M.Sc. Dissertation

The effect of fire disturbances on woody plant encroachment at Loskop, Irene and Roodeplaat Farms, South Africa

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Declaration of originality

This is to certify that the work is entirely my own and not done by any other person, unless acknowledged (including citation of published and unpublished sources). The work has never been submitted to the University of Pretoria or any other institution for assessment or any other purpose.

Signed____

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ABSTRACT

The study on bush encroachment goes as far back as 1917, which is ranked among the top three rangeland problems in South Africa with expected increase in affected areas. Bush encroachment is considered one of the most substantial forms of land degradation because it occurs at the expense of beneficial herbaceous layer. Even with substantial number of studies on bush encroachment, the studies have not provided a broad comprehension of the problem, which complicates its management. Climate change, fire regimes herbivory and excessive increase of CO_2 in the atmosphere are some of the key drivers of the current levels of bush encroachment. It is estimated that 20 million ha of South Africa's agricultural productivity and biodiversity is under the threat of bush encroachment. As a result, the economic productivity of affected rangelands is negatively affected. This study investigated the effects of fire frequency/history (the rate of fire occurrence over an area in a given time period) on tree density and plant diversity. It further investigates the contribution of fire to the current extent of bush encroachment using remote sensing data over a nineteen year-period from the year 2000 to 2019. The study sites are based on three Agricultural Research Council (ARC) farms namely Loskop, Irene and Roodeplaat. Firstly, the *in-situ* and remotely sensed moderate resolution imaging spectroradiometer (MODIS) data were used to determine how fire influences the vegetation structure (tree density and plant diversity) using Analysis of Variance (ANOVA and Kruskal-Wallis (KW-H)). Secondly, *in-situ*, MODIS and Landsat data were used to build models needed for mapping areas of tree density change. The study investigated the indicators of bush encroachment namely, tree density within the study sites. The study found that there is a low to moderate correlation between burned areas and tree density in Loskop, Irene and Roodeplaat farms with the Pearson correlation coefficients of -0.06, 0.38 and 0.38 respectively. The significant tree density models had moderate to relatively high R-squares of 0.59, 0.49 and 0.82 for Loskop, Irene and Roodeplaat farms respectively. The findings of this study showed that fire frequency did not significantly influence the bush encroachment as measured by tree density and diversity in Loskop and Roodeplaat farms. However, there was evidence of fire frequency significantly influencing an increase in tree density in Irene farm. Due to lack of herbivores in some parts of Loskop and Roodeplaat farms because of water scarcity, fire alone may have not been a frequent enough disturbance to significantly influence tree density. The models calculated in this study serve as a foundation for understanding and calculating the tree density in response to fire. The findings of this study serve as a guide for resource managers to better manage fire regimes and their effect on vegetation cover at a local scale.

Keywords: Fire, Plant diversity, Remote sensing, Tree density

LIST OF ACRONYMS

AIC	Akaike Information Criteria
ANOVA	Analysis Of Variance
ARC	Agricultural Research Council
ARVI	Atmospherically Resistant Vegetation Index
ATSR-2	Along-Track Scanning Radiometer–2
AVHRR	Advanced Very High-Resolution Radiometer
ETM+	Enhanced Thematic Mapper Plus
EVI	Enhanced Vegetation Index
GCI	Green Chlorophyll Index
ICA	Independent Component Analysis
MODIS	Moderate Resolution Imaging Spectroradiometer
NBR	Normalized Burn Ratio
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
NRT	Near Real-Time
OLI	Operational Land Imager
PCA	Principal Component Analysis
PCQ	Point Centred Quarter method
SAVI	Soil Adjusted Vegetation Index
SIPI	Structure Insensitive Vegetation Index
SMLR	Stepwise Multiple Linear Regression
SWIR	Short-wave Infrared
TM	Thematic Mapper
TRMM VIRS	Tropical Rainfall Measuring Mission Visible and Infrared Scanner
USGS	United States Geological Survey
VIIRS	Visible Infrared Imaging Radiometer Suite

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

GENERAL INTRODUCTION

1. Background

Studies on bush encroachment date back to 1917, when it was first identified as a major issue in South African rangelands (Bews, 1917). Today, bush encroachment is considered one of the top three rangeland problems in South Africa, along with overgrazing and conversion of natural veld to cropland (O'Connor, 2014, McGranahan and Kirkman, 2013). It is expected that this problem will continue to increase in the coming years given the rate and extent of woody thickening. Bush encroachment is a term interchangeable with a wide range of terminologies like bush thickening (Mndela et al., 2022), woody plant encroachment (Venter et al., 2018) and woody weed invasion (Ayers et al., 2000, Menge et al., 2017). It is defined as a prolific increase in density, cover and biomass of woody plant species such as shrubs and trees expanding into grassland or savanna ecosystems (Van Auken, 2009, Pule, 2021). This increase in woody plants is usually at the expense of grassy layer (Mogashoa, 2021). This phenomenon has become a widespread issue in savanna biomes worldwide, with consequences for both the ecology and the human communities that depend on these ecosystems for livelihood (Yassin, 2019). In addition to its ecological impacts, bush encroachment can also have social and economic consequences for communities and/or farmers that rely on savannas for resources such as timber, firewood, and grazing (Sebitloane et al., 2020).

Despite the widespread evidence of bush encroachment in South Africa, little is known about the dynamics of this phenomenon (Coetzee et al., 2008), and as such, integrated environmental management may be pivotal in understanding its drivers (Reagan, 2006). Multiple drivers can interact with each other and have a cumulative effect on the woody cover resulting in the proliferation and dominance at the expense of herbaceous species (O'connor et al., 2014). Even so, some factors are more aggressive than others in triggering the process of bush encroachment depending on the spatial scale (Belayneh and Tessema, 2017). For instance, fire and herbivory are closely related to local scale bush encroachment as opposed to carbon dioxide (CO_2) (Ward, 2005). The relative importance of these factors can vary depending on the specific ecosystem and the presence of other contributing factors. The proliferation of woody species is also considered to be a natural cycle driven by precipitation variability where continuous rainfall over a prolonged period favours woody plant seedling establishment and recruitment (Roques et al., 2001). On the contrary, prolonged dry periods may also favour woody species due to the dying off of palatable grasses, which are competitors of tree seedlings (Gemedo-Dalle et al., 2006). Various global and local factors such as global climate change, rainfall variability, edaphic factors, soil nutrients, herbivory and fire are related to the increase in woody species dominance in the savanna biome (Bond and Midgley, 2000, Tjelele et al., 2015).

Fire is one of the major local factor driver of bush encroachment (Bowman et al., 2011). This is due to its ability to maintain stability by destroying woody plant seedlings and facilitate seed germination by breaking dormancy in some species (Bradstock and Auld, 1995). This suggests that both the presence and absence of fire may trigger bush encroachment depending on the location and the type of inhabiting tree species and grasses (Simon and Pennington, 2012), as well as the management of the farm. It is known that fires can have a significant effect on species composition and density, however, ways in which fires interaction with other factors may impact the growth and survival of trees is not clear (Bär et al., 2019). There is also limited research on the long-term effects of fire on bush encroachment (González-Romero et al., 2021). Thus, fire is a natural disturbance that plays a significant role in shaping the composition and structure of many ecosystems worldwide (Bond and Keeley, 2005, Gill et al., 2002).

In other instances, frequent fires can lead to the establishment and dominance of fire-tolerant tree species, which are adapted to survive and regenerate after fires (Keeley, 2009). These tree species may have thick bark and resprout after fire from their root systems, or produce seeds that are dispersed by fire. In contrast, less frequent fires may favour the establishment and dominance of less fire-tolerant tree species, which may be more vulnerable to fire damage and less able to regenerate after a fire (Paudel et al., 2022, Tinner et al., 1999). Fire-dependent and fire-adapted vegetation are considered natural fire history archives due to the evidence they provide through tree-rings and fire-scar chronologies (Marschall et al., 2019). This evidence can provide information on the past fire patterns and ecological role (Marschall et al., 2022). Additionally, fire leaves behind a physical characteristic (i.e., soil colour alteration and tree canopy) on the landscape and therefore research can be done on this evidence, also known as burn scars using remote sensing (Rodrigues et al., 2019, White et al., 1996).

The study was conducted at three Agricultural Research Council experimental farms that are used for livestock and wildlife production. The vegetation of these farms is dominated by dense stands of various woody plants such as *Euclea* spp., *Vachellia* (previously *Acacia*) *karroo*, *Senegalia* (formerly *Acacia) caffra*, *Vachellia tortilis* and *Ziziphus mucronata*. All these farms experience accidental veld fire almost every second year because of accumulated herbaceous biomass. Many rangeland Managers prefers cost-effective and time-effective range assessment method over traditional vegetation surveys methods (Mokgotsi, 2018).

Several satellite instruments can be used to map fire history, including Moderate Resolution Imaging Spectroradiometer (MODIS) (Li et al., 2020), Soil Moisture Active Passive (SMAP) (Hyoung, 2020), and Tropical Rainfall Measuring Mission Visible and Infrared Scanner (TRMM VIRS) (Singh and Kumar, 2021). These instruments can map fire history fairly well going back to around 1995, with the exception of Kennedy Space Center (KSC), which is reliable for mapping fire going back to 1981 (Duncan et al., 2009). The MODIS data is used to derive active fires and burned area moderate resolution image products (Giglio et al., 2016). According to Boschetti et al. (2009), the active fire product is a global daily product that maps the location of burning fires four times a day. In contrast, the burned area products map the location and extent of burn scars over a period of time (Boschetti et al., 2009). These products were designed for both global change studies and small practical utilization and the products algorithms are often updated with newer technology to enhance previously recorded data (Justice and Korontzi, 2001).

Mapping fire is useful for resource conservation management, risk assessment and understanding the influence of anthropogenic activities on fire regime (Morgan et al., 2001). Fire regime is defined as the severity, intensity, frequency, seasonality, proportion, predictability, and range of fire (Guyette et al., 2002, Heinselman, 1981, Morgan et al., 2001, Pausas and Fernández-Muñoz, 2012). Monitoring fire through fire maps is vital for understanding ecological conditions and ecosystem function (Hardy et al., 1998).Fire regimes reveal a lot about an ecosystem and its dynamics like fuel load, abundance and dispersion over time (Eastment et al., 2022). This is indispensable for the understanding of fuel load accumulation or lack thereof in studies relating to fire frequency and bush encroachment (Morgan et al., 2001).

Fire effects vary from one geographic area to another and therefore it is a challenging task to determine the full impact of fire patterns over space and time (Morgan et al., 2001). Estimating the effects of fire on tree density is difficult to understand the temporal effects of fire over a large spatial scale (Crutzen and Goldammer, 1993). With that said, climate, vegetation and topography influence fire in complex ways that are not well understood (Dillon et al., 2011). Spectral indices modelling is vital in understanding the fire frequency and its impacts on tree density and plant diversity on a local scale (Lozano et al., 2007). One such index is the

Normalized Difference Vegetation Index (NDVI), which measures the amount of green vegetation present in an area (Teal et al., 2006). Research has shown that NDVI can be used to identify areas where fires have occurred and to quantify the severity of the fire (Liu et al., 2018). Additionally, the Enhanced Vegetation Index (EVI) has also been shown to be effective at detecting the impacts of fires on vegetation (Zheng et al., 2016). Both NDVI and EVI can be used to monitor the recovery of vegetation after a fire and to track changes in tree density over time. Other spectral indices, such as the Red Edge Position (REP) and the Photochemical Reflectance Index (PRI), have also been used to study the effects of fire frequency on tree density (Asner et al., 2005). This gives researchers the opportunity to study the extent and trends of tree density.

The frequency of savanna fires can have significant effects on vegetation. The impacts of fire frequency on savanna vegetation can also vary depending on the type of savanna and the dominant plant species in the affected area (Keeley, 2009). Most of the dominant bush encroaching species in South Africa belong to the genus *Acacia sp.* The following are some of the recorded encroaching species: *Acacia mellifera, Acacia reficions, Acacia tortilis, Acacia nilotica, Acacia karoo, Dischrostachys cinera, Termonalia sericia, Rhigozum trichotomum and Torchonanthus comphoratus* (Stafford et al., 2017). *Dischrostachys cinera* commonly known as Sickle bush, is the prevalent encroaching species in the study sites covered by this research namely, Loskop, Irene and Roodeplaat farms.

Understanding the impacts of savanna fire frequency on vegetation is important for managing these ecosystems and ensuring their long-term health and stability. In this study, we will explore two methods (two research papers) to examine the impacts of savanna fire frequency on vegetation, and its implications on bush encroachment and thereby providing solutions for the management of savannas.

1.1. Problem statement

Recent studies showed that bush encroachment affects 20% of the world population (Devine et al., 2017). Bush encroachment negatively affects the carrying capacity of livestock and wild grazing animals, and this could to some extent pose a threat to the agricultural economy in the arid and semi-arid regions of southern Africa (Kraaij, 2006). Approximately 20 million ha of South Africa's agricultural productivity and biodiversity is under the threat of bush encroachment (Ward, 2005). Thirteen million hectares of South Africa was already affected by bush encroachment in the 1960s and expected to worsen in the future (Van der Schijff, 1964).

Savanna biome is home to high faunal and floral biodiversity and the threat to this biome does not only endanger species richness but also threatens tourism (Eastment et al., 2022). Thus, bush encroachment has social and economic impacts on land users (Smit and Prins, 2015).

The frequency of fires in savanna biomes can have significant impacts on the density and diversity of tree species. However, understanding the relationships between fire frequency and tree density at large scales can be challenging due to the difficulties of collecting ground-based data in these often remote and vast ecosystems. This study will use remotely sensed data (i.e., satellite imagery) to map active fires and burned areas in the study areas over time between the year 2000 and 2019.

The ecological makeup of the study sites is undergoing a noticeable transformation characterized by an increase in the density of woody plant species. These sites serve as habitats for both livestock and range animals, and as such, the ecological shift caused by bush encroachment (i.e., increased tree density) has significant implications for their sustainability. Prior research conducted in the study sites covered in this thesis aimed to ascertain the extent of bush encroachment in relation to fire through in-situ observations. This study builds on that research by utilizing remotely-sensed data and secondary in-situ data (such as tree density and plant diversity) to map the extent of fire and investigate its direct impact on bush encroachment. It is noteworthy that the plant diversity data used in this study was collected from the herbaceous layer.

Aim of the study

The aim of this study was to examine the impact of fire frequency (the rate of fire occurrence over an area in a given period) on bush encroachment in Loskop, Irene, and Roodeplaat farms over a 19-year period from 2000 to 2019. This research aims to determine the relationship between the rate of fire occurrence and the extent of bush encroachment in these areas and to provide insights that can inform future fire and rangeland management strategies. This research also seeks to fill a gap in our understanding of the response of vegetation to fire spatially and temporally, and to provide insights that can inform the management of bush encroachment in the study sites (Loskop, Roodeplaat and Irene Experimental farm).

Research questions and objectives

This research was aimed at answering the following questions:

1. Does fire frequency influence tree density at local and farm scale?

2. Does fire frequency influence plant diversity at local and farm scale?
3. Could remote sensing variables such as spectral bands and vegetation indices explain the variability of tree density?
4. What is the extent and trends (increase or decrease) of remote sensing derived tree density between the year 2000 and 2019?

This research was aimed at achieving the following objectives:

1. To determine the relationship between tree density and fire frequency at local scale.
2. To determine the relationship between plant diversity and fire frequency at local scale.
3. To develop remote sensing-based models to estimate tree density.
4. To determine the extent of tree density change between 2000 and 2019.

1.2. Study outline

The research study is presented in five chapters. Chapter 1 begins with introduction covering bush encroachment, its drivers and the significance of satellite remote sensing sensors and techniques commonly utilized in bush encroachment studies. This chapter also covers the relationship between fire frequency and tree density, problem statement, research aim, research questions and objectives of this study. Chapter 2 is the literature review focusing on local scale drivers to regional scale drivers of bush encroachment. This chapter aims to give a broad understanding of factors involved in the underlying factors of bush encroachment. I further outline some of the models proposed for bush encroachment and how different conditions may influence different outcomes. The last part of the literature review covers literature on fire detection and remote sensing as a useful tool in fire mapping.

Chapter 3 presents a research paper titled: Assessing the influence of fire on tree density and plant diversity on experimental farms in Gauteng and Mpumalanga province, South Africa. This paper explored the effects of fire frequency on tree density and plant diversity. Plant diversity in this dissertation refers to the grass species collected at the study sites. The data used in this paper is a combination of remotely-sensed (MODIS active fires and burned areas) data and secondary *in-situ* data (tree density and plant diversity). The aim of this research paper was to identify the correlation between fire frequency and bush encroachment in the study sites. This paper further determines the statistical significance of that relationship using Kruskal-Wallis, ANOVA and Pearson correlation statistical analyses.

Chapter 4 is a paper chapter titled: Estimation of tree density change in relation to fire frequency using multitemporal satellite data spanning the period 2000-2019 on experimental farms in Gauteng and Mpumalanga province, South Africa. This paper further investigates the extent of bush encroachment measured as tree density in the study sites through change detection using empirical models. The empirical models used for change detection were developed using the *in-situ* data utilized in Chapter 3 along with MODIS active fires and vegetation indices developed from Landsat 7 TM and Landsat 8 OLI. The aim of this research paper was to assess the change in tree density at the points where *in-situ* tree density data was collected.

Both paper chapters (i.e. chapter 3 and 4) were formatted for submission to the African Journal of Range and Forage Science. The final chapter (Chapter 5) of this dissertation is the conclusion and recommendations for farm managers and future studies. This chapter synthesise two paper chapters and provides limitations and recommendations based on the findings of this study. Because of the structure of this dissertation, repetition of information is inevitable as Chapter 3 and Chapter 4 use the exact same data (i.e., tree density, plant diversity, and MODIS active fires)

CHAPTER 2

LITERATURE REVIEW

2.1. Bush encroachment

Bush encroachment is also known as woody plant encroachment, woody plant invasion, or bush thickening, and it is a process in which shrubs and trees increase in density at the expense of the herbaceous layer (Shikangalah and Mapani, 2020, Archer et al., 2017, Joubert and Zimmermann, 2002). This phenomenon is an ongoing process that has been active in the arid and semi-arid grasslands and savannas for over a century (D'Odorico et al., 2012, Knight and Kvaran, 2014, Moleele et al., 2002). Bush encroachment is a well-known phenomenon across the globe (Kraaij and Ward, 2006, Rundel et al., 2014) with its impact on herbaceous layer reported in southern Africa, South and North America, Australia, China and Canada (Anadón et al., 2014, Barger et al., 2011, Lunt et al., 2010, Rutherford and Westfall, 1994, Zhou et al., 2019). The causes of bush encroachment have been attributed to various factors, including among others climate variability, grazing practices, fire regimes, atmospheric CO_2, and management strategies (Coetzee et al., 2008, Shackleton and Scholes, 2011). Woody plant species can expand their territory through two methods: vegetative growth, which results in existing plants increasing their biomass, and tree density, which occurs when seed germination and production become excessive. (Smit and Rethmar, 1998).

2.2. Drivers of bush encroachment

2.2.1. Large scale drivers

To explore the underlying drivers of bush encroachment drivers in affected areas, long-term datasets are crucial for differentiating local causes like grazing and fire (Bond et al., 2003, Higgins et al., 2007, Skarpe, 1990) from global causes like atmospheric CO_2, and erratic rainfall (Bowman et al., 2010, Ward, 2010, Werner and Petty, 2010, Wiegand et al., 2005, Wigley et al., 2010).

