that the spatial extent of rangelands was decreasing in Vulindlela due to an increase in the spatial extent of built-up areas by 37.52 hectares per year from the year 2000 to 2010. A decline of 76.46 hectares per year was observed from 2010 to 2020. Meanwhile, in Inhlazuka, the rangelands decreased due to an increase in forest by 40 hectares per year between the years 2000 and 2010 and then increased by 45.28 hectares per year between 2010 and 2020. In assessing the magnitude of rangeland fragmentation in Vulindlela, an average decrease in patch size of 20.7 ha was noted, indicating extensive fragmentation. Results from the CA-Markov model predicted rangelands in Vulindlela to continue declining by 919.74 ha and an increase of 419.48 ha by the year 2040 in Inhlazuka. In 2040, rangelands in Vulindlela are to decrease because of the increase in builtup area whereas, the decline in the forested areas in Inhlazuka is to create optimal conditions for the increase in rangelands. The rangeland fragmentation in Vulindlela was also predicted to increase. The patch analysis revealed a loss in the rangeland patch connectivity in Vulindlela and an increased in rangeland patch isolation by the year 2040 in both areas of Vulindlela and Inhlazuka, respectively. The patch isolation (Euclidean Nearest Neighbor Distance (ENN_MN)) was predicted to increase from 73.0 ha in 2020 to 172.20 ha by 2040 in Vulindlela and increase from 75.0 ha to 120.60 ha in Inhlazuka within the same period. The study results suggest that there is an urgent need to monitor rangelands to establish sustainable development practices for the protection of rangelands. In addition, the study revealed that for the effective monitoring and conservation of rangelands, the use of geospatial techniques is efficient for land management.

Preface

This study was conducted in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, from January 2021 to February 2023, under the supervision of Professor Onisimo Mutanga and Doctor Mbulisi Sibanda. I declare that the work presented in this thesis has never been submitted in any form to any other institution. This work represents my original work except where due acknowledgments are made.

Xolile Zuma Signed: [redacted] Date: 09/02/2023

As the candidate's supervisor, I certify the aforementioned statement and have approved this thesis for submission.

Professor Onisimo Mutanga Signed: [redacted] Date: 09/02/2023

Doctor Mbulisi Sibanda Signed: [redacted] Date: 09/02/2023

Declaration

I Xolile Zuma, 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.

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Signed: [redacted] **Date: 09/02/2023**

Dedication

I dedicate this thesis to my family and friends as they supported and pushed me to the very end. But most importantly I dedicate this dissertation to my daughter, who has been my light from the very first day she came into my life.

Acknowledgments

Isaiah 60:22 When the Time Is Right I, the Lord Will Make It Happen. I would like to thank God for giving me the strength of reaching this stage in my academic journey. It was not easy but through His grace, I made it to the end. I would also like to extend my gratitude to the University of KwaZulu-Natal, especially the School of Agricultural, Earth, and Environmental Science for awarding me the opportunity to pursue my Masters' Degree. To Prof Mutanga my supervisor, thank you for not losing faith in me throughout this research. Working under your guidance has been such a pleasure and a fruitful experience. To Dr Sibanda, thank you so much for your patience. Thank you for sticking by me from the beginning till the very end. Your support, motivation, and criticism to ensure the success of this research are highly appreciated. Thank you, and may God bless you. To my colleague Mohamed Vawda, thank you so much for your assistance and support during the duration of this research. To Anita Masenyama, thank you so much for your academic guidance, emotional support, and motivation throughout this entire research. I appreciate it and may God bless your loving heart. To Dr Odebiri Omosalewa, Dr Mthembeni Mngadi and Dr Trylee Nyasha Matongera thank you for your assistance, guidance, and support. I highly appreciate it. To my mother, father, and brother, thank you guys so much for your support from the beginning of this research to the very end. You guys are honestly the best gift from God. I love and appreciate you so much. To my baby girl, Lindokuhle, thank you so much for giving me the strength to keep pushing every day. I love you so much mama! Lastly, I would like to applaud myself for believing in my capabilities, not giving up, and ensuring that I complete my studies.

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CHAPTER ONE

1 Introduction

Rangelands cover about 51% of the terrestrial land globally (Lund 2007). When properly managed rangelands can contribute indirectly to food security and poverty alleviation (Alkemade et al. 2013). Specifically, livestock production in communal rangelands is a source of income and food (meat and milk) for smallholder subsistence farmers (Admasu, Abule and Tessema 2010, Seré et al. 2020). Rangelands also provide multiple ecosystem services such as the protection of soil from erosion, carbon storage, and provision of habitat for wild fauna and flora (Yahdjian, Sala and Havstad 2015, Selemani 2020, Lund 2007). They also play a critical hydrological role, especially in catchments of large river systems by facilitating infiltration, percolation and reduced erosion, in turn regulating the stream flows and ground water storages (Lund 2007, Yahdjian et al. 2015, Selemani 2020, Bengtsson et al. 2019). In addition, rangelands are critical biodiversity reservoirs as they provide a habitat for diverse flora and fauna (Rija et al. 2013). Rangelands also contribute to the national revenue earned from game viewing by tourists in conservation areas and game ranches (Milton, Dean and Richardson 2003). In South Africa for example, rangelands play an important role in sustaining rural livelihoods through livestock production (Cousins 1999, Vetter 2013). However, land use land cover change (LULCC) activities such as overgrazing, conversion of rangelands into croplands as well as excessive fire administration threaten the existence and sustenance of rangelands (Hoffman and Vogel 2008, Angassa and Oba 2008). Meanwhile, climate change and the development of infrastructure are also concerning drivers behind the drastic LULCCs in rangelands (Breedt, Dreber and Kellner 2013, Abdulahi, Hashim and Teha 2016, Kipling et al. 2016). As a result of the LULCCs, the quality, and quantity of rangeland ecosystem services is declining (Ge et al. 2022). This makes the monitoring of LULCC essential to understand not only vegetation dynamics in these sensitive ecosystems but to also foster sustainable utilization of these resources (Kuule et al. 2022). In this regard, research in LULCCs is important and urgently required in assisting in the formulation of improved conservation frameworks, strategies, and policies to support sustainable rangeland management (Kuule et al. 2022). However, traditionally, rangelands were assessed using visual inspections through surveys conducted by qualified rangelands managers in point-based manner. However, this method lacks spatial representativeness and is often associated with errors as field surveys are cumbersome and expensive. In this regard, there is a need to establish spatially explicit mapping and monitoring methods and techniques for assessing rangelands.

Alternatively, the use of Remote Sensing (RS) techniques has been proven to be relatively accurate in representing the spatial variations of LULCCs through space and time (Liping, Yujun and Saeed 2018). Specifically, RS provides spatially explicit data at optimal spatial and radiometric resolutions suitable for characterizing LULCCs at limited costs and efficiently (Alqurashi and Kumar 2013). Furthermore, the use of satellite imagery in change detection studies offers multi-spectral data covering longer periods which is critically required in land use land cover change studies (Kumar and Arya 2021). Specifically, Landsat data has been utilized extensively in monitoring LULCCs (Zhu and Woodcock 2014). This is because Landsat boasts of being the longest serving mission (Wulder and Coops 2014). The first Landsat sensor was launched in 1972, giving this mission the longest running record of serving Earth Observation data. The Landsat sensors, i.e., Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI), have ideal sampling characteristics for monitoring land cover types at a regional scale dating back to the 1970s (Willis 2015). For example, it has a revisit time of 16 days and a moderate spatial resolution of 30 meter which is suitable for detecting changes in vegetation cover (Li and Roy 2017). Considering the importance of rangelands as well as the availability of remotely sensed data from missions such as Landsat, there is a need to extend research efforts of characterizing spatial extent, quality, and the quantity of the rangelands to communal areas if robust monitoring frameworks and efficient sustainable utilization strategies of grasslands areas are to be drawn.

Previously, it had been challenging to handle numerous remotely sensed datasets such as Landsat covering landscape scales when characterising the LULCCs in a GIS. This has been mainly due to the limited processing speed and space in computing resources. The advent of Google Earth Engine provided a cloud based platform as an alternative for storing, retrieving, processing, and analysing remotely sensed data efficiently at limited costs (Sidhu, Pebesma and Câmara 2018). Specifically, the platform offers tools for classifying large remotely sensed datasets such as the robust Random Forest (RF) classifier and the Classification and Regression Trees (CARTS) (Bar, Parida and Pandey 2020). The

RF is a widely used non-parametric classifier that belongs to the family of decision trees (Chan and Paelinckx 2008). RF has gained a lot of recognition within the remote sensing community due to its ability to detect and accurately discriminate different land cover types (Chan and Paelinckx 2008). Furthermore, the classifier is capable of selecting and ranking variables according to their influence and ability to discriminate target classes especially in cases where remotely sensed spectral features are characterized by high dimensionality that makes the selection of the relevant variables time-consuming and difficult (Rodriguez-Galiano et al. 2012b, Belgiu and Drăguţ 2016). In this regard, the RF integrated in the GEE platform provides a suitable tool for mapping and monitoring grassland cover changes efficiently within a catchment scale. However, the RF integrated in GEE does not perform simulations of future LULCCs like algorithms such as the Artificial Neural Networks (ANN), the Markov chain model (MC) and the Land Change Modeller (LCM) (Singh et al. 2022, Vázquez-Quintero et al. 2016, Hyandye and Martz 2017).

The Cellular Automata and the Markov chain model (CA-Markov) hypothesised to be the most widely used LULCC algorithm for accurately modelling future LULCCs because it possesses the strength from the combination of functions of the Markov Chain and Cellular Automata required in generating future LULCCs models (Sang et al. 2011). In this regard, there is a need to consider robust algorithms such as the CA-Markov if a sound understanding of future LULCCs is to be drawn as a step towards establishing effective monitoring and management strategies to facilitate the sustainable utilization of rangelands.

In this regard, the main objective of this study was to quantitatively assess the changes in the spatial distribution of rangelands in communal areas between the year 2000 and the year 2020 as well as predict their future changes/patterns between the year 2020 and the year 2040.

1.1 The Study Overall Aim

- This study aimed to assess the spatio-temporal variations in communal rangelands using geospatial techniques.

1.2 Specific Objectives of the Study

The main objective was achieved by addressing the following specific objectives:

1. To assess the LU/LC changes and the spatial extent variation of communal rangelands (between the years 2000, 2010 and 2020).

2. To predict the future changes (2020 to 2040) in the spatial distribution of rangelands in communal areas using the CA Markov model.

1.3 Structure of the Thesis

This dissertation is comprised of four chapters. Out of the four chapters, two chapters are based on research papers which are prepared and can be regarded as independent articles. However, considering that they are both addressing the same overarching objective, there are inevitable overlaps.

1.3.1 Chapter One

This chapter forms the introduction of the study. It begins by introducing the concept of rangelands and their importance at global to local scales. Specifically, rangelands are defined as areas that are dominantly covered by graminoids and grasses, typically used as grazing lands by rural communities. The chapter then outlines the major drivers of grasslands transformation in communal rangelands. Subsequently, the problem which is the lack of spatially explicit criterions and techniques for establishing robust mapping and monitoring frameworks of communal rangelands is articulated. The chapter then states the overall aim of the study, and the objectives which are to be addressed using Landsat data, the Random Forest integrated in GEE along with the CA Markov chains.

1.3.2 Chapter Two

Chapter two focuses on the first specific objective which seeks to assess the changes taking place in the rangeland areal extent between the year 2000 to 2010, 210 to 2020. Classification conducted in this chapter is conducted in the confines of GEE, using the satellite images from Landsat 7 and 8 and RF algorithm. Rangeland fragmentation is also computed using Fragmentation statistical software. Lastly this chapter considered the rate of change to determine the speed at which the rangelands are being converted into other land cover types.

1.3.3 Chapter Three

This chapter was based on the second objective of the thesis which sought predict the future changes in the spatial extent and configuration of grasslands between the 2020 and the 2040 using the CA-Markov model in IDRISI TerrSet GIS.

1.3.4 Chapter Four

This chapter reviews the objectives, major findings and conclusions drawn in assessing the specific objectives of this study. The chapter also draws a general conclusion regarding the spatial and temporal changes in grasslands in a communal rangeland. The drawn general conclusions are supported by the implications and limitations of the study. Finally, the chapter provides recommendations for future studies.

CHAPTER TWO

LAND USE LAND COVER CHANGES IN A TYPICAL COMMUNAL AREA IN SOUTHERN AFRICA

Abstract: Rangelands are globally being transformed drastically by climate change and anthropogenic activities. Human activities such as the development of settlement, the conversion of rangelands to crop farming and animal grazing activities threaten rangelands. This is compounded by the lack of spatially explicit criterion and frameworks for monitoring the magnitude and location of rangeland transformations. There is therefore a need for timely accurate and effective methods to characterise the magnitude of changes in land cover and land use as well as the extent of fragmentation in rangelands. The ability to accurately identify these changes could aid conservation management practices. In this regard, this study sought to assess the spatio-temporal variability of rangelands in selected communal areas of KwaZulu Natal from the year 2000 to 2020 using Landsat data in conjunction with the random forest classifier in Google Earth Engine (GEE). The study also assessed the level of rangeland fragmentation based on fragmentation statistical analysis. In classifying grasslands from other land cover classes, overall accuracies of 75%, 79% and 83% were obtained in Inhlazuka while accuracies of 89%, 85%, and 89% were obtained in Vulindlela for the years 2000, 2010 and 2020, respectively. Rangelands decreased at a rate of 37.52 hectares per year between 2000 to 2010 and at 76.46 hectares per year between 2010 to 2020 in Vulindlela. Meanwhile, in Inhlazuka they decreased at 40 hectares per year between the years 2000 and 2010 then increased at a rate of 45.28 hectares per year between 2010 to 2020 due to a decline in the forest class. The most frequent influential spectral features in discriminating the grasslands from other land cover types were Bands 5 and 7 which are the near infrared (NIR) and the short-wave infrared bands (SWIR). Meanwhile, the rangeland mean patch sizes in Vulindlela decreased from 32 ha to 22 ha and then to 9 ha between 2000, 2010 and 2020, respectively, as a result of the increasing built-up areas. On the other hand, in Inhlazuka the grasslands mean patch area decreased from 2 ha to a hectare between 2000 and 2010 and then it increased by 1 hectare between 2010 and 2020. The findings of this study are a step towards generating, simple, spatially explicit criterion and monitoring frameworks that are lacking and are essential for improving the communal rangelands management policies required in sustainable utilisation on natural resources.

Key words: Land use Land Cover (LULC) changes, Random Forest (RF) classifier, Google Earth Engine (GEE), Landsat 7, Landsat 8.

2 Introduction

Rangelands around the world have become one of the most threatened ecosystems due to human activities and climate variability (Abdulahi et al. 2016). These landscapes provide important ecosystem services such as the provision of food, carbon sequestration, biodiversity maintenance, fibre, clean water, recreational space, and wildlife habitat (Sala et al. 2017, Boone et al. 2018, Zhao, Liu and Wu 2020). The human population highly depends on rangelands for food production considering that several agricultural activities are conducted in grasslands. According to Bedunah and Angerer (2012) about 1.2 billion people who are surviving on less than $1 per day depend on rangelands. The limited management of rangelands in developing countries makes it difficult to determine the level of grass degradation (Bedunah and Angerer 2012). As the human population increases, food production is also anticipated to increase by about 75% in the next 30 years (Ceballos et al. 2010, Bedunah and Angerer 2012). This will exert a lot of pressure on rangelands as they will be converted into croplands to produce more food, similarly development of infrastructure and land use activities such as overgrazing and unmanaged farming practices will cause rangeland fragmentation and biodiversity loss (Palmer and Bennett 2013). Meanwhile, a large population depends on rangelands for livestock production, food and income generation (Abdulahi et al. 2016). However, the limited monitoring and management strategies of rangelands in the communal areas of developing countries make it difficult to determine the level of grass degradation (Bedunah and Angerer 2012). In South Africa, about 60% of the grassland biome has been transformed while 25% has been degraded, with approximately 15% remaining unchanged and only 2% being protected (Little et al. 2015). The lack of management of grasses in unprotected areas exacerbates the degradation of rangelands as there are limited comprehensive criterions for assessing their condition and state of fragmentation (McGranahan and Kirkman 2013). According to Al-Bukhari, Hallett et al. (2018), rangeland assessment and management performed by field specialists through field observation can be biased. Hence there is need for spatially explicit non-invasive techniques for assessing and monitoring the spatial extent and the magnitude of grassland fragmentation for sustainable utilisation of this natural capital.

The advent of earth-observation (EO) facilities has offered fast, efficient and reliable spatially explicit techniques of monitoring the extent of fragmentation and the spatial distribution of grasslands (Jin et al. 2014). Furthermore, EO facilities offer data that is frequently acquired, with high spatial and spectral resolutions, suitable for monitoring grassland attributes at local to regional scales (Ali et al. 2016). In this regard, remote sensing (RS) techniques have been widely used for monitoring rangelands attributes such as biomass (Sibanda et al. 2017), water content (Sibanda et al. 2019) and their phenology (Matongera et al. 2021). Other than monitoring grass attributes, remote sensing techniques have also been widely applied in characterising land use and land cover changes based on a variety of classification algorithms and datasets. The most widely used EO sensors in mapping LULC changes have been from the Landsat mission (Abd El-Kawy et al. 2011). This is attributed to the fact that Landsat boasts of being the world's longest uninterruptedly mission serving remotely sensed data over the land and sea (Ul Din and Mak 2021). Specifically, Landsat 1/2/3 Multi-Spectral Scanner (MSS), Landsat 5 MSS and Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper plus (ETM), and Landsat 8 Operational Land Imager (OLI) provide remotely sensed data at a 30m pixel size, 16 days intervals archived since 1972 to date making it suitable for historical mapping of LULC changes (Loveland and Dwyer 2012, Li et al. 2020). Subsequently, Landsat datasets offer better prospects of objectively detecting, mapping and monitoring the spatial and temporal variations of grassland fragmentation in communal rangelands (Xie et al. 2019).

Literature underscores the importance of integrating multi-temporal datasets with robust algorithms in accurately mapping LULC changes (Ghayour et al. 2021, Kafy et al. 2021). Specifically, machine leaning algorithms are the most renowned techniques in image classification for assessing LULC changes due to their greater accuracy and efficiency(Kafy et al. 2021, Ghayour et al. 2021). Random forest (RF) classifier is one of the machine learning algorithms that is widely renowned for its robustness in mapping LULC changes, especially in conjunction with multi-spectral and hyperspectral remotely sensed datasets (Talukdar et al. 2020). Specifically, RF widely recognised in the community of practice because of its excellent management of outliers and noisy datasets, great performance in dealing with high dimensional and multi-source datasets as well as its attainment of higher accuracies when compared to other classifiers such as the Support Vector Machine (SVM) and Maximum Likelihood Classifier (MLC) (Cengiz et al. 2023, Sheykhmousa et al. 2020). RF uses decision trees during classification, such that the trees with the most selections define the class. To date, the algorithm is the most widely used classifier in conjunction with Landsat data in assessing

LULC changes (Rodriguez-Galiano et al. 2012b, Phan, Kuch and Lehnert 2020, Thanh Noi and Kappas 2017).

Despite the optimal performance of RF and Landsat data in LULC change assessments for the sustainable management of natural resources, the provision of large-scale land cover change maps of grasslands is often inhibited by elements such as spectral complexity due to the heterogeneity of the environment as well as the limitation of software/hardware resources to store and process large remotely sensed datasets (Rodriguez-Galiano et al. 2012b, Wahap and Shafri 2020). The development of cloud computing platforms such as Google Earth Engine (GEE) has emerged as an invaluable resource for addressing data management challenges in applications such as mapping largescale LULC changes (Wahap and Shafri 2020). GEE is a free cloud-based platform which can be used for large-scale environmental analysis or mapping (Tamiminia et al. 2020). GEE, has vastly improved the access and processing of satellite imagery making it possible to conduct assessments on the spatial and temporal variations of community-shared natural resources such as the communal rangelands (Tamiminia et al. 2020). The platform provides a large amount of satellite data including Landsat, dating back to the 1970s, while it is capable of administering renowned algorithms such as the RF on the available datasets (Wang et al. 2017, Kumar and Mutanga 2018, Gorelick et al. 2017). Single date Landsat remotely sensed data sets have been widely used in remote sensing LULC (Abd El-Kawy et al. 2011, Langley, Cheshire and Humes 2001). However, grasslands are highly variable ecosystems which are greatly impacted by situational factors such as seasonality of precipitation, and variations in management practices (Cleland et al. 2013). This makes it challenging to characterise the spatial and temporal changes of grasslands based on single-date images (Price et al. 1997). Considering the relative accessibility of high spatial and temporal Landsat data coverage and the robustness of the RF algorithm, all embedded in GEE, presents opportunities for establishing cheap and reliable grassland monitoring techniques. Therefore, the objective of this study was to assess the spatio-temporal variability of rangelands within a typical southern African communal area from the year 2000 to 2020 using multi-temporal Landsat datasets in conjunction with random forest. The study also sought to assess the magnitude and extent of grassland fragmentation in these communal rangelands using fragmentation statistics.

2.1 Methods and Materials

2.1.1 Study Site

This study was conducted in Inhlazuka (centre coordinates 29° 55' 40" E and 30° 11' 34" S) and Vulindlela (centre coordinates 29º .40′ 37.3584″ S and 30º. 8′ 13.6572″ E) communal rangelands located in the uMgungundlovu District Municipality under the uMngeni Catchment in the province of KwaZulu-Natal, South Africa (Figure 2.1). The catchment hosts the country's second largest economic hub and its largest trade port (Hughes et al. 2018). Activities such as agriculture and urbanisation are causing immense pressure on the catchment's natural resources (Hughes et al. 2018). The catchment is mostly covered by grasslands, with much of its grasses being turned into cultivated land (Hughes et al. 2018). Vulindlela is located in the west of Pietermaritzburg and northwest of the Greater Edendale area, while Inhlazuka is located under the Richmond municipality and is a mountainous area with an elevation of 1313 metres. The areas of Inhlazuka and Vulindlela are rural settings with high levels of poverty. Vulindlela experiences dry winters and hot wet summers and receives on average an annual rainfall of 979 mm (Sibanda et al. 2021). The growing season in Vulindlela starts in October and ends in April, from late April to August frost conditions begin, where the growing season is restricted (Royimani et al. 2022, Sibanda et al. 2021). The average rainfall received by Inhlazuka is 852 mm which starts in October and ends in April (Mncube 2022). Land use activities in Vulindlela include scattered settlements, grazing land, cultivated lands, pockets of indigenous forest and some major timber plantations while Inhlazuka is predominantly charcterised by small and large-scale crop farming lands. Vegetation in Inhlazuka is also characterised by bushveld vegetation, which is heavily invaded by alien vegetation, such as bugweed (*Solanum mauritianum*), Lantana camara and bramble (*Rubus spp*) which are often cleared but still persisting.

