PROSOPIS INVASION IN THE NORTHERN CAPE: REMOTE SENSING ANALYSIS OF MANAGEMENT ACTION EFFECTIVENESS

By JOHANNES JACOBUS BARNARD

Thesis presented in partial fulfilment of the requirements for the degree of Master of Science at the Stellenbosch University.

Supervisors: Prof. H.M. de Klerk, Prof. B.W. van Wilgen, Dr S. Eckert

December 2021

DECLARATION

By submitting this report electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the sole author thereof (save to the extent explicitly otherwise stated), that reproduction and publication thereof by Stellenbosch University will not infringe any third party rights and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

Date: December 2021

SUMMARY

The research presented in this thesis had the goal of comparing and applying multispectral satellite imagery and trend analysis algorithms to evaluate the effectiveness of the management of invasive alien *Prosopis* trees by comparing areas that have been subjected to different management regimes in the Northern Cape over the past 20 years.

From the analysis of a remote sensing time series, I was able to detect the response of *Prosopis* cover to management, and this research provides a baseline for a feasible monitoring framework to evaluate the effectiveness of management. While management detection success rates were lower than initially expected, the BFAST and BFAST01 trend algorithms combined with NDVI values from Landsat 7 and 8 imagery provided to be well-suited for detecting clearing in a short time, as is often done by Working for Water with large teams which manually clear a site, or in the case of farmers who can afford to use earth-moving equipment to clear dense *Prosopis* thickets in a short period.

While there are some success stories where *Prosopis* was brought under control on farms, at a broader scale the problem is out of hand. Firstly, it seems that the available scarce funding will need to be focussed on priority areas where the goals of management can be met through the implementation of adequate and sustained partnerships between government-funded assistance and farmers. In other words, limited funds should not be diluted to a point where they become too thinly spread, resulting in ineffective control. Secondly, a concerted effort to find effective biological control agents needs to be made, which, if effective, could vastly increase the effectiveness of clearing operations.

The findings of this study provide valuable insights into methods that can be used to assess the efficacy of *Prosopis* management in an arid region. Further, they show that the current outcomes of management of *Prosopis* are variable and that a unified approach would be required where all stakeholders work together to find solutions to the environmental problem.

KEY WORDS

Prosopis, invasive alien plant, remote sensing, Landsat, trend analysis, BFAST, BFAST01, Google Earth Engine, Northern Cape

OPSOMMING

Die navorsing wat in hierdie tesis aangebied word, het ten doel gehad om multispektrale satellietbeelde en tendensanalise-algoritmes te vergelyk en toe te pas om die doeltreffendheid van die bestuur van *Prosopis* te evalueer deur gebiede in die Noord-Kaap te vergelyk wat in die afgelope 20 jaar onderhewig was aan verskillende beheermetodes.

Uit die ontleding van 'n reeks satellietfoto’s kon ek die uitwerking van beheer op *Prosopis*-dekking sien. Hierdie navorsing bied 'n basis vir 'n moniteringsraamwerk om die doeltreffendheid van *Prosopis*-beheer te monitor. Alhoewel die sukseskoerse vir beheeropsporing laer was as wat aanvanklik verwag is, is die gebruik van BFAST- en BFAST01-tendensalgoritmes gekombineer met NDVI-waardes van Landsat 7 en 8-beelde baie geskik om *Prosopis*-beheer op te spoor wat binne ‘n relatiewe kort tyd gedoen is, soos dikwels die geval is met Werk vir Water wat met groot spanne 'n area met die hand skoonmaak, of in die geval van boere wat dit kan bekostig om grondverskuiwingstoerusting te gebruik om digte *Prosopis*-ruigtes binne 'n kort tydperk skoon te maak.

Alhoewel daar 'n paar suksesverhale is waar *Prosopis* op plase onder beheer gebring is, is die probleem op 'n groter skaal buite beheer. Eerstens blyk dit dat die beskikbare skaars befondsing gefokus sal moet word op prioriteitsareas waar die bestuur se doelwitte bereik kan word deur die implementering van voldoende en volgehoue vennootskappe tussen staatsbefondsde hulp en boere. Met ander woorde, beperkte fondse moet nie verdun word tot 'n punt waar dit lei tot ondoeltreffende beheer nie. Tweedens moet 'n gesamentlike poging aangewend word om effektiewe biologiese bestrydingsspesies te vind, wat, indien dit effektief is, die doeltreffendheid van beheer aansienlik kan verbeter.