Global scale factors, such as CO_2 and changing climate are the proposed to be major drivers of bush encroachment (O'Connor, 2014). It has been posited that atmospheric carbon dioxide may have the effect of diminishing transpiration rates, especially in grasses. This, in turn, may lead to increased percolation of water into the subsoil, creating conditions that are advantageous for the encroachment of bushes (Ward, 2010). Although it is believed that CO_2 increase is a global driver of bush encroachment, this topic is still under debate (Bond and Midgley, 2000, Körner, 2006, Leakey and Lau, 2012). For example, Wigley et al., (2010) and Buitenweff et al., (2012) added that for increased CO_2 levels to have an impact on woody cover, other major drivers at play like fire and grazing must be existent and constant over an extended period. Bush encroachment becomes harder to manage when the driving factors are dependent on CO_2 levels (O'Connor, 2014), keeping in mind that the effects of CO_2 are greater in dry than wet environments (Eamus and Ceulemans, 2001, Leakey and Lau, 2012). The overall behaviour of an ecosystem is not only a result of the presence and interaction of individual factors but also the ratio of these interactions at play (Ghermandi et al., 2010). Studies on climate change present evidence that climate change has an impact on species distribution, diversity and structure of communities and ecosystems (Walther et al., 2005). However, a large scale event like climate change makes it a challenging task to accurately assess the local/regional implications on vegetation (Ghermandi et al., 2010).

2.2.2. Regional drivers

Among others fire and herbivory are crucial factors governing tree-grass ratios in the savanna (Kraaij and Ward, 2006). Temperature and moisture interact to influence the distribution of woody vegetation (Bond et al., 2003). In arid and semi-arid rangelands, rainfall is the most important environmental parameter governing crucial life history processes inwoody plants (Scholes and Archer, 1997b). Changes in rainfall patterns partly explain the increases in bush encroachment (Benhin, 2006), with an increase in mean annual rainfall reported to correlate with increasing woody plant encroachment (Venter et al., 2018).

In southern Africa, bush encroachment is largely influenced by anthropogenic activities especially through grazing practices (Moleele et al., 2002). Previous studies identified overgrazing as one of the causes of bush encroachment due to the excessive removal of grasses, which are direct competitors of tree seedlings (Knight and Kvaran, 2014). Poor grazing practices tend to be severe in dry seasons and often negatively affect grass growth (Smit, 2004). African savannas are rich with and dominated by browsing herbivores, which have the capability to significantly modify the structure and composition of woody species (Owen-Smith, 1988). The removal and/or a decline of browsing herbivores may be one of the triggers of bush encroachment (Styles, 1993).

Overgrazing by herbivores, reduce above ground biomass and fine fuel load needed for grassland fires (Van Auken, 2009). There is evidence that intense and frequent herbivory exerts a major influence on woody plant distribution and abundance across arid and semi-arid rangelands (Van Auken and Smeins, 2008, Van Auken, 2000) especially when coupled with reduced fire frequency. These factors create conditions that favour the establishment, survival and recruitment of woody plants over the grasses (Archer et al., 2017).

Grazing is a well-known disturbance known to affect edaphic factors and soil resources by removing grass biomass and isolating nutrients to shrubs and trees through a process called fertile island effect (Daryanto et al., 2013). In dense shrublands, this fertile island effect favours woody species dominance concentrating nutrients around woody plants leaving the interspace devoid of nutrients. This process of spatial variation in vegetation and soil resources is common in water-scarce environments (Borgogno et al., 2009). Plants are remarkable biotic drivers of soil properties distribution (Daryanto et al., 2013). The effectiveness of this influence is based on the density of the plants involved (Jackson and Caldwell, 1993). Plants can modify their surrounding soil ecosystem by accumulating nutrients and sediments derived from biotic and abiotic processes taking place in the interspace between the individual plants (Daryanto et al., 2013). Grazing, trampling, decomposition and micro-organism diversity are some of the biotic factors that directly and indirectly affect the distribution of soil properties (Stavi et al., 2008). Because the presence of animals affect nutrient distribution, change in the dynamics and spatial distribution of animals will have an impact on the distribution and composition of soil resources leading to a disturbance in the tree-grass balance (Rietkerk et al., 2000).

Although climate plays an important role in fire regime, human activities also have a significant contribution (Alvarado et al., 2017). Humans can indirectly change fire dynamics, which may further be exacerbated by climate change (Alvarado et al., 2017). Studies made on historical man-made fires have shown a reduction in fire size, changes in the timing of usual burning patterns, and length of fire season (Alvarado et al., 2017). Consequently, these alterations in burning patterns lead to environmental implications that change tree-grass dynamics (Alvarado et al., 2017). These alterations of fire dynamics, seasonality and intensity through the manipulation of fuel conditions, do not only have impacts on the vegetation structure but also on the vegetation recovery of some tree and grass species (Alvarado et al., 2017). This has generally led to the growth of environmental hazards in the savanna rangelands (Lohmann et al., 2014).

Fire serves as an important ecological driver aiding in the maintenance of tree-grass ratio (Colombaroli et al., 2018). In ecosystems dominated by trees due to moisture, fire can support grass dominance especially those that are fire tolerant (Colombaroli et al., 2018). Fire frequency in East Africa is mainly a result of precipitation dynamics though it is extremely difficult to predict this relationship over a larger area (Colombaroli et al., 2018). Devineau et al., (2010) further emphasises that fire is the main determinant of West African savannah tree-grass ratio. Severe changes in floristic composition and vegetation type are expected in savannas where biological modification takes place due to altered fire frequency and intensity (Devineau et al., 2010). Because of these alterations, fire regimes can be associated with high amount of grassy layer and its attributes like quality and composition based on their spatial locations and topography (Devineau et al., 2010). Fire has been reported to stop long range invasive species from spreading and thus, the discontinuation of fire regimes may support or promote the establishment of invasive wide range species which are more abundant in the agricultural areas where fire is absent (Devineau et al., 2010). Keeley and Pausas (2019) argue that fire itself does not cause adverse changes but rather the human actions that come with it. The co-existence of savanna fire regimes and vegetation dynamics is a complex system that requires more understanding as other influential factors at play such as climate and biotic factors play a role (Devineau et al., 2010). The fossil record show that the promotion of fires or biomass burning was related or largely influenced by various conditions like the position of the biome on geographical moisture gradient, intermediate moisture levels and aridity phases (Colombaroli et al., 2018).

2.3. Modelling bush encroachment

There are several models of bush encroachment to explain tree-grass coexistence and the two-layer soil water model is one of the most common. The two-layer soil water hypothesis (Walter, 1939) assumes that water is the primary limiting factor, where grasses are superior competitors for water in the surface soil layer than trees and shrubs, which can utilize deeper soil resources (Walker and Noy-Meir, 1982, Ward et al., 2014). When grasses are removed as a result of heavy grazing by livestock or fire, grasses absorb less water, which then becomes available for trees (Noy-Meir, 1982).

Savannas have been interpreted in the context of equilibrium, non-equilibrium and disequilibrium models (Gil-Romera et al., 2010). The difference between these models is related to the dynamics around the tree-grass relationship as competitors of water, nutrients and response to disturbances (Sankaran et al., 2004, Vetter, 2005). Sankaran (2004) suggests that one model on its own is not enough to understand bush encroachment.

2.3.1. Patch-dynamic models

The patch-dynamic model includes both equilibrium and disequilibrium models because it addresses the concepts of competition and demographic bottleneck (Meyer et al., 2009). Bush encroachment in arid environments should not be considered as an ecological catastrophe, but rather as a natural phenomenon that is governed by patch-dynamic processes (Wiegand et al., 2006, Wiegand et al., 2005). The perception of savanna biomes as either stable or unstable is largely influenced by the spatio-temporal scale (Wiegand et al., 2006, Scholes and Archer, 1997b, Skarpe, 1992). Multiscale patterns of tree-grass coexistence are crucial in understanding the savanna dynamics, however, recent reviews on this topic omit the spatio-temporal scale at which this coexistence is observed (Wiegand et al., 2006).

Trees and grasses often compete for the same resources, especially and often water and nutrients (d'Onofrio et al., 2015). It is widely accepted that competition between trees and grasses is a key determinant in maintaining a savanna structure (Moustakas et al., 2013). Conducive conditions such as rainfall, woody plant seeds can germinate *en masse* where there are patches created by a disturbance like grazing and fire (Ward, 2005). Arid savanna biome rainfall is patchily distributed both spatially and temporally with the overlapping of high frequency rainfall being rare in this biome (Sharon, 1981, Ward et al., 2004). However, it is these unlikely rainfall frequencies that produce the necessary conditions for a bush encroachment patch (Ward, 2005). The patchiness of vegetation in a savanna is only created by a patchy rainfall within long term rainfall levels. This means that low rainfall may produce enough moisture for tree germination, however, above average rainfall in these long-term levels produces dense woodlands with woody species of different ages (Belsky, 1990). Furthermore, tree-grass coexistence in a savanna biome is observed as a product of spatial heterogeneity typically created by fire and/or heterogeneous distribution of woody species seeds (Jeltsch et al., 1998).

The interspecific competition dynamics show that mature trees outcompete grasses while grasses outcompete tree seedlings, which creates imbalances in the tree-grass interactions on a small spatial scale (Moore, 1988). The introduction of a disturbance like heavy grazing or fire in such competition dynamics cripples the dominance of grasses over young trees in patches of the size directly proportional to spatial grazing extent, which in turn leads to the thriving of woody species (Ward, 2005). Through this competition, bush encroachment patch is transformed into an open savanna by tree-grass interspecific competition over time (Scholes, 1997). Sankaran (2004) uses two main models (competition based and demographic bottleneck) to explain the co-existence of trees and grasses. Demographic bottleneck models emphasise and explore the effects of climate variability and other factors that may affect tree life cycle as opposed to interspecific competition between trees and grasses as a measure of co-existence (O'Connor, 2014).

2.3.1.1. Disequilibrium models

Disequilibrium mechanisms refer to savannas as an unstable state and its existence is due to disturbances, which maintain the tree-grass coexistence preventing the complete dominance of trees or grasses (Sankaran et al., 2004). Jeltsch et al., (2000) developed ecological buffering mechanisms model based on two factors. Firstly, factors that prevent savannas from transitioning into a forest or thicket and secondly, factors that prevent savannas from transitioning into open grasslands (Jeltsch et al., 2000). Buffering mechanisms like fire and herbivory were identified as important factors that prevent savannas from transitioning into dense thickets (Gordijn, 2010). Among browsing and grazing, other variables such as climate and edaphic factors were also considered. Jeltsch et al., (2000) noted that without these buffering mechanisms, savannas that experience more than 500mm of annual rainfall were more likely to transition into thickets or forests. Microsites like fertile island effect, termite mounds and seed deposition through herbivore dung favour the development of woody plants and therefore prevent savannas from transitioning into open grasslands (Hennenberg et al., 2005, Jeltsch et al., 2000).

2.3.1.2. Equilibrium models

Equilibrium mechanisms refer to savannas where tree-grass co-existence is not dependent on rainfall variation or disturbances such as fire and herbivory (Scholes and Archer, 1997b). Equilibrium co-existence arises because a superior competitor (grasses) becomes self-limiting at a biomass insufficient to exclude the inferior competitor, trees (Sankaran et al., 2004, Tjelele et al., 2014). It was previously accepted that the root niche differentiation was responsible for tree-grass balance regardless of rainfall variation and other disturbances such as fire and herbivory (Walker and Noy-Meir, 1982). However, field data and theoretical models do not support this root niche differentiation model (Ward, 2005). The two-layer model explains the coexistence of trees and grasses as a result of water availability between the top soil dominated by grass roots and deep soil dominated by woody plants roots (Walter, 1939, Walter, 1971). According to this model, grasses outcompete woody plants due to their rapid absorption of moisture in the top soil leaving woody plants to only use moisture that percolates the deep soil (Walter, 1939, Walter, 1971). In the presence of disturbances like herbivory and fire, the grass layer is removed and water percolates the deep soil giving woody species a competitive advantage over grasses, leading to bush encroachment (Gordijn, 2010). In contradiction with Walter's two-layer model, some savannas have a single and too shallow soil layer to allow for root niche differentiation to exist (Wiegand et al., 2005). Competition-based models are based on competitive interactions to determine tree-grass co-existence where co-existence is driven by spatial or temporal niche separation (Maphanga et al., 2022).

2.3.2. Non-equilibrium models

Non-equilibrium mechanisms refer to savannas where tree-grass co-existence is dependent on inter-annual rainfall variability and disturbances such as fire and grazing that switch the competitive balance between trees and grasses and/or provide opportunities for tree germination and establishment (Sankaran et al., 2004, Tjelele et al., 2014)(Sankaran et al., 2004). This model is said to be reliable in mesic savannas where fuel loads are high enough to facilitate fire intensities at low resprouting rates.

Van Langevelde (2003)'s non-equilibrium model also deals with the relationship between fire and grazing. According to this model, heavy grazing rids the biomass, making fire less intense with minimal damage to trees, which in turn facilitates the proliferation of woody plant species (Ward, 2005). This is said to lead to savannas transforming into woodlands (Van Langevelde, 2003). Furthermore, browsers reduce the woody biomass and consequently and indirectly increasing the grass biomass. This in turn leads to much more intense fires which is to sustain a tree-grass balance (Ward, 2005). According to this model, anthropogenic fires lead to woody species dominance due to increasing practice of lighting fires at the end of a wet season in order to obtain nutritious regrowth as compared to fires at the beginning of a wet season (Van Langevelde, 2003). This is said to raise challenges like high fuel moisture, which reduces the fire intensity per unit fuel load and in turn, leading to woody species dominance (Van Langevelde, 2003). Ward (2005) argues that this model is biologically flawed because fires at the beginning of a wet season will give rise to high germination probability. Fires will be effective in keeping woody species at bay by killing young tree seedlings at the end of a wet season (Ward, 2005). Furthermore, Van Langevelde (2003)'s model ignores the spatiotemporal rainfall variations which play a crucial role in African savannas.

A demographic bottleneck can be created by intense fires as explained in (Higgins, 2000), as is referred to as a fire-trap model. Although seedling recruitment is limited by lack of moisture, the saplings are limited by intense fires, stopping them from growing beyond the flame zone (O'Connor, 2014). Because of this, sapling survival is considered crucial to adult tree recruitment. This model suggests that bush encroachment depends on the rate of growth in the absence of fire and is promoted by factors that reduce fire frequency and intensity, therefore allowing saplings to escape the fire-trap (O'Connor, 2014). Weak fires can promote coppicing by partially burning trees and as such, contribute to adult tree recruitment (Balfour, 2008). The fire-trap model was supported as a solution in mesic and moist savanna of southern Africa (O'Connor, 2014).

2.3.3. Empirical models

There are various empirical models that have been developed to study bush encroachment such as NDVI-based and Biomass-based models (Seo et al., 2019, Piñeiro et al., 2006), Random Forest models (Ludwig et al., 2016), Markov Chain models (Teferi, 2021). These models are based on observations and measurements of bush encroachment dynamics and are used to understand the factors that contribute to the expansion of woody plants and to make predictions about future bush encroachment patterns (Cao et al., 2019). Additionally, empirical models are based on empirical relationships or correlations that are derived from data. Empirical models are useful for describing and predicting the behaviour of systems, processes or phenomena when the underlying theory or mechanism is not well understood (Dan et al., 2012). However, Empirical models that are affected by background noise such as collinearity often have difficulty providing accurate estimates (Cao et al., 2019).

A study by Seo et al., (2019) hypothesized that the biomass-based models would perform better than the NDVI-based models, and the results showed that the performance of the biomass-based models was mostly indifferent from the NDVI-based models. It was further suggested that because of this indifference, accumulated vegetation indices modelling such as NDVI and Enhanced Vegetation Index (EVI) can be used as proxies for crop net primary production and biomass growth when biomass modelling is infeasible (Seo et al., 2019). The study reported that the indifferent performance of the biomass-based models may be due to the predictors used in the study are highly correlated with NDVI and may be affected by estimation errors (Seo et al., 2019). The study expressed that biomass-based models are still a valuable option because they have the potential for further development and improvement due to their flexibility (Seo et al., 2019).

While these methods can be informative, the performance of remote sensing models has not been extensively compared to ground observations and the use of secondary vegetation indices can add complexity to the monitoring system (Yang et al., 2011). This is substantiated by Ramoelo et al., (2012) in their study aimed at estimating and mapping foliar and canopy nitrogen at a regional scale using a high-resolution multispectral sensor. Using 24 vegetation indices to train their model, the study found that the red-edge band improved the accuracy of estimating foliar and canopy nitrogen content when compared to conventional vegetation indices (Ramoelo et al., 2012). This approach emphasises the idea that using a large number of appropriate vegetation indices can significantly improve the accuracy of the models.

Fire data, such as fire severity maps and Normalized Burn Ratio Index (NBRI) can be used in conjunction with vegetation indices to estimate the density of trees and other vegetation in an area before and after a fire (Medler and Ofren, 2001, Lozano et al., 2007). This combination is crucial for estimating fire-vegetation dynamics (Arnett et al., 2015). Empirical models, such as fire-succession models are commonly used to study these dynamics and can simulate the effects of fire on vegetation in various ecosystems (Cary et al., 2006, Keane et al., 2004). Examples of these models include the Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS) and The Landscape Fire and Resource Management Planning Tools (LANDFIRE). These models can predict changes in vegetation cover and structure in response to fire (Noonan-Wright et al., 2014, Ryan and Opperman, 2013, Cary et al., 2006).

2.4. Measures to bush encroachment

Measures of bush encroachment often point to prevention, eradication and management of the phenomenon (Mutunga, 2018). At the rate that it is going, it is of utmost urgency that bush encroachment be halted in areas where it is only starting to occur and eradicated in already affected areas (Birhane et al., 2017). The reasons behind woody plants increase in an ecosystem are diverse and complex, making the understanding of bush encroachment complex. The restoration of encroached areas is of economic significance to land owners (Smit, 2004). Scott (1967) stated that prior to extensive farming practices taking place in affected areas, moderate grazing left behind enough fuel load to burn annually or at shorter intervals. The grass fuel left behind used to be enough to create hot enough fires to destroy tree seedlings and these grasses recovered faster than the woody species after fire. Competition between trees and grasses maintained the balance in the savannas alongside herbivores grazing and browsing on these plants (Isaacs et al., 2013). Due to the introduction of livestock farming practices in these natural areas, not only was the grass kept shorter than usual through the year but little to none was left to burn (Scott, 1967). Lohman et al., (2014) reported that seedlings often face post-fire mortalities after moderately hot fires except for when grazing intensity is too high. Without sufficient hot fires, the woody plant seedlings have a chance to mature into adult trees. Areas with high potential of bush encroachment should be grazed below their grazing carrying capacity and burned at intervals of three to five years to allow grasses to recover and compete (Scott, 1967). Fire is expected to keep the woody species from overgrowing without totally eradicating them. Once woody species seedlings grow into adult trees and shrubs, a considerable amount of heat is required to kill them, a difficult factor to achieve with little to no fuel load on the ground (Kraaij and Ward, 2006, Donaldson, 1966).