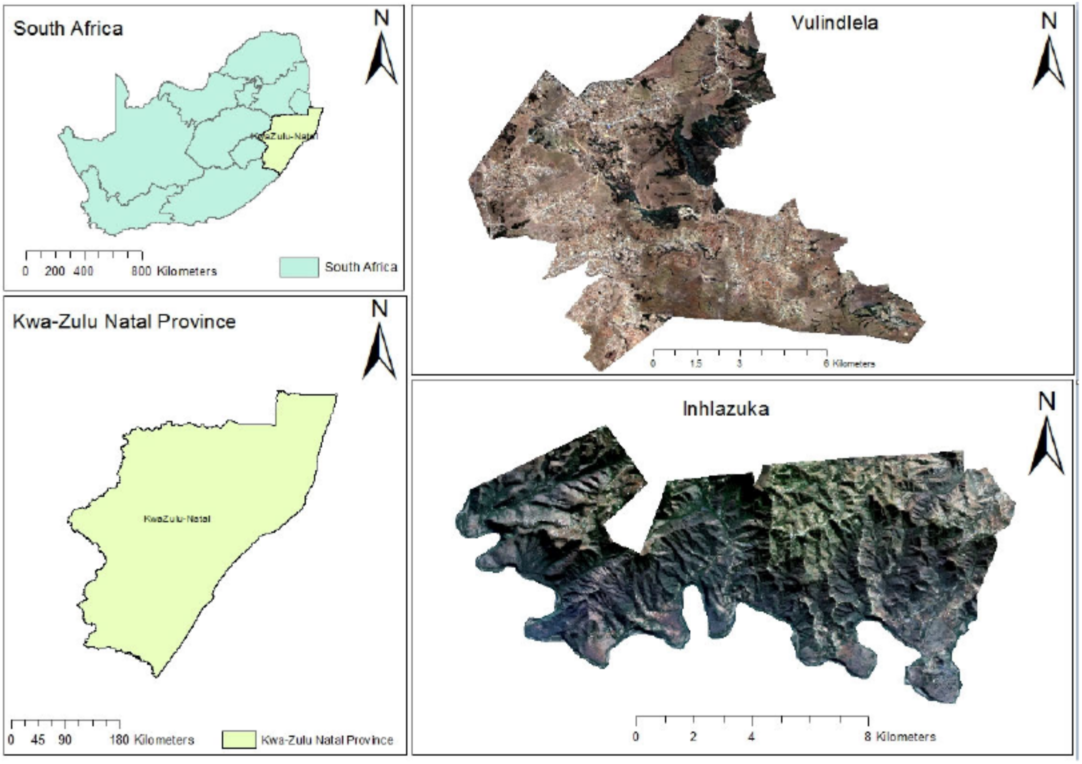


Figure 2.1: Inhalzuka and Vulindlela communal areas In Pietermaritzburg, KwaZulu Natal South Africa.

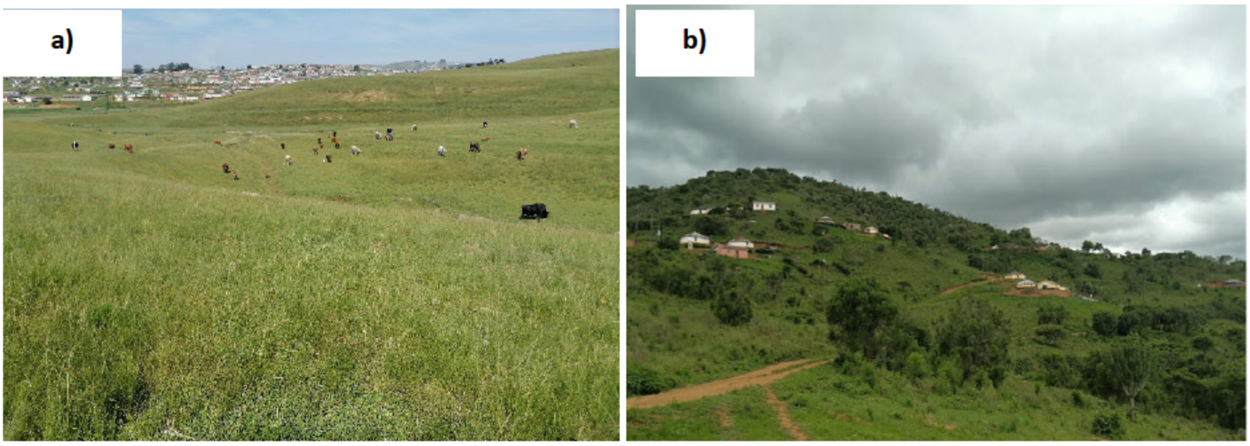


Figure 2.2: Typical communal rangeland areas in a) Vulindlela and b) Inhlazuka.

2.1.2 Satellite Data

The study utilised cloud-free and atmospherically corrected multi-temporal Landsat 7 and Landsat 8 Top of atmosphere (TOA) reflectance remotely sensed data to characterise land covers in the years 2000, 2010, and 2020. The GEE platform provides pre-processed images that will have gone through atmospheric correction. These images were selected and used to conduct the classification in the GEE platform (Gorelick et al. 2017). The study also used the median reducer for image processing. The median reducer applies a title by tile processing method where each scene is divided into several tiles, which results in each tile being sent to various Google servers, to be processed (Sidhu et al. 2018). The servers work in parallel and independently to one another and the result is the reduced image(s), which are the product of the tile reconstruction of the satellite images (the median reducer produces a single image constructed from the different tiles of the satellite images) (Sidhu et al. 2018). All images used in the study were projected to the Universal Transverse Mercator (UTM) coordinate system 1984, zone 36 south.

The dry season/winter images were selected, downloaded and used to characterise the rangelands. This is because during the summer season the sky is often overcast (cloudy) and there is a lot of crop farming occurring. To avoid the misclassification of the rangelands as croplands, the dry season images (June, July, and August) were used. Specifically, available cloud free multi-temporal images covering the dry season were selected and used in this study.

2.1.3 Classification and Change Detection

Classifications were conducted using a stack of multiple images on the GEE platform covering the dry season of each of the years 2000, 2010 and 2020. These images were acquired during dry season months (June, July and August). A median reducer in the GEE platform was used to compile and average all the images obtained during the dry season of each year. The GEE median reducer function reduces image collections by calculating the median of all values at each pixel across the stack of all matching bands to produce a single image. In addition, this process does not only reduce image data volume but equally produces high accuracies same as the time series data and improves classification accuracies (Phan et al. 2020, Carrasco et al. 2019). The advantage of using the median reducer is that it significantly reduces the volume of data thus making it easier and faster to process and analyse the bulky remotely sensed data (Phan et al. 2020). Above all, the utility of multi-temporal images avoids the possible impact of atmospheric influence on the spectral signatures while addressing the spectral variability of grasses induced by the variability of grass species and their management practices (Carrasco et al. 2019). The Random Forest Classifier was then used to discriminate and map rangelands from other LULC types. In utilising the RF, the three hyperparameters, *ntree*, *mtry* and nodesize were tuned accordingly (Odebiri et al. 2020). Specifically, the *ntree*, which is the number of regression trees used during observation performance was set to be at 500 (Mutanga, Adam and Cho 2012). After iterations, the optimal ntree identified and used in this study was 100. The *mtry* which is the number of predictors tested at each node was set to a default value which was the square root of the number of variables considered in this study. Lastly, the node size which is the minimal size of the terminal nodes of the trees was set to 1 (Mutanga et al. 2012). Sampling points covering various LULC classes were collected during a field survey. However, sampled points for the previous years (2000 and 2010) were verified using Google Earth Pro (Ghorbani and Pakravan 2013, Pu et al. 2020). Feature classes that were used in the classifications were bare-land (areas that were not covered by any vegetation and were mostly bare soil), grasslands (areas that were covered by grasses only), forests (areas covered by indigenous forests or timber plantations), water (all water bodies such as rivers, and streams) and built-up area (areas where there were buildings and concrete surfaces). Furthermore, vegetation indices were computed and used to characterise the spatial variation of the rangelands. Specifically, the Normalized Difference Vegetation Index (NDVI), the Soil Adjusted Vegetation Index (SAVI), the Green Normalized Difference Vegetation Index (GNDVI), the Normalized Difference Water Index (NDWI), the Infrared Percentage Vegetation Index (IPVI), the Visible Atmospherically Resistant Index (VARI), the Ratio Vegetation Index (RVI), the Difference Vegetation Index (DVI) and the Enhanced Vegetation Index (EVI) were computed and used in this study. These indices were selected and used in this study based on their optimal performance in literature (Xue and Su 2017, Ranjan et al. 2019, da Silva et al. 2020). Vegetation indices were also considered in this study because they have been proven in literature to improve accuracies while resisting the noise from the sun, topography and clouds, atmospheric changes, and soil background signals (Xue and Su 2017).

2.1.4 Rate of Change

Using the classified image, the spatial extent of each land cover type was computed in a GIS environment. The Rate of change (ROC) in the spatial extent of grassland patches were calculated to understand the magnitude of change in their spatial extent in relation to other land cover types and across different years. The study also sought to assess the extent of grassland cover fragmentation as a measure of rangeland degradation. To conduct this, the classified maps were exported from GEE into ArcMap where the spatial extent (area) of each land cover class was calculated for the three periods. The grassland cover classes were then extracted for fragmentation analysis. Fragstats 4.2 was utilised to compute and characterise the extent of grasslands fragmentation. Fragmentation was calculated at the class level metrics. Specifically, landscape (PLAND), the number of patches (NP), patch density (PD), largest patch index (LPI), patch area (AREA_MN), Euclidean nearest neighbour distance (ENN_MN) and effective mesh size (MESH) were computed and used to assess the extent of fragmentation and as a proxy for rangeland degradation. To measure the degree of fragmentation within the rangelands, the NP, PD, LPI were specifically used and the AREA_MN, ENN_MN, PLAND and MESH were utilised to measure extent of grass patches spatial dispersion (Parker and Mac Nally 2002, Midha and Mathur 2010). These Fragmentation metrics were derived from each of the time periods considered in the study and were compared using the analysis of variance test after the data did not significantly deviate from the normal distribution.

Table 2.1: Class level Fragmentation Metrics and their descriptions

Name	Abbreviation	Description
Percentage of Landscape	PLAND	PLAND is described as the 'Area and Edge metric'. It represents the landscape percentage belonging to each class. PLAND is 0 when the proportional class area is decreasing and is equal to 100 when one big patch is present.
Number of Patches	NP	Determines the number of subpopulations in a spatially dispersed population. (Number of patches can be used to determine fragmentation; the higher the number of patches, the more fragmented the class).
Patch Density	PD	Refers to the number of patches of corresponding patch type divided by total area. (The higher the density of a particular class, the more fragmented it is).
Patch Area	Area MN	Is the average size of patches in a particular of a specific land cover type. It can be computed at the class level, or at the landscape level.
Largest Patch Index	LPI	Quantifies the percentage of the total landscape area compromised by the largest patch.
Effective Mesh Size	MESH	Quantifies the degree of landscape fragmentation. The effective mesh size is based on the probability that two randomly chosen points in a region will be in the same non-fragmented area of land. The higher the mesh size, the less fragmented a particular habitat is.
Euclidean Nearest Neighbor Distance	ENN_MN	The sum of the distance (m) to the nearest neighboring patch of the same type, based on the nearest edge to edge distance, for each patch of the Corresponding patch type, divided by the number of patches of this same type.

The study went on to utilize rainfall data to assess the influence of rainfall on the rangeland spatial distribution changes. Rainfall data was requested from the South African Weather Services (SAWS). The requested data from SAWS was of the years used for classifications (2000, 2010 and 2020) and nine weather stations surrounding the study areas were used by the study to calculate the rainfall patterns in Inhlazuka and Vulindlela by performing Interpolation with the use of ArcMap 10.6. The type of interpolation that was applied by the study was that of the Inverse Distance Weight (IDW). After the application of interpolation, grassland points collected on the field were then overlaid over the study areas to extract the rainfall data. After the extraction of the rainfall data in ArcMap, rainfall averages of the years 2000, 2010 and 2020 in both study areas were calculated with the use of Excel.

2.2 Results

2.2.1 Classifications

The land use land cover changes were classified into five classes which are grasslands, water, forest, built-up area and bareland. In assessing, the performance of RF classification models based on spectral bands, vegetation indices independently and the combination of both vegetation indices, the ANOVA test showed that there were no significant difference in the overall accuracies. Subsequently, the classification based on combined datasets were used in this study and all results presented were based on these models. In classifying grasslands from other land cover classes, overall accuracies of 75%, 79% and 83% were obtained in Inhlazuka while accuracies of 89%, 85%, and 89% were obtained in Vulindlela for the years 2000, 2010 and 2020, respectively (Figure 2.3). Meanwhile, kappa accuracy scores of 65%, 68% and 73% were exhibited by the Inhlazuka images classification while Vulindlela exhibited scores of 81%, 75% and 83% for the years 2000, 2010 and 2020, respectively (Figure 2.3). Following a variable importance analysis, the most frequently optimal discrimination spectral features selected by RF across all classifications were Bands 5 and 7, the near infrared (NIR) and the short-wave infrared bands (SWIR), respectively (Figure 2.4)

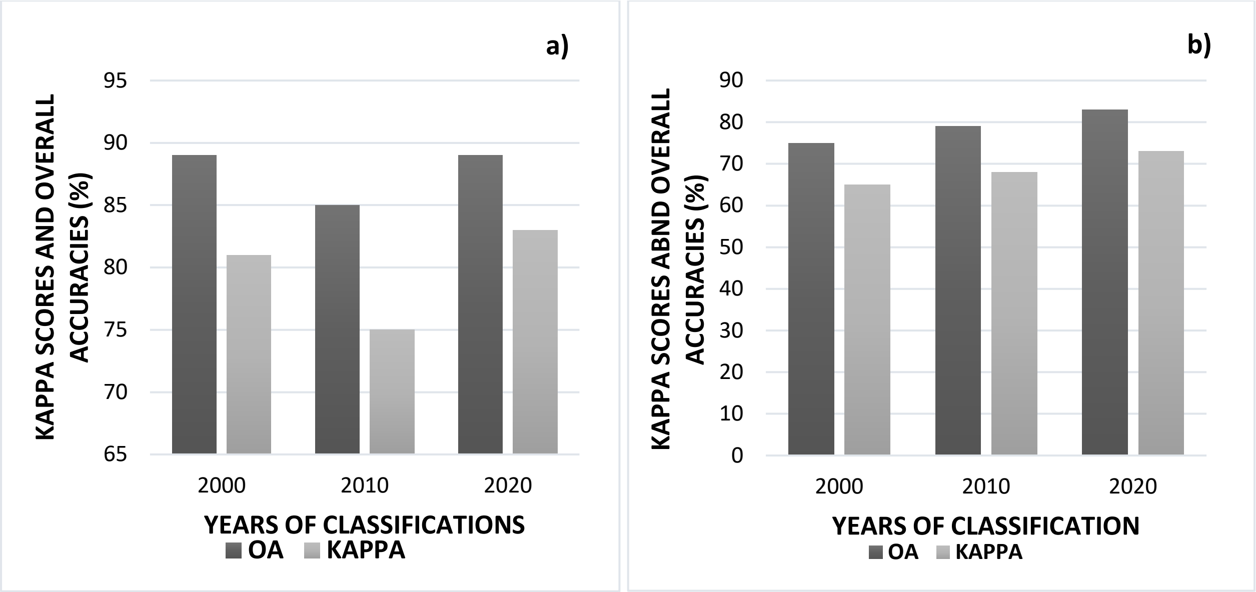
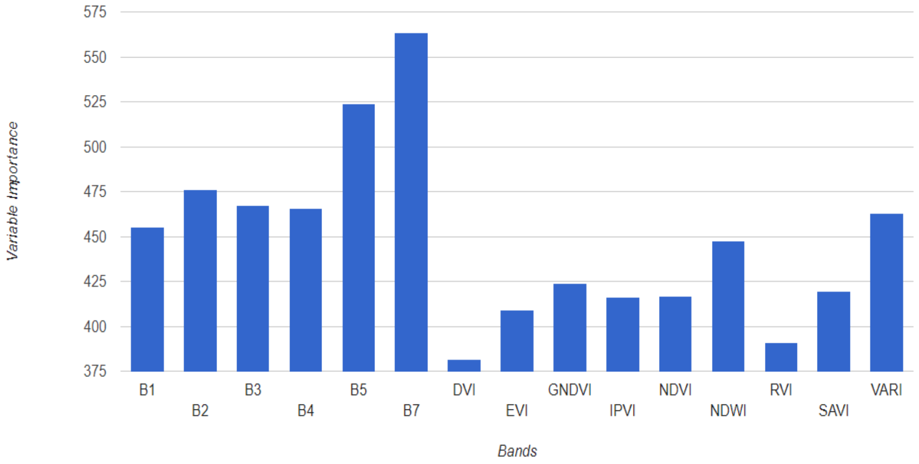


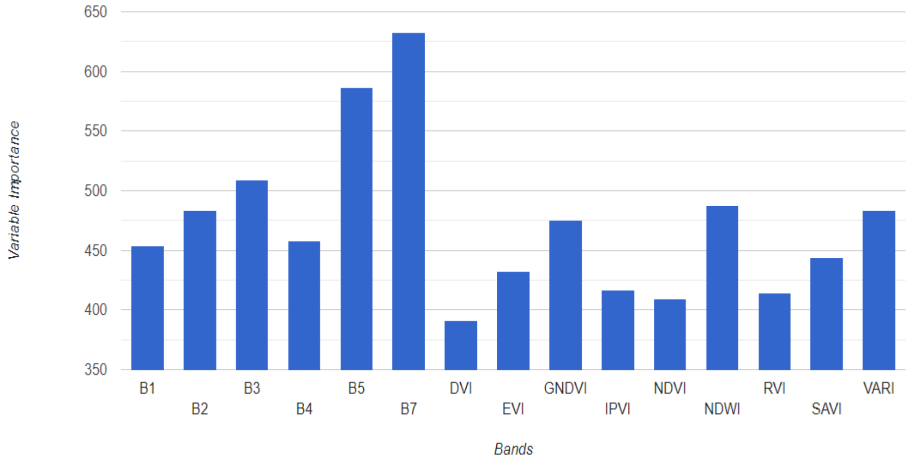
Figure 2.3 Classification overall accuracies and kappa scores in the areas of a) Vulindlela and b) Inhlazuka

a)



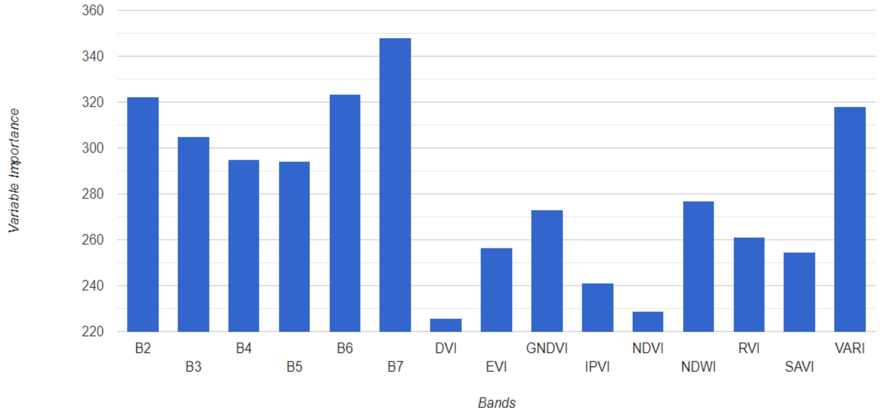
Variable Importance
575
550
525
500
475
450
425
400
375
B1
B2
B3
B4
B5
B7
DVI
EVI
GNDVI
IPVI
NDVI
NDWI
RVI
SAVI
VARI
Bands

b)



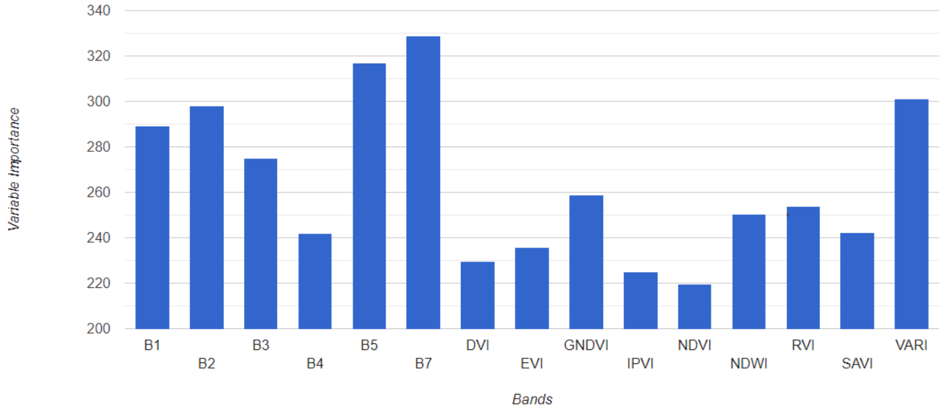
Variable Importance
650
600
550
500
450
400
350
B1
B2
B3
B4
B5
B7
DVI
EVI
GNDVI
IPVI
NDVI
NDWI
RVI
SAVI
VARI
Bands

c)

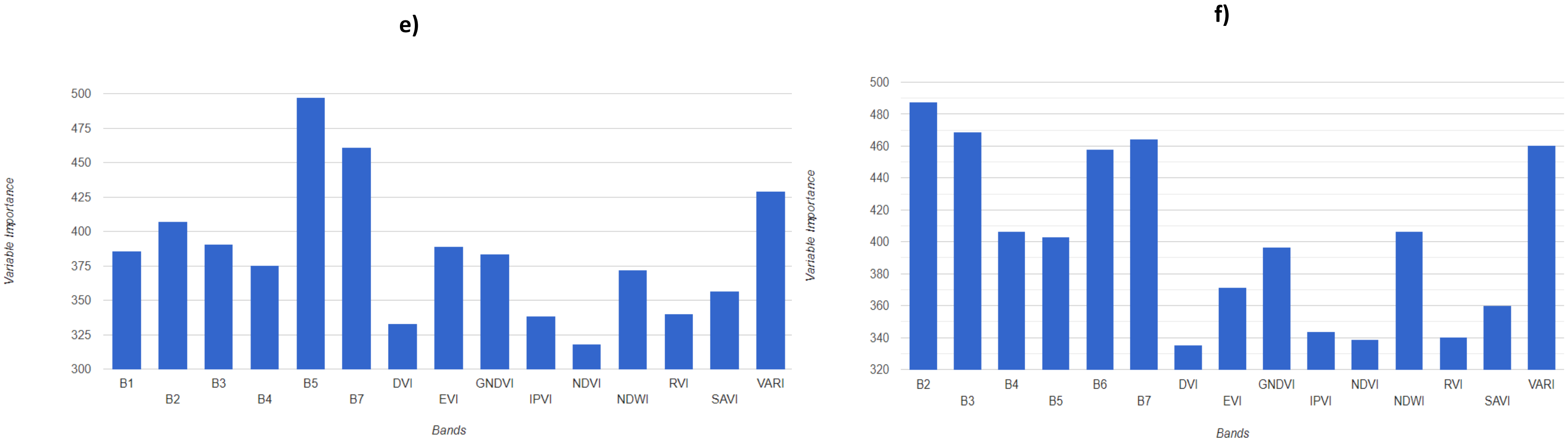


Variable Importance
360
340
320
300
280
260
240
220
B2
B3
B4
B5
B6
B7
DVI
EVI
GNDVI
IPVI
NDVI
NDWI
RVI
SAVI
VARI
Bands

d)



Variable Importance
340
320
300
280
260
240
220
200
B1
B2
B3
B4
B5
B7
DVI
EVI
GNDVI
IPVI
NDVI
NDWI
RVI
SAVI
VARI
Bands



Figures 2.4. Variable importance scores from the image classifications in Vulindlela for the year a) 2000, b) 2010, and c) 2020 as well as Nhlazuka for the year d) 2000, e) 2010, and f) 2020.