Die bevindings van hierdie studie bied waardevolle insigte oor metodes wat gebruik kan word om die doeltreffendheid van *Prosopis*-bestuur in 'n droë gebied te bepaal. Verder toon dit aan dat die huidige sukses van die bestuur van *Prosopis* wisselvallig is en dat 'n eenvormige benadering nodig sal wees waar alle belanghebbendes saamwerk om oplossings vir die omgewingsprobleem te vind.

SLEUTELWOORDE

Prosopis, indringende uitheemse plant, afstandswaarneming, Landsat, tendensanalise, BFAST, BFAST01, Google Earth Engine, Noord-Kaap

ACKNOWLEDGEMENTS

I sincerely thank:

- My supervisors, Prof Helen de Klerk, Prof Brian van Wilgen and Dr Sandra Eckert for their excellent guidance, invaluable advice and continuous support and encouragement throughout my research.
- Prof Brian van Wilgen for applying his incredible editing skills to my thesis throughout the writing journey, as well as providing me with the opportunity to do this research.
- The Swiss Programme for Research on Global Issues for Development (r4d), funded by the Swiss National Science Foundation (SNSF) and the Swiss Agency for Development and Cooperation (SDC), for funding my research as part of the multinational project titled "Woody invasive alien species in East Africa: Assessing and mitigating their negative impact on ecosystem services and rural livelihood" (Grant Number: 400440_152085).
- The members of the "Woody Weeds" project, specifically Dr Urs Schaffner, for his advice regarding my research.
- Janine Basson and Prof Jaco le Roux at the Centre of Excellence for Invasion Biology at Stellenbosch University, for assisting with field trip arrangements and managing my project funding diligently.
- The staff at the Department of Geography and Environmental Studies for constructive criticism during research feedback sessions.
- My parents for their love and support.
- My friends and lecturers for ensuring my time at Stellenbosch University was great and an experience I will always remember.

This research project forms part of a larger project titled "Woody invasive alien species in East Africa: Assessing and mitigating their negative impact on ecosystem services and rural livelihood". More information about this project is available at woodyweeds.org.

CONTENTS

TABLES

FIGURES

APPENDICES

ACRONYMS AND ABBREVIATIONS

BFAST	Breaks for additive season and trend
CART	Classification and regression tree
CD:NGI	Chief Directorate: National Geospatial Information
DEM	Digital elevation model
EMR	Electromagnetic radiation
GEE	Google Earth Engine
GIS	Geographical information systems
GNSS	Global navigation satellite system
IAP	Invasive alien plants
L1TP	Level-1 terrain and precision corrected
LandTrendr	Landsat-based detection of trends in disturbance and recovery
LaSRC	Landsat surface reflection code
LEDAPS	Landsat Ecosystem Disturbance Adaptive Processing System
LiDAR	Light detection and ranging
MODIS	Moderate Resolution Imaging Spectrometer
MSAVI	Modified soil-adjusted vegetation index
NDMI	Normalised difference moisture index
NDVI	Normalised difference vegetation index
NIR	Near-infrared
RADAR	Radio detection and ranging
RF	Random forest
SLC	Scan line corrector
SVM	Support vector machine
SWIR	Shortwave-infrared
VHR	Very high resolution
WfW	Working for Water
WIMS	Water Information Management System

CHAPTER 1: INTRODUCTION

Humans have facilitated the spread of species into areas far from their origins. This has often been done deliberately in cases like the introduction of agricultural plant species as well as unintentionally where imported goods contain concealed species (Mack, Ruiz & Carlton 2003). Quite often the negative impact of invasive species outweighs the positive, leading to declines in ecosystem services and loss of biodiversity (Maundu et al. 2009; Wise, van Wilgen & Le Maitre 2012). Their management is therefore important if negative impacts are to be avoided or reduced.

1.1 *PROSOPIS* AS AN INVASIVE SPECIES

Trees in the genus *Prosopis* (also known as mesquite) are an example of such invasive species, and they are a significant problem in the Northern Cape Province of South Africa (Henderson 1991). Previous studies have shown that *Prosopis* trees spread rapidly and form dense thickets which cannot be utilised (Bekele et al. 2018; Mwangi & Swallow 2005; Shackleton et al. 2015a).

Numerous *Prosopis* species were introduced from the Americas to the arid parts of South Africa to provide fodder, fuelwood and shade trees to aid farmers and local communities. *Prosopis* has since become invasive. Several species of *Prosopis* have hybridised, and the invasive population contributes a hybrid swarm which has become the second most widespread invasive tree genus in South Africa after Australian acacias (Henderson 2007).