Savanna ecosystems are water-limited with extreme cases leading to the decline of herbaceous layer exacerbated by bush encroachment (Smit, 2004). South African savannas are divided into moist and arid savannas with regard to the availability of moisture (Trollope, 1980). As a result of moisture availability in moist savannas, the grasses grow rapidly to create sufficient fuel load for the type of fires that control bush encroachment (Lohmann et al., 2014). In arid and semi-arid savannas, due to low fuel loads, fire does not burn enough to kill off adult woody species and shrub saplings (Higgins et al., 2007). However, even though fire is said to have minimal effect on adult woody species in arid and semi-arid savannas, seedling establishment in these regions have been demonstrated to be inhibited by fire regardless of the low fuel load (Joubert et al., 2012, Midgley et al., 2010). Goats can be a good biocontrol method for woody species (Morand-Fehr et al., 1983). However, Scott (1967) states that this only holds when there is no enough grass to graze on, making this a solution for already heavily affected areas.

Some range managers have utilized the clearing method to control bush encroachment, however, this yields contradicting results because the vegetation response to clearing is dependent on the vegetation type and other involved dynamics like soil moisture and climate among others (Smit, 2004). Clearing has the capacity to produce both negative and positive results (Teague and Smit, 1992). This method requires extensive knowledge about the encroaching species and how it grows because errors or mishandling of the plants may be detrimental rather than useful (Scott, 1967). Cutting woody plants above ground results in coppice shoots instead of one stemmed plant, making the plant even bushier than it would have been before cutting (Hare et al., 2020). Method of eradication must therefore include the destruction of dormant buds that grow into coppices when the main stem is cut (Scott, 1967). The mechanical eradication methods have shown to aggravate the issue and therefore economically unsuccessful. These methods include the winch method, felling, bulldozing, stumping and ring barking (Campbell, 2004, Jones, 2007). The eradication method that has shown positive response is cutting below ground, severing the roots. However, this method is labour and expense intensive and more often than not impractical (Scott, 1967). The mechanical methods of eradication are said to be more effective than fire because cutting does not enhance seedling establishment like fire does with some species like *E. horridum* (Alados et al., 2019). Shrubs have been found to increase seedling emergency after fire.

Long-term and short-term solutions to bush encroachment rely on our understanding around this phenomenon in order to be successful, this makes bush encroachment a persistent environmental problem because the understanding of bush encroachment is still developing with research (Smit, 2004, Daryanto et al., 2019). The uncertainty in implementation of rehabilitation methods means that the deployed methods must be ecologically and economically justified (Smit, 2004). Only a handful of rehabilitation methods implemented in southern Africa were considered successful (Smit and Rethmar, 1998). Bush encroachment rehabilitation programs are often attempted in commercial farmlands and therefore making the restoration methods delicate, considering the financial consequences. Encroaching woody species are normally known for being unpalatable, this presents an adverse impact on herbivores' food source, leading to the reduction in carrying capacity of grazing animals in the affected areas (Kraaij, 2006).

2.5. The cost of bush encroachment

Bush encroachment is one of the most adverse forms of land degradation in arid and semi-arid regions around the globe (De Klerk, 2004, Joubert et al., 2008, Schröter et al., 2011). The arid and semi-arid environments account for 25 percent of the land surface of the earth, with over one billion people earning their living from these ecosystems (Lukomska et al., 2014). Due to global climate change and human activities, savannas and grasslands ecosystems are facing constant invasion by woody plants in arid and semi-arid regions (Shen et al., 2022). This invasion of woody plants has been linked with a decrease in soil organic matter, water use efficiency and grazing capacity (Laliberte et al., 2004). Lukomska (2014) defines rangelands in arid and semi-arid regions as savannas that are characterized by the interaction and coexistence of trees and grasses mainly influenced by unpredictable precipitation and fires managed mainly for the purpose of livestock. This definition clarifies that agricultural practices in these ecosystems can be unpredictable and volatile from ecological-economic point of view. Bush encroachment has a major negative effect on rangelands by reducing carrying capacity for livestock and increasing costs associated with livestock management (Kgosikoma et al. 2012). By reducing the grazing capacity, the functioning of ecosystems and biodiversity, bush encroachment is responsible for the annual decline in global Gross Domestic Product (GDP) by 10-17% (Ramoelo et al., 2018, Cho and Ramoelo, 2019). Rangeland management involves the adaptation to these variable conditions while constantly facing the income risk (Lukomska et al., 2014).

An increase in the density of woody plants in historically arid and semi-arid environments not only has socio-economic implications but also has an impact on the ecology and ground water recharge (Huxman et al., 2005). In addition, there is evidence that bush encroachment has a profound impact on sustainable water management in water-limited ecosystems (Acharya et al., 2018). Countries like Namibia have approximately 70 percent of their national agricultural output produced in rangelands highly prone to this phenomenon called bush encroachment (Lukomska et al., 2014). In South Africa and Namibia, the decline of ecosystem is facilitated by bush encroachment (Kraaij and Ward, 2006, Walker et al., 2004). The estimated area of bush encroachment in Namibia is between 26 and 30 million hectares, while in South Africa it ranges between 10 to 20 million hectares. (Stafford et al., 2017). To this day, bush encroachment remains a puzzling phenomenon for both the scientists, land managers, farmers and communities (Smit, 2004). High rate of bush encroachment is often recorded in communal rangeland where the human population and livestock farming practices are high, consequently leading to overgrazing (Kraaij and Ward, 2006). Thus, the economic output of rural communities relying on agricultural procedures like cattle farming is directly impacted upon by bush encroachment (Espach, 2006). Encroaching plant species are often unpalatable due to their chemical and physical defence systems, making them a poor food source for herbivores both in the wild and livestock (Kraaij and Ward, 2006, Rohner and Ward, 1997). This consequently threatens the economic output of the affected land (Kraaij and Ward, 2006).

2.6. Assessment of bush encroachment using remote sensing

Since shrub expansion is said to be scale dependent, studies approaching this issue on different scales and disciplines are valued for their comprehensive understanding and depth on the matter. These studies provide future direction on land management (Naito, 2011). (O'Connor,

2014) suggested that bush encroachment in Africa be studied differently due to its unique ecological and political history. Among the methods used to study bush encroachment, the remote sensing approach excels at providing consistent temporal data (Kennedy et al., 2014). Furthermore, remote sensing technology provides an opportunity for the collection of large area and less labour-intensive data free of human errors with high precision and long-term records (Boswell et al., 2017).

Remote sensing is defined as the acquisition of spectral data about an object or phenomenon near the surface of the earth or atmosphere without being in physical contact with it using a camera or sensor equipment (Read and Torrado, 2009, Sehgal et al., 2017). Remote sensing sensors are governed by four types of resolutions namely spatial, spectral, temporal and radiometric resolutions (Huang et al., 2013). Spatial resolution refers to the smallest feature that can be detected by a sensor (Al-Wassai and Kalyankar, 2013). Spectral Resolution refers to the ability of a sensor to measure specific or number of wavelengths of the electromagnetic spectrum (Coops and Tooke, 2017). Temporal resolution refers to the frequency of a satellite or sensor at which it measures the same area in a given period of time (Coulter et al., 2012). Whereas radiometric resolution refers to the sensor’s ability to differentiate distinguish between slight reflectance values (Jong et al., 2004).

2.6.1. Mapping bush encroachment

Remote sensing has shown to be a valuable tool in recording land observation data for management and planning purposes, particularly in the mapping of vegetation attributes such as physiognomic and biochemical characteristics, phenology, distribution, and biomass (Herold et al., 2002, Mutanga et al., 2009). While *in-situ* field surveys have previously been used to monitor bush encroachment (Dube et al., 2019, Meyer and Okin, 2015), the advancement of remote sensing technologies, including aerial and satellite methods has allowed for more comprehensive and efficient monitoring (Bagheri, 2017, Kaszta et al., 2016, Maphanga et al., 2022, Ramoelo et al., 2011). However, *in-situ* data collection techniques, such as fluorescence spectroscopy, remain valuable in providing detailed information (Feng et al., 2017).

Remote sensing offers a range of advantages in the monitoring of bush encroachment, including the ability to assess rangeland status, the extent of bush encroachment and its ecological impacts, and other forms of land degradation (Dube and Mutanga, 2015, Maphanga et al., 2022). Despite ongoing gaps in our understanding of bush encroachment dynamics, the use of remote sensing has proven crucial in providing alternative natural resource management strategies and improving conservation efforts (Oldeland et al., 2010). A variety of data analysis methods have been applied to remotely-sensed data in bush encroachment studies, with demonstrated success (Rohde and Hoffman, 2012, Shekede et al., 2018).

The use of remote sensing data is gradually becoming more common among natural science studies, with emphasis on land cover change, plant species identification, vegetation biomass assessments, vegetation health and vegetation quality (Song et al., 2020). This technology can be used for fuel load quantification in rangelands and assist in grazing management practices (Mutanga et al., 2016). For this reason, vegetation indices are crucial in the assessment of vegetation response to environmental conditions.

Vegetation indices are widely employed to evaluate the status of vegetation, including factors such as vegetation cover, phenology, and health and disease (Feng et al., 2017, Hadjimitsis et al., 2010). Among the various vegetation indices available, such as the Enhanced Vegetation Index (EVI) and the Soil Adjusted Vegetation Index (SAVI), the Normalized Difference Vegetation Index (NDVI) is particularly prevalent (Ke et al., 2015). Normalized Difference Vegetation Index is a valuable remote sensing tool and can provide accurate results in the absence of other influential factors such as soil, water, complex terrain, atmospheric interference and even human activities (Hammill and Bradstock, 2006). However, when mapping tree density to estimate the extent of bush encroachment, these factors are known to be prevalent across a vast area. To account for these interferences, it is recommended to use additional vegetation indices in conjunction with NDVI, particularly when training an empirical model to estimate tree density (Seo et al., 2019). Some commonly used indices include the Leaf Area Index (LAI), the Atmospheric Resistant Vegetation Index (ARVI), and the Enhanced Vegetation Index (EVI) (Huete et al., 1997, Kaufman and Tanre, 1992). It is important to emphasise that no single index is a perfect indicator of vegetation condition, and it may be necessary to use multiple indices in order to gain a comprehensive understanding of the state of vegetation in an area (Atzberger et al., 2011).

A study that used a combination of field observations, NDVI data (a measure of vegetation health), and a machine learning algorithm called random forest to map bush-encroached rangelands is found effective (Liao et al., 2018). In contrary, areas with higher NDVI values (indicating dense vegetation) were often not good for grazing animals because they were mostly bushes, while good grazing land had lower NDVI values (Liao et al., 2018). Similarly, another study using remote sensing and GIS that aimed to evaluate the extent of bush encroachment on commercial cattle farms in central Namibia found inconclusive results (Schröter et al., 2011). The authors of the study (Schröter et al., 2011) used Geographic Information Systems (GIS) and remote sensing techniques to distinguish between areas covered by bushes and open rangeland. They also use data from a survey of commercial cattle farms to link their remote sensing results with on-site observations of bush encroachment. The researchers found that using remote sensing and different indices to analyse bush encroachment led to ambiguous results. Generally, the different methods they used to classify vegetation did not give consistent or clear results about the extent of bush encroachment on the commercial cattle farms they studied (Schröter et al., 2011).

2.6.2. Use of remote sensing to map fire patches

A variety of earth observation satellites with a wide range of resolutions are in use today (Mutanga et al., 2016). With technological advancement, data processing and application of remote sensing improves remarkably (Green et al., 1994, Toth and Jóźków, 2016). Remote sensing technology is a vital tool with a wide range of application like analyses of physical and environmental processes and comprehension of socio-economic spatial patterns (Mutanga et al., 2016). Not only did remote sensing technology progress from in-situ handheld instruments to aerial photography to satellite earth observation but all these levels have improved exceptionally to hyperspectral level (Adam et al., 2010, Han et al., 1998, Nigon et al., 2015, Ramoelo et al., 2013). These instruments have improved from RGB images to multispectral and hyperspectral imagery (Banerjee and Shanmugam, 2021, Larar et al., 2016). Some of the instruments include first generation multispectral scanner (MSS), second generation Landsat Thematic Mapper (TM) and Satellite Pour l'Observation de la Terre (SPOT) series delivering accuracy and precision (Mutanga et al., 2016). Although not widely available, hyperspectral remote sensing is especially preferred for studying vegetation due to numerous narrowly defined wavebands that give detailed information about the landscape (Madonsela et al., 2017).

MODIS instruments have been of great importance in providing the science and research community with crucial data on global land, oceans and atmosphere since November 2000 to date (Giglio et al., 2018). The recent upgrade on burned area algorithms merged the capabilities of both burned area and active fire detection approaches, which significantly improved the detection capability of burned areas (Fornacca et al., 2017), making the burned area product MCD64A1 a distinguished compound in global fire monitoring database (Giglio et al., 2018).

The collection 6 MCD64A1 product is superior to its predecessors MCD45A1 and MCD64A1 collection 5 (Giglio et al., 2018). The availability of MCD45A1 product started in mid-2008 in the collection 5 (C5) MODIS land product suite (Giglio et al., 2018) on NASA's Terra and Aqua satellites (da Silva Cardozo et al., 2012). With additions of correction algorithms, the product improved to a new version collection 5.1 (C5.1) released in mid-2013 as an effort to detect slightest changes in thermal data on the Earth surface (Giglio et al., 2018). The MCD45A1 and MCD64A1 are said to have exhibited errors of omitting data with MCD64A1 better than MCD45A1 due to the latter being more susceptible to atmospheric pollution (Giglio et al., 2018). Fornacca et al., (2017) further adds that the older versions of MCD45A1 and MCD14ML products are better than the hybrids collection 6 (C6) MCD64A1 products on the Sørensen index (F1 score). In a study by Tsela et al., (2010), the accuracy of MODIS burned area products was tested in various ecosystems including savannas, grasslands, fynbos, and commercial pine forests in South Africa. The results showed that the accuracy varies depending on factors such as the vegetation type, spatial distribution, and reflectance of the burned areas. This study shows that the likelihood of correctly identifying a burned area within a MODIS pixel is related to the percentage of the pixel that is burned (Tsela et al., 2010).

The accuracy of Landsat 8 Operational Land Imager (OLI) surface reflectance product is analysed over the Aerosol Robotic Network (AERONET) sites through accurate atmospheric correction based on in-situ measurements (Vermote et al., 2016). The OLI surface reflectance products are generated using the Land Surface Reflectance Code (LaSRC) algorithm (Version 1.5.0) while the TM surface reflectance products are generated using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm (Version 3.4.0) https://www.usgs.gov/landsat-missions/landsat-collection-2-level-2-science-products [accessed 15/01/2022]. These algorithms are responsible for correcting the temporal, spatial and spectral scattering and absorb the effects of atmospheric fluids to better characterize the surface of the earth (Knight and Kvaran, 2014). Table 2.1 below demonstrates the major current earth observation satellite sensors that provide data commonly used to map fire.

Table 2.1: Description of some of the widely used earth observation satellites (Szpakowski and Jensen, 2019).

Sensor(s)	Spatial Resolution	Advantages	Disadvantages
Landsat MSS, TM, ETM+, OLI	15–30 * m	Free and easily accessible	Lack of canopy penetration, low temporal resolution
Sentinel-2	10–60 m	Free, relatively high spatial and temporal resolution, multiple near infrared (NIR) bands	Lack of canopy penetration
MODIS	250 m–1 km	Free and easily accessible, high temporal resolution, large area analysis	Lack of canopy penetration, coarse spatial resolution limits analysis of smaller areas
ASTER	15–90 m	Free and easily accessible, hyperspectral sensor, several short-wave infrared (SWIR) bands	Lack of canopy penetration, low temporal resolution
IKONOS	0.8–4 m	High spatial resolution	Decommissioned, limited spectral resolution, high cost
AVIRIS	4–20 m	High spatial resolution, hyperspectral sensor	High cost, complicated data processing
GOES	1–4 km	High temporal resolution, large area analysis	Lack of canopy penetration, coarse spatial resolution limits fine scale analysis
MGS-SERIVI	3 km	Very high temporal resolution, large area of analysis	Lack of canopy penetration, coarse spatial resolution limits fine scale analysis

2.6.3. Analysis methods used for remote sensing data

2.6.3.1. Image classification

Image classification is a multi-step workflow process of grouping pixels into designated meaningful classes (Abburu and Golla, 2015). Image classification is mainly divided into two categories: supervised image classification and unsupervised image classification (Domadia and Zaveri, 2011). Supervised image classification requires a training stage where pixels are selected from pixel classes called training pixels. In this classification, the characteristics of training pixels are matched with pixels of the same characteristics on the map (Domadia and Zaveri, 2011, Smith et al., 2007). The advantage of supervised image classification is that errors can be manually detected and corrected, however, missing of errors leads to the shortcoming of this technique. Furthermore, this technique is time consuming and costly (Greiwe, 2006). In unsupervised image classification, training stage is not a necessity, instead, different algorithms are utilized to cluster the pixels. Unsupervised image classification is appropriate for images that have insufficient amount of information (Domadia and Zaveri, 2011). The advantage of unsupervised image classification is that it is time efficient and free from human error. Having maximally-separable clusters is the main disadvantage of this technique (Greiwe, 2006).

Image classification is a complex method that is susceptible to various challenges that may lead to errors (Lu and Weng, 2007). Factors like heterogeneous landscapes, selected remotely sensed data and image-processing and the approach of classification have an impact on the success of the image classification (Lu and Weng, 2007). The review of classification methods and techniques is necessary to accommodate recent classification algorithms and techniques in guiding the remote sensing community and research (Gallego, 2004). Image classification remote sensing results are valued for their diverse application in many environmental and socio-economic problems (Lu and Weng, 2007). Scientists and practitioners have made a considerable effort in advancing classification approaches and techniques (Franklin et al., 2002). Hyperspectral imagery is used in image classification containing over hundred spectral bands and it is for this reason that traditional image processing tools often come short in processing hyperspectral data (Huang et al., 2016). Various different hyperspectral image classification algorithms have been developed to accommodate the high spectral resolution images (Plaza et al., 2009). The classification of hyperspectral data involves the use of pixel-wise methods such as Principal Component Analysis (PCA), Independent Component Analysis (ICA) and neural networks (Prasad and Bruce, 2008).

2.6.3.2. Change detection

Change detection is achieved through the comparison of type, amount, location and configuration of the change between two or more images taken at different times, though a minimum of two images is usually enough (Keno and Suryabhagavan, 2014). Due to how change detection works, multitemporal dataset is considered indispensable in land monitoring projects and change detection studies (Cohen, 2004).

For consistency and accuracy of the calculations when doing change detection, anniversary dates for image acquisition is often preferred because it reduces the discrepancies in reflectance due to seasonality and position of the sun (Gillanders et al., 2008a). In addition to identification of land cover change through change detection, the quantification of that change is also an important factor in understanding the rate and consistency of change (Gillanders et al., 2008a).

Various change detection methods have been utilised in bush encroachment studies (Britz and Ward, 2007, Munyati et al., 2011, Oldeland et al., 2010). Some of the change detection methods suitable for studying bush encroachment include image differencing, vegetation index differencing, image regression and change vector analysis (JHA and Unni, 1994, Johnson, 1994, Lambin, 1996, Lyon et al., 1998, Muchoney and Haack, 1994). A change detection study usually provides information such as the area and rate of change, spatial distribution and direction of change, and accuracy assessment of change detection results (Macleod and Congalton, 1998). Among other image pre-processing requirements, multitemporal image registration, radiometric and atmospheric corrections are the most important (Lu et al., 2004). Furthermore, Lu et al., (2004) emphasizes the importance of converting digital numbers from satellite data into radiance or surface reflectance values for a study of change detection because the digital numbers (DN) that are recorded by a satellite sensor do not directly correspond to the physical properties of the Earth's surface. Change detection can be used in studies such as anthropogenic influence on landcover (Narumalani et al., 2004), vegetation change (Gandhi et al., 2015) and fire patterns and fire history (Liu et al., 2020).