A general decrease in spatial extent of grasslands was observed in Vulindlela from the year 2000 to 2020 while in Inhlazuka, a decrease in the areal extent of rangelands is observed between the years 2000 and 2010 and an increase between the years 2010 to 2020 (Figure 2.5 and 2.6). In Vulindlela, between 2000 to 2020, when grasslands were reduced, built up areas increased rapidly. Specifically, grasslands decreased at a rate of 37.52 hectares per year between the 2000 and 2010. Then from 2010 to 2020, grasslands further decreased at a rate of 76 hectares per year while settlement development continued to increase. Meanwhile, the increase in built-up area from the year 2000 to 2010 was at a rate of 43.15 hectares per year and at a rate of 114.55 ha per year from the year 2010 to 2020. In addition, there was also a relative increase in bareland between these periods, although not at the magnitude of increase in spatial extent of built-up areas.

Inhlazuka is mostly characterised by forests, shrubby vegetation and relatively less grasslands compared to Vulindlela. The forest class increased between 2000 and 2010 by 86.54 hectares per year thus causing a decline in rangelands. Between 2010 and 2020, there was an increase in rangelands due to a decrease in forests at a rate of 113.84 ha per year. The decrease in rangelands in Inhlazuka between the periods of 2000 to 2010 was at 40.19 ha per year and the increase in rangelands experienced between 2010 and 2020 was at a rate of 45.27ha per year. In addition, in Inhlazuka there was also an increase in builtup areas at a rate of 41.7 ha/per year from 2010 to 2020. However, the increase of built-up area in Inhlazuka did not cause a significant decrease in rangelands when compared to Vulindlela.

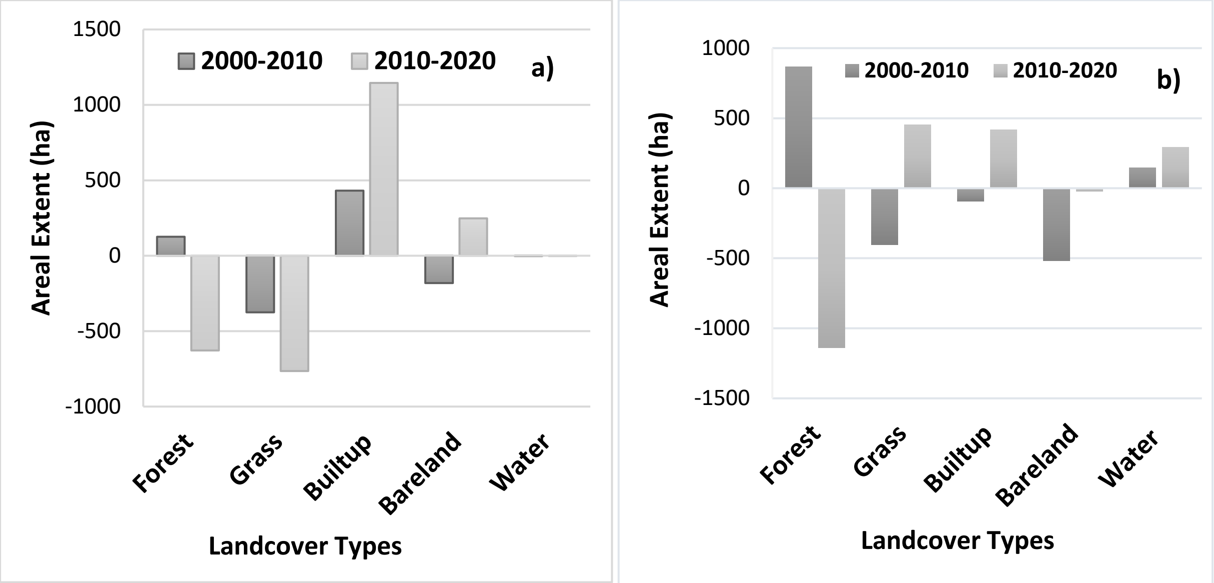


Figure 2.5. Changes in the mapped land cover types in a) Vulindlela and b) Inhlazuka

2.2.2 Changes in the Spatial Extent of Rangelands

The Vulindlela grasslands in 2000 occupied 7799.8 ha, which decreased to 7424.6 ha in 2010 then further decreased to 6660 ha in 2020 while in Inhlazuka, it decreased from 2516.7 ha in 2000, to 2114.7 ha in 2010 then increased to 2567.5 ha in 2020 (Figure 2.6 and Figure 2.7).

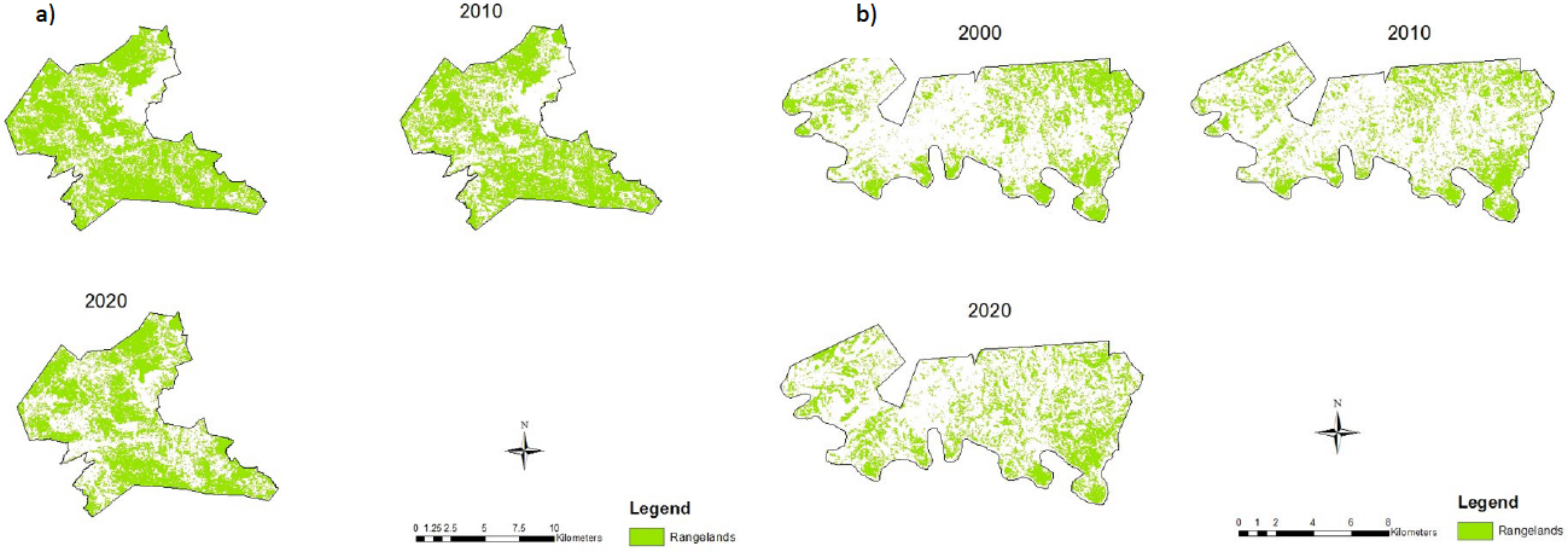
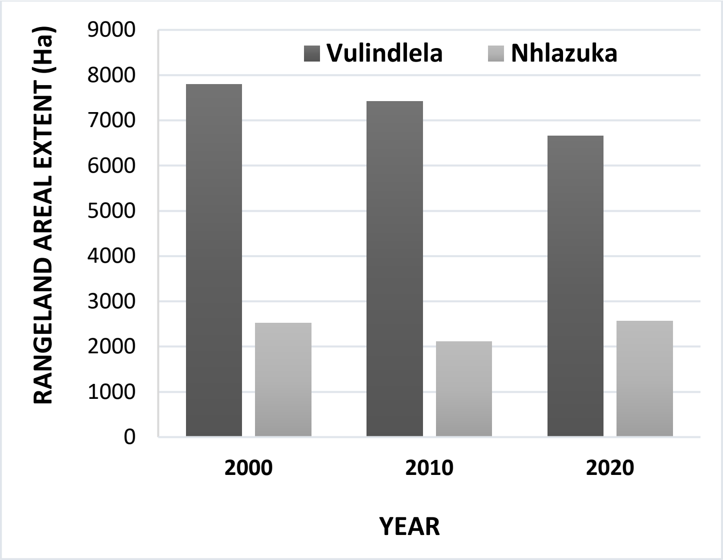


Figure 2.6. Spatial distribution of grasslands in a) Vulindlela and b) Inhlazuka from 2000 to 2020



Figures 2.7 Changes in the rangeland spatial extent from 2000 to 2020 in Vulindlela and Inhlazuka.

2.2.3 Patch Analysis at Class Level Metric

Table 3 shows fragmentation statistics in Vulindlela and Inhlazuka. Percentage of Landscape (PLAND) decreased from 69.9, 59.6 between 2000, and 2020 indicating an increase in grassland fragmentation. The number of patches (NP) increased from 244 to 342 in 2010 and then it rapidly increased to 780 patches in 2020. The increment in the number of patches therefore is an indication of increased rangeland fragmentation in Vulindlela. Meanwhile, patch density increased from 21 in 2000 to 31.0 in 2010, then increased again to 6.9 ha in 2020 in Vulindlela. The mean patch area (AREA_MN) on the other hand decreased from 31.9 ha in 2000 to 8.5 ha in 2020. The largest patch index (LPI) decreased from 68.3ha in 2000 to 62.6ha in 2010. This further decreased to 43.0ha in 2020. The Euclidean nearest neighbour distance (ENN_MN) is an indicator of isolation within the patches that increased from 71.1 ha in 2000 to 74.7 ha in 2010 and finally increased to 8.5 ha in 2020. Lastly, the effective mesh size (MESH) decreased from 5204.4ha in 2000, to 4380.4 ha and subsequently to 2188.8ha in 2020.

In Inhlazuka, the NP increased from 1392 in 2002 to 1581 in 2010, then declined to 1443 in 2020. The PD was 15.4 in 2000, then it increased to 17.5 in 2010 then decreased in 2020 to 16.0. Meanwhile, the AREA_MN was 1.8 ha in 2000, and then it decreased to 1.3 ha in 2010, and then increased in 2020 to 1.7 ha. On the other hand, the ENN_MN was higher in 2000 and 2010 when compared to 2020, indicating that the grasses were more isolated in 2000 to 2010. The LPI decreased from 7.1 ha in 2000 to 3.5 ha in 2010 then increased to 5.4 ha in 2020, while the PLAND and MESH of grassland were relatively lower in 2010. The MESH size results also show that the rangelands were more fragmented in 2010 and in 2020 as compared to 2000.

Table 2.2: Vulindlela and Inhlazuka grassland patch metrics variations between 2000 and 2020

	GRASS	PLAND	NP	PD	LPI	AREA_MN	ENN_MN	MESH
Vulindlela	2000	69.9	244	2.1	68.3	31.9	71.1	5204.4
	2010	66.6	342	3.0	62.6	21.7	74.7	4380.4
	2020	59.6	780	6.9	43.0	8.5	73.0	2188.8
Inhlazuka	2000	28.0	1392	15.4	7.1	1.8	79.5	55.5
	2010	23.5	1581	17.5	3.5	1.3	79.3	20.8
	2020	28.6	1443	16.0	5.4	1.7	75.0	35.4

2.3 Discussion

This study sought to assess the spatial variation in the areal extent of the rangelands as well as their magnitude of fragmentation using a Landsat time series in conjunction with random forest in a typical communal rangeland of southern Africa between the years 2000, 2010 and 2020. Results of this study showed that the spatial variability of rangelands and other land cover types could be optimally mapped in Vulindlela and Inhlazuka, respectively based on the NIR (Bands 5) and short-wave infrared (SWIR) (Band 7) spectral variables in conjunction with RF in GEE platform. Specifically, overall accuracies (OA) of 75%, 79% and 83% in Inhlazuka as well as OAs 89%, 85%, and 89% in Vulindlela for the years, 2000, 2010, and 2020, respectively, were obtained in this study. The optimal performance of the NIR and short wave infrared (SWIR) bands could be attributed to their sensitivity to grass biochemical and physical properties such as foliar nitrogen, lignin and starch (Ramoelo et al. 2015, Zhao et al. 2022). The NIR section of the electromagnetic spectrum is highly sensitive to the biochemical and biophysical properties of vegetation (Matongera et al. 2017, Mngadi et al. 2021). Specifically, the foliar spongy mesophyll facilitates the high reflectance of the NIR energy by plants with a high vigour (Wang et al. 2008, Kumar, Arya and Jain 2022).

The study results also showed that in Vulindlela, rangelands were rapidly being fragmented and converted into built-up and bare areas and a significant change in the spatial configuration of the grasslands was observed. This could be explained by population growth and the demand for land to develop residential areas as well as increasing agricultural production as the major drivers of rangeland fragmentation in rural areas (Abdulahi et al. 2016). According to the Municipality (2016) the population of Vulindlela in 2013 was 161 562 with an estimate of 85 033 structures. The population was estimated to grow at 2% each year to about 183 583, in 2020. The population increase could explain the rapid decrease in grasslands, which are being converted into built-up areas (Figure 2.8) to accommodate the burgeoning population. There is growing body of literature which shows that activities such as housing development and overgrazing are the major anthropogenic activities that have extensively degraded rangelands globally (Lu et al. 2017, Dowdy et al. 2019). Also, the lack of effective livestock management practices, generally results in increased grazing activities with limited breaks given to the grassland ecosystem to self-regulate and recover from over grazing.

Meanwhile, in Inhlazuka, the spatial extent of rangelands decreased while the areal extent of built-up areas increased between 2000 to 2010. The decrease in the spatial extent of forest between 2010 to 2020 could be attributed to the increase in population and demand for residential areas. The increase in rangelands in Inhlazuka in 2020 could be explained by clearance of shrubby and tree like alien invasive species which is a typical exercise in Inhlazuka. Specifically, *Lantana camara* is the most dominant alien invasive plant in the rangelands of Inhlazuka. Lantana is said to be the most widespread alien invasive plant which invades agricultural and natural ecosystems (Parveen, Ravinder and Daizy 2011). For instance, Dube, Maluleke and Mutanga (2022) makes an example of the Bushbuckridge area where the grasslands have been replaced by the alien plant lantana thus decreasing available forage for livestock and wildlife (Terefe 2015). To circumvent this, uMgungundlovu district municipality implements continuous alien invasive plant removal programmes regulating the variation in the spatial extent of grasslands especially in Inhlazuka. This then explains in the decreases and increases associated with the rangelands in Inhlazuka (Figures 2.7 and 2.6) between 2000, 2010 and 2020. If the alien plant species are not controlled, the communal rangelands of Inhlazuka may be at a risk of being replaced by the Lantana alien plant.

Results also showed that barelands in Vulindlela were increasing. This could be explained by the limited rangeland management interventions which are conducive for unregulated administration of fires. Fire as a management tool in rangelands, is used to improve forage quality and production, to manipulate plant populations (plant composition and structure) and maintain habitats for grazing animals (Little, Hockey and Jansen 2015). However, if fire is frequently and improperly administered, it becomes destructive. Specifically, it reduces the seedling recruitment of grasses, while burning and depleting the seedbanks on the topsoil (Ghasempour, Erfanzadeh and Török 2022). Subsequently, the ground is exposed as bareland. Community members in Vulindlela customarily burn grass during the winter season as a tool to promote its growth as feed for livestock (Cho, Onisimo and Mabhaudhi 2021). However, this results in grass failing to recruit seedlings and replenish its populations as the seed banks will be depleted and the topsoil crusted by regular burns (Fidelis et al. 2010, Ghasempour et al. 2022). Literature also illustrates that in the forest and grasslands biomes in Southern Africa, the dominancy of grasses or trees (forests) is a function of fire and precipitation (Baudena et al. 2015, Accatino et al. 2010).

Rainfall plays a significant role in the growth of vegetation (Beier et al. 2012, Lipiec et al. 2013). The lack of rainfall in rangelands results in the decrease of forage and rangeland resources therefore, negatively impacting biomass productivity (Derner and Augustine 2016, Sibanda et al. 2021). This means that the compromised growth of rangelands as a result of the decrease in precipitation causes a decline in the spatial distribution of rangelands, as there is not enough soil moisture to provide conditions for growth, due to rainfall being the main driver of rangeland vegetation dynamics (Palmer and Bennett 2013, Polley et al. 2013). In Vulindlela, the spatial extent of the rangelands in the year 2000 was 7799.8 ha and the average rainfall received was 61.79 mm. The rainfall received in the year 2000 may have played a role in the area of rangelands in the year 2000. From the year 2000 to the year 2010, the rangeland area decreased to 7424.6 ha and the average rainfall received in 2010 was 61.74 mm, between the year 2000 and 2010 there is not much difference in the average rainfall received, however, there was a decrease of 375.2 ha in the rangelands. Then in 2020, the average rainfall received in Vulindlela was 67.09 mm which is an increase in the rainfall received in 2010. The increase in rainfall in 2020 did not result in the increase of rangelands, instead further decrease was experienced from 7424.6 ha in 2010 to 6660 ha in 2020. Based on the rainfall patterns in Vulindlela, rainfall has limited influence on the declining rate of the communal rangelands. Therefore, the increase of bareland and builtup areas in Vulindlela are the main drivers of the depletion of the rangelands in combination with other land use activities taking place in Vulindlela. In the area of Inhlazuka, the average rainfall of the year 2000 was 65.6 mm, and the area of rangelands was 2516.7 ha. In 2010, rainfall received decreased to 52.34 mm and the spatial extent of rangelands in 2010 also decreased from 2516.7 ha in 2000 to 2114.7 ha in 2010. Rainfall received in the year 2000 in Inhlazuka decreased in 2010. The decrease in rainfall in 2010 may have played a role in the decrease of the spatial extent of rangelands in 2010 as the decrease in rainfall resulted in a decrease in the area of rangelands. In 2020, the average rainfall of 2020 was 69.63 mm, this is an increase from the rainfall received in 2010. The increase in rainfall resulted in an increase in the areal extent of rangelands in 2020 from 2114.7 ha in 2010 to 2567.5 ha in 2020. The rainfall patterns in Inhlazuka from the year 2000 to 2020 suggest that in Inhlazuka rainfall has an influence in the spatial distribution of rangelands as there was a decrease in rainfall in the year 2010 which resulted in the decrease of rangelands in 2010 and the increase of rainfall in 2020 resulted in the increase of the area of rangelands. However, the alien plants within the area of Inhlazuka may have played an additional role in the decrease of rangelands in the year 2010 especially if there were limited activities of alien removal in 2010. Then in 2020, the removal of the alien plants together with increased rainfall patterns could have created optimal growing conditions for the rangelands in Inhlazuka in the year 2020 therefore, an increase in the areal extent of rangelands.

2.4 Conclusion

The aim of this study was to characterise rangelands and quantify their variability in spatial extent and fragmentation over the period of 20 years in communal areas. Based on the findings of this study, it can be concluded that LULCCs can be optimally characterised using Landsat’s bands in combination with the vegetation indices. In addition, the NIR and the SWIR bands were the variables of importance thus, mapping the rangeland changes at high accuracies. Settlement expansion and an increase in crop fields are the main driver of rangeland decline. Fragmentation of rangelands is increasing with time as more grassland patches are getting more isolated and relatively smaller in spatial extent with the increase in built-up area. The findings of this study are a step towards building robust spatially explicit quantitative techniques for monitoring the spatio-temporal variations of grasslands. This is a very important step required if a geospatial Framework for Monitoring grassland ecosystems that will provide actionable information services for grassland assessment and monitoring across different key land management areas is to be realised.

CHAPTER THREE

ASSESSING CURRENT AND FUTURE DYNAMICS OF USING THE CA-MARKOV MODEL IN TYPICAL COMMUNAL RANGELANDS SOUTHERN AFRICA

Abstract:

Perpetual anthropogenic pressures on the grasslands have significantly increased the severity, extent, and frequency of land use changes (LUCs) in the ecosystems. Grasslands are the most extensive terrestrial ecosystems globally, sustaining livestock production and several ecosystem services. The unprecedented LUCs necessitate the establishment of robust monitoring frameworks to support conservation and management strategies for grassland ecosystems. In this regard, this study sought to classify grasslands for the year 2020 using Random Forests and predict the future (i.e., 2040) spatial distribution of rangelands using the Cellular Automata and Markov model (CA-Markov Model) in a typical Southern African communal rangeland. Specifically, the study was conducted in Vulindlela and Inhlazuka communal rangelands of the KwaZulu-Natal Province, South Africa. The results of the study showed that the spatial extent of grasslands in Vulindlela will continue to decline from 6660.04 ha in 2020 to 5740.30 ha by 2040, whereas in Inhlazuka, the grasslands are expected to increase from 2567.55 ha in 2020 to 2987.03 ha by 2040. Results also showed that the patch area (AREA_MN) is predicted to increase from 8.5 ha in 2020 to 55.94 ha by 2040 in Vulindlela and increase in Inhlazuka from 1.7 ha in 2020 to 7.20 ha by 2040. Meanwhile, patch isolation (Euclidean Nearest Neighbor Distance (ENN_MN)) was predicted to increase from 73.0 ha in 2020 to 172.20 ha by 2040 in Vulindlela and increase from 75.0 ha to 120.60 ha in Inhlazuka within the same period. The results of the study highlight the urgent need for the development of robust spatially explicit rangeland monitoring mechanisms for implementing sound conservation strategies. Furthermore, the findings of this study underscore the prospects of utilising RS data in detecting LUCs as well as monitoring rangeland as a step towards the development of effective conservation strategies.

Key words: CA-Markov, Landsat data, Remote Sensing, Land Use Land Cover Changes, Fragmentation

3 Introduction

Human activities have extensively altered the quality and quantity of grasslands through urbanisation and agricultural activities, exacerbated by climate change, high runoff and soil erosion amongst other environmental challenges (Mohamed, Anders and Schneider 2020, Clark and Tilman 2017, Hicks et al. 2008). The continuous improvements in technology, changes in climate and the increase in human population is an indication that more land use changes are yet occur. This makes a study on LULCCs important to gain a better understanding of their patterns to manage and preserve grasslands as a natural capital (Hossen, Hossain and Uddin 2019, Mondal et al. 2016). Grasslands offer ecosystem services such as erosion control, climate regulation and food provision (Zhao et al. 2020, Sollenberger et al. 2019). In this regard, the degradation of grasslands results in the loss of these ecosystem services (Bengtsson et al. 2019, Wen et al. 2013). As a result, rangeland degradation urgently requires robust fast and effective frameworks for mapping and monitoring rangelands in a spatially explicit manner. Previously, traditional survey methods were utilised to assess rangeland degradation based on visual assessment at different points.