Prosopis is most abundant in the arid Northern Cape Province, where it covered an estimated 1.5 million hectares in 2007, with the potential to invade up to 8 million hectares in this province alone (van den Berg 2010). About 160 000 of the 1.5 million hectares were covered by very dense *Prosopis* stands, which can't be efficiently utilised as intended for fodder or shade. Between 1974 and 2007 *Prosopis* had an estimated mean annual spread rate of 7.4% (Wise, van Wilgen & Le Maitre 2012). Invasive stands of *Prosopis* now pose threats to biodiversity, ecosystem services and human well-being in South Africa.

The environmental impacts of *Prosopis* include decreasing dung beetle (Steenkamp & Chown 1996) and bird diversity (Dean et al. 2002), as well as plant diversity (Shackleton et al. 2015a) in invaded areas. Grazing livestock and wildlife populations also decrease due to loss of grazing capacity (Ndhlovu, Milton-Dean & Esler 2011; Wise, van Wilgen & Le Maitre 2012). After a *Prosopis* invasion reaches about 80% canopy cover, grass and other herbaceous plants are no longer found under the trees (Shackleton et al. 2015a). Such dense invasions have a significant impact on groundwater levels and cause water stress in indigenous trees (Dzikiti et al. 2017; Schachtschneider & February 2013). Research by Muller et al. (2017) has demonstrated that West

African villages with *Prosopis* invasions can support more mosquitoes, creating a malaria health hazard. Wise, van Wilgen & Le Maitre (2012) found that the value of benefits decreases with an increase in areas invaded and density increases of *Prosopis*. At a point in time the negative impacts become greater than the benefits, and without intervention would continue to become increasingly negative.

1.2 MANAGEMENT OF INVASIONS

An integrated approach to managing *Prosopis* is being implemented in South Africa to reduce the impacts of invasions. Mechanical and chemical control is carried out by the state-run program Working for Water (WfW) since 1995, but private landowners also control *Prosopis* (Shackleton et al. 2017). Biological control in the form of seed-feeding insects has also been introduced to supplement the mechanical and chemical control, but it has up to now not been very effective (Impson, Moran & Hoffmann 1999); however, a more damaging biological control agent (*Evippe* species) was released in 2021.

Invasive alien plant control in the Northern Cape focused on *Prosopis* and more than 85% of control costs in arid biomes between 1995 and 2008 were attributed to *Prosopis* management (van Wilgen et al. 2012). Only four percent of the invasion in the Northern Cape was treated at a cost of 435 million rands during this period. Furthermore, research suggests that that *Prosopis* invasions are increasing at an exponential rate despite clearing efforts. Van den Berg (2010) found that the extent of *Prosopis* in the Northern Cape grew from about 77 000 condensed hectares in 1990 to 360 000 condensed hectares in 2007 – an increase of 363% over 17 years. Several studies have suggested that a different approach to the management of *Prosopis* in the Northern Cape is needed as the threat of increasing *Prosopis* population is a significant concern (Shackleton et al. 2017; van Wilgen et al. 2012; Wise, van Wilgen & Le Maitre 2012).

The current performance indicators used by Working for Water (WfW) requires them to focus on project inputs, rather than the effectiveness of the control (van Wilgen & Wannenburgh 2016). These indicators include the area of plants treated, the number of sites where beetles were released for biological control, the number of emerging invasive alien plants controlled, and the number of jobs created. Additionally, a significant portion of WfW funding is sourced from the Extended Public Works Programme (EPWP), with additional employment targets. The findings from Van Wilgen & Wannenburgh (2016) suggest that the two goals of Working for Water, namely employment creation and ecosystem conservation, lead to confusion about priorities and can hinder the effective management of *Prosopis*.

For efficient management planning and the execution thereof, reliable data and methods for monitoring the success of *Prosopis* clearing over time are required.

1.3 REMOTE SENSING AS A DECISION SUPPORT TOOL

Field mapping of the species' geographical extent and cover is difficult over large and rugged areas. Remote sensing is known for its ability to map various plant features over large aerial extents and over repeat time steps (Huang & Asner 2009). Several authors have used remote sensing as a tool to map the presence and abundance of invasive plant species, including mapping the distribution of Phragmites in the United States (Liu et al. 2016), detecting alien tree presence in Chile's temperate forest (Martin-Gallego et al. 2020) and mapping the extent of *Spartina alterniflora* in the Yellow River delta in China (Ren et al. 2021).