2.7. Research gaps and limitations

While it is clear that fire can have significant impacts on tree density, the specific mechanisms by which fire affects tree growth and survival are not well understood (Bär et al., 2019). Further research is needed to identify the factors that influence the response of trees to fire, such as the intensity and duration and extent of the fire, the frequency of fires, and the species and age of the trees involved (Haslem et al., 2011, Ward, 2005, Ward et al., 2014). It is likely that there are critical thresholds at which the frequency of fires becomes a major driver of bush encroachment (Gordijn et al., 2012). Further research is needed to identify these thresholds and to understand how they vary across different types of savanna ecosystems and under different conditions.

Most studies of the effects of fire on bush encroachment have focused on short-term or intermediate-term impacts, and there is relatively little research on the long-term effects of fire on bush encroachment (González-Romero et al., 2021). More research is needed to understand how the frequency and severity of fires influence the long-term dynamics of bush encroachment. Fire is just one of many factors that can influence bush encroachment, and it is likely that there are complex interactions between fire and other drivers, such as grazing, land use change, and climate change (Jeltsch et al., 2000). Further research is needed to understand these interactions and how they influence the dynamics of bush encroachment. There is unlikely to be a single cause of bush encroachment, but rather a combination of interacting factors (van Auken 2009; Grellier *et al*. 2012). The limitation of this study is that it solely focusses on the effects of fire on tree density. The results may not be conclusive on fire as the driver of bush encroachment in the study area but may simply reveal the correlation and not causality.

Some vegetation indices are not able to distinguish between different types of vegetation, such as grasses and woody plants, which can make it difficult to accurately map the distribution and density of different plant species (Adam et al., 2010). Environmental factors such as temperature, precipitation, and soil moisture can all affect the health and productivity of vegetation, and these factors can also influence the values of vegetation indices (Baret and Guyot, 1991). Additionally, many vegetation indices upon which empirical models are based on rely on data that is collected at regular intervals, such as every 16 days or every month (Zhang et al., 2019). This can make it difficult to capture rapid changes in vegetation cover, such as those that may occur following a fire or other disturbances. This study used remotely-sensed data collected at 1 year intervals and that is an additional limitation to our research as a lot of factors may temper with vegetation in a period of 1 year. Our methodology's limitation necessitates further comprehensive research in the future.

CHAPTER 3

Assessing the influence of fire on tree density and plant diversity on experimental farms in Gauteng and Mpumalanga, South Africa

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Abstract

Remote sensing technology allows us to observe changes in vegetation structure and composition over large areas, providing valuable insights into the relationship between fire frequency and bush encroachment. The aim of this study was to investigate the effects of fire frequency (active fires and burned areas products derived from Moderate Resolution Imaging Spectroradiometer (MODIS)) on tree density and plant diversity thereby assessing the relationship between fire and bush encroachment in three Agricultural Research Council (ARC) experimental farms namely Loskop, Irene and Roodeplaat. The MODIS fire product was used to determine the Pearson correlation between fire frequency (burned areas) and, firstly, tree density and, secondly, plant diversity. To substantiate the Pearson correlation results, Analysis of Variance (ANOVA) and Kruskal-Wallis (KW-H) tests were additionally used to investigate the significance of fire frequency (active fires) on tree density and plant diversity. The correlation between tree density and burned areas in Loskop, Irene, and Roodeplaat farms is -0.06, 0.38, and 0.38 respectively with *p-values* of 0.8, 0.05, and 0.08. The ANOVA *p-values* and KW-H *p-values* for tree density in relation to active fires were significantly larger than 0.05 for all three farms: Loskop ($F = 0.5751$, $p = 0.6351$ and $H = 1.7308$, $p = 0.6301$), Irene ($F = 0.5645$, $p = 0.7749$ and $H = 7.4971$, $p = 0.3790$), Roodeplaat ($F = 2.2316$, $p = 0.1516$ and $H = 2.5355$, $p = 0.1113$). The correlation results show no significant link between burned areas, tree density, and plant diversity, except for tree density in Irene farm. Additionally, both ANOVA and KW-H tests indicated no significant difference between active fires, tree density and plant diversity. The findings of this study should assist the farm management in choosing the appropriate management tools and methods against bush encroachment.

Keywords: active fires, burned areas, plant diversity, tree density

3.1. Introduction

Bush encroachment is a major ecological change that has affected rangelands worldwide. It is defined as a prolific increase in density, cover and biomass of indigenous and/or alien trees and shrubs at the expense of desirable herbaceous layer (Anadón et al., 2014, Van Auken, 2009). By the late nineteenth century, bush encroachment was already evident in southern Africa (O'connor et al., 2014). Research shows that this phenomenon is an indicator of land degradation threatening over one billion people on earth (Symeonakis and Higginbottom, 2014, Oldeland et al., 2010, Tjelele et al., 2015). Due to its alteration to habitat structure and decrease of herbaceous growth, bush encroachment is widely considered a major threat to socio-economic activities such as livestock production and nature conservation in southern Africa (O'connor et al., 2014). The decrease of palatable grasses by an increase in bush thickening unpalatable bushes has led to a considerable amount of rangelands degraded (Symeonakis and Higginbottom, 2014). As a result, the livelihoods of many farmers and communities are affected by this phenomenon as the decrease of herbaceous layer negatively affect livestock production and in turn affecting the food security (Bettencourt et al., 2015). Furthermore, species composition and richness can be further affected by bush encroachment (Angassa and Oba, 2008) posing a threat to biodiversity.

The causes of bush encroachment in rangelands worldwide are well documented (Archer et al., 2017, Bond and Midgley, 2000, Kraaij and Ward, 2006), yet the extent of encroachment is still increasing excessively. This increase is due to a number of global and local factors such as climate change, atmospheric CO_2 concentrations, fire, grazing and browsing regimes, and the extent of nitrogen deposition and fixation, that alone or in combination, cause bush encroachment (Ward, 2005, Wiegand et al., 2005). The interactions between these factors and the specific mechanisms driving bush encroachment are not fully understood (Belayneh and Tessema, 2017).

The balance between trees and grasses is, to a certain extent, determined by the indirect interactive effects of herbivory and fire. These effects are based on the positive feedback between grass biomass and fire intensity. An increase in the level of extended grazing leads to reduced fuel load, which makes fire less intense and, thus, less damaging to trees and, consequently, results in an increase in woody vegetation. The system then switches from a state with trees and grasses to a state with solely trees (Van Langevelde et al., 2003). However, it is not clear how different frequencies of fires affect the different stages of bush encroachment or what fire regime is sufficient to control or trigger bush encroachment (Lutz et al., 2011). While it is known that frequent fires can help to manage bush encroachment, it is not clear how often fires should be set in order to effectively control bush encroachment (Mariani et al., 2022). This lack of knowledge makes it difficult to develop integrated management strategies for controlling bush encroachment. Lutz et al. (2011) explored a holistic approach to fire assessment. The study uses Landsat data to examine wildland fires in a specific region in California and calculates fire frequency and annual area burned. They also use a measure of fire severity called differenced Normalized Burn Ratio (dNBR) and compares these three fire regime attributes. The study suggests that a more comprehensive summary of a given fire year can be obtained by considering all three metrics (number of fires, size of fires, and severity of fires) together (Lutz et al., 2011). Additionally, the study emphasises the importance of understanding the relationship between different attributes of a fire regime, such as fire frequency, area burned, and fire severity. It mentions that there are few studies that have quantified these interrelationships, and that using area burned alone as a summary of a fire season may not be accurate (Lutz et al., 2011).

A study by Veldman et al., (2014) reports on how multiple factors including fire frequency and agricultural land use can impact plant diversity. This study was conducted in pine savannas of the South-Eastern United States. The study modelled the direct and indirect effects among multiple factors that were thought to have a broad influence on plant diversity in savanna ecosystems. They reported that understorey plant species richness is reduced in areas where there has been a history of fire exclusion and agricultural land use (Veldman et al., 2014). This is supported by Peterson et al., (2008) which states that high plant species richness in savannas is a result of both a high number of different plant species found at individual sample locations (sample point species richness) and a high level of variation in the types of plant communities found across different sample locations (community heterogeneity). The study also suggests that these factors are maintained by intermediate fire frequencies and variable tree canopy cover (Peterson and Reich, 2008). In most Mediterranean fire-prone systems, there is a spike in plant species richness immediately following a fire, but this is followed by a gradual decrease as the species that were present reach the end of their lifespan and are not replaced by new ones (Knuckey et al., 2016).

Tree density increased with increasing fire frequency, suggesting that fire may be positively influencing tree density and plant diversity (O'connor et al., 2014). For instance, a study by O'connor et al. (2014) found that tree density was positively related to plant diversity, implying that fire frequency may be a critical factor maintenance of plant diversity. Conversely, frequent fires, along with light grazing, can combat and reverse shrub encroachment (Roques et al., 2001). The study further suggests that burning more often than once every 3 years is relatively inefficient in terms of using grass fuel to combat encroachment, but small changes in fire frequency can have a large positive impact on encroachment (Roques et al., 2001). The ratio of woody to herbaceous cover which determines a savanna is modified by fire, preventing tree canopy closure which results in an open, woody system (Scholes and Archer, 1997a). However, fire and herbivory tend to be insignificant in locations where plants have significantly adapted to withstanding fire and herbivory disturbances (Mills et al., 2013).

The broad temporal and spatial scales associated with bush encroachment have made field work challenging, however, satellite imagery can be a potential solution (Ramoelo and Cho, 2018, Roques et al., 2001). This proves that remote sensing can provide a useful support to land managers and researchers. With its course spatial resolution of 500m for burned areas and 1km for active fires (MCD64A1 and MCD14ML respectively), Moderate Resolution Imaging Spectroradiometer (MODIS) sensor is suitable for studying the impacts of fire on bush encroachment over a large area (Boschetti et al., 2015). Because MODIS sensor maps a large area per pixel providing spatial and seasonal trends, it has been used to map fire occurrences on a global scale (Giglio et al., 2018, Hantson et al., 2013). However, this course resolution comes at a challenge of accurately mapping fire extent as small fires of less than half a pixel of 500m are not detected by the sensor (Giglio et al., 2018). Landsat data is often used as validation data for MODIS global burned area products because of its moderate 30m spatial resolution (Hantson et al., 2013). However, due to the 16 days revisit period of the Landsat satellite, it is not possible to acquire daily active fire data from this sensor. Other studies have explored the hybrid method of combining fire products with products from other sensors (e.g. MODIS-Advanced Very High Resolution Radiometer (AVHRR)) to accurately map the burned areas (Alonso-Canas and Chuvieco, 2015, Boschetti et al., 2015, Liu et al., 2019, Lizundia-Loiola et al., 2020).

The overarching aim of this study was to investigate the effects of fire frequency on tree density, plant diversity and their contribution on bush encroachment. The specific objectives of this study were twofold:

1. To determine the relationship between tree density and fire frequency at local scale.
2. To determine the relationship between plant diversity and fire frequency at local scale.

3.2. Materials and Methods

3.2.1. Study Area

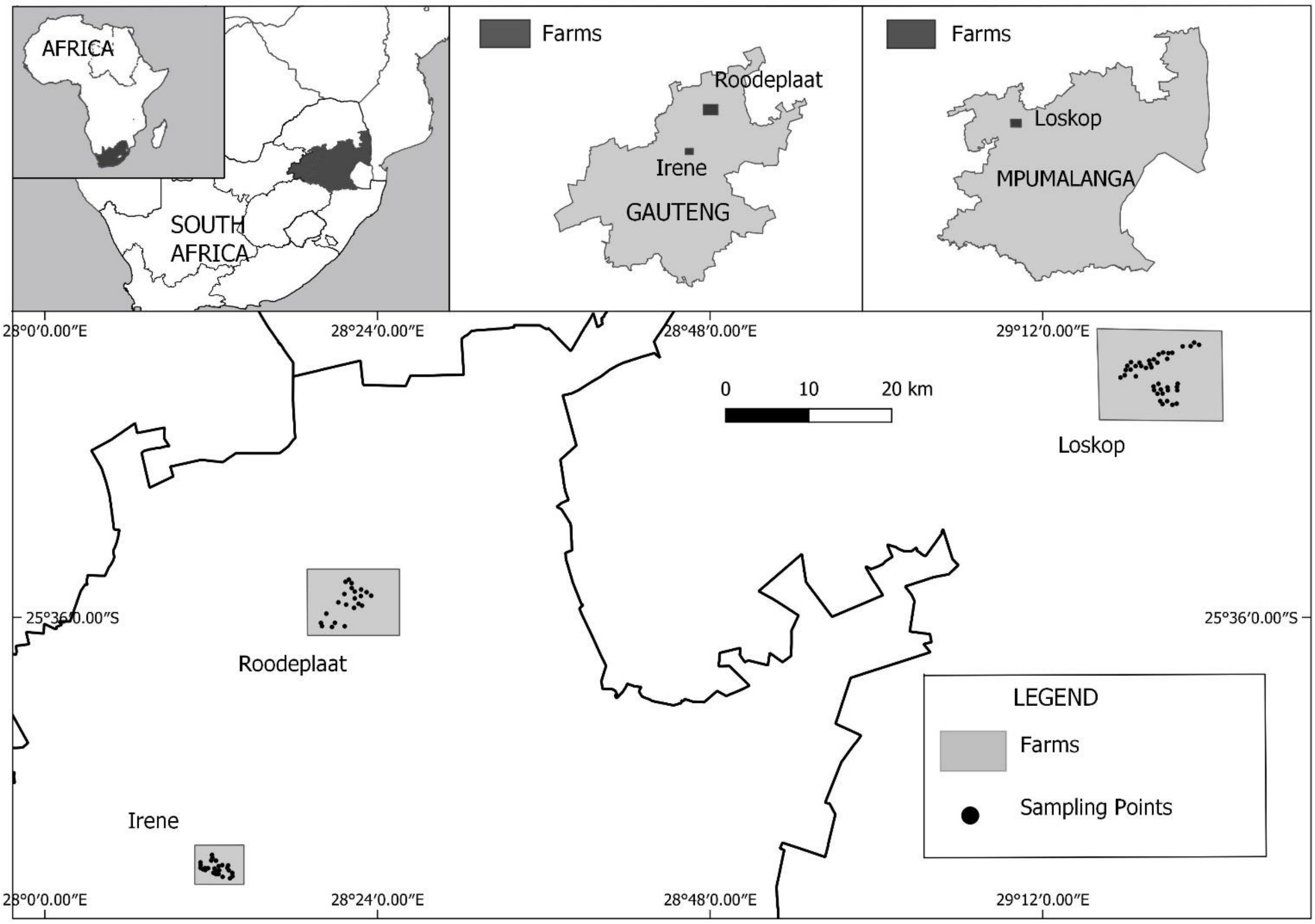

Figure 3.1: Map showing study sites in ARC Loskop, Irene and Roodeplaat farms, Mpumalanga and Gauteng Provinces where data was collected identified as sampling points in this study.

The study was conducted at the ARC experimental farms mainly Loskop, Irene and Roodeplaat. The study sites are located at the following coordinates, Loskop (25°18'7.56"S 29°18'20.772"E), Irene (25°53'56.6484"S 28°12'32.2416"E) and Roodeplaat (25°33'25.9236"S 28°21'41.8068"E) South Africa. Loskop farm is situated in Mpumalanga, near a village called Ntwane located 8 kilometres outside Limpopo Province (Pambu-Gollah et al., 2000). Ntwane is 1216 m above sea level in a semi-arid climate with relatively low annual rainfall of approximately 617 mm and mean annual temperature of 18.5 degree Celsius (Barrett et al., 2010). The dominant woody species in Loskop farm are *Dichrostachys cinerea*, *Gymnosporia buxifolia*, *Combrectum apiculatum*, *Euclean crispa*, *Vachellia nilotica* and *Vichellia tortilis*.

The main grass species of this farm are *Aristia congest sp, Digitaria eriantha, Eragrostis sp, Heteropogon contortus* and *Thermada triandra*.

Irene experimental farm is located in Centurion, Gauteng Province and has an altitude of 1430 m above sea level with mean annual temperature of about 17.1 °C (Montjane et al., 2020). Centurion has a warm and temperate climate with summer rainfall of approximately 708 mm per annum (Montjane et al., 2020). The dominant woody species in this farm is *Vachellia karoo*, among other species like *Senegalia caffra* and *Searsia pyroides*. The dominant grass species found in Irene farm are *Eragrostis species, Digitaria ariantha, Aristida congesta and Eragrostis species.*

Roodeplaat is situated at approximately 10 km North-east of the Pretoria Central Business District (CBD). The natural vegetation component of Roodeplaat farm that is used for livestock and wild-herbivore production makes up an area of approximately 2100 ha. This farm has an altitude of 1281 m above sea level (Mkhize, 2015). The vegetation type is Marikana Thornveld (Mucina and Rutherford, 2006), which is characterized by *Vachellia karroo* and *Senegalia caffra* (Kyalangalilwa et al., 2013). The farm is also dominated by *V. tortilis*, *Ziziphus mucronata*, and some *Euclea* species. The main grass species on the site are *Digitaria eriantha, Panicum coloratum, Setaria sphacelata, Eragrostis curvula, Themeda triandra* and *Heteropogon contortus*. The mean annual rainfall is 646 mm, which largely falls between November and March. The minimum and maximum summer and winter temperature ranges from 20-29 °C and 2-16 °C, respectively (Panagos et al., 1998). The study area is situated on the Roodeplaat Igneous Complex with average annual rainfall of 646 mm (Panagos et al., 1998).

Some camps were not used/grazed in Loskop and Roodeplaat because of water scarcity and as such this will have a bearing on herbaceous biomass and fire regime. Animals were rarely spotted in the areas without water as most of them gravitated towards supplied drinking points. There are no planned burning practices in all three farms.

3.2.2. Sampling design and field data collection

This study used random GPS coordinates as sampling points to collect data on tree density and plant diversity. The in-situ data (tree density and plant diversity) was collected by the ARC – Range and Forage Sciences research team. The sampling points were selected based on NDVI values determined before data collection, and areas that had statistically similar NDVI values were excluded when placing the transect lines for data collection. Data for both tree density and plant diversity was obtained using the same transect line for each sample point. This data was gathered during the wet season of October 2018 and March 2019 and the dry season is from April to September 2019. The sampling points were different in quantity among the three farms studied, Loskop had 41, Irene had 26 and Roodeplaat had 22 due to logistical challenges and the farm size. These were the same sampling points used to collect satellite data. Both active fire data and burned are data were sampled within a threshold of these sampling points.

By excluding the areas of similar NDVI values, the data collected was more representative of the range of vegetation conditions within the study area, rather than being dominated by a single condition. Therefore similar NDVI values indicate similar vegetation density or condition (Pettorelli et al., 2005). Values were excluded unevenly from each farm, leading to uneven sampling points.

Savannas without frequent disturbances like herbivory and fire tend to be unstable and favour woody species in high fuel areas (Scholes and Archer, 1997b). This is expected to be the case in the unused sections of Loskop and Roodeplaat farms. When data was collected, some of the sampling points were in the unused sections of the farms and that may have had significant impact on the results of this study.