Considering that traditional field surveys are inefficient and expensive, several researchers have recently resorted to remote sensing techniques that can uncover and analyse near-real time land cover patterns (Lawley et al. 2016). RS methods are commonly used in LULC change detection studies due to high revisit frequency and data acquisition, of expansive spatially explicit data (Abd El-Kawy et al. 2011). Performing change detection studies using RS includes the use of multi-date images to assess the changes occurring between the acquisition dates of the satellite images as a result of environmental conditions and human activities within a specified period (Abd El-Kawy et al. 2011, Shen, Meng and Zhang 2016). For instance, Landsat remotely sensed data has been proven to be invaluable in LULCC studies (Alam, Bhat and Maheen 2020). This is due to their optimal moderate spatial resolution and historical data archives which date back to the 1970s until the current date (Alam et al. 2020, Hansen and Loveland 2012).

Landsat data have been widely used in classification studies (Phiri and Morgenroth 2017, Cai et al. 2018, Zhu and Woodcock 2014, Sawalhah et al. 2018). For instance DeVries et al. (2016) used Landsat data to characterise forest changes by assessing the use of local expert data in combination with Landsat Time Series to characterize forest change processes. On the other Parihar et al. (2013) utilised Landsat data in a wetland post classification change detection study of East Kolkata Wetlands. The above-mentioned examples highlight the high prospects associated with Landsat remotely sensed data in detecting and mapping LCCs.

Generally, Landsat is often used in conjunction with robust machine learning algorithms which optimise the classification accuracies. For instance Phan et al. (2020) used Landsat data in conjunction with RF to analyse the effect of different composition methods and input images on classification results. RF has been widely engaged by the community of practice because of its simplicity, ability to utilise small sample size using it bagging mechanism and being able to avoiding overfitting models (Rodriguez-Galiano et al. 2012a, Thanh Noi and Kappas 2017). However, RF does not possess the capability to predict future changes.

Models such as the artificial neural networks (ANN), Markov Chain model (MC), and the Cellular Automata (CA) have been widely used in LULC change predictions (Mondal et al. 2016, Yirsaw et al. 2017, Liu et al. 2017). However, literature states that these models have limitations when they are applied singularly as compared to when they are combined into a hybrid algorithim (Munthali et al. 2020, Halmy et al. 2015). For example, the Cellular Automata – Markov model (CA- Markov) is an example of a hybrid cellular based model, which is robust and widely used in predicting future Land use changes (Yirsaw et al. 2017, Subedi, Subedi and Thapa 2013).

The CA-Markov model is said to be the most suitable model for LULC change prediction as it is a combination of the robust Cellular Automata and the Markov chain model (Yirsaw et al. 2017, Wu et al. 2019). Furthermore, the model is effective in mapping future land use land cover changes dynamic simulation capability, high efficiency, simple calibration, and ability to simulate multiple land covers and complex patterns spatially and temporally (Gidey et al. 2017, Jalayer et al. 2022, Liping et al. 2018, Sang et al. 2011), thus making the model appropriate in mapping future rangeland land use land cover changes.

The CA-Markov model has been proven to be robust, efficient and reliable for producing accurate spatio-temporal prediction of land cover types (Khawaldah, Farhan and Alzboun 2020, Ghalehteimouri et al. 2022, Wu et al. 2019). In this regard, this study sought to predict the future spatial distribution of grasslands in communal rangelands using the CA-Markov model between the year 2020 and 2040. This study also compared the magnitude of grass fragmentation in the forthcoming 20 years since the same year intervals were considered in generating input maps for modelling. Furthermore, 20 year intervals were chosen and used in this study because they were deem to be the minimum period when changes could be detected in a landscape. This will be a step towards the development assist developers in coming up with recommendations to preserve the rangelands within communal areas.

3.1 Methods and Materials

3.1.1 Study Site

- Refer to chapter two

3.1.2 Satellite Data

This study made use of cloud free Landsat 7 & 8 Top f Atmosphere (TOA) reflectance images from Google Earth Engine (GEE). GEE is a cloud-based computing platform which has satellite imagery of over 40 years to the present time. GEE provides images which have been atmospherically corrected, however, original images are provided by the platform. Satellite images available for analysis can be retrieved from the google earth catalog (https://developers.google.com/earth-engine/datasets/catalog/). In this study, pre-processed Landsat images were selected and used to conduct the classification. Then, the median reducer in the GEE platform was utilised to reduce the images into a portable cube. The median reducer reduces bulky images into one image for easier analysis. The reduced image is created through tile reconstruction. Tile reconstruction is a process where each tile for each image is processed by different google servers and the end product is a single image made up of the rearranged tiles of the images for better and improved quality of the image (refer to chapter two).

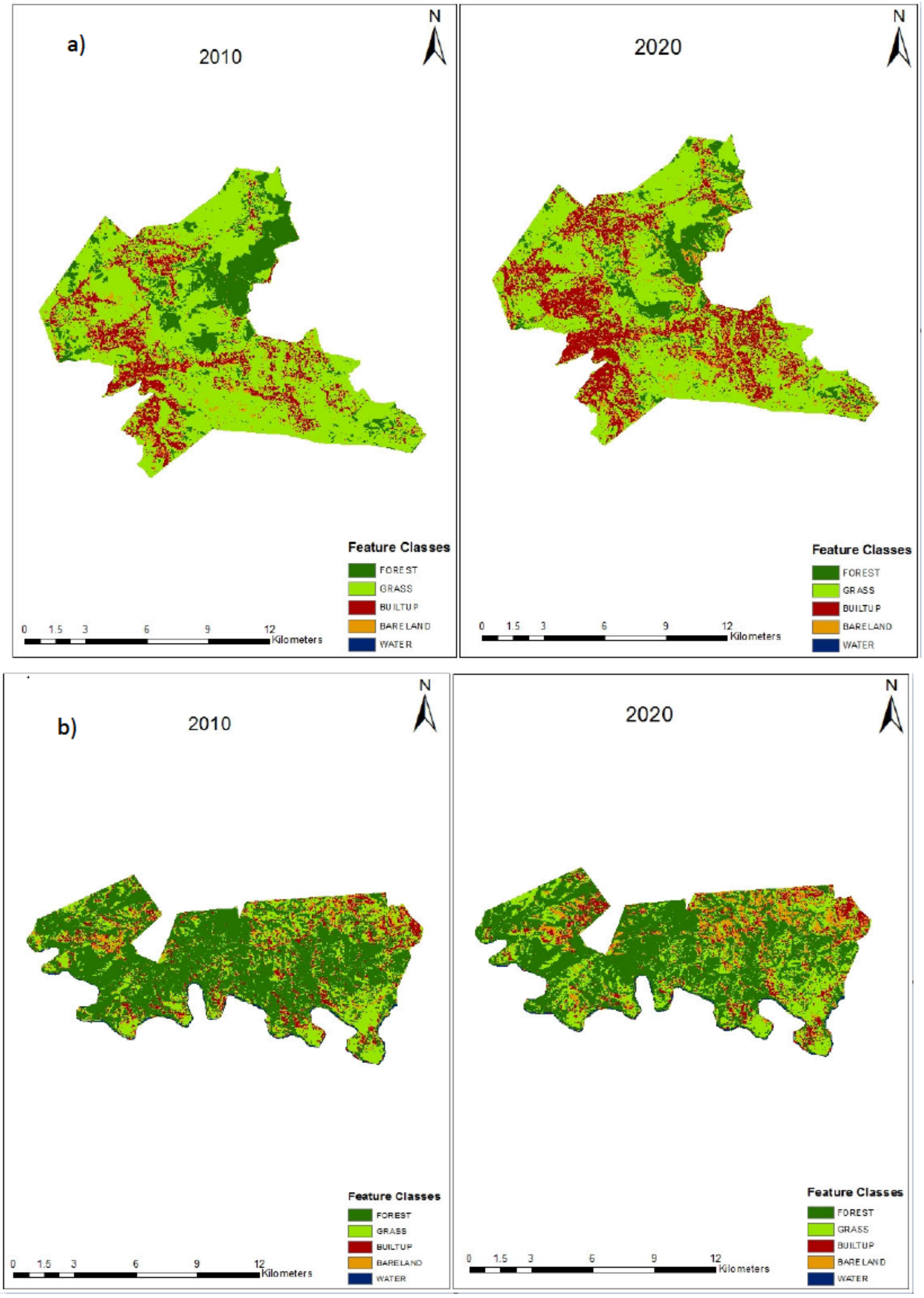
Table 3.1. Image collections used in the study

Years	**Number of Satellite Images which were available**	**Acquired date of images**		**Years**	**Number of Satellite Images which were available**	**Acquired date of images**
	VULINDLELA AREA				**NHLAZUKA**	
2010	16	1. 2010/06/08 2. 2010/06/08 3. 2010/06/24 4. 2010/06/24 5. 2010/07/10 6. 2010/07/10 7. 2010/07/17 8. 2010/07/17 9. 2010/07/26	10. 2010/07/26 11. 2010/08/02 12. 2010/08/02 13. 2010/08/18 14. 2010/08/18 15. 2010/08/27 16. 2010/08/27	2010	5	1. 2010/06/08 2. 2010/06/24 3. 2010/07/10 4. 2010/07/26 5. 2010/08/27
2020	22	1. 2020/06/02 2. 2020/06/02 3. 2020/06/11 4. 2020/06/11 5. 2020/06/18 6. 2020/06/18 7. 2020/06/27 8. 2020/06/27 9. 2020/07/04 10. 2020/07/04 11. 2020/07/13	12. 2020/07/13 13. 2020/07/20 14. 2020/07/20 15. 2020/07/29 16. 2020/07/29 17. 2020/08/05 18. 2020/08/05 19. 2020/08/14 20. 2020/08/14 21. 2020/08/21 22. 2020/08/21	2020	5	1. 2020/06/11 2. 2020/06/27 3. 2020/07/13 4. 2020/07/29 5. 2020/08/14

3.1.3 Projections

The study used already classified images from the years 2010 and 2020 from GEE to predict the spatial distribution of rangelands in the year 2040 (Figure 3.1). Images used for the classification were cloud free images. The classified images were a combination of images (temporal images) available between the months of June, July and August reduced to one image by the use of the median reducer in GEE. The median reducer in GEE combines the values of available images, calculates the aggregate of those images, and produces a single image. The use of such an image is important in rangeland studies as rangelands are sensitive to environmental changes. Therefore, using an image that is the result of temporal images is useful in accurately mapping the changes taking place in rangeland ecosystems. In addition, the use of the median reducer improves the quality of an image hence producing high classification accuracies in LULC studies (refer chapter two).

Classifications were performed with the use of the Random Forest (RF) classifier. Feature classes that were selected for the classified images were bare-land areas (which include areas in the study area with no vegetation cover), water bodies (being all water bodies within the study site such as dams, streams and rivers), built-up area (all areas of settlement development), the forest class (all forms of plants within the study site such as alien plant species, indigenous forest, plantations and woodland) and grasslands (being all areas covered with grass). Classifications were performed over a period of 10 years from 2010 to 2020. The study collected sample points for various land cover classes during field observation. Included were the grass points in both the study sites with the use of the hand held Trimble GPS. The study then proceeded to make use of google earth pro for the verification points of the previous years (Cha and Park 2007). The Random Forest classifier was used for the classification of the land use cover changes. The RF makes use of decision tress when performing classifications and in this study 100 decision trees were used which produced accuracies between 79% to 89%. The use of the decision trees however, does not guarantee an increase in the overall accuracies. Optimal parametrization was set from a range of 10 to 180 decision trees and at a 100-decision tress optimal parametrization was reached with overall accuracy being uniform thereafter (meaning that after 100 decision trees there was not much of a difference in the overall accuracies obtained). Vegetation indices were also computed during the LULCC classification process (refer to chapter two). The vegetation indices were utilized in image classifications in combination with the spectral bands as means to improve classification accuracies (Sinha, Sharma and Nathawat 2015, Koley and Chockalingam 2022).



Figures 3.1, The already classified images of land use land cover changes in a) Vulindlela and b) Inhlazuka during the years 2010 and 2020

3.1.4 CA-Markov

The CA-Markov combines the functions of both the CA and Markov chain analysis to optimize the outcome of the prediction, therefore, creating the opportunity of the model to perform long term predictions of any type of spatial patterns/changes (Mathanraj, Rusli and Ling 2021).

The study first calculated the gains and losses for each class by making use of the Land Change Modeler (LCM) Module in TerrSet, performed to get an insight of what was happening in each class from 2010 to 2020. Performing the gains and losses on the LCM in Terrset produced the drivers causing a change in rangelands. The study then used the CA-Markov module in Terrset to perform the predictions. Prior the predictions, transition probabilities were created which gave the percentages/probability of one class transitioning into another. The Markov transition estimator module in Terrset was used to create probability transitions. In creating the transition probabilities, the classified images of 2010 and 2020 were used. The output probabilities from the 2010 and 2020 images in combination with the originally classified image of 2020 was used for the predictions of the year 2040 in the CA-Markov module of Idrisi TerrSet with a contingency filter of 5 and 10 Cellular Automata iterations.

3.1.5 Accuracy assessment

For the accuracy assessment of the CA-Markov model predictions, three indicators were used (i.e., kappa for no ability (K_{no}), kappa for location ($K_{location}$) and kappa for quantity ($K_{quantity.}$). The K_{no} performs the accuracy of the simulation run (Hamad, Balzter and Kolo 2018), while the $K_{location}$ and $K_{quantity}$ validate the location and quantity between the original classified images and the prediction images (Hamad et al. 2018). These indicators are said to be the best indicators for the validation of simulated maps and literature also states that 0.80% is an acceptable accuracy rate for the performance of future prediction maps (Eastman 2015). For further accuracy assessment of the model, the study predicted the year 2020 in both study areas using the classified images of the years 2000 and 2010. The predicted 2020 image was then compared with the originally classified image of 2020.

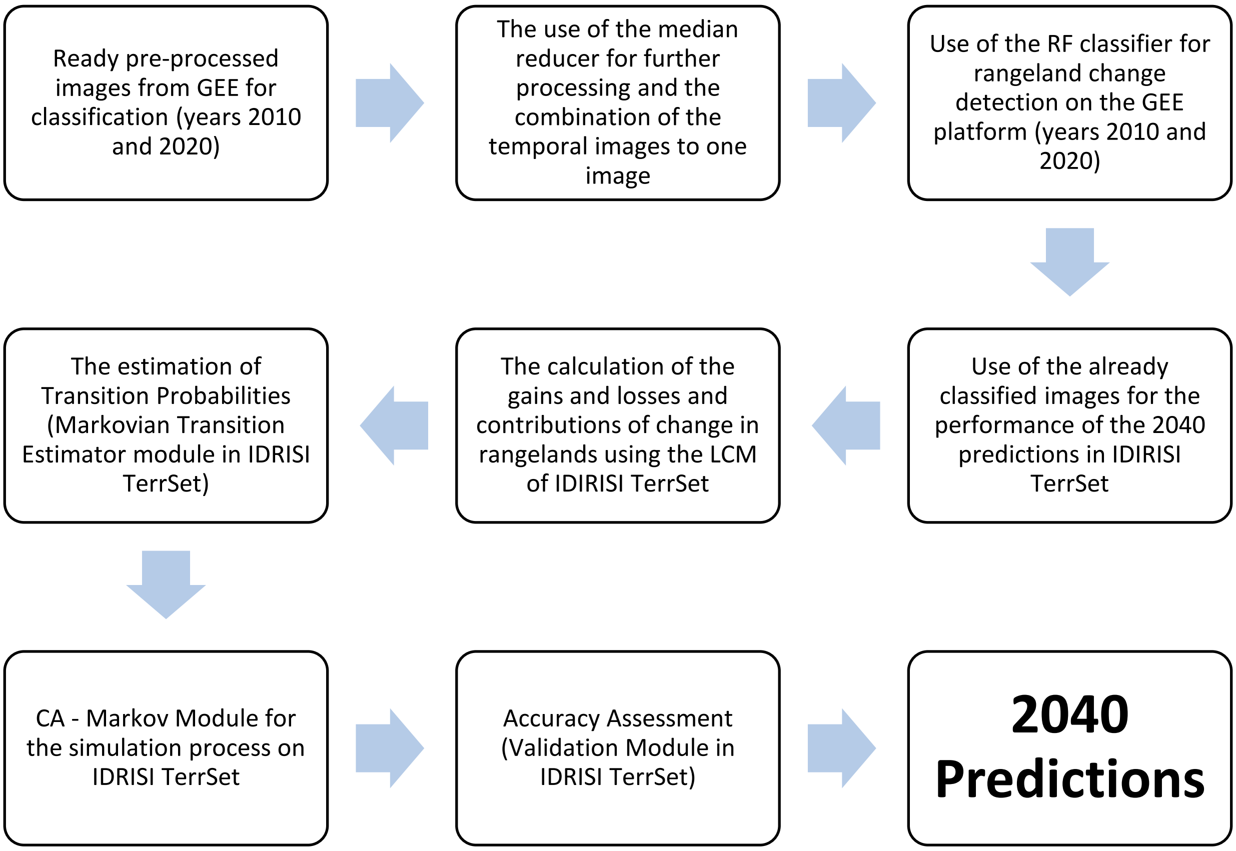


Figure 3.2. A flow chart of the simulation process.

3.1.6 Rangeland Patch Analysis for the projected year 2040

The study calculated fragmentation within the communal rangelands of Inhlazuka and Vulindlela using the Fragstats 4.2 software as a measure of rangeland degradation. To compare the rangeland fragmentation between the year 2020 and the year 2040, the rangeland patch analysis was performed for both years. This was done to compare the extent and level of fragmentation for the current year with that of 2040 to assess the changes in rangeland fragmentation after 20 years. The projected images of 2040 of Vulindlela and Inhlazuka were exported from IDRISI TerrSet to ArcMap 10.6. In ArcMap the projected maps were extracted as GeoTiff images into Fragstats. The 2020 classified image was extracted from Google Earth Engine (GEE) to ArcMap 10.6 then extracted as a GeoTiff image to Fragstats 4.2. The measurement of fragmentation within both study areas was performed at a class level metrics. The class level metrics calculate the fragmentation of each feature class of the classified map. The metrics used in performing the patch analysis were that of the Percentage of landscape (PLAND), patch area (AREA_MN), the number of patches (NP), largest patch index (LPI), patch density (PD), Euclidean nearest neighbour distance (ENN_MN) and effective mesh size (MESH) were used to measure the extent of fragmentation within the communal rangelands. However, the metrics of NP, PD and LPI were applied by the study to measure the extent of fragmentation within each of the feature classes. Then the metrics of ENN_MN, AREA_MN, PLAND, and MESH, were applied by the study to assess the patch area of each of the feature classes specifically the rangelands. The measurement of fragmentation in the study was performed for the projected year 2040 to be compared with the patch analysis of the year 2020 to compare the level of rangeland degradation between these years.

3.2 Results

3.2.1 Image Classifications

The study performed classifications to monitor the rangelands changes using the Random Forest Classifier (RF). Classifications were performed using the combination of the spectral bands of the Landsat images with vegetation indices. Feature classes that were used during the classification process were that of water, bareland, built-up area, forest and grasses. The overall accuracies (OAs) achieved during the classification of rangelands were that of 85% and 89% in Vulindlela and OAs of 79% and 83% were obtained in Inhlazuka for the years 2010 and 2020 respectively (Figure 3.3). The kappa coefficient was applied in the measurement of the classification accuracies and the Kappa scores were that of 75% and 83% in Vulindlela and in Inhlazuka Kappa scores were 68% and 73% for the years 2010 and 2020, respectively (Figure 3.3). The variables of importance obtained from the classifications, selected by the RF were that of bands 5 and 7 which represent the Shortwave Infrared bands (SWIR) and the Near Infrared bands (NIR) (refer to chapter two).

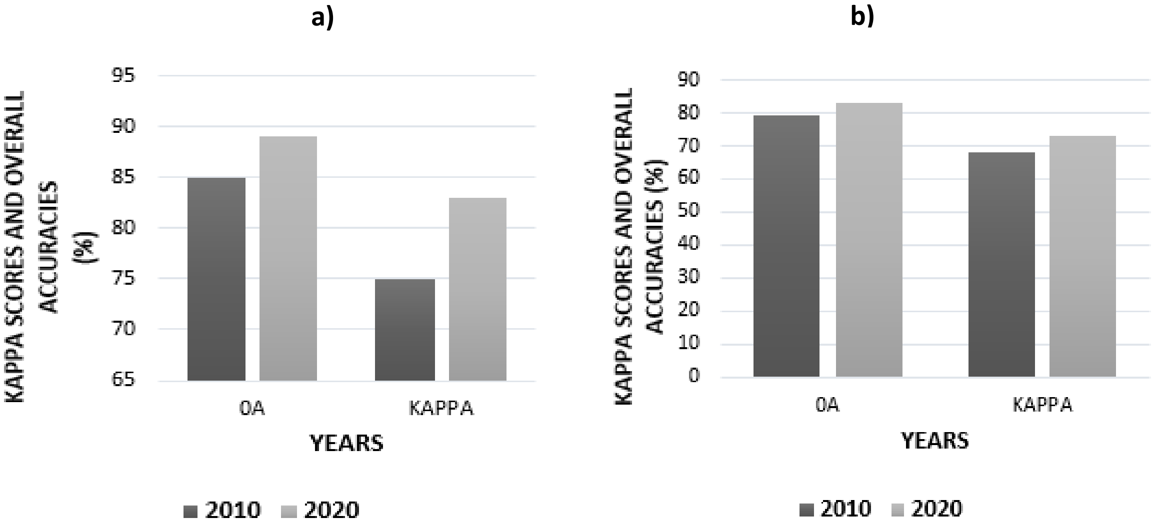


Figure 3.3. Classification overall accuracies and kappa scores in the areas of a) Vulindlela and b) Nhlazuka.

3.2.2 Model Validation

In validating the prediction capability of the CA-Markov model of IDRISI TerrSet, the study performed predictions of the year 2020 (Figure 3.4). The 2020 predictions were performed using the RF already classified images of the years 2000 and 2010. Once the predictions were performed the modelled images were validated by comparing the predicted 2020 image with that of the originally classified 2020 image in GEE. The kappa statistics in Vulindlela for the modelled images were between 84% and 86% whereas in Inhlazuka the kappa statistics ranged between 74% and 76%. For the 2020 images classified in GEE the overall accuracy (OA) in Vulindlela was 89% while the kappa score was 83%. In Inhlazuka the OA was 83% and the kappa score was 73% for the 2020 classified image. Therefore, the model results (Table 3.2) proved the CA-Markov model to be reliable and efficient in conducting future land use land cover change predictions. This is supported by the Kappa statistics of the RF classified 2020 images in GEE and the 2020 modelled images, the difference between the kappa scores is small as the kappa scores are similar. Therefore validating the capability of the CA-Markov model in performing future LULCCs predictions.