Remote sensing has been used for *Prosopis* mapping in several countries, as *Prosopis* is such a widespread invasion. A recent study by Mbaabu et al. (2019) has used a time series of moderate resolution satellite imagery to map *Prosopis* spread at stand level in the Baringo county in Kenya between 1988 and 2016. Accuracies of above 90% were achieved by this study. Another study by Ng et al. (2017) focused on mapping *Prosopis* distribution for the same study area using high (Sentinel-2) and very high resolution (Pleiàdes) imagery, as well as an object-oriented machine learning classification method. The authors have shown that it is viable to use slightly lower resolution imagery to map stands of *Prosopis*. In Ethiopia, Wakie et al. (2014) determined the extent and predicted the spread of *Prosopis* using low-resolution satellite imagery and geospatial modelling techniques. Robinson, van Klinken & Metternicht (2008) has used panchromatic aerial imagery to extract *Prosopis* distribution for Western Australia.

The distributional extent of the Northern Cape *Prosopis* invasion was mapped using remote sensing and a geographic information system (GIS) from 1974 to 2007 (van den Berg 2010; van den Berg, Kotze & Beukes 2013). Spectral analysis of seasonal profiles, various resolution image inputs, spectral indices and ancillary data were used for image classification. Areas of *Prosopis* invasion were mapped using coarse resolution imagery and field data using relationships between actual *Prosopis* occurrence, spectral response, soils and terrain unit. To quantify the distribution and density as well as the spatial dynamics of *Prosopis* over time multi-temporal Landsat images and a 500m x 500m point grid was used, which enabled vector analysis and statistical analysis for accuracy.

Remote sensing has been proven to be effective for the monitoring of land-use change and phenological trends over time and can be well-suited for the task of monitoring *Prosopis* management efforts over time.

1.4 RESEARCH PROBLEM FORMULATION

Knowing how effectively the *Prosopis* invasion is being managed by different groups and the combination of these management efforts is important when planning management strategies. Given that the Northern Cape spans an area of 372 889 km^2, it is not viable to send large teams out to map the occurrence and increase in cover of *Prosopis* using traditional field mapping methods involving counting trees in measured plots (Shackleton et al. 2015a). Estimating cover from a ground-based perspective can also be challenging and yield very subjective results. Furthermore, it is not possible to analyse the historical increase in cover with in-situ methods if the data was not captured in the past.

In an era where spatial data are becoming more accessible, analysis of remotely-sensed imagery offers new and improved methods to address ecological problems (Buchanan et al. 2015; Buchanan et al. 2009) such as the mapping of invasive alien plant species (Cord, Klein & Dech 2010; Huang & Asner 2009). Multispectral imagery has been used before to map the *Prosopis* invasion in the Northern Cape (van den Berg 2010), however so far these monitoring studies have not considered the aspects of management effectiveness in reducing the growing abundance of the *Prosopis* invasion in the Northern Cape province.

To evaluate management effectiveness and make recommendations for an appropriate method for future use new remote sensing trend analysis methods, that may capture detailed *Prosopis* cover dynamics over time, should be investigated (Bullock 2018; Drusch et al. 2012; Kennedy, Yang & Cohen 2010; Zhu & Woodcock 2014).

1.5 RESEARCH AIM AND OBJECTIVES

This study aims to compare and apply multispectral satellite imagery and trend analysis algorithms to evaluate the effectiveness of control of *Prosopis* by comparing areas that have been subjected to different management regimes in the Northern Cape over the past 20 years.

To fulfil the aim, five objectives were set up, namely to:

1. Carry out a literature review to become familiar with past and current techniques used to assess the *Prosopis* invasion and to identify suitable trend analysis strategies.
2. Identify farms with *Prosopis* that have been subjected to different management regimes and obtain field data through interviews, participatory mapping and fieldwork.
3. Analyse remote sensing time series algorithms to estimate the change in cover of the *Prosopis* invasion on selected farms in the Northern Cape.

4. Assess the effect of management actions on the cover of the *Prosopis* invasion in the Northern Cape.

5. Synthesise the findings into a research report.

1.6 METHODOLOGY AND RESEARCH DESIGN

Quantitative analysis of remotely sensed imagery together with field-based point or polygon data combined with interviews from farmers will be used to map the effect of different management regimes of *Prosopis* on selected farms in the Northern Cape. This study is experimental as novel methods will be tested and applied. Qualitative interview data from landowners/managers will be used to collect data on approaches used to control *Prosopis*, and to corroborate results on where and when clearing occurred.