3.2.2.1. Tree density data

Tree density data was collected along the line transects (Beyene, 2015) of 50 meters long and 2 meters wide. The area derived from the transect was then computed to be 100 m^2. Therefore, the number of tree species per 100 m^2 (expressed as 1/100th of a hectare) was defined as tree density. The total number of trees per transect was multiplied by 100 to get the number of trees per hectare for each sampling point.

3.2.2.2. Plant diversity data

The point centred quarter method (PCQ) was used to collect the grass species plant diversity data in 1 m^2 quadrats along a 50-meter line from each sampling point (Flombaum and Sala, 2007). Five 1 m^2 quadrats were placed at every 10 meters starting from 0 meters. The Simpson index (Equation 3.1) was calculated for every sampling point to generate one value for the PCQ data (Hunter and Gaston, 1988). The Simpson Index measures diversity using the number of species found in a location and the relative abundance of the recorded species (Hunter and

Gaston, 1988), and is considered as a dominance index and therefore unbiased and appropriate for this study (Simpson, 1949).

The Simpson Index equation:

$$D = 1 - \left(\frac{\sum n(n-1)}{N(N-1)}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{Equation 3.1}$$

n = Total number of organisms in one species.

N = Total number of all recorded organisms in all available species.

3.2.2.3. Satellite remote sensing data

MODIS burned area and active fire products (MCD64A1 and MCD14ML respectively) were downloaded from https://modis.gsfc.nasa.gov/data/dataprod/mod45.php for the period of November 2000 to December 2019. Both MODIS burned area and active fire satellite products were received in WGS84 geographic projection. Due to the thermal sensors commencing function in the year 2000, the data is available from November 2000 to date with some gaps of data missing in the years 2001, 2002, 2007 and 2009. Visible Infrared Imaging Radiometer Suite (VIIRS) thermal day data is also available along with MODIS data. Landsat 8 Operational Land Imager (OLI), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 5 Thematic Mapper (TM) data was also used to try and enhance burned areas through image differencing. This attempt did not improve the detection of fire or burned areas extent in the study areas, so the results were excluded from this study.

3.2.2.3.1. MODIS burned area product (MCD64A1)

The burned area product is a monthly product with 500 m spatial resolution where a pixel is classified as burned when 50% of the pixel is burned and detected (Fornacca et al., 2017). This product was used to generate fire frequency data by counting each burned pixel falling within 500 meters buffer zone of each sampling point. In instances where two buffer zones shared a pixel, the pixel was assigned to the buffer zone containing a larger area of the pixel. The product was clipped to three study sites to focus on the desired burned areas. The MODIS land surface reflectance bands and their associated quality assessment information are gridded into a level 2G format. This format stores sensed data over a 12-h period and this is defined in sinusoidal projection in geolocated tiles, where every tile has fixed earth-locations covering an area of 1200 km^2 (Roy et al., 2005). The L2G data is processed to delete inaccurate data such as high solar Zenith (>65^o), high view Zenith (>65^o) and atmospheric obscurities. Additionally, the algorithm applies a bidirectional reflectance change detection method derived from a Bi-directional Reflectance Distribution Function (BRDF) model comparing a minimum of seven bands over a minimum period of sixteen days (Tsela, 2011). The collection 6 MCD64A1 product is superior to its predecessors MCD45A1 and MCD64A1 collection 5 (Giglio et al., 2018). The availability of MCD45A1 product started in mid-2008 in the collection 5 (C5) MODIS land product suite (Giglio et al., 2018) on NASA's Terra and Aqua satellites (da Silva Cardozo et al., 2012).

3.2.2.3.2. MODIS active fire product (MCD14ML)

"The MODIS Active Fire product is produced using a contextual algorithm that applies thresholds to the brightness temperatures from the middle-infrared and thermal infrared channels of the MODIS instrument" (Giglio et al., 2018). MODIS collection 6 (M6) active fire product was downloaded for the three study sites. The product is available in Near Real-Time (NRT) format generated few hours after observation known as MCD14DL and is later replaced by a more consistent standard quality fire data known as MCD14ML, usually available two to three months after NRT data generation (Fornacca et al., 2017). The NRT fire data has less fire accuracy than the processed MCD14ML which is processed more than once. The MODIS sensor has a spatial resolution of 1 km and a fire point is generated in the centre of the pixel and not the exact location of the fire with the capacity of detecting a fire within 50 m^2 (Giglio et al., 2018, Giglio et al., 2016). The product contains the date, geographical location and auxiliary data for each detected pixel and series of tests like rejection tests are performed on the pixels to improve accuracy (Fornacca et al., 2017).

3.3. Data analysis

3.3.1. Data preparation

The remotely sensed data was used to map points where the fire started using active fire product (MCD64A1 collection 6) and how far the fire spread using burned area product (MCD64ML collection 6) (see Figure 3.2). The active fire points for the whole South Africa were collected going back twenty years from year 2000 to 2019. GPS coordinates (sampling points) collected by the ARC research team were used as the independent variables (Figure 3.2). A 500-meter buffer zone was created around each coordinate, and active fire points falling within these buffers were selected and separated from the rest to be utilized as active fire data in the study (Figure 3.2). Initially 250 m was the decided buffer zone however, most fires were beyond these buffer zones. The dates of each fire point in the buffered areas were identified and the correlating Julian date of burned area product was used to determine how many pixels burned in the 500 m buffer zones of each sampling point to create burned area data per sampling point. This was achieved by adding the number of pixels falling within the 500 m buffer zones. Figure 3.2 below demonstrates that only four days (25th, 26th, 27th and 30th) of June 2011 burned according to the Julian calendar used by the burned area mapping algorithm.

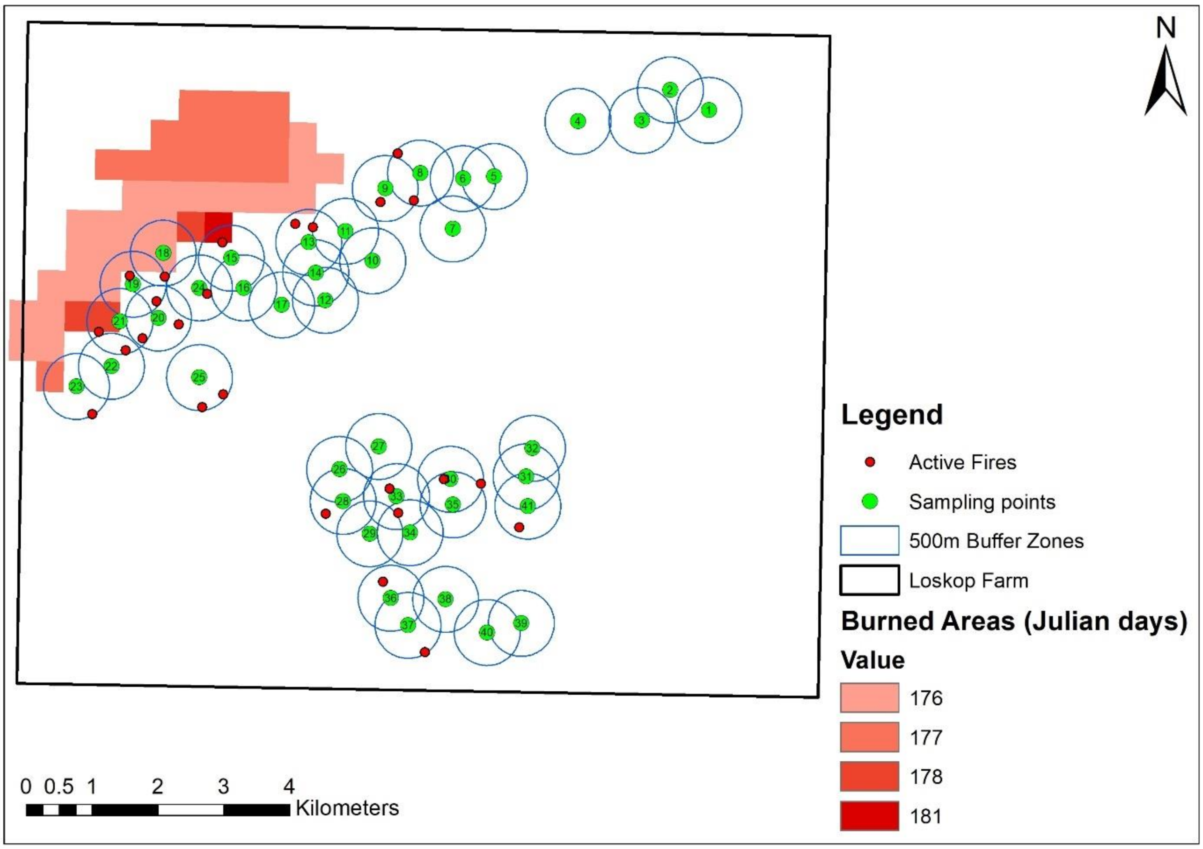

Figure 3.2: A map of Loskop farm showing GPS coordinates where in-situ data was collected, 500-meter buffer zones, Active fires (MCD64A1 collection 6) and burned areas (MCD64ML collection 6) for the month of June 2011.

3.3.2. Statistical analysis

The Pearson correlation was used to determine the strength of the relationship between burned areas, tree density and plant diversity. Correlation is defined as a statistical measure of how closely related two variables are to each other (Emerson, 2015). The results were tested for significance followed by ANOVA and Kruskal-Wallis tests. One-way ANOVA compares the means of the samples (Kim, 2014) to determine whether or not there is a significant difference between active fires, tree density and plant diversity. A Kruskal-Wallis test is a non-parametric statistical technique used to determine the relationship between active fires, tree density and plant diversity. This test does not assume the normal distribution of sample data (Xia, 2020). Both of these statistical tests were calculated in the excel software. Pearson correlation coefficient is only useful for continuous variables, and it doesn't account for other factors that may be influential to the relationship between two variables. Therefore, it is important to use other methods and statistical tests to support the conclusion, and to consider other possible explanations for the relationship being observed (Armstrong, 2019).

Due to MODIS' course resolution (suitable for mapping large scale fires as opposed to small regional scale fires) (O'connor et al., 2014), active fires were considered to be a closely related factor that can influence tree density and plant diversity. Active fires were detected by the MODIS sensor, however, if the fires don't spread over a large enough area >500 m, they are not detected by the sensor. For this reason, we assumed that every fire spreads to some extent and expected to have an effect on both tree density and plant diversity. To substantiate the Pearson correlation test results on burned areas in relation to tree density and plant diversity, ANOVA and Kruskal-Wallis were used to investigate the effects of active fires on the same parameters (tree density and plant diversity). This justifies the assumption that yearly fires had similar variances. Since the data is not normally distributed, the use of both ANOVA and Kruskal-Wallis tests is also justified.

3.4. Results and discussion

3.4.1. Descriptive statistics

The descriptive statistics, i.e. the minimum and maximum values, mean, standard deviation and coefficient of variation values of tree density, plant diversity, burned areas and active fires were computed using the R programming language for all three study sites/farms. The standard deviations for tree density, plant diversity, burned area and active fire are generally higher than the means as seen in Table 3.1. This indicates that the data points are significantly spread out from the mean indicating the existence of outliers in the data. The higher the value of CV, the greater the level of dispersion around the mean (Fisher and Marshall, 2009). The burned area CV values are over 250% in all the three farms demonstrating highly variable fires. Burned area data was calculated by counting the number of burned pixels and therefore this means higher variability in the spread of fire between the year 2000 and 2019 in all the farms.

Table 3.1: The illustration of measures of central tendency and measures of variability of the datasets from the three farms. This descriptive statistics reports the minimum and maximum values, mean, standard deviation and coefficient of variation (CV).

Variables	Min	Max	Mean	Standard deviation	CV (%)
Loskop					
Tree density(trees/ha)	0	11500	2020	2727,46	135,02
Plant diversity	0	0,9	0,42	0,41	97,05
Burned areas	0	16	1,25	3,37	270,38
Active fires	0	3	0.6	0.78	129.6
Irene					
Tree density(trees/ha)	0	9300	1273,07	2449,09	192,37
Plant diversity	0	0,9	0,35	0,39	112,54
Burned areas	0	12	1	2,54	254,55
Active fires	0	7	2.65	2.06	77.5
Roodeplaat					
Tree density(trees/ha)	0	7500	2400	2798,03	116,58
Plant diversity	0	0,9	0,49	0,44	89,04
Burned areas	0	11	0,71	2,45	343,33
Active fires	0	1	0.43	0.51	118.3

*Coefficient of variation (CV%), Active fires – number of fires in twenty years from 2000-2019 during the wet season.

3.4.2. Relationship between vegetation structure (tree density and plant diversity) and burned areas

To test for the significance of the Pearson correlation coefficients, the following hypotheses were formulated and tested at 5% significance (i.e., α=0.05) and the results are presented in Table 3.2.

$H_\circ$: There is no correlation between burned areas and, tree density and plant diversity.

H_1: There is correlation between burned areas and, tree density and plant diversity.

The correlation between vegetation structure and burned areas is similar in Irene farm and Roodeplaat as opposed to Loskop farm. There was a positive correlation between vegetation structure and burned areas in Irene and Roodeplaat farms but not enough to be statistically significant (Table 3.2). There were no significant differences for tree densities and plant diversity for the three farms with the exception of tree density at Irene farm (see Table 3.2).

Table 3.2: Pearson's correlation results for the three study sites

	df	Pearson r	R Square	F value	P-Value
Loskop					
Tree Density(trees/ha)	40	-0,04	0,002	0,06	0,80
Tree Diversity	40	-0,06	0,004	0,15	0,69
Irene					
Tree Density(trees/ha)	24	0,38	0,15	4,26	0,05
Tree Diversity	24	0,11	0,01	0,34	0,56
Roodeplaat					
Tree Density(trees/ha)	20	0,38	0,14	3,32	0,08
Tree Diversity	20	0,10	0,01	0,19	0,67

*df - degrees of freedom

3.4.3. Test for the significant difference between vegetation structure (tree density and plant diversity) and active fires

One-way Analysis Of Variance (ANOVA) was also used to compensate for the error of non-recorded burned areas for regions that have recorded active fires. This led to the formulation of the following hypotheses tested at 5% significance level (i.e., α=0.05) for both parametric (One-Way ANOVA) and non-parametric (Krustal-Wallis) tests in Table 3.3.

$H_{\circ}$: There is no significant difference between active fires and tree density.

$H_{\circ}$: There is no significant difference between active fires and plant diversity.

ANOVA is necessary for testing the difference between group means (Wilcox, 1995) of the data as an alternative method in addition to the Pearson correlation analysis to scrutinize the significance of active fires on tree density and plant diversity. Additionally, Krustal-Wallis test was also used to scrutinize the significant differences between tree density and plant diversity against active fires. As shown in the second and fourth columns in Table 3.3, The ANOVA *p-values* and Krustal-Wallis *p-values* are significantly larger than 0.05 for all three farms. Therefore, we do not reject the null hypotheses. There is no significant difference between tree density and active fires and, between plant diversity and active fires.

Table 3.3: ANOVA and Krustal-Wallis (KW-H) results used for significance test analysis.

	ANOVA		Krustal-Wallis	
	F-value	P-value	KW-H	P-value
Loskop				

Tree Density(trees/ha)	0.5751	0.6351	1.7308	0.6301
Tree Diversity	0.6047	0.6162	1.9065	0.5920
Irene				
Tree Density(trees/ha)	0.5645	0.7749	7.4971	0.3790
Tree Diversity	1.2457	0.3300	7.8877	0.3426
Roodeplaat				
Tree Density(trees/ha)	2.2316	0.1516	2.5355	0.1113
Tree Diversity	2.5664	0.1256	1.4092	0.2352

3.4.4. Discussion

This study aimed at investigating the effects of fire frequency (burned areas and active fires) on tree density and plant diversity, and to investigate the relationship between fire frequency and tree density and plant diversity at a local scale in the study areas: Loskop, Irene and Roodeplaat farms. By so doing, this study assessed the contribution of fire to bush encroachment in the study areas. To our knowledge, the assessment of the effects of fire on bush encroachment was never conducted in the study areas between the year 2000 and 2019. The Pearson correlation, ANOVA and Kruskal-Wallis tests showed no statistically significant relationship between fire frequency and tree density and plant diversity. The results of the Pearson correlation test showed a statistically significant relationship between burned areas and tree density in Irene farm. However, this significant relationship was not confirmed by the ANOVA or Kruskal-Wallis tests. This indicates that fire is not a good predictor of bush encroachment in these study areas.

Due to the absence of large mammal herbivory in some parts of Loskop and Roodeplaat farms, and highly variable burned areas, this study is consistent with Staver et al., (2009)s' study which reported that fire on its own is not enough to suppress woody plants cover (Staver et al., 2009). The cummulative effect of fire frequency and herbivory are necessary to suppress woody species proliferation (Moreira et al., 2003). The presence of highly variable burned areas indicate that the observation of increase in bush encroachment by the management of the farms may be a result of coppicing (Trollope, 1980). This is consistent with a study by Higgins et al., (2007) stating that, in arid and semi-arid savannas, due to low fuel loads, fire does not burn hot enough to kill off adult woody species and shrub saplings (Higgins et al., 2007). As a result, partially-burned adult woody plants resprout multiple shoots that grow into bushier shrubs (Mudongo et al., 2016). The same would not be true for savannas with high rainfall due to high fuel load. With that being said, low R-squares in this study indicate low correlation between burned areas, tree density and plant diversity in all three farms. Some studies have documented fire as a determinant of tree density (Sankaran et al., 2005, Scholes and Archer, 1997b). Fire among other factors has been ruled as the main driver of bush encroachment (O'connor et al., 2014, Angassa and Oba, 2008). However, Ward (2002)'s experimental study argues that fire had no effect in the increase of woody species, supported by Moleele et al., (2002). Areas of high fire frequency and low grazing, happened to be areas where bush encroahment was not observed (Moleele et al., 2002). A study on effects of fire on vegetation structure reported post-fire fast understory growth with insignificant difference in overall vegetation structure (Moreira et al., 2003). In this study, both the Krustal-wallis and ANOVA demostrated *p-values* significantly larger than 0.05 for both tree density and plant diversity in all three farms. Furthermore, the plant diversity *p-values* for both statistical analyses were all recorded at >0.5. Therefore, there is no significant difference between fire frequency and tree density and plant diversity within the study areas.

The results indicate that the relationship between tree structure (i.e tree density and plant diversity) and fire frequency in Irene is consistent with that in Roodeplaat though Irene farm experiences a higher correlation between burned areas and tree density. Both Irene and Roodeplaat farms exhibited a positive correlation between tree density, plant diversity and burned areas. This is the opposite for Loskop farm for both tree density and plant diversity. However, according to the results, it was established that fire is not a recommended measure of bush encroachment in Roodeplaat and Loskop farms, but could be useful in measuring tree density in Irene farm with more research and higher sampling size. Although statistically insignificant, the climate in Loskop may be too isolated and may be influenced by the regional climate (Murphy and Bowman, 2012). Therefore, fire may be rendered as a lesser useful tool to measure bush encroachment as compared to Irene and Roodeplaat farms surrounded by residential areas. The proximity to residential areas may have an influence on the mesoclimate of Irene and Roodeplaat farms.