Table 3.2: The kappa coefficient scores for the modelled 2020 images and the RF classified 2020 images

2020 Projections for Vulindlela	**2020 already classified images in Vulindlela**	**2020 Projections for Nhlazuka**	**2020 already classified images in Inhlazuka**
Kno = 0.8391	OA = 89%	Kno = 0.7371	OA = 83%
Klocation = 0.8562	Kappa Score = 83%	Klocation = 0.7646	Kappa Score = 73%
Klocationstrata = 0.8562		Klocationstrata = 0.7646	
Kstandard = 0.7814		Kstandard = 0.6908	

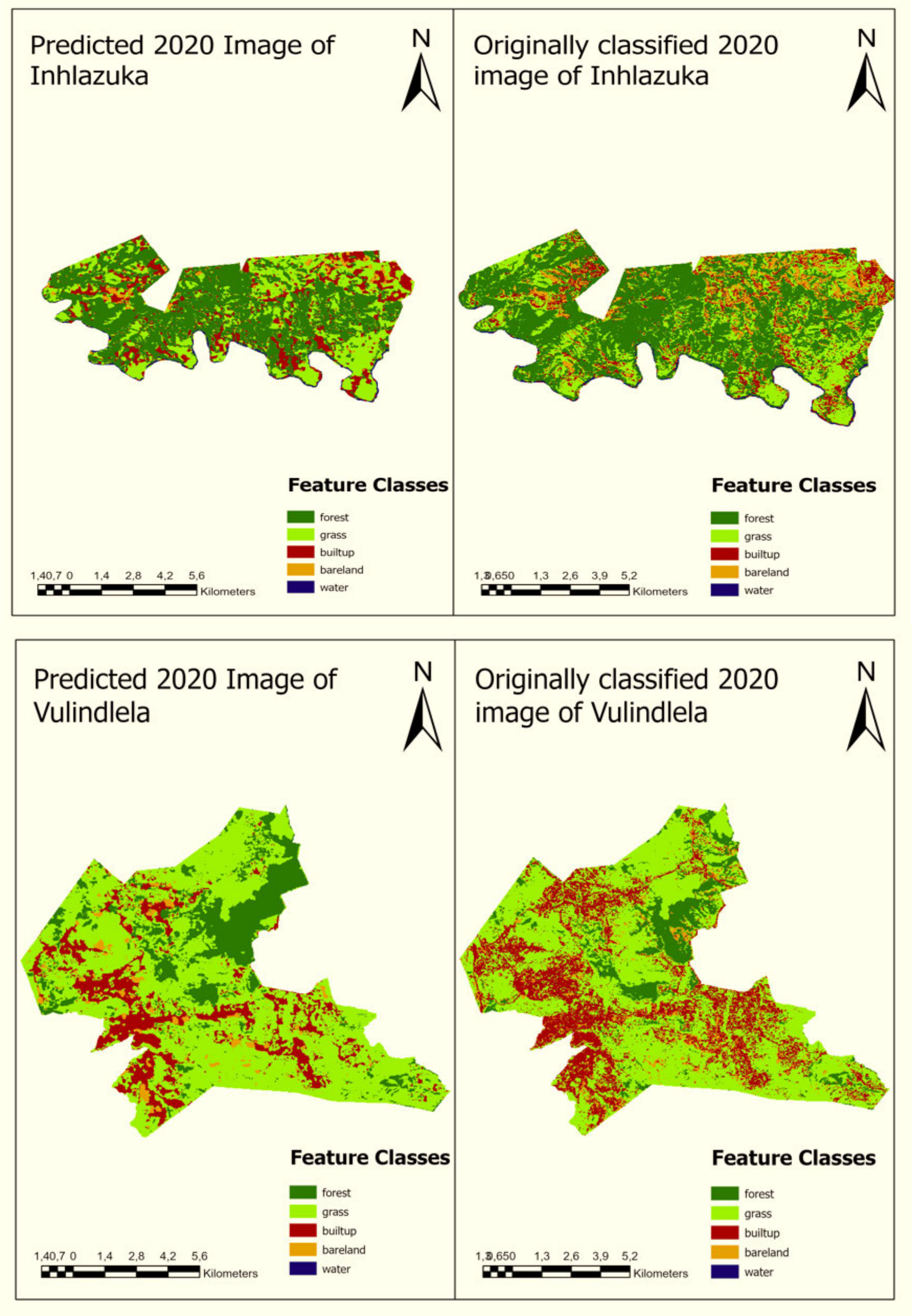


Figure 3.4. 2020 Prediction images of a) Inhlazuka and b) Vulindlela

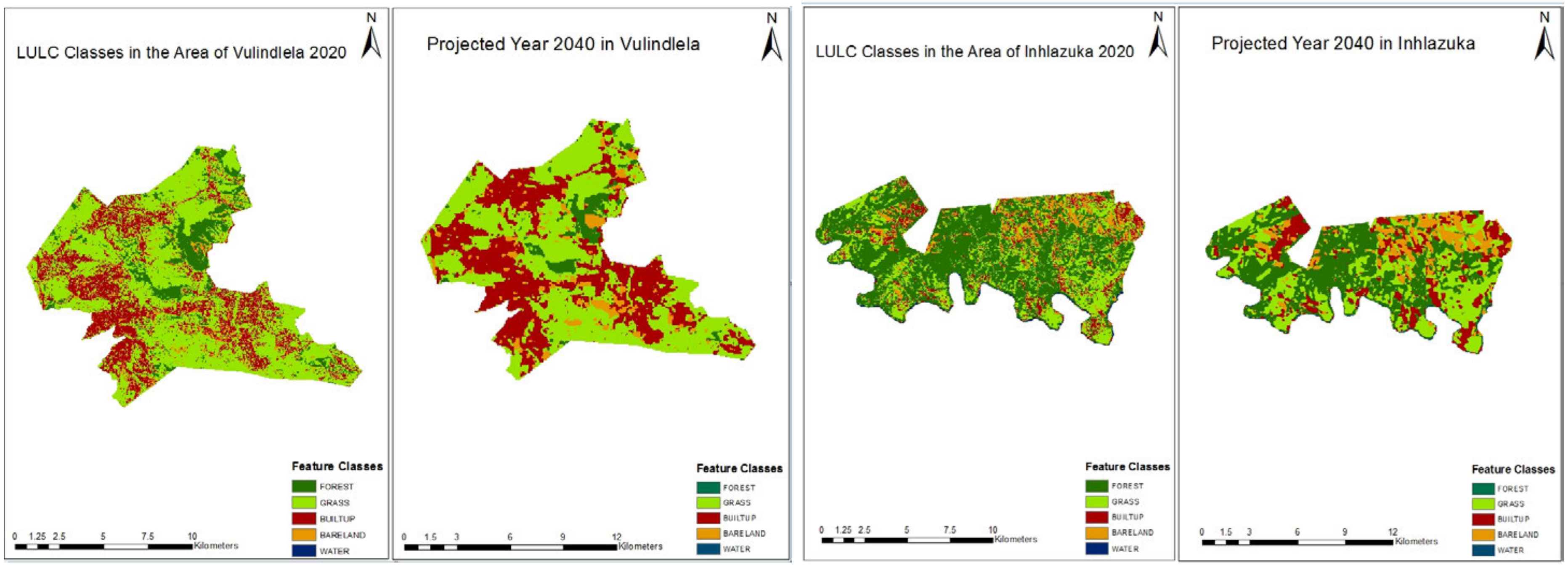
3.2.3 Projections

The 2040 projections were performed using the CA-Markov model. Accuracy assessments of the model were performed using the Validation Model of IDRISI TerrSet. The kappa coefficient scores for the projected images are presented below in table form.

Table 3.3: The kappa coefficient scores for quantity and location for the 2040 prediction.

Projections for Vulindlela	**Projections for Nhlazuka**
Kno = 0.8741	Kno = 0.8374
Klocation = 0.9208	Klocation = 0.9032
Klocationstrata = 0.9208	Klocationstrata = 0.9032
Kstandard = 0.8308	Kstandard = 0.8087

Figure 3.5 below illustrates the CA-Markov model prediction changes in the areas of Vulindlela and Inhlazuka for the year 2040. In Vulindlela, the rangelands are predicted further decrease while the rangelands in Inhlazuka are predicted to increase. The area of rangelands in Vulindlela for the year 2020 was 6660.04 ha and the projected area of rangelands in 2040 is 5740.30 ha. Therefore, in Vulindlela about 919.74 ha of rangelands are to be lost by the year 2040 thus a loss of 46 ha per year of rangelands. The loss in rangelands will be caused by the further increase in builtup and bareland areas but mostly settlement development as it will increase at a higher rate than the bareland class. In the area of Inhlazuka, the spatial extent of rangelands for 2020 is 2567.55 ha and the projected area of the communal rangelands is 2987.03 ha, meaning that in Inhlazuka an increase of 419.48 ha in rangelands is expected in 2040 with an increase of 21 ha per year in rangelands.



a)

b)

Figures 3.5. The projected changes in a) Vulindlela and b) Inhlazuka for the year 2040.

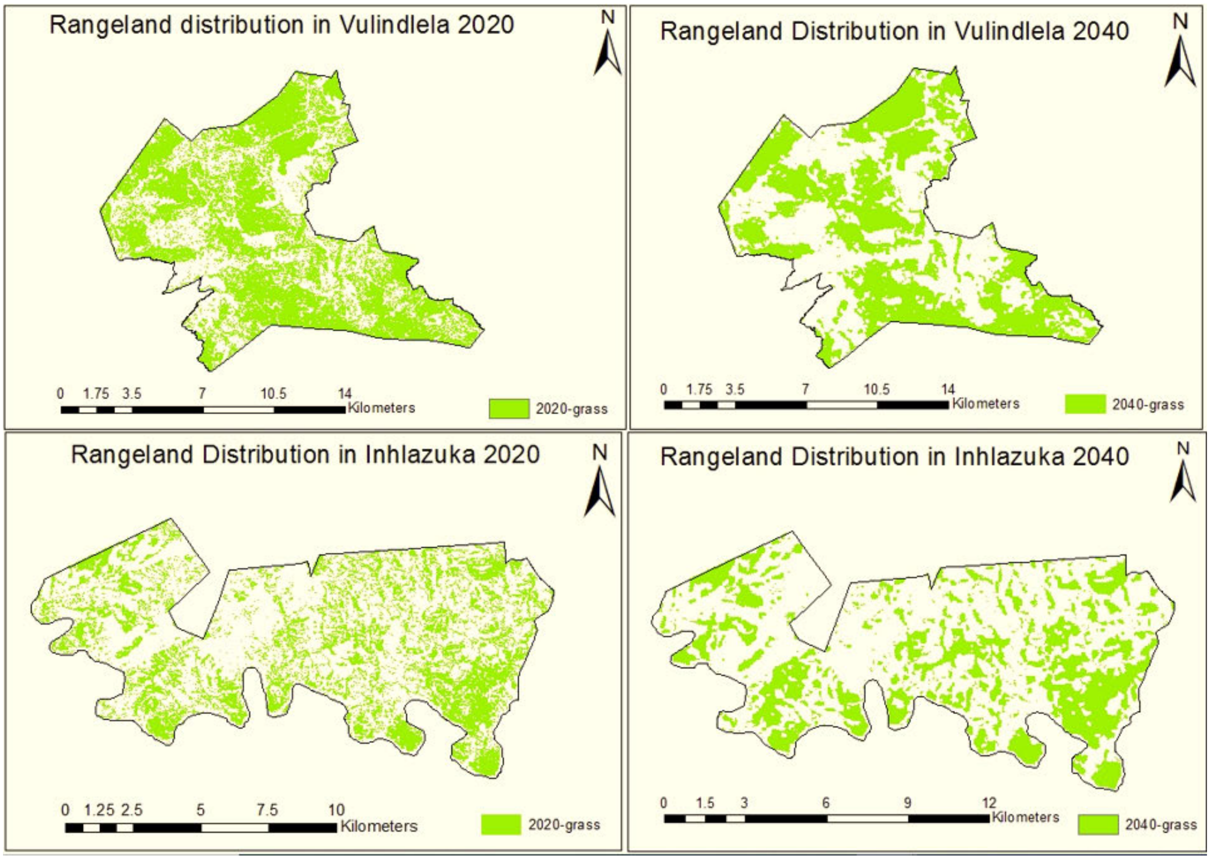


Figure 3.6. A comparison in the rangeland distribution between 2020 and 2040

In Vulindlela rangelands are threatened by the continued increase in builtup area which is projected to increase in 2040 (Figures 3.5 and 3.7). The spatial extent of builtup area in Vulindlela for 2020 is 2821.88 ha and the projected areal extent in 2040 for builtup area is 4157.2 ha, therefore builtup area is expected to have grown by 1335.32 ha by the year 2040 and increase at a rate of 67 ha per year.

In Inhlazuka, the growth of rangelands and builtup area is causing a decline in the forest class (Figures 3.5 and 3.7). The area of the forest class for 2020 is 4632.09 ha and the projected area for the forest class in 2040 is 3462.18 ha thus, a loss of 1169.91 ha of the forest class by 2040. The forest class shall decrease at a rate of 58.45 ha per year. The builtup area in Inhlazuka for the year 2020 is 2567.55 ha and the project area is 2987.03 ha meaning, by the year 2040, built-up area would have increased by 419.48 ha, therefore increasing at a rate of 21 ha per year. Hence, the increase in rangelands and builtup area will cause a decrease in the forest class by 2040.

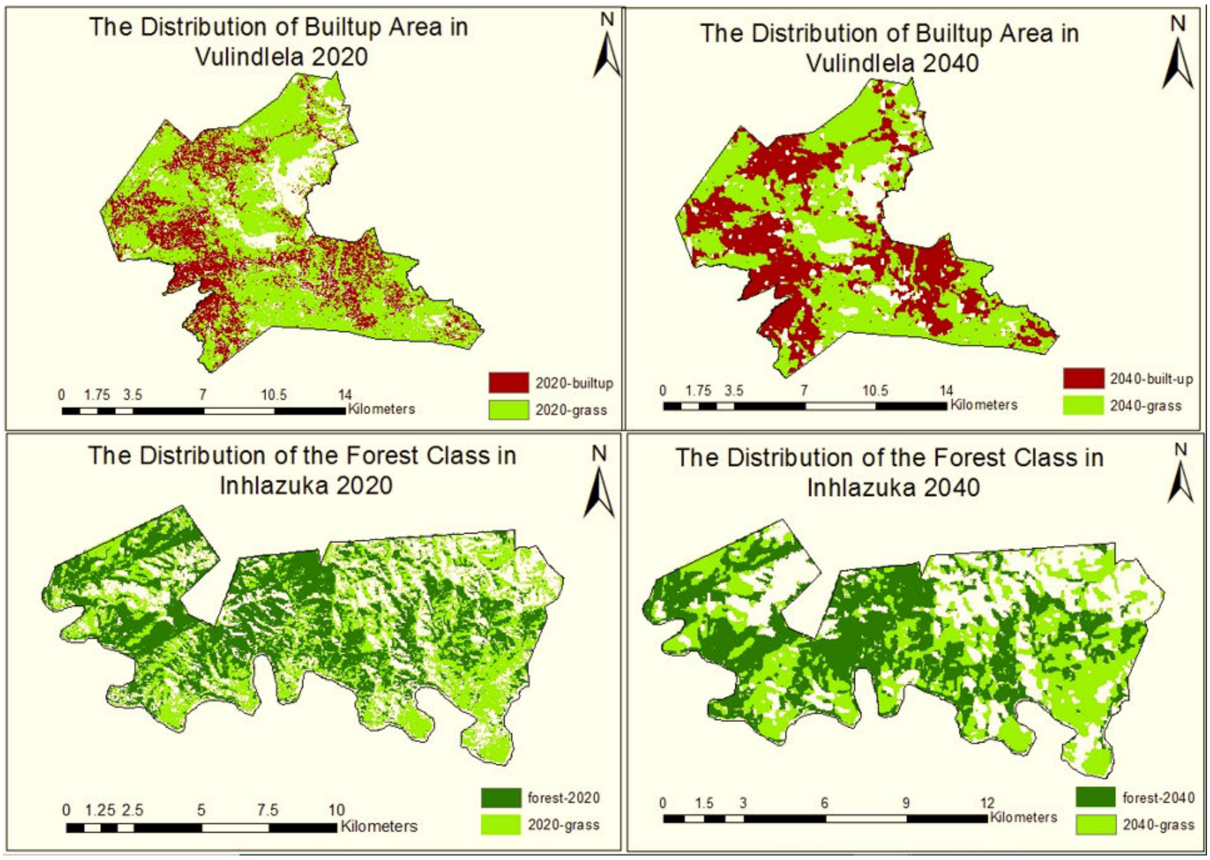


Figure 3.7. The changes in the distribution of rangelands between 2020 and 2040.

Figure 3.1 presented the LULCCs variations taking place within Vulindlela and Inhlazuka between the years 2010 and 2020. From Figure 3.1, it can be observed that the rangelands are declining as a result of the increasing builtup area in Vulindlela, meaning that the communal rangelands in Vulindlela are declining as a result of the increasing population. In Inhlazuka, the builtup area increased, the forest class decreased and rangelands increased. Furthermore, the gains and losses were calculated using the LCM of TerrSet to present the changes within each class in Vulindlela and Inhlazuka (Figure 3.8) with Figure 3.9 presenting the changes in area of the mapped land cover classes.

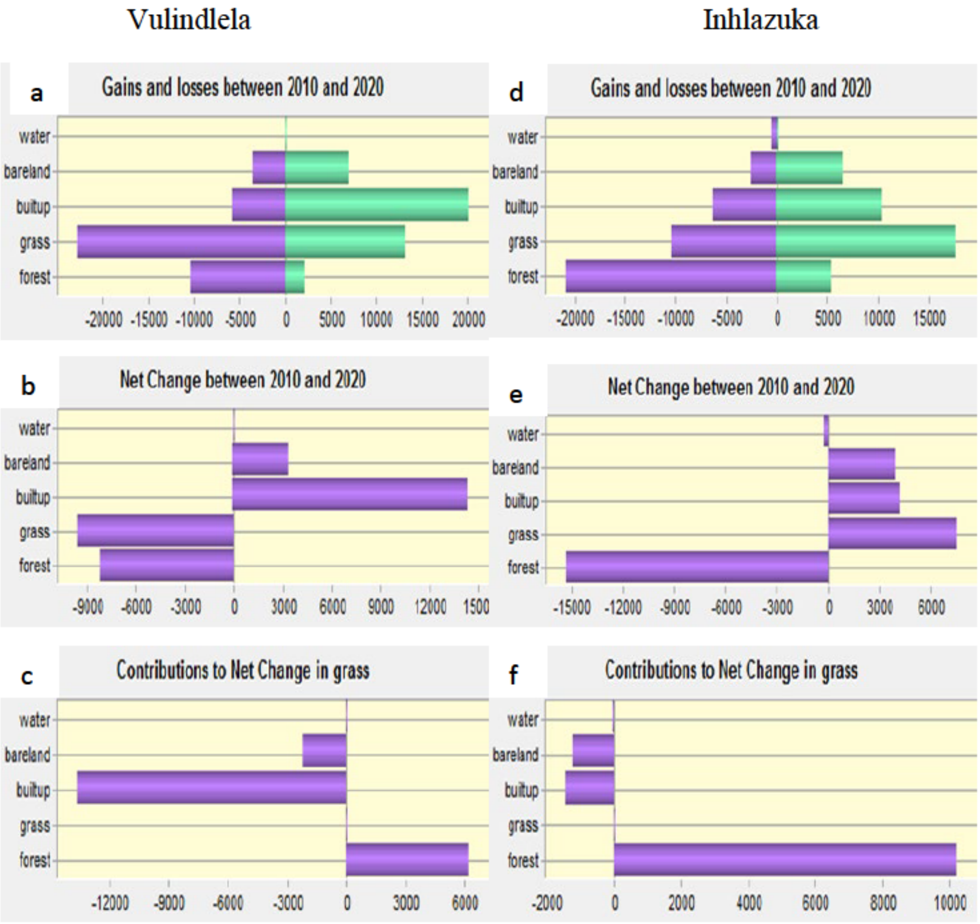
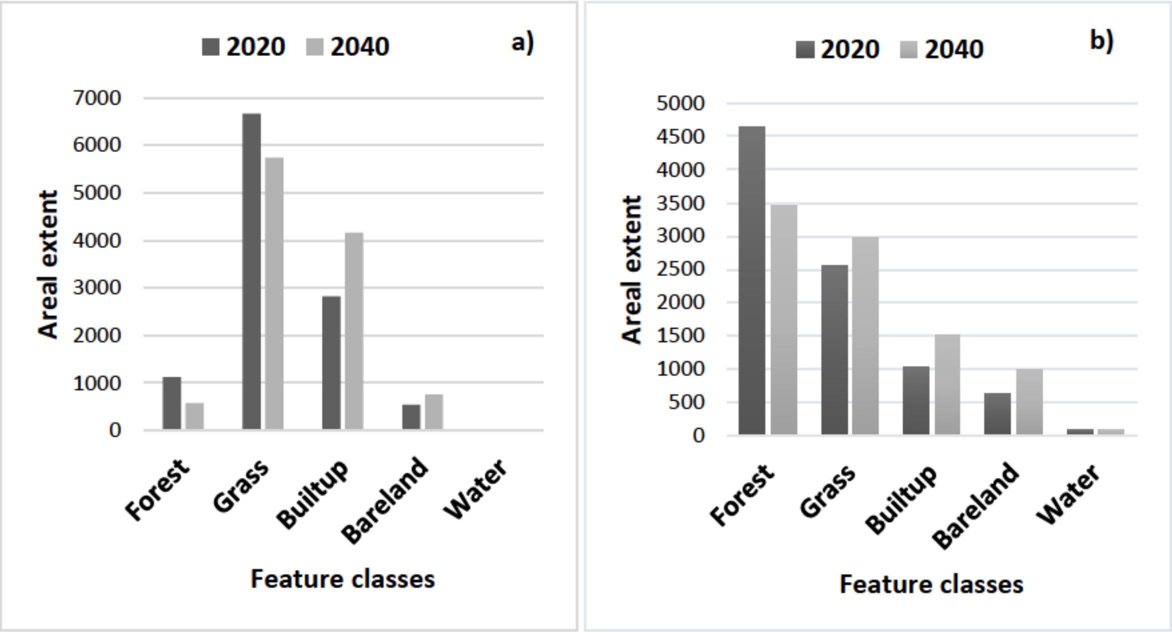


Figure 3.8 a, b and c, is presenting the gains and losses of each feature class and the Net changes in grasslands in Vulindlela between the years 2010 and 2010 and d, e, f, presenting the grassland changes in Inhlazuka, respectively.



Figures 3.9. The areal difference in the land cover types between 2020 and 2040 in the areas of a) Vulindlela and b) Nhlazuka

3.2.4 Rangeland Patch Analysis 2020 and 2040 comparison

The rangeland patch analysis was performed to measure rangeland degradation comparing the year 2020 with the projected year 2040 (Table 3.4). The results of the Percentage of landscape (PLAND) in Vulindlela suggest that there shall be an increase in the fragmentation of rangelands in the year 2040 as the patch analysis presents a decrease in the PLAND from the year 2020 at 59.6 ha to 51.35 ha. The number of patches (NP) in Vulindlela will decrease from 780 in 2020 to 103 patches in 2040. The patch density (PD) in 2020 will also decrease from 6.9 in 2020 to 0.92 in 2040. The Largest Patch Index (LPI) will decrease from the year 2020 from 43.3 ha to 18.37 ha. The patch area (AREA_MN) shall increase from 8.5 ha to 55.94 ha suggesting an increase in the patch sizes from the year 2020 to the year 2040. The Euclidean nearest neighbour distance (ENN_MN) and the effective mesh size (MESH) propose that there will be an increase in the extent of fragmentation in 2040 due to the increase in the ENN_MN in Vulindlela from the year 2020 from 73.0 ha to 172.20 ha in 2040. This suggests that the isolation of the rangeland patches will increase in 2040. The increase in isolation between the patches is further presented by the MESH as it is expected to decrease from the year 2020 at 2188.8 ha to 743.35 ha in 2040 indicating that the rangeland patches in Vulindlela will lose connectivity. The rangeland patch analysis of Vulindlela therefore, suggests that the rangelands in Vulindlela will become more isolated in 2040 compared to the year 2020 with larger rangeland patches in 2040 compared to 2020.