The research design is shown in Figure 1.1. It includes the relevant objectives and chapters for the final thesis (encircled in grey). This document already provides the conceptual framework for the project, introducing the research problem, aim, objectives, design and study area.

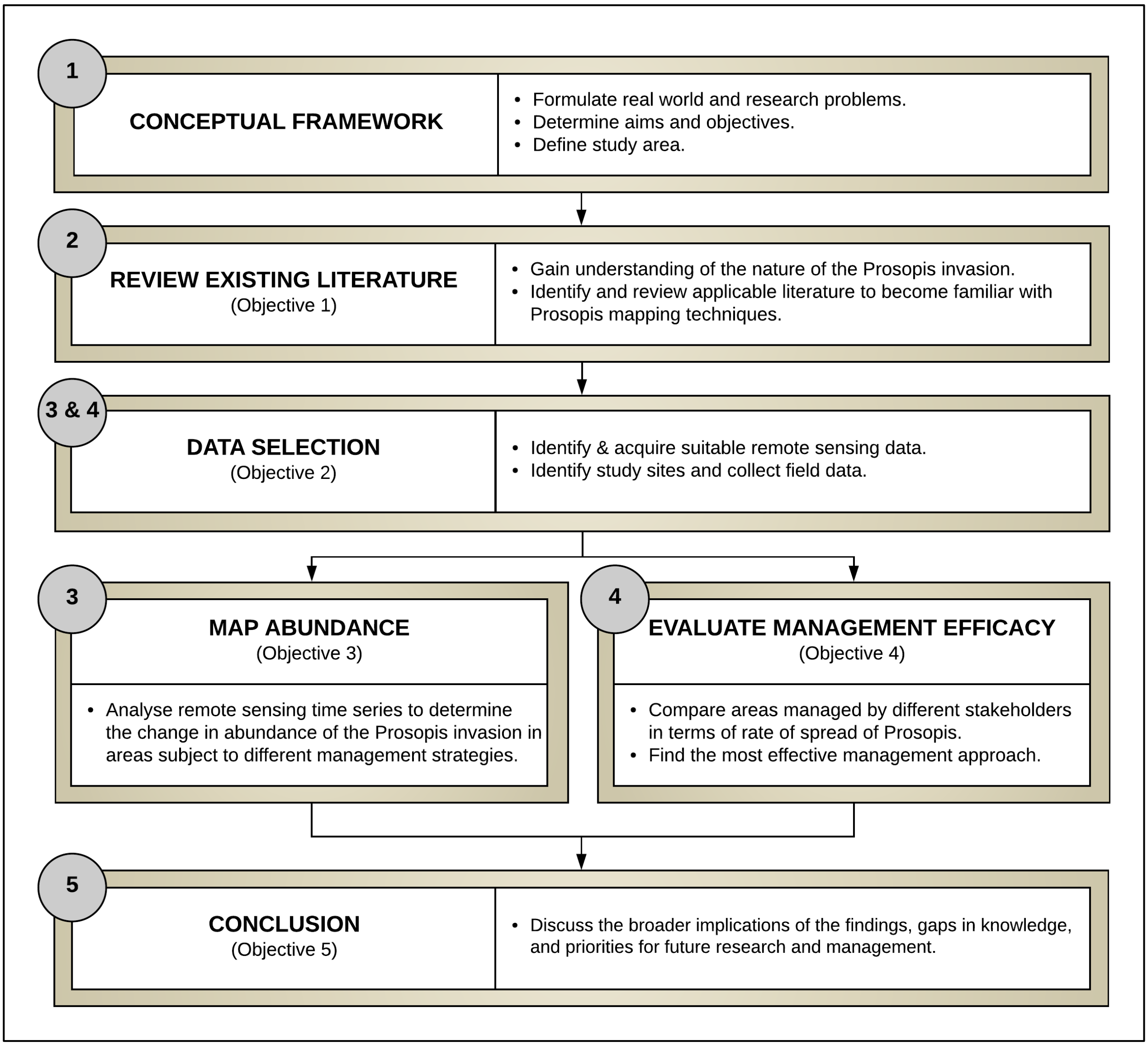

Figure 1.1 Research design with objectives and chapters (encircled)

The next chapter provides some theoretical background and reviews academic literature on remote sensing of invasive alien plants and the management strategy thereof. Chapter 3 deals with determining the change in abundance of *Prosopis* in areas subject to different management strategies in the Northern Cape using remote sensing trend analysis algorithms of satellite imagery between 1999 and 2020. The efficacy of management of *Prosopis* on these sites is evaluated in Chapter 4 based on outputs from the third chapter, as well as farmer interviews. The study is concluded in Chapter 5 with a summary and findings from both Chapters 3 and 4.