The burned area data relies on only detected pixels where half a pixel needs to burn for the MODIS sensor to record it. This means that a research relying on this data alone as the independent variable will have reduced accuracy or higher error in measuring the relationship between fire and tree density as smaller fires are considered null. Future studies are therefore encouraged to use burn ratio indices to demacate burned areas. Satellites like Landsat with moderate spacial resolution may yield better burn area results than coarse spatial resolution satellite sensors like MODIS.

3.5. Conclusion

While the ecological and socio-economic effects of bush encroachment are undeniably extent in the savannas and grasslands across the world, the full understanding of the exact driving factors is still a work in progress in the science community. By testing for the relationship between fire, tree density and plant diversity, this study established that fire is not a strong indicator of bush encroachment in the study areas (Roodeplaat, Loskop and Irene farms). All three farms experience bush encroachment as observed by the farm management teams. However, the calculations indicate that this increase in woody plants is not directly linked to fire frequency with exception of Irene farm as indicated by the *P-values* in the Pearson correlation test. Because some sections in Loskop and Roodeplaat farms are not used as a result of water crisis, this may lead to lack of disturbances and accumulation of fuel load. Thus the occurrence of bush encroachment in these farms may be an indication of equilibrium model, which states that the absence of disturbances favours woody plant dominance in savannas experiencing annual rainfall of >500mm which is true for Loskop and Roodeplaat farms. Future research, therefore, should focus on multivariate studies to better pin-point the specific conditions responsible for bush encroachment in each farm. This study will assist resource managers in understanding the extent of bush encroachment in the three farms and how fire played a role and serve as a management tool for future purposes. Should the management choose to use fire as a measure of preference in combating bush encroachment, the findings of this study may serve as a guide for the management to start implementing controlled burning practices. It is recommended that burning practices be guided by a map of paths and rows of prefered satellite which provides burned area products in order to assist with pixel-based delineation of burning areas.

CHAPTER 4

Estimation of tree density change in relation to fire frequency using multitemporal satellite data spanning the period 2000-2019 on experimental farms in Gauteng and Mpumalanga, South Africa

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Abstract

The use of remote sensing has been identified as a cost-effective method for detecting and monitoring environmental change over a large area. Due to its broad view and consistency over time, multitemporal dataset is considered indispensable in land monitoring projects and change detection studies. The overarching aim of this study was to estimate the change in tree density in relation to fire over a nineteen-year period from 2000 to the year 2019 in the three Agricultural Research Council farms namely Loskop, Irene and Roodeplaat. This is done by performing change detection between two model-generated images. Multiple linear regression analysis was a crucial method in developing the models used in completing change detection for this study. The findings of this study show that fire is not a strong indicator of bush encroachment in Loskop and Roodeplat farm with exception of Irene farm. The tree density models for Loskop, Irene and Roodeplaat farms have R-squares of 0.59, 0.81 and 0.49 respectively. These values were used to choose the best performing model that best represents the tree density of the farms. Fire is experienced in all three farms however the results indicate that only one farm experiences bush encroachment as a result of fire frequency. The findings of this study serve as a guide for resource managers to better manage fire regimes and their effect on a local scale.

Keywords: active fires, change detection, remote sensing, stepwise multiple regression, tree density

4.1. Introduction

Bush encroachment negatively impacts the agricultural productivity and biodiversity of an estimated 10-20 million hectares in South Africa (Ward, 2005). Despite the widespread research on the causes of bush encroachment, it is still not well understood (Ward 2005,(Pienaar et al., 2017). Some studies define bush encroachment as the increase of trees and shrubs at the expense of herbaceous layer or grasses (Hudak and Wessman, 2001, O'Connor and Crow, 1999, Scott, 1967, Belayneh and Tessema, 2017, Ludwig et al., 2016, Stafford et al., 2017). Factors such as global climate change, variability in rainfall patterns, soil nutrients, herbivory and fire frequency have a contribution towards increasing woody species dominance (Tjelele et al., 2015, Ward, 2010, Belayneh and Tessema, 2017). The interaction of these factors largely determines the tree-grass ratio (Kraaij and Ward, 2006). Bush encroachment is considered a form of land degradation, given the extent and density of woody plants, which negatively affect ecosystem services such as the herbaceous layer (O'connor et al., 2014, Ward, 2005). Additionally, bush encroachment reduces the grazing capacity of rangelands, and therefore, it is widely regarded as undesirable by livestock farmers and land managers (Hudak and Wessman, 2001, Ward, 2005).

The use of remote sensing technology and various other methods, such as pixel-based and object-based, are being employed to closely examine and monitor the extent of bush encroachment (Vogel and Strohbach, 2009). An important factor in assessing and monitoring land degradation is doing so through access to an overview of affected areas and comprehension of large-scale events in relation to regional and local processes, and the accurate tool for this is Earth observation data (Symeonakis and Higginbottom, 2014). In the early 1970s, Landsat satellite data was widely recommended for temporally observing the changes that took place over a large area (Symeonakis and Higginbottom, 2014). However, even with remote sensing technology at our disposal, resource managers still need the assistance of remote sensing specialists to assist with the implementation of the monitoring programs based on the available data in relation to expectations and limitations (Kennedy et al., 2009). One such monitoring program is the monitoring of fires across various ecosystems around the world and their impact on human life, bush encroachment and the environment at large.

The management of fire is a practice that has been used by land managers and farmers long before modern technology (Ansell and Evans, 2020). Although the full effect of changes in traditional fire regimes in Africa hasn't been fully studied (Butz, 2009), there is evidence that natural fire regimes altered by human interference (i.e. fuel fragmentation, fire suppression, increased fire regimes) often result in adverse impacts in ecosystems ultimately leading to increased dominance by the fire-sensitive plant species (Duncan et al., 2009). Recent environmental laws prohibit and condemn planned burning and recognize it as a land degradation catalyst alongside modern conservationists frowning upon traditional burning practices (Butz, 2009). However, (Trauernicht et al., 2015) argues that planned burning is sustainable because it creates pyrodiversity and conserves resources. Monitoring the management of fire regimes in agriculture is necessary in the evaluation of adaptive management, comparison of natural fire regimes to controlled regimes, and for future management goals (Duncan et al., 2009). Therefore, temporal satellite data is becoming a necessity for land management. While MODIS datasets are considered useful for creating time series, their low level of detail makes them less suitable for use in areas with a variety of different types of vegetation (Khazieva et al., 2022).

With its broad view and consistency over time, satellite remote sensing serves as an excellent tool for land monitoring and resource management (Kennedy et al., 2009). Satellite remote sensing presents an opportunity to study both abrupt and slow environmental changes (Verbesselt et al., 2010), making countermeasures more effective (Kennedy et al., 2009). The detection and characterization of change on the surface of the Earth provides an opportunity to study vegetation dynamics over large areas with no easy access like thicket biomes and hazardous areas like Chernobyl (Gemitzi, 2020, Hyvärinen et al., 2019). This is a valuable resource for assessing long-term projects such as rehabilitation programs with limited budget (Kennedy et al., 2009).

A number of satellite tools like Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, Along-Track Scanning Radiometer–2 (ATSR-2) and Tropical Rainfall Measuring Mission Visible and Infrared Scanner (TRMM VIRS) have been widely used to map active fire and as a result, led to archives of fire history that are freely accessible to the general public (Duncan et al., 2009). In a study by Chen et al., (2017) investigating fire regimes and their characteristics using MODIS fire products, it was found that among other factors, vegetation was a driver of fire patterns (Chen et al., 2017). White et al., (1996) suggests that fire leaves behind a physical characteristic/burn scar (e.g., Soil colour alteration and tree canopy) on the landscape, which can be studied using remote sensing fire products. The use of remote sensing has been identified as a cost-effective method for detecting and monitoring environmental change over a large area (Gillanders et al., 2008a). Satellite data can be used to detect these physical changes from fire and to map the severity and intensity of the fire temporally and spatially (White et al., 1996). Because fire affects vegetation recovery, soil exposure, texture and soil colour, it ultimately affects the reflectance properties of these elements, making it possible to map tree changes like tree density over time (Jakubauskas, 1996) by studying the spectral reflectance through a technique called change detection (White et al., 1996).

Understanding the effects of fire on vegetation is crucial for predicting long-term plant distribution and patterns. For instance richness and density of tree and herbaceous seedlings in a long-unburned and burned areas was found that seedlings were more abundant in unburned areas than burned areas (Salazar and Goldstein, 2014). This suggests that fire hindered seedling establishment in this study areas especially less fire-adapted species. Although frequent fires are known to exacerbate tree mortality in savannas, it is still uncertain how it affects the growth of surviving trees (Hoffmann et al., 2002). Repeated burning reduces the number of trees but could also stimulate growth by decreasing competition and thereby directly affecting tree density change (Frost and Robertson, 1985).

Various change detection methods have been utilised in bush encroachment studies (Britz and Ward, 2007, Munyati et al., 2011, Oldeland et al., 2010). Some of the change detection methods suitable for studying bush encroachment include image differencing, image regression, vegetation index differencing and change vector analysis (JHA and Unni, 1994, Johnson, 1994, Lambin, 1996, Lyon et al., 1998, Muchoney and Haack, 1994). The broadly common method of detection of change in tree density as a result of fire is through the use of Normalized Difference Vegetation Index (NDVI) where a comparison of two spectral images is made (Ke et al., 2015). This method investigates the relative vegetation greenness across a landscape by generating a pixel-by-pixel representation of the study area before and after fire (Hammill and Bradstock, 2006). Among other vegetation indices like Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI) and more, NDVI remains the commonly used (Ke et al., 2015). Normalized Difference Vegetation Index is a useful tool in remote sensing and can be highly accurate in the absence of other influential factors like soil, water, complex landscape, atmospheric interference and sometimes even anthropogenic activities (Hammill and Bradstock, 2006). Using multiple indices may be necessary to gain a comprehensive understanding of the state of vegetation in an area, as no single index is a perfect indicator of vegetation condition (Atzberger et al., 2011).

Lu et al., (2004) demonstrated the difficulty in choosing the appropriate change detection method for specific studies and outlined various methods, their merits and demerits. Image differencing is the method of choice in this study due to its accommodation of models and single bands. This study investigated the extent of bush encroachment in relation to fire at the Agricultural Research Council (ARC) farms namely Loskop, Irene and Roodeplaat by performing change detection between two model-generated images over time (i.e. between years 2000 and 2019).

The overarching aim of this study was to estimate the change in tree density over a nineteen year-period from 2000 to the year 2019. This study investigated change in tree density in relation to fire frequency in three study sites located in Mpumalanga and Gauteng. The specific objectives of this study were to:

1. To develop remote sensing-based statistical models to estimate tree density.
2. To determine the extent of tree density change between 2000 and 2019.

4.2. Materials and Methods

4.2.1. Study Area

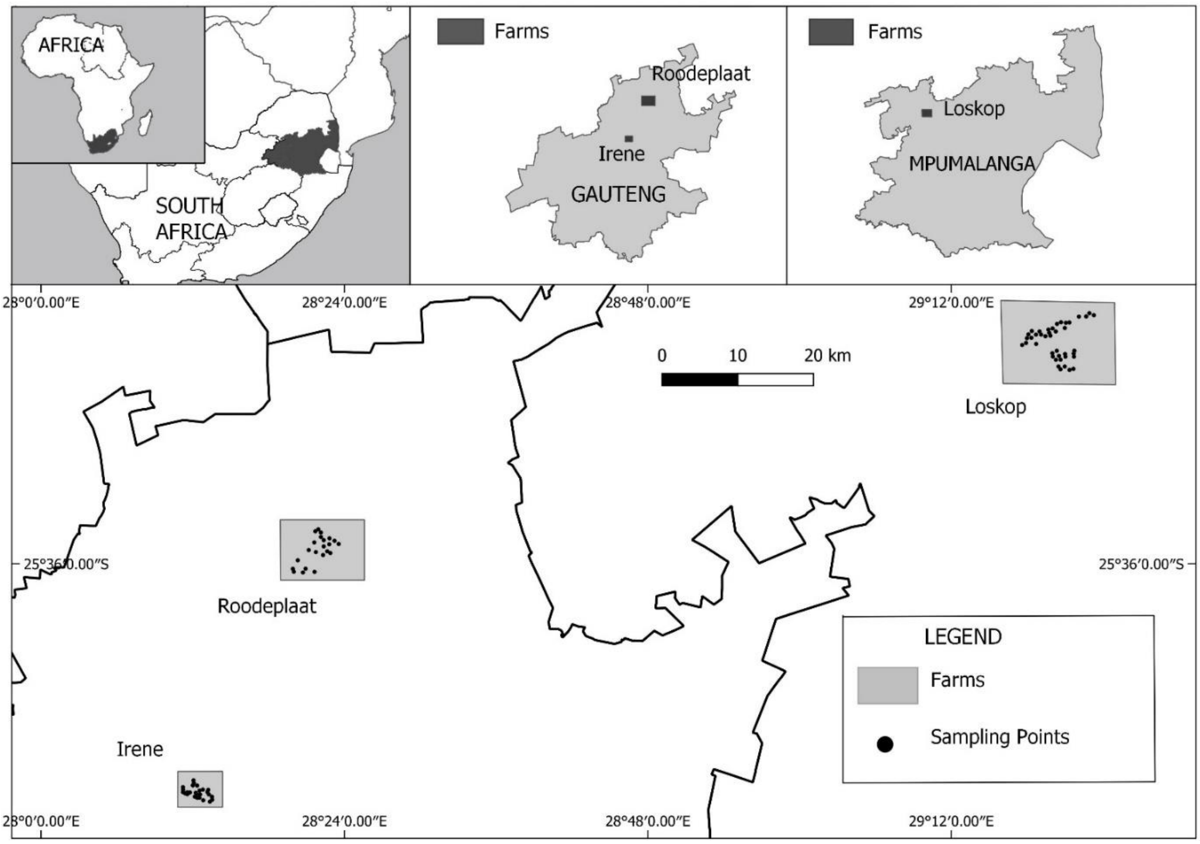

Figure 4.1: Map showing study sites at ARC Roodeplaat, Irene and Loskop farms in Gauteng and Mpumalanga Provinces.

The study was conducted at the ARC experimental farms: Loskop, Irene and Roodeplaat. The farms are located at the following coordinates, Loskop (25°18'7.56"S 29°18'20.772"E), Irene (25°53'56.6484"S 28°12'32.2416"E) and Roodeplaat (25°33'25.9236"S 28°21'41.8068"E) South Africa. Loskop farm is located in the Mpumalanga province, close to a village named Ntwane. It is situated 8 kilometres outside the Limpopo Province. (Pambu-Gollah et al., 2000). Ntwane is 1216 m above sea level in a semi-arid climate with relatively low annual rainfall of approximately 617 mm and mean annual temperature of 18.5 degree Celsius (Barrett et al., 2010). The most prevalent woody species on Loskop farm are *Dichrostachys cinerea, Gymnosporia buxifolia, Combrectum apiculatum, Euclean crispa, Vachellia nilotica* and *Vichellia tortilis*. The dominant grass species on this farm are *Aristia congest sp, Digitaria eriantha, Eragrostis sp, Heteropogon contortus* and *Thermada triandra*.

The Irene experimental farm is specifically located in Centurion, Gauteng Province, it sits at an altitude of 1430 m above sea level with an average annual temperature of around 17.1 degree Celsius (Montjane et al., 2020). Centurion has a warm and temperate climate with summer rainfall of approximately (708 mm per annum) (Montjane et al., 2020). The most prevalent woody species in this farm are *Vachellia karoo,* among other species like *Senegalia caffra* and *Searsia pyroides*. The dominant grass species found in Irene farm are *Eragrostis sp, Digitaria ariantha, Aristida congesta and Eragrostis sp.*

Roodeplaat is situated at approximately 10 km North-east of the Pretoria Central Business District (CBD). The natural vegetation component of Roodeplaat farm that is used for livestock and wild-herbivore production makes up an area of approximately 2100 ha. This farm has an altitude of 1281 m above sea level (Mkhize, 2015). The vegetation type is Marikana Thornveld (Mucina and Rutherford, 2006), which is characterized by *Vachellia karroo* and *Senegalia caffra* (Kyalangalilwa et al., 2013). The farm is also dominated by *V. tortilis*, *Ziziphus mucronata*, and some *Euclea* species. The main grass species on the site are *Digitaria eriantha, Panicum coloratum, Setaria sphacelata, Eragrostis curvula, Themeda triandra* and *Heteropogon contortus*. The mean annual rainfall is 646 mm, which largely falls between November and March. The minimum and maximum summer and winter temperature ranges from 20-29 °C and 2-16 °C, respectively (Panagos et al., 1998). The study area is situated on the Roodeplaat Igneous Complex with average annual rainfall of 646 mm (Panagos et al., 1998).

Because of water shortages, certain areas of the Loskop and Roodeplaat farms were not used for grazing. This is likely to have an impact on the herbaceous layer and ultimately, the likelihood of fires. Animals were rarely seen in these areas as they congregated around the available water points. There are no intentional burning practices in all three farms, and any fires that occur in the farms are accidental.

4.2.2. Sampling design and data collection

In this study, random GPS coordinates were chosen as sampling points to gather data on tree density and plant diversity. The sampling points were chosen based on the NDVI values determined before data collection. Points that had statistically similar NDVI values were excluded when placing the Transect lines for data collection to calculate tree density and plant diversity. Data for both tree density and plant diversity was obtained using the same transect line for each sample point. This data was gathered during the wet season of 2018 which overlapped into early 2019. The wet season in South Africa starts in October and ends in March of the following year with the dry season lasting all winter through to September. The number of sampling points varied among the three farms in the study, with 41 sampling points in Loskop, 26 in Irene, and 22 in Roodeplaat.

Excluding areas with similar NDVI values ensures that the data collected is more representative of the variety of vegetation conditions within the study area, rather than being skewed towards a single condition. This is because NDVI values that are similar tend to indicate similar vegetation density or condition (Pettorelli et al., 2005). However, the exclusion of these values was not applied consistently across all the farms, resulting in uneven sampling points.

4.2.2.1. Tree density data

Data on tree density was gathered along a belt or line transect measuring 50 meters in length and 2 meters in width, resulting in an area of 100 square meters. The tree density was calculated as the number of tree species per 100 square meters (1/100th of a hectare). To obtain the number of trees per hectare for each sampling point, the total number of trees per transect was multiplied by 100 (Beyene, 2015).

4.2.2.2. Plant diversity data

The point centered quarter method (PCQ) was used to measure the grass species in 1 square meter plots located along a 50-meter line at each sample point. (Flombaum and Sala, 2007). Five 1 square meter plots were placed at intervals of 10 meters starting from 0 meters. The Simpson Index (Equation 4.1) was calculated for each sample point to produce one value for the PCQ data (Hunter and Gaston, 1988). The Simpson Index evaluates diversity by taking into account the number of species found in a location and the relative abundance of the recorded species, and it is considered a dominance index, unbiased and appropriate for this study (Hunter and Gaston, 1988, Simpson, 1949).

The Simpson Index equation:

$$D = 1 - \left(\frac{\sum n(n-1)}{N(N-1)}\right) \quad \text{……………………………Equation 4.1}$$

n = Total number of organisms in one species.

N = Total number of all recorded organisms in all available species.