In Inhlazuka, the patch metrics results for the PLAND shall increase from 28.6 in 2020 to 32.89 in 2040 therefore a decrease in fragmentation in the year 2040. The NP and PD shall also decrease from the year 2020 to the year 2040. The NP in Inhlazuka will decrease from 1443 to 414 and the PD shall decrease from 16.0 to 6.52. The AREA_MN in 2040 will increase from 1.7 ha to 7.20 ha in 2040 hence larger rangeland patches. However, the increase in the ENN_MN by the year 2040 suggests isolated rangeland patches. The ENN_MN presents an increase from 75.0 ha to 120.60 ha by the year 2040, however the MESH shall increase from 35.4 ha to 58.89 ha in 2040 thus the rangeland patches being more connected in 2040 than in 2020. The results of the patch analysis in Inhlazuka therefore suggests that the rangelands shall increase in patch sizes in the year 2040 however; the rangelands will become more isolated with an increased rangeland patch connectivity when compared to the year 2020.

Table 3.4. Rangeland Patch Analysis of the year 2020 and 2040

	GRASS	PLAND	NP	PD	LPI	AREA_MN	ENN_MN	MESH
Vulindlela	**2020**	59.6	780	6.9	43.0	8.5	73.0	2188.8
	2040	51.35	103	0.92	18.37	55.94	172.20	743.35
Inhlazuka	**2020**	28.6	1443	16.0	5.4	1.7	75.0	35.4
	2040	32.89	414	4.57	6.52	7.20	120.60	58.89

3.3 Discussion

The overall aim of this study was to map the future spatio-temporal variations of communal rangelands with the use of Landsat imagery using the CA-Markov model of IDRISI TerrSet. The study used classified Landsat images in Google Earth Engine using the Random Forest classifier to characterise LULC types during the year 2020 based on Near Infrared bands (NIR) (Band 5) and Shortwave Infrared bands (SWIR) Band 7.

The CA-Markov model results showed that rangelands will increase in spatial extent in Inhlazuka in the year 2040 (figures 3.4 and 3.5) due to the decrease in forested areas whereas in Vulindlela, they were predicted to decrease as a result of the increase in settlement (Figure 3.5). The projected increase in built-up area in Vulindlela implies that there will be an increase in population. This is supported by the Municipality (2016) which stated that the population is expected to increase in future. In addition, the population growth in the area of Vulindlela could be associated with a possible increase in livestock densities in the grazing lands. The increased number of grazing animals within Vulindlela could result in the rangelands being over grazed and eventually degraded. Furthermore, activities such as unmanaged fire practices for rangeland management and increased agricultural activities in Vulindlela may also contribute to the decline of rangelands in the year 2040. This calls for the practice of sustainable grazing patterns in Vulindlela for the preservation of rangelands.

The increasing barelands in both the areas of Vulindlela and Inhlazuka are due to development which could take place in future alongside the increase in population. In Vulindlela, grasslands are being cleared for residential areas and the development of roads. In addition, activities such as rock mining are also taking place in Vulindlela causing increased bareland areas. In Inhlazuka, bareland could also be caused by the removal of the forest class for development, the construction of roads and the removal of plantations. this suggest that development activities in both study areas are the drivers of increased bareland in conjunction with activities of fire and grazing activities. As a result of the prediction models, the bareland class is projected to increase in Vulindlela and Inhlazuka (Figure 3.9), meaning the increasing barelands shall be as a result of increased development activities. Literature also states that activities of development, unmanaged fire and agricultural practices leave the soil exposed therefore causing an increase in bareland (Mussa, Teka and Mesfin 2017, Tsegaye et al. 2010, Lehnert et al. 2014). However, the changes in temperature and precipitation received could also contribute to the increase in the spatial extent of bareland.

Climate change variabilities in Southern Africa, have brought about a marked seasonality in feed quantity and quality of rangelands which have been deteriorated as a result of the frequent dry seasons in certain parts of the region (Assan 2014). Therefore, the future patterns in temperature and rainfall will influence the growth of grass in these rangelands. The projected decline in rangelands in the areas of Vulindlela could also be attributed to the changing climates through reduced precipitation and increased temperature that restricts growth in rangelands as a result of increased temperatures and decreased rainfall patterns, however, if sufficient rainfall and moderate temperatures are received in the future, then rangelands shall be presented with growing conditions which will not hinder their growth and quality. This also applies to the rangelands of Inhlazuka, with suffice rainfall and moderate levels of temperature, the communal rangelands will grow producing quality forage production. However, the increase in the communal rangelands in Inhlazuka depends on both the climatic conditions as well as the maintained and consistent removal of the alien plants, thus creating ideal conditions for growth.

Fragmentation results showed that in both study areas, the grassland patch sizes shall increase meaning that the grassland patches of Vulindlela and Inhlazuka shall be larger compared to the rangeland patches of 2020. In Vulindlela, the patch area is to increase by an average of 32.22 ha by the year 2040 and in Inhlazuka the patch area shall increase by an average of 4.45 ha. Meanwhile the isolation extent (ENN_MN) predicted is to increase by an average of 122.6 ha in Vulindlela and by an average of 97.8 ha in Inhlazuka. However, results also showed a decrease in the of connectivity (The MESH) of patches in Vulindlela by the year 2040. In Inhlazuka rangeland connectivity is to increase by an average size of 47.14 ha by the year 2040 and decrease by an average size of 1466.07 ha in Vulindlela. The drivers behind the future isolation of the rangelands in Vulindlela are as a result the development activities, particularly that of residential development (Figure 3.4 and 3.6). Furthermore, the increase in development in Vulindlela is reducing the connectivity of rangeland therefore, increased fragmentation and loss of rangelands. In Inhlazuka, the increase in the AREA_MN of the rangelands could be caused by the increasing rangelands thus larger grassland patches however, the increase in the isolation of rangelands could be the result of increasing built-up and bareland areas and the decline in the forest class. This is because though the built-up, bareland and forest classes are not affecting the rangeland areal extent, the change in these classes has an influence over the distribution patterns. The increase in the fragmentation in the communal rangelands especially in the area of Vulindlela suggests an urgent need for protecting rangelands due to fragmentation depleting them in Vulindlela. And with continued unmanaged activities of fire, grazing patterns and agriculture, rangeland fragmentation in Vulindlela is to increase causing further degradation and loss of rangelands (Spanowicz and Jaeger 2019, Soons et al. 2005).

Rangelands are important ecosystems which regulate our climate, control carbon emissions, produces medicines, fuel wood, is base for wildlife-based tourism and play an important role in water provision meaning that rangeland landscapes are important and should be protected (O'Connor and van Wilgen 2020). Rangelands also play a role of providing income to livestock owners therefore, contributing to the economy. As a result of the lack of management practices in communal rangelands, sustainable development methods within rangelands are important to ensure that the people, economy and the environment are all balanced and with the use of RS in monitoring rangelands policies to protect rangelands can be put in place to manage the degradation of rangelands. The findings of this study can henceforth, assist the communities residing within these areas and the development planners to perform more sustainable practices of development as well as educate the residents of these areas on sustainable practices of grazing, crop farming and the use of fire as a management tool.

3.4 Conclusion

In conclusion the study successfully performed the 2040 simulations using the CA-Markov model of IDRISI TerrSet with high accuracy. The 2040 predictions illustrate that settlement will increase due to the increase in population. The increase in settlement in Vulindlela is to take place at 67 ha per year and rangelands are to decrease at a rate of 46 ha per year. The patch metrics of Vulindlela and Inhlazuka presented the increase in rangeland fragmentation as a result of the loss of connectivity in rangelands and increased isolation particularly in Vulindlela as a result of development activities. The increase in settlement development in Vulindlela suggest an urgent need to develop rangeland management plans for the growing rangeland degradation as a result of rangeland fragmentation. To end off, the study results presented that land use land cover changes are consistently changing and for this reason the use of Remotely Sensed data is important in monitoring LULCC studies to capture all the changes taking place as a result of human or environmental conditions. The use of RS for the spatial monitoring of rangelands and land rehabilitation will also assists in the creation of rangeland conservation policies.

CHAPTER 4

STUDY SYNTHESIS

4 Introduction

Rangelands are critical ecosystems, especially for rural and peri-urban populations in developing countries (Mansour, Mutanga and Everson 2012). This is because they provide a variety of ecosystem services such as fibre, food, and water through regulation of hydrological processes, and are a livelihood to people globally. However, socioeconomic changes, competing land uses, climate events (i.e., droughts), and overgrazing are some of the drivers that are degrading the rangelands(Wassie 2020, Smith et al. 2016). Subsequently, rangeland degradation as a global environmental issue will directly impact about 250 million people globally (Mansour et al. 2012). In this regard, there is a need for robust spatially explicit mechanisms for mapping and monitoring grasslands if these ecosystem services are to be sustained. The lurking challenge is that there are currently limited criterions for mapping and monitoring the transformation of rangelands, especially in communal areas where resources are limited. Specifically, access to up-to-date spatial information on the extent of rangeland is of high importance if proper conservation measures are to be put in place (Mansour et al. 2012, Keno and Suryabhagavan 2014). Remote Sensing (RS) techniques have been extensively demonstrated to be sufficient and accurate in monitoring the condition of rangelands. The use of RS in rangeland management provides the opportunity to predict, observe and recognize the ecological threats in rangelands (Al-Bukhari, Hallett and Brewer 2018). In addition, RS data has the ability to cover large areas with frequent repetitive image acquisition across multiple wavelengths (Zhu et al. 2018). However, hardware, and software systems that were currently available in the past decades were limited in terms of storage and processing power of remotely sensed data. In this regard, the introduction of the Google Earth Engine (GEE) cloud base platform as well as other algorithms such as the CA Markov have extensively improved the applications such as quantitatively enumerating past, present and future LULCCs in ecosystems such as rangelands. In this regard this study sought to map the spatio-temporal variability of rangelands using geospatial techniques. To accomplish this overarching aim, the following specific objectives were established:

1. To assess the LU/LC changes and the spatial extent variation of communal rangelands (between the years 2000, 2010 and 2020).

2. To predict the future changes in the spatial distribution of rangelands in communal areas using the CA Markov model.

This chapter seeks review the objectives in relation to the conclusions drawn. The chapter also outlines the implications of the study, general conclusion, limitations of the study and recommends the direction for future studies.

4.1 A review of the Study's Objectives

4.1.1 Assessing the LU/LC changes and the spatial extent variation of communal rangelands (between the years 2000, 2010 and 2020).

In assessing the impacts of land use land cover change on rangelands using the GEE platform for the years 2000, 2010, and 2020, classification overall accuracies of 75%, 79% and 83% were obtained in Inhlazuka while accuracies of 89%, 85%, and 89% were obtained in Vulindlela, respectively. Meanwhile, the kappa accuracy scores of 65%, 68% and 73% were exhibited by the Inhlazuka images classification while Vulindlela exhibited scores of 81%, 75% and 83% for the years 2000, 2010 and 2020, respectively. The most influential spectral variables that exhibited these classification accuracies were that of near infrared (NIR) (Bands 5) and short-wave infrared bands (SWIR) (Band 7), and their derivatives. Results also showed that rangelands in Vulindlela are decreasing as a result of the increase in built-up area. The rangelands in Vulindlela decreased at a rate of 37.52 hectares per year between the years 2000 and 2010 and further decreased at a rate of 76 hectares per years of 2010 and 2020. Meanwhile, the built up areas (settlements) in Vulindlela increased at a rate of 43.15 hectares per year from 2000 to 2010 and at 114.55 ha per year from the year 2010 to 2020. In Inhlazuka, the forest class was dominant increased at a rate of 86.54 hectares per year between the years 2000 and 2010 while rangelands decreased, possible due to the increase in alien invasive species. Rangelands decreased at 40.19 ha per year. Between the periods of 2010 and 2020 the forest class decreased at 113.84 ha per year and rangelands increased at 45.27ha per year as the municipality facilitated the clearance of alien invasive species. In addition, the result revealed that the built-up area and the rangelands are causing a decrease in the forest class in Inhlazuka with built-up area increasing at 41.7 ha/per year from 2010 to 2020. Interims of fragmentation, an increases in the number of patched (NP) from 244 to 780 from the year 2000 to 2020 was noted, suggesting fragmentation activities. Also patch density (PD) in Vulindlela increasing presence from 2.1 in the year 2000 to 6.9 in the year 2020 indicating transformation into smaller patches. In Inhlazuka, rangeland fragmentation was slower in relation to that occurring in

Vulindlela. InInhlazuka, number of NP increased from 1392 in the year 2000 to 1443 in 2020 while patch density increased from 15.4 in 2000 to 16.0 in 2020. The findings of this study suggest that there is a need for rangeland conservation policies to be put in place in these communal areas reduce the rate of grassland transformation. Also, these findings underscore the prospects, efficiency and effectiveness of the geospatial techniques integrated in GEE as a platform for establishing rangeland monitoring and management frameworks.

4.1.2 Predicting future changes in the spatial distribution of rangelands in communal areas using the CA Markov model.

In employing the CA Markov model to predict the future (2040) land use changes in the areas of Vulindlela and Inhlazuka based on the recent-past state of grasslands (i.e., 2020 RF derived landcover maps), rangelands were predicted to decrease as a result of the increasing settlement. Specifically, a loss of 919.74 ha at 46 ha per year in the spatial extent of rangelands was predicted occur in the year 2040 in Vulindlela. Meanwhile, in Inhlazuka, the rangelands were predicted to increase to 419.48 ha at a rate of 21 ha per year because of a decrease in the spatial extent of forest areas to 1169.91 ha at a rate of 58.45 ha per year between the year 2020 to the year 2040. In terms of rangeland fragmentation, the findings project that fragmentation will continue to increase and rangeland patches will become more isolated and less connected as indicted by the Euclidean nearest neighbour distance (ENN_MN) and the effective mesh size (MESH) statistics. In Vulindlela, the grassland inter-patch distances (ENN _MN) will increase from 73.0 in the year 2020 to 172.20 in the year 2040 suggesting an increase in the isolation of rangelands. The increase in isolated and less connected rangeland patches is revealed by the decrease of the MESH from 2188.8 ha in the year 2020 to 743.35 ha in 2040. The loss of rangeland connectivity and isolation in rangeland patches is of the result of the increase in the built-up area. In Inhlazuka an increase in the isolation is also projected by the findings of this study. Specifically, the grassland inter-patch distances (ENN_MN) are predicted to increase from 75.0 to 120.60 in the year 2040 while the patch connectivity (MESH) increases from 35.4 ha to 58.89 ha in 2040 thus increased rangeland connectivity in 2040 compared to 2020 in Inhlazuka. In Vulindlela the Area_MN is to increase from 8.5 ha in the year 2000 to 55.94 ha in the year 2040. Then in Inhlazuka the Area_MN is predicted to increase from 1.7 ha to 7.20 ha respectively. The findings of the study suggest that rangeland fragmentation is to increase in future. This will necessitate robust spatially explicit monitoring frameworks if these land use changes are to be cubed and ecosystem service retained.

4.2 Conclusions

The aim of this study was to map the spatio-temporal changes of grasslands in communal rangelands using geospatial techniques. Based on the study findings the use of the GEE platform proved to be both efficient and proficient in characterising the changes of rangelands over the period of 20 years from 2000 to 2020 in both areas of Vulindlela and Inhlazuka. In this regard, based on the findings of this study it can be concluded that; rangeland spatio-temporal changes were successfully mapped with the use of the Random forest classifier embedded in the GEE platform based on Landsat Near Infrared (NIR) bands and the Shortwave Infrared (SWIR) bands as well as their derivatives as optimal discrimination spectral features.

Rangelands in Vulindlela are decreasing and being fragmented as a result of the increasing built-up areas while in Inhlazuka they are increasing with a decrease in the forest class. The combination of GEE based RF and the CA-Markov model successfully predicted the rangeland the future spatial distribution rangelands between 2020 and 2040 in Vulindlela and Inhlazuka.

Overall, the study findings of this study suggests the use of RS and Geographic Information Systems (GIS) methods have proven quite valuable in mapping the past present and future changes in the spatial extent of rangelands. In this regard, they are a proactive robust and effective and efficient platform for establishing rangeland monitoring and management frameworks required to support their sustainable utilisation and provision ecosystem services.

4.2.1 Implications and recommendations of the Study

The high fragmentation of grasslands as well as a reduction in their spatial extent imply that there is a need drawing up policies that foster their sustainable utilisation within communal areas. Sustainable utilisation practices within communal rangelands will ensure support the socioeconomical needs of the communities (in terms of agriculture and livestock grazing) fostering their conservation. In addition, the community members of Vulindlela and Inhlazuka need to be educated on the importance of rangelands, and the ecosystem services they provide so as to implement sound sustainable utilisation practices.

4.4 Challenges of the study and opportunities for Future research

In Inhlazuka there may have been some misclassifications of the rangelands and forestry making it difficult to discriminate between these classes in certain areas using the Landsat sensor. This could be explained by the rapid emergence and clearance activities of alien invasive species in the area.

The land use land cover patterns taking place within the communal rangelands of Vulindlela and Inhlazuka indicate that extensive rangeland fragmentation is occurring resulting in their degradation. Based on the findings of this study, there is a need to increased research efforts on rangeland management strategies that can be implemented in these communal areas to create awareness on the vital importance of protecting these ecosystems. Future studies could also assess the impact of activities such as livestock production and grazing intensity/patterns as well as fire administration in these communal areas as individual agents impacting on the quality and quantity rangelands.

References

Abd El-Kawy, O., J. Rød, H. Ismail & A. Suliman (2011) Land use and land cover change detection in the western Nile delta of Egypt using remote sensing data. *Applied geography,* 31**,** 483-494.

Abdulahi, M. M., H. Hashim & M. Teha (2016) Rangeland degradation: Extent, impacts, and alternative restoration techniques in the rangelands of Ethiopia. *Tropical and Subtropical Agroecosystems,* 19.

Accatino, F., C. De Michele, R. Vezzoli, D. Donzelli & R. J. Scholes (2010) Tree–grass co-existence in savanna: interactions of rain and fire. *Journal of theoretical biology,* 267**,** 235-242.

Admasu, T., E. Abule & Z. Tessema (2010) Livestock-rangeland management practices and community perceptions towards rangeland degradation in South Omo zone of Southern Ethiopia. *Livestock Research for Rural Development,* 22.

Al-Bukhari, A., S. Hallett & T. Brewer (2018) A review of potential methods for monitoring rangeland degradation in Libya. *Pastoralism,* 8**,** 1-14.

Alam, A., M. S. Bhat & M. Maheen (2020) Using Landsat satellite data for assessing the land use and land cover change in Kashmir valley. *GeoJournal,* 85**,** 1529-1543.

Ali, I., F. Cawkwell, E. Dwyer, B. Barrett & S. Green (2016) Satellite remote sensing of grasslands: from observation to management. *Journal of Plant Ecology,* 9**,** 649-671.

Alkemade, R., R. S. Reid, M. van den Berg, J. de Leeuw & M. Jeuken (2013) Assessing the impacts of livestock production on biodiversity in rangeland ecosystems. *Proceedings of the National Academy of Sciences,* 110**,** 20900-20905.

Alqurashi, A. & L. Kumar (2013) Investigating the use of remote sensing and GIS techniques to detect land use and land cover change: A review. *Advances in Remote Sensing*.

Angassa, A. & G. Oba (2008) Herder perceptions on impacts of range enclosures, crop farming, fire ban and bush encroachment on the rangelands of Borana, Southern Ethiopia. *Human ecology,* 36**,** 201-215.

Assan, N. (2014) Possible impact and adaptation to climate change in livestock production in Southern Africa. *IOSR J Environ Sci Toxicol Food Technol,* 8**,** 104-112.

Bar, S., B. R. Parida & A. C. Pandey (2020) Landsat-8 and Sentinel-2 based Forest fire burn area mapping using machine learning algorithms on GEE cloud platform over Uttarakhand, Western Himalaya. *Remote Sensing Applications: Society and Environment,* 18**,** 100324.

Baudena, M., S. C. Dekker, P. M. van Bodegom, B. Cuesta, S. I. Higgins, V. Lehsten, C. H. Reick, M. Rietkerk, S. Scheiter & Z. Yin (2015) Forests, savannas, and grasslands: bridging the knowledge gap between ecology and Dynamic Global Vegetation Models. *Biogeosciences,* 12**,** 1833-1848.

Bedunah, D. J. & J. P. Angerer (2012) Rangeland degradation, poverty, and conflict: how can rangeland scientists contribute to effective responses and solutions? *Rangeland Ecology & Management,* 65**,** 606-612.

Beier, C., C. Beierkuhnlein, T. Wohlgemuth, J. Penuelas, B. Emmett, C. Körner, H. de Boeck, J. H. Christensen, S. Leuzinger & I. A. Janssens (2012) Precipitation manipulation experiments–challenges and recommendations for the future. *Ecology letters,* 15**,** 899-911.

Belgiu, M. & L. Drăguţ (2016) Random forest in remote sensing: A review of applications and future directions. *ISPRS journal of photogrammetry and remote sensing,* 114**,** 24-31.

Bengtsson, J., J. Bullock, B. Egoh, C. Everson, T. Everson, T. O'Connor, P. O'Farrell, H. Smith & R. Lindborg (2019) Grasslands—more important for ecosystem services than you might think. *Ecosphere,* 10**,** e02582.

Boone, R. B., R. T. Conant, J. Sircely, P. K. Thornton & M. Herrero (2018) Climate change impacts on selected global rangeland ecosystem services. *Global change biology,* 24**,** 1382-1393.

Breedt, J. A., N. Dreber & K. Kellner (2013) Post-wildfire regeneration of rangeland productivity and functionality–observations across three semi-arid vegetation types in South Africa. *African Journal of Range & Forage Science,* 30**,** 161-167.

Cai, Y., K. Guan, J. Peng, S. Wang, C. Seifert, B. Wardlow & Z. Li (2018) A high-performance and in-season classification system of field-level crop types using time-series Landsat data and a machine learning approach. *Remote sensing of environment,* 210**,** 35-47.

Carrasco, L., A. W. O'Neil, R. D. Morton & C. S. Rowland (2019) Evaluating combinations of temporally aggregated Sentinel-1, Sentinel-2 and Landsat 8 for land cover mapping with Google Earth Engine. *Remote Sensing,* 11**,** 288.

Ceballos, G., A. Davidson, R. List, J. Pacheco, P. Manzano-Fischer, G. Santos-Barrera & J. Cruzado (2010) Rapid decline of a grassland system and its ecological and conservation implications. *PloS one,* 5**,** e8562.

Cengiz, A., M. Budak, N. YAĞMUR & F. BALÇIK (2023) Comparison between random forest and support vector machine algorithms for LULC classification. *International Journal of Engineering and Geosciences,* 8**,** 1-10.

Cha, S.-y. & C.-h. Park (2007) The utilization of Google Earth images as reference data for the multitemporal land cover classification with MODIS data of North Korea. *Korean Journal of Remote Sensing,* 23**,** 483-491.