CHAPTER 2: LITERATURE REVIEW

This chapter provides a brief overview of the management of invasive alien plants in South Africa, as well as remote sensing and its use in invasive alien plant mapping, with relevant literature cited. Knowing how remote sensing is used to detect processes and objects on the earth's surface is important for understanding processing procedures and interpreting results. Firstly, an overview of *Prosopis* management in South Africa is provided, followed by an overview of remote sensing as a science.

2.1 *PROSOPIS* TREES IN SOUTH AFRICA

Trees in the genus *Prosopis* (also known as mesquite) are leguminous thorny trees that are drought tolerant with deep taproots (Pasiecznik et al. 2001; Zimmermann 1991). These trees are deciduous and have a peak growing season from spring to autumn – which roughly corresponds to the period between September to April in South Africa (Agricultural Research Council 2014). *Prosopis* trees are aggressive invaders and can spread rapidly and form dense thickets which are of very little value (Bekele et al. 2018; Mwangi & Swallow 2005; Shackleton et al. 2015b).

2.1.1 History of *Prosopis* in South Africa

Numerous *Prosopis* species were introduced from the Americas, where it is native, to the arid parts of South Africa from the 1880s (Pasiecznik et al. 2001). Alston (1914), a farmer in the Vanwyksvlei area where *Prosopis* is currently a significant problem, received seeds from a friend, John Marquard, and started planting them on his farm in 1885. Until the 1960's the planting of *Prosopis* was encouraged by the government because of the plant's ability to grow in very dry conditions (Poynton 1990). *Prosopis* pods are high in sugar, carbohydrates and protein, making them a good source of fodder (Choge et al. 2007). In the Karoo where native trees are scarce, communities make use of the shade and fuelwood that these trees provide (Shackleton et al. 2015a).

Dense *Prosopis* stands, however, significantly reduce groundwater levels and cause water stress in indigenous trees (Dzikiti et al. 2017; Schachtschneider & February 2013). After a *Prosopis* invasion reaches about 80% canopy cover, grass and other herbaceous plants are no longer found under the trees (Wise, van Wilgen & Le Maitre 2012).

In the years between the 1960s and 1980s, *Prosopis* became an increasing problem in South Africa and was declared as an invasive species by 1983 (Henderson & Harding 1992). At least six species of *Prosopis* are known to occur in South Africa, and the invasive population contributes to a hybrid swarm which is the second most widespread invasive tree genus in South Africa after Australian acacias (Henderson 2007).

2.1.2 Ecology of *Prosopis* and why it is spreading successfully

When *Prosopis* was brought into South Africa, no natural enemies were brought with it. This meant that *Prosopis* had more than 100 years to establish and spread along river courses and in low-lying areas (van den Berg 2010). *Prosopis* roots can reach into water tables, and they outcompete other plants which don't have such extensive root systems (Dzikiti et al. 2017). Deep soils also aid *Prosopis* in reaching water tables more easily. Furthermore, years with above-average rainfall have been shown to correlate to a rapid spread of *Prosopis* (Harding 1988), because the associated flow in otherwise dry river beds spreads the seeds over large distances. To worsen the problem, the Department of Agriculture actively encouraged farmers to plant *Prosopis* as a dry-land fodder plant (Harding 1988; de Klerk 2004).

2.1.3 Negative impacts of *Prosopis*

The Northern Cape is a water-scarce area with some areas declared disaster areas in 2020 due to the influence of a long drought. The high water use of *Prosopis* is thus a significant problem as it rapidly uses what little rain falls and contributes to the depletion of groundwater resources (Davis 2020; Dzikiti et al. 2013; Evans 2019; Van der Spuy 2019). A report by the Department of Water Affairs and Forestry (2005) shows that annually about 17% of groundwater is lost due to *Prosopis* invasions, which could otherwise have been used for socially beneficial economic purposes. This is equal to the groundwater proportion of the total recharge registered for use in the region. *Prosopis* also has a direct impact on grazing capacity. Shiferaw et al. (2021) estimated that *Prosopis* uses more than 3 billion m^3 of water per year in their study area in the Afar region of Ethiopia.