4.2.2.3. Landsat data

Because the *in-situ* data used in this study was collected in a wet season of 2018 (i.e., November 2018 to March 2019), the satellite images used in this study were also acquired for the wet season. The images used were from the Landsat 8 Operational Land Imager (OLI) and Landsat 5 Thermal Mapper (TM) satellite sensors. The satellites images are on path 170 and row 78. The surface reflectance data with level 2 correction was downloaded from United States Geological Survey (USGS) earth explorer website https://earthexplorer.usgs.gov/ [accessed on 17th of November 2021]. Both Landsat 8 and Landsat 5 data were downloaded in atmospherically corrected format (Table 4.1). Data pre-processing was performed to rescale the reflectance values into percentage. This data was used to calculate the indices and for the extraction of single bands values used in the calculation of the regression models used to create the change detection maps.

Table 4.1: A table showing the corresponding bands, their wavelengths and resolution between Landsat 8 OLI and Landsat 5 TM.

Band name	Landsat 8	Landsat 5	Resolution
BLUE	BAND 2 (0.45-0.51 µm)	BAND 1 (0.45 - 0.52 µm)	30 m
GREEN	BAND 3 (0.53-0.59 µm)	BAND 2 (0.52 - 0.60 µm)	30 m
RED	BAND 4 (0.64-0.67 µm)	BAND 3 (0.63 - 0.69 µm)	30 m
NIR	BAND 5 (0.85-0.88 µm)	BAND 4 (0.76 - 0.90 µm)	30 m
SWIR 1	BAND 6 (1.57-1.65 µm)	BAND 5 (1.55 - 1.75 µm)	30 m

4.2.2.4. MODIS active fire product (MCD14ML)

The MODIS Active Fire product is created using an algorithm that uses specific criteria of brightness thresholds to analyse the temperature data from the middle-infrared and thermal infrared channels of the MODIS instrument to detect active fires (Giglio et al., 2018). The MODIS collection 6 (M6) active fire product was obtained for the three study areas, covering the entire year, for nineteen years between the years 2000 and 2019. The product is available in Near Real-Time (NRT) format generated few hours after observation known as MCD14DL and is later replaced by a more consistent standard quality fire data known as MCD14ML, usually available two to three months after NRT data generation (Fornacca et al., 2017). The NRT fire data has less fire accuracy than the processed MCD14ML, which is processed more than once. The MODIS sensor has a spatial resolution of 1km, and the location of the detected fire is not pinpointed to its exact location but rather in the center of the pixel. It has the ability to recognize fires within an area of 50m^2 (Giglio et al., 2018, Giglio et al., 2016). The product includes the date, geographic location, and additional information for each identified pixel. Additionally, a series of validation tests are carried out on the pixels to enhance its accuracy (Fornacca et al., 2017). The active fire locations data also included fire data from the 350m Visible Infrared Imaging Radiometer Suite (VIIRS). This data was downloaded from https://modis.gsfc.nasa.gov/data/dataprod/mod45.php [Accessed 17 January 2020] and no further pre-processing was done. This data was used as a variable in the calculation of the multiple regression models.

4.2.3. Data analysis

Surface reflectance data corresponding to each sampling point was extracted from the Landsat images for all three farms (Loskop, Roodeplaat and Irene) to execute statistical analysis.

The vegetation indices listed in Table 4.2 below were computed from the extracted surface reflectance data.

The initial dataset used in this study consisted of tree density, plant diversity and active fires data acquired from MODIS active fire product. For each farm (i.e. Loskop, Irene and Roodeplaat), active fires were observed and recorded for a period of nineteen years from the year 2000 to 2019 within 500m buffer zone of each GPS coordinate where *in-situ* data was collected. The period of nineteen years is the longest possible period to study fire using the MODIS sensor because it started operation in the year 2000.

Individual Landsat spectral bands and six vegetation indices were chosen for this study to calculate the significant models needed to predict the tree density in all three farms. These indices were chosen based on their relevant accuracy in vegetation analysis. The spectral bands used to calculate the six indices were also included in the calculations of the significant models. The significant models were further used to calculate tree density maps. For the calculation of vegetation indices, the Near Infrared (NIR) band and the red band were crucial because NIR is highly reflected, while Red band is highly absorbed by healthy plants (Pettorelli et al., 2006). These two bands are found in five of the six indices demonstrated in Table 4.2 below.

Table 4.2: List of all 6 indices used in this study

Index	Conventional formulae	Reference
SAVI	$((1 + L) * R_{NIR} - R_{RED})/((R_{NIR} + R_{RED}) + L)$	Huete (1988)
NDVI	$(R_{NIR} - R_{RED})/(R_{NIR} + R_{RED})$	Gitelson et al. (1996)
ARVI	$(R_{NIR} - (2*R_{RED}) + R_{BLUE})/(R_{NIR} + (2*R_{RED}) + R_{BLUE})$	Kaufman and Tanre (1992)
EVI	$2.5 * (R_{NIR} - R_{RED})/R_{NIR} + (6 * R_{RED}) - (7.5 * R_{BLUE}) + 1$	Huete et al. (1997)
GCI	$(R_{NIR}/R_{GREEN})-1$	Boegh et al, (2002)
SIPI	$(R_{NIR} - R_{BLUE})/(R_{NIR} - R_{RED})$	Pe˜nuelas et al. (1995)

SAVI = soil adjusted vegetation index, NDVI = normalized difference vegetation index, ARVI = atmospherically adjusted vegetation index, EVI = enhanced vegetation index, GCI = green chlorophyl index, SIPI = structure insensitive pigment index.

4.2.3.1. Multivariate analysis for tree density models

Tree density models based on remote sensing variables were calculated using Stepwise Multiple Linear Regression (SMLR). The predictor variables used to formulate a significant model for each farm consisted of tree density, plant diversity, active fires, Normalized Difference Vegetation Index (NDVI) (Gitelson et al., 1996), Soil Adjusted Vegetation Index (SAVI) (Huete, 1988), Atmospherically Resistant Vegetation Index (ARVI) (Kaufman and

Tanre, 1992), Enhanced Vegetation Index (EVI) (Huete et al., 1997), Green Chlorophyll Index (GCI) (Boegh et al., 2002), Structure Insensitive Vegetation Index (SIPI) (Pen Uelas et al., 1995), Red band, Blue band, Green band, Near Infrared (NIR) and Short-wave Infrared (SWIR). The optimal model was selected based on the lowest Akaike Information Criteria (AIC) value. The AIC value is a mathematical criterion used to select the best-fit model (Wagenmakers and Farrell, 2004). The models with the lowest two AIC values were selected for comparison in deciding the best-fit model based on additional statistical coefficients and validation.

The dataset was processed and analysed using R software, a free software environment for statistical computing and graphics https://www.r-project.org/ [accessed 06th of March 2022]. The most statistically significant multiple regression linear model was substituted into the linear equation: Y = mx + c, where Y is the tree density in a farm, mx is the gradient of the linear equation and c is the intercept.

Validation of the regression model

To validate the selected regression models, hundred bootstrap samples were calculated for the variables within significant models for the three study areas. Furthermore, a simple linear regression between observed and predicted tree density values was calculated. The R-squares, RMSE and RRMSE were calculated and used to determine the accuracy of the calculated tree density models subsequently used for change detection.

4.2.3.2. Change detection – image differencing

Image differencing is categorized as one of the least complex change detection methods (Lu et al., 2014, Lu et al., 2004). One of the disadvantages of image differencing is that it does not provide detailed change matrix and therefore requires thresholds to identify areas of change and no change (Fung and LeDrew, 1988). Several methods such as combining different indices to overcome this drawback are in use today. Combining different indices such as NDVI and NDWI or NDBI can give more detailed information about changes that have occurred in the area. By using multiple indices, you can identify changes in different types of features, such as tree density change (Madasa et al., 2021).

This study focused on change detection around sampling points and therefore the visual change analysis was not a high priority. The tree density change image was generated by subtracting the before image from the after image and the pixel values were extracted to sampling points for quantitative analysis using raster calculator tool in ArcGIS software.

To calculate the change detection image, the statistical coefficients (AIC, *p-value*, and R-squared) calculated in stepwise regression were used to identify a significant model used to calculate the tree density maps for the years 2000 and 2019. The difference between the after image (2019 map) and the before image (2000 map) indicated the areas of change and no-change on a map. After differencing the two images, the final tree density map was used to extract values from the map to the sampling points. The tree density values at the sampling points were sorted into positive and negative values. The positive values indicated an increase in tree density while the negative values indicated a decrease in tree density.

4.3. Results

4.3.1. Descriptive statistics

Table 4.3 below illustrates measures of central tendency and measures of variability of the datasets from the three farms. The descriptive statistics reports the minimum and maximum values, mean, standard deviation and correlation coefficient (CV) computed using R programming software. High values of CV represent high level of dispersion around the mean (Fisher and Marshall, 2009). Remote sensing variables, i.e., spectral bands and vegetation indices have similar means for all three farms with CV predominantly lower than 30%. The *in-situ* variables, i.e., tree density, plant diversity and active fires have CV close or larger than 100% for all three farms signifying higher variability.

Table 4.3: Descriptive statistics of the data used in this study.

Variables	Min	Max	Mean	Standard Deviation	Coefficient of variation (%)
			Loskop		
DENSITY	0	11500	2020	2727,46	135,02
DIVERSITY	0	0.9	0,42	0,41	97,05
FIRES	0	3	0.6	0.78	129.6
NDVI	0.31	0.61	0.43	0.07	16.28
SAVI	0.08	0.15	0.11	0.02	18.18
ARVI	0.09	0.41	0.22	0.07	31.82
EVI	0.16	0.32	0.23	0.04	17.39
GCI	1.29	3.11	1.97	0.46	23.35
SIPI	1.12	1.56	1.29	0.09	6.976
NIR	0.17	0.25	0.2	0.02	10
BLUE	0.03	0.07	0.05	0.01	20
RED	0.05	0.1	0.08	0.01	12.5

GREEN	0.05	0.09	0.07	0.01	14.29
SWIR1	0.18	0.3	0.25	0.03	12
			Irene		
DENSITY	0	9300	1273,07	2449,09	192,37
DIVERSITY	0	0.9	0,35	0,39	112,54
FIRES	0	7	2.65	2.06	77.5
NDVI	0.37	0.69	0.55	0.08	14.55
SAVI	0.19	0.33	0.26	0.04	15.38
ARVI	0.14	0.51	0.34	0.1	29.41
EVI	0.22	0.43	0.32	0.06	18.75
GCI	1.86	3.44	2.57	0.43	16.73
SIPI	1.06	1.43	1.18	0.1	8.475
NIR	0.21	0.29	0.25	0.02	8
BLUE	0.03	0.05	0.04	0	0
RED	0.05	0.11	0.07	0.01	14.29
GREEN	0.05	0.09	0.07	0.01	14.29
SWIR1	0.2	0.28	0.24	0.02	8.333
			Roodeplaat		
DENSITY	0	7500	2400	2798,03	116,58
DIVERSITY	0	0.9	0,49	0,44	89,04
FIRES	0	1	0.43	0.51	118.3
NDVI	0.38	0.58	0.49	0.06	12.24
SAVI	0.16	0.26	0.23	0.03	13.04
ARVI	0.17	0.37	0.28	0.06	21.43
EVI	0.19	0.32	0.28	0.03	10.71
GCI	1.56	2.71	2.1	0.32	15.24
SIPI	1.12	1.33	1.21	0.06	4.958
NIR	0.18	0.26	0.23	0.02	8.696
BLUE	0.04	0.06	0.05	0.01	20
RED	0.06	0.1	0.08	0.01	12.5
GREEN	0.06	0.09	0.07	0.01	14.29
SWIR1	0.18	0.29	0.24	0.03	12.5

Density – Trees/hectare, Diversity – plant diversity, Fires – active fires.

4.3.2. Remote sensing models for predicting tree density

Models A1, A3 and A5 are selected optimal models with the lowest AIC values (Table 4.4). The *p-values* for all selected optimal models are far below the 5% margin of error (α=0.05) with moderate to high calibration R-squares. Table 4.5 shows the optimal models variables and their statistical contribution from bootstrapping hundred samples for all three study sites. Most variables in the models for all three farms score above 50%. Validation R-squares values for the optimal models range from low to moderate. The Loskop model has the highest RMSE values and lowest RRMSE as compared to Irene and Roodeplaat models (Table 4.5). In creating the change detection/image differencing maps, the tree density before images were subtracted from the after images to acquire the tree density image difference maps in Figure

4.2, Figure 4.3 and Figure 4.4 below. The values in these maps range from negative values demonstrated in red colour and increase to positive values demonstrated in green colour, symbolizing areas of tree density increase.

Table 4.4: A table showing two best optimal models for Loskop, Irene and Roodeplaat farms.

Model	Selected Variables	P-Value	R^2	Adjusted R^2
	Loskop			
A1	GREEN, SWIR1, ARVI, NDVI, BLUE, RED	0.000004	0.5959	0.5382
A2	DIVERSITY, GCI, NIR, GREEN	0.0000081	0.5631	0.5146
	Irene			
A3	ARVI, NDVI, EVI, BLUE, SWIR1	0.0017	0.49	0.4204
A4	FIRES, GREEN, SWIR1	0.3377	0.1393	0.02191
	Roodeplaat			
A5	ARVI, GCI, NIR, BLUE, RED, SWIR1	0.0003	0.8183	0.7275
A6	FIRES, ARVI, NDVI, GCI, EVI, NIR, GREEN, SWIR1	0.0322	0.66	0.4507

Table 4.5: A table showing statistical significance of model variables and the R-squares, RMSE and RRMSE values from bootstrap results.

Variables statistical significance (%)		Model performance		
		R-squared	**RMSE**	**RRMSE%**
Loskop		0.0308	4444	5.684
ARVI	74.03			
NDVI	73.61			
RED	71.43			
GREEN	60.87			
BLUE	58.73			
SWIR1	42.86			
ARVI	74.03			
Irene		0.0354	2854	40.49
NDVI	69.23			
SWIR1	55.56			
BLUE	52.50			
EVI	50.00			
ARVI	42.42			
Roodeplaat		0.4329	2910	29.86
ARVI	92.55			
RED	90.82			
GCI	86.90			
BLUE	81.93			
SWIR1	81.61			
NIR	69.51			

RMSE - Root Mean Square Error, RRMSE – Relative Root Mean Square Error.

4.3.2.1. Loskop farm

Figure 4.2 shows the change in tree density between the year 2000 and 2019 in Loskop farm. The green colour shows increase, and the red colour shows decrease in tree density. The model (Equation 4.2) was used to generate tree density images for the year 2000 and 2019. A difference of the two images was calculated to get the change detection image shown in the map below (Figure 4.2). Figure 4.2 also shows the sampling points where tree density values of increase and decrease were extracted. The low and high values in the legend represent the overall pixel values for the entire tree density map of Loskop farm.

The Loskop optimal model used to generate the 2000 and 2019 tree density maps:

Tree density = GREEN + SWIR1 + ARVI + NDVI + BLUE + RED……………. Equation 4.2.

Final significant model with estimates from R software substituted into Y = mx + C:

Tree density = GREEN * -6.7514 + SWIR1 * 3.9525 + ARVI * 214662 + NDVI * -208609 + BLUE * -460624 + RED * 268692 + 42961

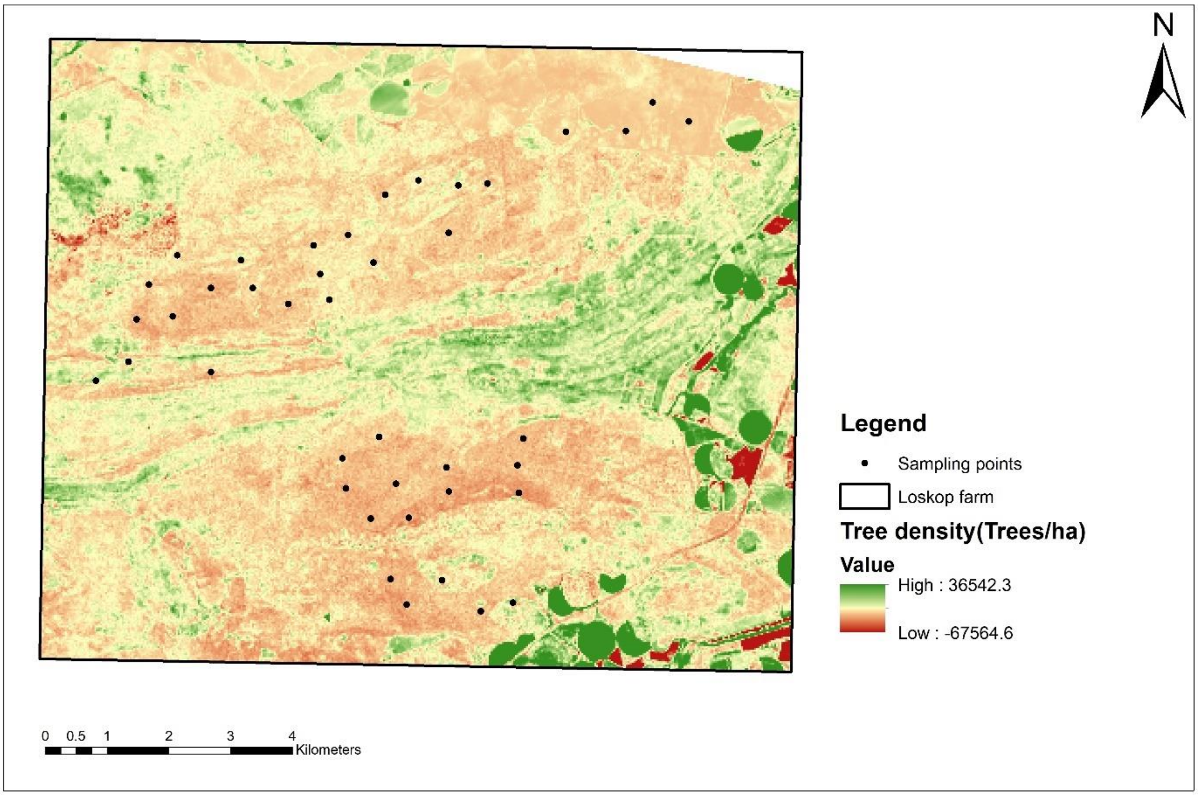

Figure 4.2: A map of Loskop farm study site showing the sampling points and areas of low tree density (Demonstrated in red) to high tree density (Demonstrated in green).

4.3.2.2. Irene farm

Figure 4.3 shows the change in tree density between the year 2000 and 2019 in Irene farm. The green colour shows increase, and the red colour shows decrease in tree density. The model (Equation 4.3) was used to generate tree density images from the year 2000 and 2019. A difference of the two images was calculated to achieve the change detection image shown below in Figure 4.3. Figure 4.3 also shows the sampling points where tree density values of increase and decrease were extracted. The low and high values represent the overall pixel values for the whole tree density map of Irene farm.

The Irene optimal model used to generate the 2000 and 2019 tree density maps:

Tree density = ARVI + NDVI + EVI + BLUE + SWIR1…………………. Equation 4.3.