Chan, J. C.-W. & D. Paelinckx (2008) Evaluation of Random Forest and Adaboost tree-based ensemble classification and spectral band selection for ecotope mapping using airborne hyperspectral imagery. *Remote Sensing of Environment,* 112**,** 2999-3011.

Cho, M. A., M. Onisimo & T. Mabhaudhi (2021) Using participatory GIS and collaborative management approaches to enhance local actors' participation in rangeland management: the case of Vulindlela, South Africa. *Journal of Environmental Planning and Management***,** 1-20.

Clark, M. & D. Tilman (2017) Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice. *Environmental Research Letters,* 12**,** 064016.

Cleland, E. E., S. L. Collins, T. L. Dickson, E. C. Farrer, K. L. Gross, L. A. Gherardi, L. M. Hallett, R. J. Hobbs, J. S. Hsu & L. Turnbull (2013) Sensitivity of grassland plant community composition to spatial vs. temporal variation in precipitation. *Ecology,* 94**,** 1687-1696.

Cousins, B. (1999) Invisible capital: The contribution of communal rangelands to rural livelihoods in South Africa. *Development Southern Africa,* 16**,** 299-318.

da Silva, V. S., G. Salami, M. I. O. da Silva, E. A. Silva, J. J. Monteiro Junior & E. Alba (2020) Methodological evaluation of vegetation indexes in land use and land cover (LULC) classification. *Geology, Ecology, and Landscapes,* 4**,** 159-169.

Derner, J. D. & D. J. Augustine (2016) Adaptive management for drought on rangelands. *Rangelands,* 38**,** 211-215.

DeVries, B., A. K. Pratihast, J. Verbesselt, L. Kooistra & M. Herold (2016) Characterizing forest change using community-based monitoring data and Landsat time series. *PloS one,* 11**,** e0147121.

Dowdy, A. J., H. Ye, A. Pepler, M. Thatcher, S. L. Osbrough, J. P. Evans, G. Di Virgilio & N. McCarthy (2019) Future changes in extreme weather and pyroconvection risk factors for Australian wildfires. *Scientific reports,* 9**,** 10073.

Dube, T., X. G. Maluleke & O. Mutanga (2022) Mapping rangeland ecosystems vulnerability to Lantana camara invasion in semi-arid savannahs in South Africa. *African Journal of Ecology*.

Eastman, J. R. (2015) TerrSet manual. *Accessed in TerrSet version,* 18.

Fidelis, A. T., M. D. Delgado Cartay, C. C. Blanco, S. C. Muller, V. d. P. Pillar & J. S. Pfadenhauer (2010) Fire intensity and severity in Brazilian campos grasslands. *Interciencia: revista de ciencia y tecnologia de america. Caracas. Vol. 35, n. 10 (Oct. 2010), p. 739-745*.

Ge, G., J. Zhang, X. Chen, X. Liu, Y. Hao, X. Yang & S. Kwon (2022) Effects of land use and land cover change on ecosystem services in an arid desert-oasis ecotone along the Yellow River of China. *Ecological Engineering,* 176**,** 106512.

Ghalehteimouri, K. J., A. Shamsoddini, M. N. Mousavi, F. B. C. Ros & A. Khedmatzadeh (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.

Ghasempour, M., R. Erfanzadeh & P. Török (2022) Fire effects on soil seed banks under different woody plant species in Mazandaran province, Iran. *Ecological Engineering,* 183**,** 106762.

Ghayour, L., A. Neshat, S. Paryani, H. Shahabi, A. Shirzadi, W. Chen, N. Al-Ansari, M. Geertsema, M. Pourmehdi Amiri & M. Gholamnia (2021) Performance evaluation of sentinel-2 and landsat 8 OLI data for land cover/use classification using a comparison between machine learning algorithms. *Remote Sensing,* 13**,** 1349.

Ghorbani, A. & M. Pakravan (2013) Land use mapping using visual vs. digital image interpretation of TM and Google earth derived imagery in Shrivan-Darasi watershed (Northwest of Iran). *European Journal of Experimental Biology,* 3**,** 576-582.

Gidey, E., O. Dikinya, R. Sebego, E. Segosebe & A. Zenebe (2017) Cellular automata and Markov Chain (CA_Markov) model-based predictions of future land use and land cover scenarios (2015–2033) in Raya, northern Ethiopia. *Modeling Earth Systems and Environment,* 3**,** 1245-1262.

Gorelick, N., M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau & R. Moore (2017) Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote sensing of Environment,* 202**,** 18-27.

Halmy, M. W. A., P. E. Gessler, J. A. Hicke & B. B. Salem (2015) Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Applied Geography,* 63**,** 101-112.

Hamad, R., H. Balzter & K. Kolo (2018) Predicting land use/land cover changes using a CA-Markov model under two different scenarios. *Sustainability,* 10**,** 3421.

Hansen, M. C. & T. R. Loveland (2012) A review of large area monitoring of land cover change using Landsat data. *Remote sensing of Environment,* 122**,** 66-74.

Hicks, R. L., B. C. Parks, J. T. Roberts & M. J. Tierney. 2008. *Greening aid?: Understanding the environmental impact of development assistance*. OUP Oxford.

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

Hossen, S., M. Hossain & M. Uddin (2019) Land cover and land use change detection by using remote sensing and GIS in Himchari National Park (HNP), Cox's Bazar. *Bangladesh. J. Sci. Technol. Environ. Inform,* 7**,** 544-554.

Hughes, C., G. De Winnaar, R. Schulze, M. Mander & G. Jewitt (2018) Mapping of water-related ecosystem services in the uMngeni catchment using a daily time-step hydrological model for prioritisation of ecological infrastructure investment–Part 2: Outputs. *Water SA,* 44**,** 590-600.

Hyandye, C. & L. W. Martz (2017) A Markovian and cellular automata land-use change predictive model of the Usangu Catchment. *International journal of remote sensing,* 38**,** 64-81.

Jalayer, S., A. Sharifi, D. Abbasi-Moghadam, A. Tariq & S. Qin (2022) Modeling and predicting land use land cover spatiotemporal changes: a case study in chalus watershed, Iran. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* 15**,** 5496-5513.

Jin, Y., X. Yang, J. Qiu, J. Li, T. Gao, Q. Wu, F. Zhao, H. Ma, H. Yu & B. Xu (2014) Remote sensing-based biomass estimation and its spatio-temporal variations in temperate grassland, Northern China. *Remote Sensing,* 6**,** 1496-1513.

Kafy, A.-A., R. M. Shuvo, M. N. H. Naim, M. S. Sikdar, R. R. Chowdhury, M. A. Islam, M. H. S. Sarker, M. H. H. Khan & M. A. Kona (2021) Remote sensing approach to simulate the land use/land cover and seasonal land surface temperature change using machine learning algorithms in a fastest-growing megacity of Bangladesh. *Remote Sensing Applications: Society and Environment,* 21**,** 100463.

Keno, B. & K. Suryabhagavan (2014) Multitemporal remote sensing of landscape dynamics and pattern change in Dire district, southern Ethiopia. *Journal of Geomatics,* 8**,** 189-194.

Khawaldah, H., I. Farhan & N. Alzboun (2020) Simulation and prediction of land use and land cover change using GIS, remote sensing and CA-Markov model. *Global Journal of Environmental Science and Management,* 6**,** 215-232.

Kipling, R. P., P. Virkajärvi, L. Breitsameter, Y. Curnel, T. De Swaef, A.-M. Gustavsson, S. Hennart, M. Höglind, K. Järvenranta & J. Minet (2016) Key challenges and priorities for modelling European grasslands under climate change. *Science of the Total Environment,* 566**,** 851-864.

Koley, S. & J. Chockalingam (2022) Sentinel 1 and Sentinel 2 for cropland mapping with special emphasis on the usability of textural and vegetation indices. *Advances in Space Research,* 69**,** 1768-1785.

Kumar, L. & O. Mutanga (2018) Google Earth Engine applications since inception: Usage, trends, and potential. *Remote Sensing,* 10**,** 1509.

Kumar, S. & S. Arya (2021) Change detection techniques for land cover change analysis using spatial datasets: A review. *Remote Sensing in Earth Systems Sciences,* 4**,** 172-185.

Kumar, S., S. Arya & K. Jain (2022) A SWIR-based vegetation index for change detection in land cover using multi-temporal Landsat satellite dataset. *International Journal of Information Technology,* 14**,** 2035-2048.

Kuule, D. A., B. Ssentongo, P. J. Magaya, G. Y. Mwesigwa, I. T. Okurut, K. Nyombi, A. Egeru & J. R. S. Tabuti (2022) Land use and land cover change dynamics and perceived drivers in Rangeland areas in central Uganda. *Land,* 11**,** 1402.

Langley, S. K., H. M. Cheshire & K. S. Humes (2001) A comparison of single date and multitemporal satellite image classifications in a semi-arid grassland. *Journal of Arid Environments,* 49**,** 401-411.

Lawley, V., M. Lewis, K. Clarke & B. Ostendorf (2016) Site-based and remote sensing methods for monitoring indicators of vegetation condition: An Australian review. *Ecological Indicators,* 60**,** 1273-1283.

Lehnert, L. W., H. Meyer, N. Meyer, C. Reudenbach & J. Bendix (2014) A hyperspectral indicator system for rangeland degradation on the Tibetan Plateau: A case study towards spaceborne monitoring. *Ecological Indicators,* 39**,** 54-64.

Li, J. & D. P. Roy (2017) A global analysis of Sentinel-2A, Sentinel-2B and Landsat-8 data revisit intervals and implications for terrestrial monitoring. *Remote Sensing,* 9**,** 902.

Li, W., R. Dong, H. Fu, J. Wang, L. Yu & P. Gong (2020) Integrating Google Earth imagery with Landsat data to improve 30-m resolution land cover mapping. *Remote Sensing of Environment,* 237**,** 111563.

Lipiec, J., C. Doussan, A. Nosalewicz & K. Kondracka (2013) Effect of drought and heat stresses on plant growth and yield: a review. *International Agrophysics,* 27**,** 463-477.

Liping, C., S. Yujun & S. Saeed (2018) Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PloS one,* 13**,** e0200493.

Little, I. T., P. A. Hockey & R. Jansen (2015) Impacts of fire and grazing management on South Africa's moist highland grasslands: A case study of the Steenkampsberg Plateau, Mpumalanga, South Africa. *Bothalia-African Biodiversity & Conservation,* 45**,** 1-15.

Liu, X., X. Liang, X. Li, X. Xu, J. Ou, Y. Chen, S. Li, S. Wang & F. Pei (2017) A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landscape and Urban Planning,* 168**,** 94-116.

Loveland, T. R. & J. L. Dwyer (2012) Landsat: Building a strong future. *Remote Sensing of Environment,* 122**,** 22-29.

Lu, X., K. C. Kelsey, Y. Yan, J. Sun, X. Wang, G. Cheng & J. C. Neff (2017) Effects of grazing on ecosystem structure and function of alpine grasslands in Qinghai–Tibetan Plateau: A synthesis. *Ecosphere,* 8**,** e01656.

Lund, H. G. (2007) Accounting for the world's rangelands. *Rangelands,* 29**,** 3-10.

Mansour, K., O. Mutanga & T. Everson (2012) Remote sensing based indicators of vegetation species for assessing rangeland degradation: Opportunities and challenges. *Afr. J. Agric. Res,* 7**,** 3261-3270.

Mathanraj, S., N. Rusli & G. Ling. 2021. Applicability of the CA-Markov Model in Land-use/Land cover Change Prediction for Urban Sprawling in Batticaloa Municipal Council, Sri Lanka. In *IOP Conference Series: Earth and Environmental Science*, 012015. IOP Publishing.

Matongera, T. N., O. Mutanga, T. Dube & M. Sibanda (2017) Detection and mapping the spatial distribution of bracken fern weeds using the Landsat 8 OLI new generation sensor. *International journal of applied earth observation and geoinformation,* 57**,** 93-103.

Matongera, T. N., O. Mutanga, M. Sibanda & J. Odindi (2021) Estimating and monitoring land surface phenology in rangelands: A review of progress and challenges. *Remote Sensing,* 13**,** 2060.

McGranahan, D. A. & K. P. Kirkman (2013) Multifunctional rangeland in Southern Africa: Managing for production, conservation, and resilience with fire and grazing. *Land,* 2**,** 176-193.

Milton, S. J., W. R. J. Dean & D. M. Richardson (2003) Economic incentives for restoring natural capital in southern African rangelands. *Frontiers in Ecology and the Environment,* 1**,** 247-254.

Mncube, N. L. 2022. Investigating the contribution of social cash transfers to the food security situation of agricultural-based rural households of Nhlazuka, Richmond Municipality, South Africa.

Mngadi, M., J. Odindi, K. Peerbhay & O. Mutanga (2021) Examining the effectiveness of Sentinel-1 and 2 imagery for commercial forest species mapping. *Geocarto International,* 36**,** 1-12.

Mohamed, M. A., J. Anders & C. Schneider (2020) Monitoring of changes in land use/land cover in Syria from 2010 to 2018 using multitemporal Landsat imagery and GIS. *Land,* 9**,** 226.

Mondal, M. S., N. Sharma, P. K. Garg & M. Kappas (2016) Statistical independence test and validation of CA Markov land use land cover (LULC) prediction results. *The Egyptian Journal of Remote Sensing and Space Science,* 19**,** 259-272.

Municipality, M. Vulindlela Local Area Plan: Spatial Framework. 2016. *Pietermaritzburg, KwaZulu-Natal*.

Munthali, M., S. Mustak, A. Adeola, J. Botai, S. Singh & N. Davis (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.

Mussa, M., H. Teka & Y. Mesfin (2017) Land use/cover change analysis and local community perception towards land cover change in the lowland of Bale rangelands, Southeast Ethiopia. *International Journal of Biodiversity and Conservation,* 9**,** 363-372.

Mutanga, O., E. Adam & M. A. Cho (2012) High density biomass estimation for wetland vegetation using WorldView-2 imagery and random forest regression algorithm. *International Journal of Applied Earth Observation and Geoinformation,* 18**,** 399-406.

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

Odebiri, O., O. Mutanga, J. Odindi, K. Peerbhay & S. Dovey (2020) Predicting soil organic carbon stocks under commercial forest plantations in KwaZulu-Natal province, South Africa using remotely sensed data. *GIScience & Remote Sensing,* 57**,** 450-463.

Palmer, A. R. & J. E. Bennett (2013) Degradation of communal rangelands in South Africa: towards an improved understanding to inform policy. *African Journal of Range & Forage Science,* 30**,** 57-63.

Parihar, S. M., S. Sarkar, A. Dutta, S. Sharma & T. Dutta (2013) Characterizing wetland dynamics: a post-classification change detection analysis of the East Kolkata Wetlands using open source satellite data. *Geocarto International,* 28**,** 273-287.

Parveen, K. D., K. K. Ravinder & R. B. Daizy (2011) Impact of Lantana camara L. invasion on riparian vegetation of Nayar region in Garhwal Himalayas (Uttarakhand, India). *Journal of Ecology and the Natural Environment,* 3**,** 11-22.

Phan, T. N., V. Kuch & L. W. Lehnert (2020) Land Cover Classification using Google Earth Engine and Random Forest Classifier—The Role of Image Composition. *Remote Sensing,* 12**,** 2411.

Phiri, D. & J. Morgenroth (2017) Developments in Landsat land cover classification methods: A review. *Remote Sensing,* 9**,** 967.

Polley, H. W., D. D. Briske, J. A. Morgan, K. Wolter, D. W. Bailey & J. R. Brown (2013) Climate change and North American rangelands: trends, projections, and implications. *Rangeland Ecology & Management,* 66**,** 493-511.

Price, K. P., S. L. Egbert, M. D. Nellis, R.-Y. Lee & R. Boyce (1997) Mapping land cover in a high plains agro-ecosystem using a multidate Landsat thematic mapper modeling approach. *Transactions of the Kansas Academy of Science (1903)***,** 21-33.

Pu, D., J. Sun, Q. Ding, Q. Zheng, T. Li & X. Niu (2020) Mapping urban areas using dense time series of landsat images and google earth engine. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences,* 42**,** 403-409.

Ramoelo, A., M. Cho, R. Mathieu & A. K. Skidmore (2015) Potential of Sentinel-2 spectral configuration to assess rangeland quality. *Journal of applied remote sensing,* 9**,** 094096-094096.

Ranjan, R., A. K. Chandel, L. R. Khot, H. Y. Bahlol, J. Zhou, R. A. Boydston & P. N. Miklas (2019) Irrigated pinto bean crop stress and yield assessment using ground based low altitude remote sensing technology. *Information Processing in Agriculture,* 6**,** 502-514.

Rija, A., J. Kideghesho, K. A. Mwamende & I. Selemani (2013) Emerging issues and challenges in conservation of biodiversity in the rangelands of Tanzania.

Rodriguez-Galiano, V., M. Chica-Olmo, F. Abarca-Hernandez, P. M. Atkinson & C. Jeganathan (2012a) Random Forest classification of Mediterranean land cover using multi-seasonal imagery and multi-seasonal texture. *Remote Sensing of Environment,* 121**,** 93-107.

Rodriguez-Galiano, V. F., B. Ghimire, J. Rogan, M. Chica-Olmo & J. P. Rigol-Sanchez (2012b) An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS journal of photogrammetry and remote sensing,* 67**,** 93-104.

Royimani, L., O. Mutanga, J. Odindi, M. Sibanda & S. Chamane (2022) Determining the onset of autumn grass senescence in subtropical sour-veld grasslands using remote sensing proxies and the breakpoint approach. *Ecological Informatics,* 69**,** 101651.

Sala, O. E., L. Yahdjian, K. Havstad & M. R. Aguiar (2017) Rangeland ecosystem services: Nature's supply and humans' demand. *Rangeland systems: Processes, management and challenges***,** 467-489.

Sang, L., C. Zhang, J. Yang, D. Zhu & W. Yun (2011) Simulation of land use spatial pattern of towns and villages based on CA–Markov model. *Mathematical and Computer Modelling,* 54**,** 938-943.

Sawalhah, M. N., S. D. Al-Kofahi, Y. A. Othman & A. F. Cibils (2018) Assessing rangeland cover conversion in Jordan after the Arab spring using a remote sensing approach. *Journal of Arid Environments,* 157**,** 97-102.

Selemani, I. S. (2020) Indigenous knowledge and rangelands' biodiversity conservation in Tanzania: success and failure. *Biodiversity and conservation,* 29**,** 3863-3876.

Seré, C., A. Ayantunde, A. Duncan, A. Freeman, M. Herrero, S. A. Tarawali & I. Wright (2020) Livestock Production and Poverty Alleviation--Challenges and Opportunities in Arid and Semi-Arid Tropical Rangeland Based Systems.

Shen, H., X. Meng & L. Zhang (2016) An integrated framework for the spatio–temporal–spectral fusion of remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing,* 54**,** 7135-7148.

Sheykhmousa, M., M. Mahdianpari, H. Ghanbari, F. Mohammadimanesh, P. Ghamisi & S. Homayouni (2020) Support vector machine versus random forest for remote sensing image classification: A meta-analysis and systematic review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* 13**,** 6308-6325.

Sibanda, M., O. Mutanga, T. Dube, T. S Vundla & P. L Mafongoya (2019) Estimating LAI and mapping canopy storage capacity for hydrological applications in wattle infested ecosystems using Sentinel-2 MSI derived red edge bands. *GIScience & Remote Sensing,* 56**,** 68-86.

Sibanda, M., O. Mutanga, M. Rouget & L. Kumar (2017) Estimating biomass of native grass grown under complex management treatments using worldview-3 spectral derivatives. *Remote Sensing,* 9**,** 55.

Sibanda, M., M. Onisimo, T. Dube & T. Mabhaudhi (2021) Quantitative assessment of grassland foliar moisture parameters as an inference on rangeland condition in the mesic rangelands of southern Africa. *International Journal of Remote Sensing,* 42**,** 1474-1491.

Sidhu, N., E. Pebesma & G. Câmara (2018) Using Google Earth Engine to detect land cover change: Singapore as a use case. *European Journal of Remote Sensing,* 51**,** 486-500.

Singh, V. G., S. K. Singh, N. Kumar & R. P. Singh (2022) Simulation of land use/land cover change at a basin scale using satellite data and markov chain model. *Geocarto International***,** 1-26.

Sinha, S., L. K. Sharma & M. S. Nathawat (2015) Improved land-use/land-cover classification of semi-arid deciduous forest landscape using thermal remote sensing. *The Egyptian Journal of Remote Sensing and Space Science,* 18**,** 217-233.

Smith, P., J. I. House, M. Bustamante, J. Sobocká, R. Harper, G. Pan, P. C. West, J. M. Clark, T. Adhya & C. Rumpel (2016) Global change pressures on soils from land use and management. *Global change biology,* 22**,** 1008-1028.

Sollenberger, L. E., M. M. Kohmann, J. C. Dubeux Jr & M. L. Silveira (2019) Grassland management affects delivery of regulating and supporting ecosystem services. *Crop Science,* 59**,** 441-459.

Soons, M., J. Messelink, E. Jongejans & G. Heil (2005) Habitat fragmentation reduces grassland connectivity for both short-distance and long-distance wind-dispersed forbs. *Journal of Ecology,* 93**,** 1214-1225.

Spanowicz, A. G. & J. A. Jaeger (2019) Measuring landscape connectivity: On the importance of within-patch connectivity. *Landscape Ecology,* 34**,** 2261-2278.

Subedi, P., K. Subedi & B. Thapa (2013) Application of a hybrid cellular automaton–Markov (CA-Markov) model in land-use change prediction: a case study of Saddle Creek Drainage Basin, Florida. *Applied Ecology and Environmental Sciences,* 1**,** 126-132.

Talukdar, S., P. Singha, S. Mahato, S. Pal, Y.-A. Liou & A. Rahman (2020) Land-use land-cover classification by machine learning classifiers for satellite observations—A review. *Remote Sensing,* 12**,** 1135.

Tamiminia, H., B. Salehi, M. Mahdianpari, L. Quackenbush, S. Adeli & B. Brisco (2020) Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing,* 164**,** 152-170.

Terefe, D. 2015. Impacts of invasive plants (Lantana camara and Parthenium hysterophorus) on livestock and rangeland production in pastoral and agro pastoral areas of Somali Region, Ethiopia. In *32nd annual research and extension workshop. Haramaya University, Alemaya*, 24-32.

Thanh Noi, P. & M. Kappas (2017) Comparison of random forest, k-nearest neighbor, and support vector machine classifiers for land cover classification using Sentinel-2 imagery. *Sensors,* 18**,** 18.

Tsegaye, D., S. R. Moe, P. Vedeld & E. Aynekulu (2010) Land-use/cover dynamics in Northern Afar rangelands, Ethiopia. *Agriculture, ecosystems & environment,* 139**,** 174-180.

Ul Din, S. & H. W. L. Mak (2021) Retrieval of Land-Use/Land Cover Change (LUCC) Maps and Urban Expansion Dynamics of Hyderabad, Pakistan via Landsat Datasets and Support Vector Machine Framework. *Remote sensing,* 13**,** 3337.

Vázquez-Quintero, G., R. Solís-Moreno, M. Pompa-García, F. Villarreal-Guerrero, C. Pinedo-Alvarez & A. Pinedo-Alvarez (2016) Detection and projection of forest changes by using the Markov Chain Model and cellular automata. *Sustainability,* 8**,** 236.