At low densities (canopy cover <40%) positive impacts of *Prosopis* such as increased moisture content in the upper soil layers can be seen (Wise, van Wilgen & Le Maitre 2012). The loss of grass is compensated for by the *Prosopis* pods at this stage of the invasion. However, when stands become dense, *Prosopis* outcompetes grasses around them, leading to loss of grazing capacity, as *Prosopis* pods cannot be utilized when impenetrable thickets form and livestock cannot gain access to the pods on the ground (Smit 2005).

Schachtschneider & February (2013) found that there is a significant increase in the mortality of an indigenous tree, *Vachellia erioloba*, in the Kuruman River due to water stress caused by *Prosopis*. Furthermore, Dzikiti et al. 2015 concluded that *Prosopis* uses more groundwater at stand level when compared to indigenous plant species. This is due to their rapid growth compared to indigenous trees. The authors also found that dense invasions of *Prosopis* in their study area used approximately 2.72 megalitres of water per hectare per year. Similarly, Shiferaw et al. (2021) measured that, in the Afar region of Ethiopia, a *Prosopis* tree consumes about seven litres of water per day.

2.2 PRINCIPLES OF REMOTE SENSING

All objects on the surface of the earth emit electromagnetic radiation (EMR) and reflect radiation emitted by other objects. By capturing this radiation from earth-orbiting satellites or aerial platforms and bearing in mind the interaction the signal might have had with atmospheric particles, it is possible to develop a knowledge of characteristics of surface features such as vegetation, soils, water bodies and structures (Campbell & Wynne 2011).

Usable information is stored in the structure of EMR, which consists of both an electric and magnetic component. Both the amplitude and wavelength of the wave can vary. The amplitude is measured as the maximum extent of a wave's oscillation from its equilibrium position, while the wavelength is the distance between successive peaks or troughs on the wave (Campbell & Wynne 2011). Frequency is inversely proportional to the wavelength and is measured as the number of waves that passes a fixed point per second. Variation in the frequency/wavelength of a wave can be grouped into regions, known as wavebands or spectral bands (Chuvieco 2018).

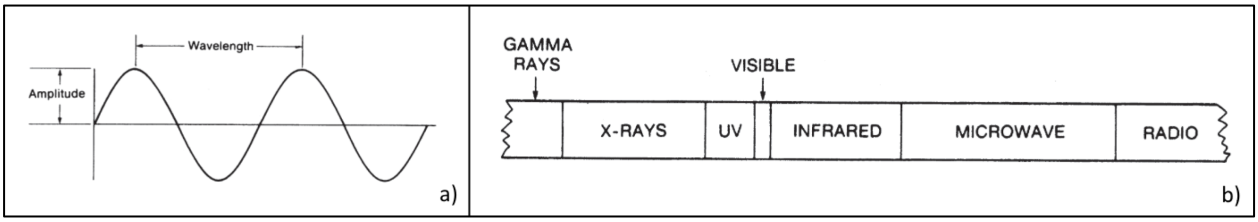

Figure 2.1 Amplitude and wavelength of a wave (a) and the electromagnetic spectrum (b)

Source: Campbell & Wynne (2011)

The most well-known portion of the EMR is visible light. Other regions of the EMR spectrum with value to remote sensing include near-infrared and shortwave-infrared.

Not all wavelengths of the spectrum can be used for remote sensing purposes. In certain portions of the electromagnetic spectrum, light is absorbed or reflected by the atmosphere and consequently would not reach objects on the earth's surface (Conway 1997). These areas do not allow light to pass through at all or only partially. Generally, remotely sensed data is captured in regions of the spectrum where atmospheric opacity is lower. These sections of the spectrum are referred to as atmospheric windows (Figure 2.2).