Final significant model with estimates substituted into Y = mx + C:

Density = ARVI * 28.674 + NDVI * -27.578 + EVI * -8.395 + BLUE * -351415.4 + SWIR1 * 66741.1 – 908.9

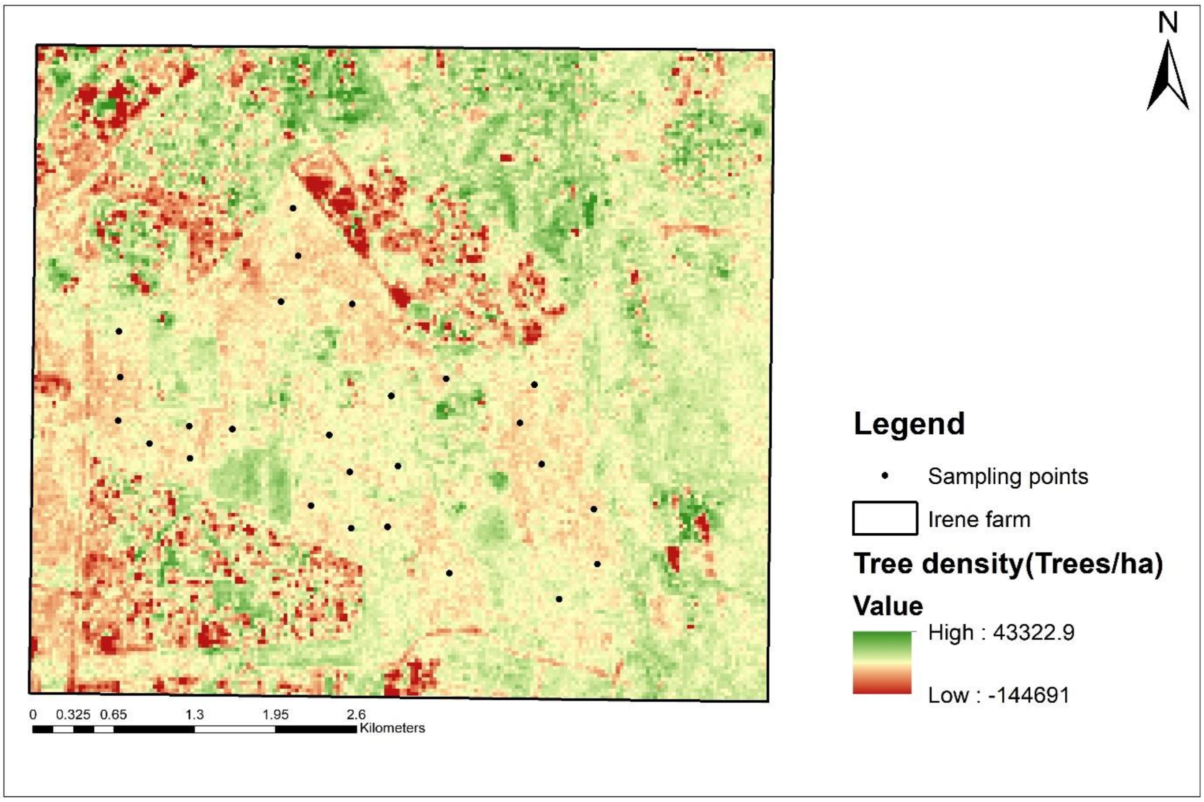

Figure 4.3: A map of Irene farm study site showing the sampling points and areas of low tree density (Demonstrated in red) to high tree density (Demonstrated in green).

4.3.2.3. Roodeplaat farm

Figure 4.4 shows the change in tree density between the year 2000 and 2019 in Roodeplaat farm. The green colour shows increase, and the red colour shows decrease in tree density. The model (Equation 4.4) was used to generate tree density images from the year 2000 and 2019. A difference of the two images was calculated and the result is a change detection image shown below in Figure 4.4. Figure 4.4 also shows the sampling points where tree density values of increase and decrease were extracted. The low and high values represent the overall pixel values for the entire tree density map of Roodeplaat farm.

The Roodeplaat optimal model used to generate the 2000 and 2019 tree density maps:

Tree density = ARVI + GCI + NIR + BLUE + RED + SWIR1………………Equation 4.4

Final significant model with estimates substituted into Y = mx + C:

Tree density = ARVI * -297076.7 + GCI * 18244.6 + NIR * 341386.2 + BLUE * 867590.1 + RED * -1640791.3 + SWIR1 * 79197.4 + 34214.4

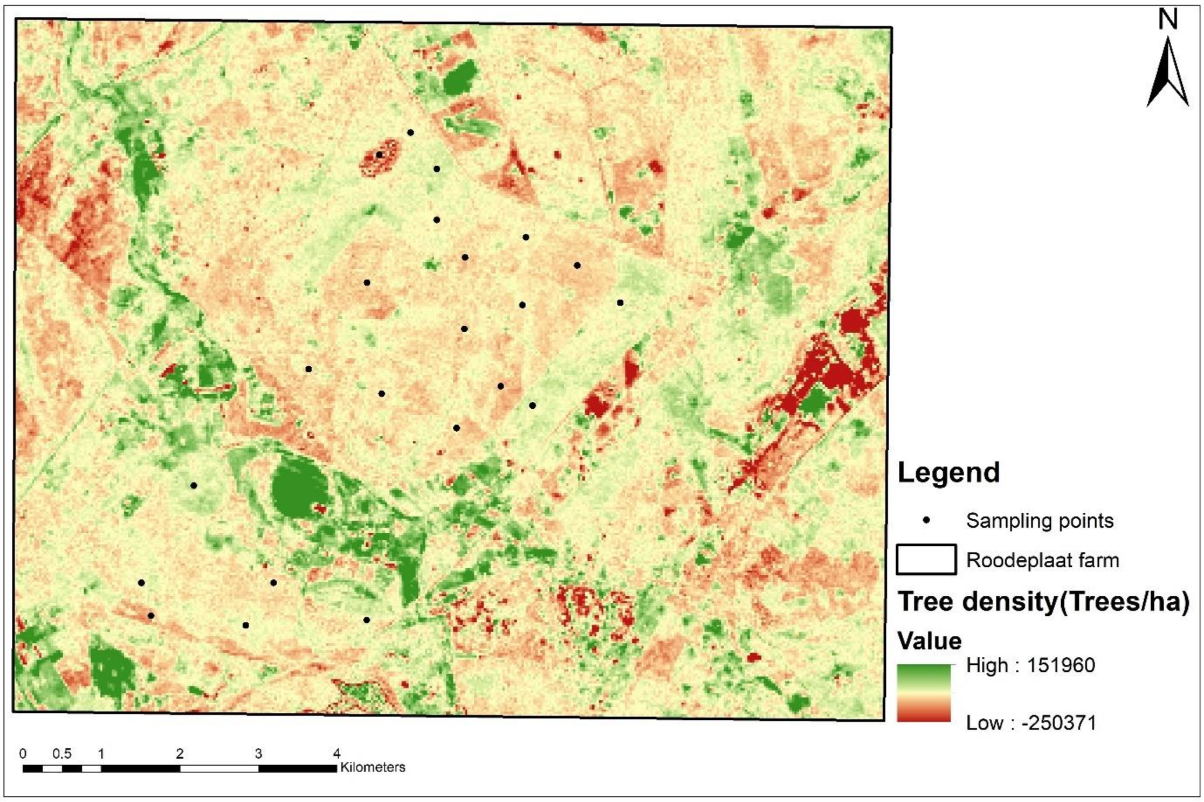

Figure 4.4: A map of Roodeplaat farm study site showing the sampling points and areas of low tree density (Demonstrated in red) to high tree density (Demonstrated in green).

4.3.3. Change detection

Table 4.6 below shows the change detection results where positive and negative values were sorted, and positive values demonstrate an increase in tree density while negative values demonstrate a decrease in tree density within a period of nineteen years from 2000 to 2019. These values were extracted from the tree density maps (Loskop, Irene and Roodeplaat) to the sampling points using a GIS software. Therefore Table 4.6 shows the quantitative representation of the tree density change at the sampling points.

Table 4.6: A table showing the change detection values extracted from the image difference map (2019-2000) for all three study sites/farms.

	Sampling Size	**Positive Values**	**Negative Values**
Loskop	41	1	40
Roodeplaat	22	2	20
Irene	26	14	12

4.4. Discussion

This study sought to estimate the change in tree density over a nineteen-year period from the year 2000 to the year 2019 in three ARC farms: Loskop, Irene and Roodeplaat. The outcome will assist in determining the extent of bush encroachment in the three study sites/farms and how fire played a role if at all using remotely sensed data from the year 2000 to 2019.

The calculated models for all three farms were significant as per the *p-values*, R squares, and adjusted R squares values. The findings of this study showed that the vegetation indices had the highest contribution to optimal models as demonstrated by the bootstrapping results. Data derived from remotely sensed imagery can be significantly enhanced by the use of vegetation indices (Baret and Guyot, 1991). However, despite the optimal models' significant calibration R squares (0.59 for Loskop, 0.49 for Irene and 0.82 for Roodeplaat), the bootstrapping results yielded low to moderate validation R squares. The validation R squares for Loskop, Irene and Roodeplaat are statistically insignificant at 0.03, 0.04 and 0.4 respectively. This renders the models as overfitting. Overfitting models describe random error in the data rather than the relationship between variables (Ghojogh and Crowley, 2019). The model is defined as an overfit when the calibration coefficients are statistically significant while the validation coefficients are statistically insignificant (Hawkins, 2004).

The tree density maps demonstrate both areas of increase and decrease in tree density between the year 2000 and 2019. Furthermore, the maps indicate that Irene farm experiences a larger distribution of areas of increase as compared to Loskop and Roodeplaat farms. However, Irene farm is smaller than Loskop and Roodeplaat farms and therefore zoomed in on the map and thereby showing more areas of tree density increase. Conversely, Irene farm tree density map also shows more areas of tree density decrease than Loskop and Roodeplaat farms. This may also be a result of scaling. A farm can experience variation in tree density across vegetation types and between camps (Bester, 1999). Roodeplaat farm tree density map shows both the highest and the lowest values of increase and decrease respectively followed by Irene and lastly Loskop. There is visual evidence of patchiness in all three farms on the change detection tree density maps which is consistent with Meyer (2009). Patchiness is created by uneven dominance by woody plants across a rangeland (Meyer et al., 2009). The integration of multiple regression analysis and satellite remote sensing has proven to be appropriate in estimating areas of change in tree density (Waser et al., 2008). A study done on the encroaching shrub *Prosopis juliflora* indicated that systematic selection of models was successful in predicting woody biomass (Birhane et al., 2017). Waser (2008) noted that different image acquisition times raised systematic errors in the predicted values of the models and these errors could affect how the results are interpreted. It is difficult not to wonder if the same errors exist in this study given the insignificant validation results.

Fire is observed in all three farms with Irene experiencing most fires in the period of nineteen years. Because there are more negative tree density values in Loskop and Roodeplaat farms, with relatively equal negative and positive values in Irene farm, this study suggests that fire is not a strong driver of bush encroachment in Loskop and Roodeplat farms with exception of Irene farm. In fact, the results demonstrate that there is a decrease in tree density in Loskop and Roodeplaat farms. Previous studies have shown that some areas experience a decrease in tree density as a response to increase in fire occurrences (Hoffmann, 1999, Innes, 1972, Russell-Smith et al., 2003).

Due to the spatial scale of this study, small fires may have been undetected by the MODIS sensor. It is a challenge for the MODIS sensor to detect small cooler fires because small and cool fires do not emit enough radiation to be detected or distinguished from non-fire radiation on the surface of the earth (Wang et al., 2007). Although the Terra and Aqua satellites have a relatively high temporal resolution of four times a day, the 1k m spectral resolution for MCD14ML active fires and 500 m spectral resolution for MCD64A1 burned area products are considered low by satellite spectral resolution standards (Zhukov et al., 2005). The MODIS sensor records active fires when the fire is hot enough and in case of burned areas, when over 50% of the pixel is burned (Giglio et al., 2018). Savannas with patchy fuel or discontinuous organic matter due to overgrazing burn less intensively and with small patchy fires (Bachelet et al., 2000). Considering that the MODIS sensor only detect hot and big enough fires, it might not be a good choice for fire products when studying fire regime that has a high potential of not being detected (Andersen et al., 2005, Frost and Robertson, 1985, Smit et al., 2016). MODIS sensor has a potential of missing or not detecting a significant amount of small fires burning at low temperatures due to overgrazing, making MODIS fire products unsuitable for fire assessment in arid and semi-arid savannas commonly known for low fire intensities (Zhukov et al., 2005).

The results also show that most of the sampling points in this study are generally located in areas of low tree density. This could be areas of grass dominance relative to high tree density areas, which would have been inaccessible during the *in-situ* data collection. Grasses tend to favour high moisture areas (Bond, 2008) and therefore future studies may explore the moisture distribution data to determine the relationship between moisture distribution and plant types. Moist savannas are said to grow more grass biomass due to the availability of moisture, leading to more aggressive fires that affect the woody species establishment (Balfour and Howison, 2002).

The sample size for each farm in this study is slightly lower than recommended for the computation of the models involved. It is recommended that for every three variables in a regression model, the research needs 30-40 observations (Babyak, 2004). This study used twelve dependent variables (i.e., active fires, plant diversity, NDVI, SIPI, SAVI, GCI, ARVI, NBR, Red band, Green band, Blue band, NIR and SWIR) interacting with one independent variable and that may have had an effect on the accuracy of the model, whereby the model represents the random error in the dataset than the relationship between the variables. All observations in the three farms were below forty-five and thus increasing the risk of collinearity and overfitting. The management of the farms might have influenced the areas of shrub dominance and non-dominance in the farms by introducing drinking points (Meyer et al., 2009). This could have resulted in an uneven grazing pressure across the farms. The findings of this study will assist in livestock and range management programs for better decision-making and planning.

4.5. Conclusion

As bush encroachment continues to degrade the savanna rangelands across the globe, innumerable number of people are affected both directly through loss of biodiversity and land productivity, and indirectly through loss of habitats and grazing land. By developing remote sensing-based statistical models, this study was able to estimate the tree density changes between the year 2000 and 2019. This study established that there are changes in tree density in the three study sites with Loskop and Roodeplaat experiencing a decrease and Irene experiencing an increase around the sampling points. The results also showed that the farm with the highest recorded number of fires (Irene farm) experienced an increase in tree density as compared to Loskop and Roodeplaat with lowest recorded fires.

Because Irene farm experiences more rainfall and more fires than Loskop and Roodeplaat farms, this is an indication that Irene farm may be located in a mesic savanna. Therefore, more frequent fires may serve as a good control measure for bush encroachment in Irene farm (Williams et al., 2002). It is advisable for future researchers on this topic to invest in the collection of new data that better accommodates the study objectives and, also to include rainfall data in the study. To balance ecosystem functions with anthropogenic demands, resource managers require the knowledge about ecosystem response to ecological changes (Gillanders et al., 2008b). This knowledge will assist in sustainable resource management, making long term landcover monitoring essential. The study also established that the MODIS sensor may not be the best source of fire data for studying local effects of fire on bush encroachment. This is due to its inability to detect small and cool fires. The SWIR1 and blue bands were common in all three remote sensing-based statistical models used to estimate tree density changes. This will assist in future research when choosing the variables for model formulation. The findings of this study serve as a guide for resource managers to help with managing fire regimes and their effect on tree density on a local scale.

The aim was to study the effects of fire frequency on tree density and the collection of data did not prioritize the areas of fire occurrence for *in-situ* data collection. Therefore, there were other factors more common than fire in the variables during model formulation. Future studies could map out burned areas and active fires and collect *in-situ* data in these areas instead of areas selected only using NDVI. Due to time constraints, new data could not be collected using the proposed method and, also to address the issue of sampling points insufficiency.

CHAPTER 5

CONCLUSION

5.1. Conclusions

This chapter is a summary of the key findings relative to the research questions and research aims. It further concludes by summarising the contribution of the two research papers covered in this study. The first paper chapter (i.e. chapter 3) aimed at assessing the influence of fire frequency on tree density and plant diversity in three experimental farms in South Africa: Loskop, Irene and Roodeplaat farms. The second paper chapter (i.e. chapter 4) aimed at estimating the tree density change in relation to fire frequency using multitemporal satellite data spanning the period of 19 years in the same farms as the first paper and using the same *in-situ* data and same MODIS active fires data. The value of this study and its contribution are also explored in this chapter as well as the limitations. This chapter will also propose recommendations for future research.

Despite the compelling amount of literature on bush encroachment, this phenomenon continues to degrade the quality of savanna rangelands across the globe effecting millions of people and threatening biodiversity and food security. The aim of this study was to investigate the effects of fire frequency on bush encroachment in ARC farms over a period of 19 years from the year 2000 to 2019. The findings suggest that the frequency of fires does not appear to significantly affect tree density and plant diversity in the study sites, except for at Irene farm. In the second paper chapter, it was also established that spectral bands and vegetation indices can explain variability in tree density. Furthermore, it was found that Irene farm experiences an increase in tree density as opposed to Loskop and Roodeplaat farms. The conclusion of this study is that it was found that the frequency of fires does not appear to lead to a notable increase in bush encroachment in the study areas, except at Irene farm, over the time period of 2000 to 2019. However, it was observed that at Loskop and Roodeplaat farms, the frequency of fires was associated with a decline in tree density.

This study will contribute to the knowledge of bush encroachment studies and fire mapping using remote sensing through the publication of two papers that used remote sensing to scrutinize fire’s temporal effects through statistical analyses and change detection. It was also established in this study that local scale fires are challenging to study or map using satellite remote sensing with coarse spatial resolution. To understand bush encroachment and tree-grass coexistence, we need to fully understand related dynamics like fire behaviour, fire-induced tree damage and tree recruitment and seed establishment (Higgins et al., 2000). The savanna fire regime is governed by the type of savanna as it has been found that moist savannas experience frequent fires than arid and semi-arid savannas (Trollope, 1980). This study adds to the understanding of these complex dynamics governing the savanna tree-grass interaction. By understanding the dynamics in the study areas, farm management will have better tools and understanding to manage the farms without loss of biodiversity and land productivity. Additionally, by understanding patterns of tree and grass dominance, land managers can better prepare for the change and act accordingly to sustain minimal adverse impacts brought by bush encroachment. This serves to minimize the economic impacts of bush encroachment. This study established that the effects of fire frequency are different in Irene farm as compared to Loskop and Roodeplaat farms. Therefore, it is necessary for future studies to assess the difference between these three farms along with bush encroachment research.

5.2. Recommendations for further study

It would be of significant value to collect more *in-situ* sampling points upon which data will be collected for a greater chance of increasing the confidence in the statistical analysis. MODIS fire products are better suited for studying forest fires or larger fires that surpass small savanna fires (Zhukov et al., 2005). It is therefore recommended that researchers seek other satellite dataset like the experimental Bi-spectral IR Detection (BIRD) mission of DLR in operation since the end of 2001 until the beginning of 2004 (Zhukov et al., 2005, Briess et al., 2003). Alternatively, Landsat thermal data can be used to map fire provided the sampling size is large enough to account for smaller fires that don't spread over a wide area. The relevant statistical analysis is invaluable when it comes to data analysis and therefore this must be chosen carefully in accordance with the sampling size limitations to the analysis methods themselves.

This study used red band in the formulation of vegetation indices. However, it has been found that the red edge band improves estimation accuracy of the vegetation indices (Ramoelo et al., 2012). The use of a less accurate red band contributes to the shortcomings of this study. Additionally, more *in-situ* variables like moisture content data and edaphic factors data could have given more depth to the study. However, due to more advanced sensors only being introduced recently outside of the temporal jurisdiction of this study, older sensors were the best options over modern advanced ones. This study found that areas of high tree density are not synonymous with areas of high fire frequency in the study areas. This could have had an impact on the outcome of the results. For future research, tree density and plant diversity data could be collected in areas of high fire frequency to study this close relationship. The findings of this study serve as a guide for resource managers to better manage fire regimes and their effect on vegetation cover at a local scale.

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