Vetter, S. (2013) Development and sustainable management of rangeland commons–aligning policy with the realities of South Africa's rural landscape. *African journal of range & forage science,* 30**,** 1-9.

Wahap, N. & H. Z. Shafri. 2020. Utilization of Google earth engine (GEE) for land cover monitoring over Klang Valley, Malaysia. In *IOP Conference Series: Earth and Environmental Science*, 012003. IOP Publishing.

Wang, J., X. Xiao, Y. Qin, J. Dong, G. Geissler, G. Zhang, N. Cejda, B. Alikhani & R. B. Doughty (2017) Mapping the dynamics of eastern redcedar encroachment into grasslands during 1984–2010 through PALSAR and time series Landsat images. *Remote sensing of environment,* 190**,** 233-246.

Wang, L., J. J. Qu, X. Hao & Q. Zhu (2008) Sensitivity studies of the moisture effects on MODIS SWIR reflectance and vegetation water indices. *International Journal of Remote Sensing,* 29**,** 7065-7075.

Wassie, S. B. (2020) Natural resource degradation tendencies in Ethiopia: a review. *Environmental systems research,* 9**,** 1-29.

Wen, L., S. Dong, Y. Li, X. Li, J. Shi, Y. Wang, D. Liu & Y. Ma (2013) Effect of degradation intensity on grassland ecosystem services in the alpine region of Qinghai-Tibetan Plateau, China. *PloS one,* 8**,** e58432.

Willis, K. S. (2015) Remote sensing change detection for ecological monitoring in United States protected areas. *Biological Conservation,* 182**,** 233-242.

Wu, H., Z. Li, K. C. Clarke, W. Shi, L. Fang, A. Lin & J. Zhou (2019) Examining the sensitivity of spatial scale in cellular automata Markov chain simulation of land use change. *International Journal of Geographical Information Science,* 33**,** 1040-1061.

Wulder, M. A. & N. C. Coops (2014) Satellites: Make Earth observations open access. *Nature,* 513**,** 30-31.

Xie, Z., S. R. Phinn, E. T. Game, D. J. Pannell, R. J. Hobbs, P. R. Briggs & E. McDonald-Madden (2019) Using Landsat observations (1988–2017) and Google Earth Engine to detect vegetation cover changes in rangelands-A first step towards identifying degraded lands for conservation. *Remote Sensing of Environment,* 232**,** 111317.

Xue, J. & B. Su (2017) Significant remote sensing vegetation indices: A review of developments and applications. *Journal of sensors,* 2017.

Yahdjian, L., O. E. Sala & K. M. Havstad (2015) Rangeland ecosystem services: shifting focus from supply to reconciling supply and demand. *Frontiers in Ecology and the Environment,* 13**,** 44-51.

Yirsaw, E., W. Wu, X. Shi, H. Temesgen & B. Bekele (2017) Land use/land cover change modeling and the prediction of subsequent changes in ecosystem service values in a coastal area of China, the Su-Xi-Chang Region. *Sustainability,* 9**,** 1204.

Zhao, Y., Z. Liu & J. Wu (2020) Grassland ecosystem services: a systematic review of research advances and future directions. *Landscape Ecology,* 35**,** 793-814.

Zhao, Y., W. Zhu, P. Wei, P. Fang, X. Zhang, N. Yan, W. Liu, H. Zhao & Q. Wu (2022) Classification of Zambian grasslands using random forest feature importance selection during the optimal phenological period. *Ecological Indicators,* 135**,** 108529.

Zhu, L., J. Suomalainen, J. Liu, J. Hyyppä, H. Kaartinen & H. Haggren (2018) A review: Remote sensing sensors. *Multi-purposeful application of geospatial data***,** 19-42.

Zhu, Z. & C. E. Woodcock (2014) Continuous change detection and classification of land cover using all available Landsat data. *Remote sensing of Environment,* 144**,** 152-171.

Appendix

Table 1A. Kappa scores of the classifications in Vulindlela

Years	Feature classes for Vulindlela	User accuracy	Producer accuracy
2000	Forest	1,00	0,98
	Grass	0,93	0,72
	Built-up	0,34	0,73
	Bare-land	0,48	0,55
	Water	0,80	1,00
OVERALL ACCURACY = 0,88 KAPPA SCORE =0, 81			
2010	Forest	1,00	0,96
	Grass	0,85	0,62
	Built-up	0,41	0,80
	Bare-land	0,28	0,32
	Water	0,81	1,00
OVERALL ACCURACY = 0.85 KAPPA SCORE = 0.75			
2020	Forest	0,99	0,99
	Grass	0,94	0,78
	Built-up	0,65	0,81
	Bare-land	0,32	0,38
	Water	0,85	1,00
OVERALL ACCURACY = 0.89 KAPPA SCORE = 0.83			

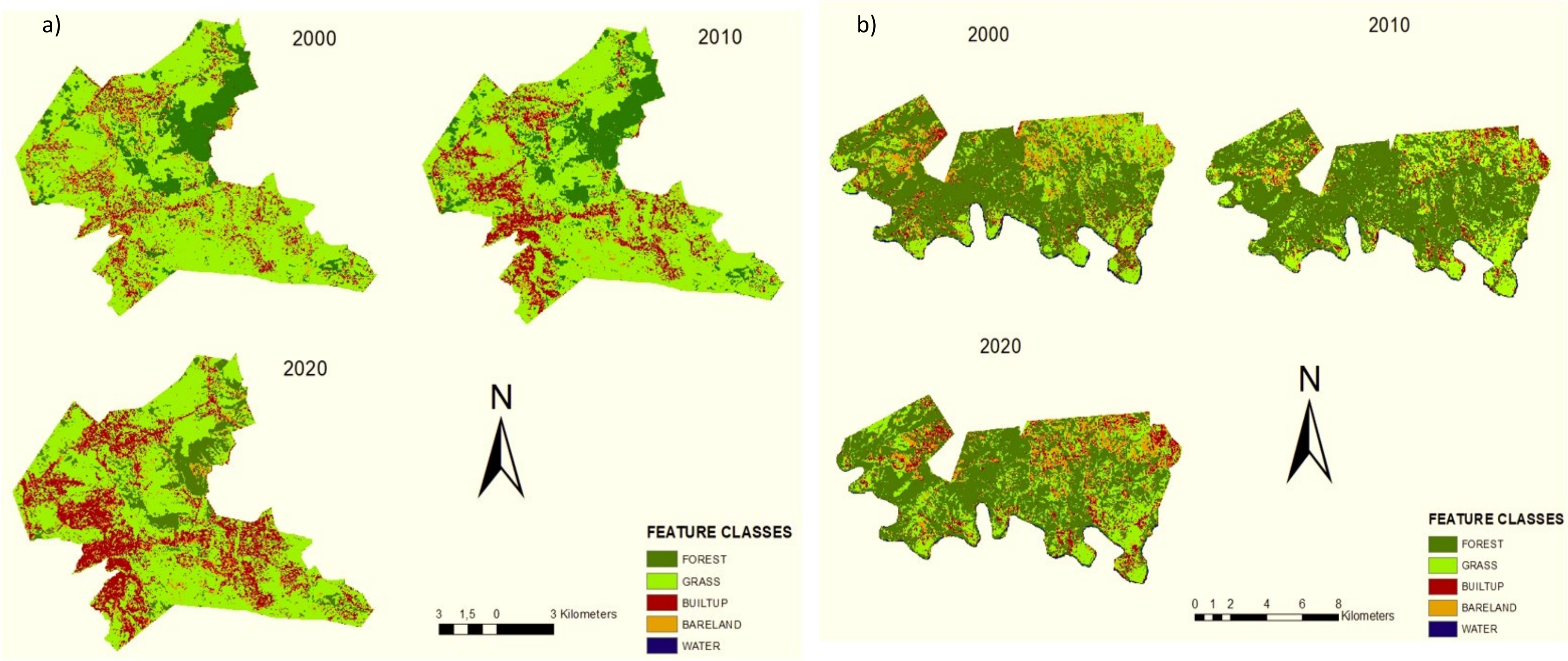
Table 1B. Kappa scores of the classifications in Inhlazuka

Years	Feature classes for Nhlazuka	User accuracy	Producer Accuracy
2000	Forest	0,87	0,92
	Grass	0,88	0,73
	Built-up	0,18	0,17
	Bare-land	0,54	0,49
	Water	0,67	0,99
OVERALL ACCURACY = 0,75 KAPPA SCORE = 0,65			
2010	Forest	0,98	0,82
	Grass	0,68	0,72
	Built-up	0,47	0,77
	Bare-land	0,47	0,55
	Water	0,84	1,00
OVERALL ACCURACY = 0,79			

KAPPA SCORE = 0,68

2020	Forest	1,00	0,93
	Grass	0,69	0,77
	Built-up	0,66	0,56
	Bare-land	0,19	0,35
	Water	0,72	1,00

OVERALL ACCURACY = 0.83
KAPPA SCORE = 0.73



Figures 1. Showing Image Classifications of Land Cover Changes in the areas of a) Vulindlela and b) Inhlazuka in 2000, 2010 and 2020.

Table 2. Showing image collections used in the study

Years	Number of Satellite Images which were available	Acquired date of images	Years	Number of Satellite Images which were available	Acquired date of images
		VULINDLELA AREA			**NHLAZUKA**
2000	7	1. 2000/06/19 2. 2000/06/28 3. 2000/07/14 4. 2000/07/21 5. 2000/07/21 6. 2000/08/15 7. 2000/08/15	2000	2	1. 2000/06/28 2. 2000/08/15
2010	16	17. 2010/06/08 18. 2010/06/08 19. 2010/06/24 20. 2010/06/24 21. 2010/07/10 22. 2010/07/10 23. 2010/07/17 24. 2010/07/17 25. 2010/07/26 26. 2010/07/26 27. 2010/08/02 28. 2010/08/02 29. 2010/08/18 30. 2010/08/18 31. 2010/08/27 32. 2010/08/27	2010	5	6. 2010/06/08 7. 2010/06/24 8. 2010/07/10 9. 2010/07/26 10. 2010/08/27
2020	22	23. 2020/06/02 24. 2020/06/02 25. 2020/06/11 26. 2020/06/11 27. 2020/06/18 28. 2020/06/18 29. 2020/06/27 30. 2020/06/27 31. 2020/07/04 32. 2020/07/04 33. 2020/07/13 34. 2020/07/13 35. 2020/07/20 36. 2020/07/20 37. 2020/07/29 38. 2020/07/29 39. 2020/08/05 40. 2020/08/05 41. 2020/08/14 42. 2020/08/14 43. 2020/08/21 44. 2020/08/21	2020	5	1. 2020/06/11 2. 2020/06/27 3. 2020/07/13 4. 2020/07/29 5. 2020/08/14

Table 3A. Fragmentation analysis of Vulindlela

2000	PLAND	NP	PD	LPI	AREA_MN	ENN_MN	MESH
GRASS	69.9	244	2.1	68.3	31.9	71.1	5204.4
BARE-LAND	4.2	1839	16.4	0.1	0.2	100.3	0.0
FOREST	14.5	502	4.5	7.6	3.2	133.5	67.9
BUILT-UP	11.1	2214	19.8	0.4	0.5	85.6	1.1
WATER	0.0	25	0.2	0.0	0.1	847.9	0.0
2010	**PLAND**	**NP**	**PD**	**LPI**	**AREA_MN**	**ENN_MN**	**MESH**
GRASS	66.6	342	3.0	62.6	21.7	74.7	4380.4
BARE-LAND	2.6	1230	11.0	0.0	0.2	108.6	0.0
FOREST	15.6	563	5.0	8.4	3.1	125.1	81.5
BUILT-UP	14.9	1078	9.6	3.8	1.5	90.2	23.2
WATER	0.0	7	0.0	0.0	0.0	1930.6	0.0
2020	**PLAND**	**NP**	**PD**	**LPI**	**AREA_MN**	**ENN_MN**	**MESH**
GRASS	59.6	780	6.9	43.0	8.5	73.0	2188.8
BARE-LAND	4.8	1951	17.4	0.0	0.2	97.8	0.0
FOREST	10.1	551	4.9	3.5	2.0	130.5	17.3
BUILT-UP	25.3	1282	11.4	11.7	2.2	86.1	172.9
WATER	0.0	6	0.0	0.0	0.0	1050.7	0.0

Table 3B. Fragmentation analysis of Inhlazuka

2000	PLAND	NP	PD	LPI	AREA_MN	ENN_MN	MESH
Grass	28.0	1392	15.4	7.1	1.8	79.5	55.5
Forest	54.7	549	6.1	42.0	8.9	81.5	1624.0
Bare-land	7.9	1218	13.5	0.3	0.5	99.1	0.5
Built-up	7.1	2107	23.4	0.2	0.3	87.7	0.1
Water	2.2	166	1.8	0.4	1.1	188.5	0.3
2010	**PLAND**	**NP**	**PD**	**LPI**	**AREA_MN**	**ENN_MN**	**MESH**
Grass	23.5	1581	17.5	3.5	1.3	79.3	20.8
Forest	64.2	522	5.8	58.0	11.0	74.4	3025.0
Bare-land	3.8	968	10.7	0.1	0.3	110.6	0.0
Built-up	6.9	1829	20.3	0.2	0.3	91.2	0.1
Water	1.4	135	1.5	0.1	0.9	191.3	0.0
2020	**PLAND**	**NP**	**PD**	**LPI**	**AREA_MN**	**ENN_MN**	**MESH**
Grass	28.6	1443	16.0	5.4	1.7	75.0	35.4
Forest	51.5	565	6.2	43.6	8.2	80.2	1711.4
Bare-land	7.0	759	8.4	0.3	0.8	107.7	0.5
Built-up	11.5	1768	19.6	0.5	0.5	87.2	1.2
Water	1.1	132	1.4	0.0	0.7	148.9	0.0

Table 4A. Showing the Patch Matrics for 2020 and 2040 in Inhlazuka

2020	PLAND	NP	PD	LPI	AREA_MN	ENN_MN	MESH
Grass	28.6	1443	16.0	5.4	1.7	75.0	35.4
Forest	51.5	565	6.2	43.6	8.2	80.2	1711.4
Bare-land	7.0	759	8.4	0.3	0.8	107.7	0.5
Built-up	11.5	1768	19.6	0.5	0.5	87.2	1.2
Water	1.1	132	1.4	0.0	0.7	148.9	0.0

Fragmentation analysis of Inhlazuka 2040

2040	**PLAND**	**NP**	**PD**	**LPI**	**AREA_MN**	**ENN_MN**	**MESH**
Grass	32.89	414	4.57	6.52	7.20	120.60	58.89
Forest	38.44	152	1.68	19.11	22.92	150.01	395.65
Built-up	16.58	490	5.41	2.46	3.07	151.23	11.09
Bareland	11.05	214	2.36	1.23	4.68	216.32	4.83
Water	1.04	110	1.21	0.05	0.86	135.90	0.02

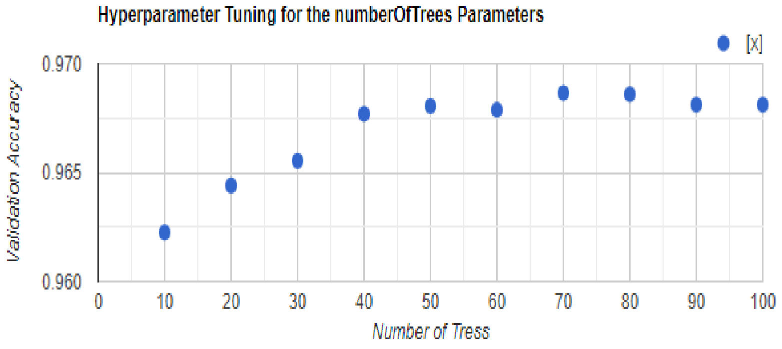
Table 4B. Showing the Patch Matrics for 2020 and 2040 in Vulindlela

2020	PLAND	NP	PD	LPI	AREA_MN	ENN_MN	MESH
Grass	59.6	780	6.9	43.0	8.5	73.0	2188.8
Bareland	4.8	1951	17.4	0.0	0.2	97.8	0.0
forest	10.1	551	4.9	3.5	2.0	130.5	17.3
Built-up	25.3	1282	11.4	11.7	2.2	86.1	172.9
Water	0.0	6	0.0	0.0	0.0	1050.7	0.0

Fragmentation analysis of Vulindlela 2040

2040	**PLAND**	**NP**	**PD**	**LPI**	**AREA_MN**	**ENN_MN**	**MESH**
Grass	51.35	103	0.92	18.37	55.94	172.20	743.35
Forest	5.09	59	0.53	2.48	9.68	345.18	7.85
Builtup	37.12	177	1.58	25.19	23.53	158.71	756.89
Bareland	6.43	253	2.26	0.73	2.85	239.44	1.41
Water	0.00	2	0.02	0.00	0.27	4892.48	0.00

a)


Hyperparameter Tuning for the numberOfTrees Parameters
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Validation Accuracy
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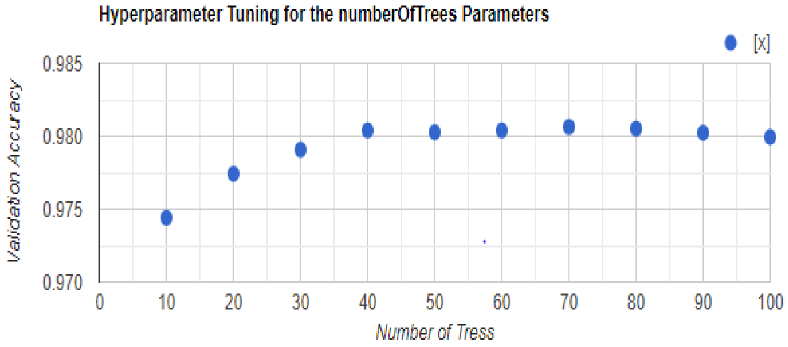
0.960
0
10
20
30
40
50
60
70
80
90
100
Number of Tress

b)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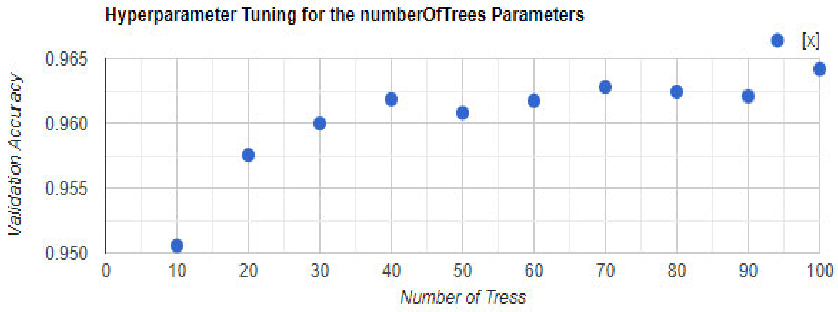
Number of Tress

c)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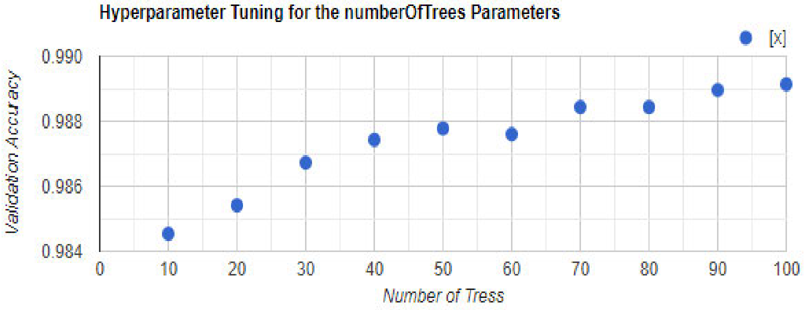
90
100
Number of Tress

d)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90
100
Number of Tress

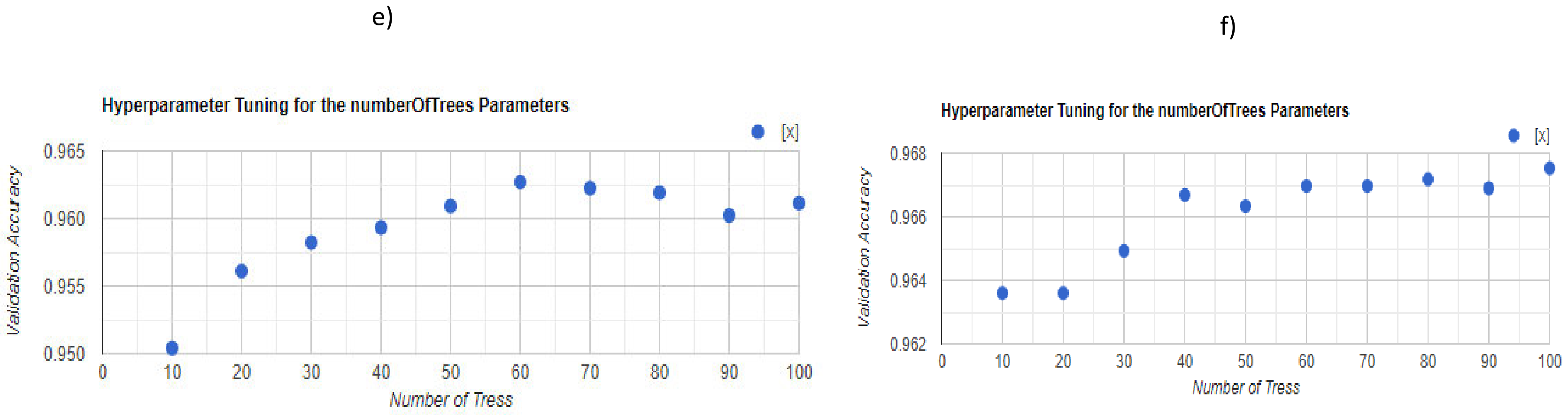

Figure 2. Hyparameters derived from the classifications in Vulindlela a) 2000, b) 2010 and c) 2020 and Inhlazuka d) 2000, e) 2010 and f) 2020.

Tables 5A. Showing the probability transition matrix for 2010 to 2020 in Vulindlela

Probability Transition Matrix Of 2010-2020 In Vulindlela:					
	FOREST	**GRASS**	**BUILTUP**	**BARELAND**	**WATER**
FOREST	0.3103	0.4940	0.1421	0.0535	0.0001
GRASS	0.0292	0.6257	0.2894	0.0556	0.0001
BUILTUP	0.0052	0.2694	0.6245	0.1010	0.0000
BARELAND	0.0168	0.3833	0.5036	0.0963	0.0000
WATER	0.1349	0.6741	0.1505	0.0403	0.0001

Tables 5B. Showing the probability transition matrix for 2010 to 2020 in Inhlazuka

Probability Transition Matrix Of 2010-2020 In Nhlazuka:					
	FOREST	**GRASS**	**BUILTUP**	**BARELAND**	**WATER**
FOREST	0.5570	0.2739	0.1044	0.0611	0.0036
GRASS	0.2273	0.4513	0.1968	0.1202	0.0045
BUILTUP	0.1643	0.3338	0.2826	0.2144	0.0047
BARELAND	0.1155	0.2804	0.3284	0.2736	0.0021
WATER	0.2014	0.0893	0.1549	0.0391	0.5153