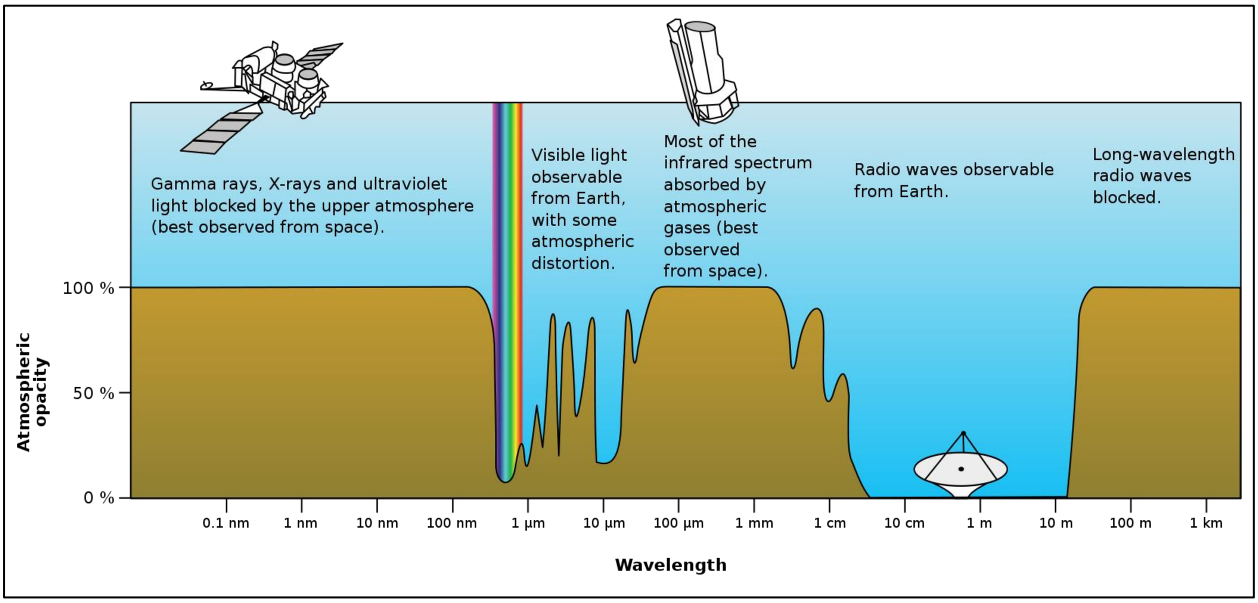

Figure 2.2 Atmospheric windows Source: GIS Geography (2018)

Notable atmospheric windows include the visible, near-infrared and radio regions. Short and infrared wavelengths are absorbed by gases such as ozone, nitrogen, carbon dioxide and water vapour (Liou 2007).

2.2.1 Sensor resolution

The amount of information captured by different sensors can vary – this is commonly referred to as the resolution of the data. Image resolution is a combination of spatial, spectral, temporal and radiometric resolution (Campbell & Wynne 2011).

2.2.1.1 Spatial resolution

The resolution of remotely sensed imagery that is mostly referred to is spatial resolution. It is a measure of the smallest object that can be resolved by a sensor (Chuvieco 2018). In other words, the smallest object visible on a remotely sensed image is determined by the spatial resolution at which the data was captured. If a sensor captures imagery at a 30-metre spatial resolution, then the smallest distinguishable object will be about 30 metres in size. The concept is shown in Figure 2.3.

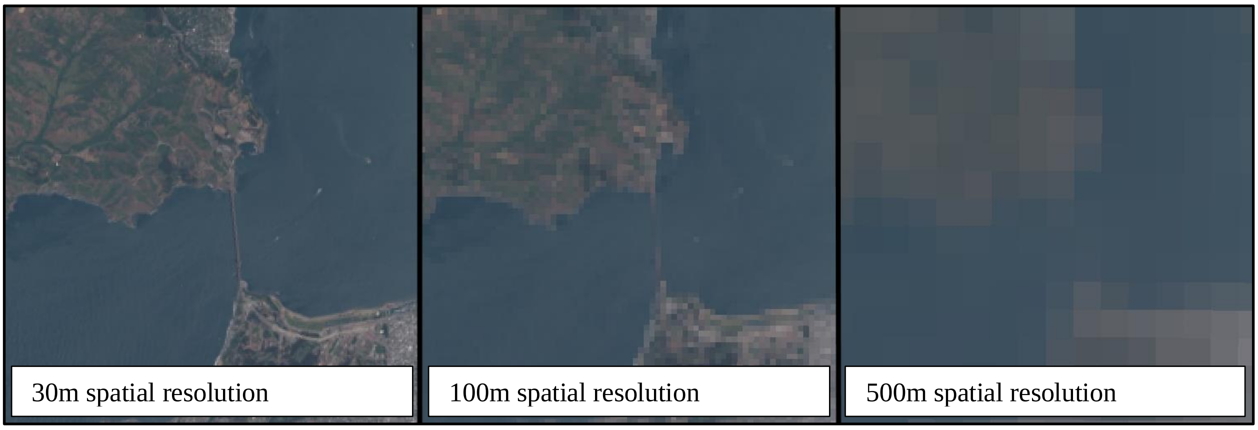

Figure 2.3 Effect of spatial resolution on satellite imagery of San Francisco – fine (left) to coarser resolution (right)

A suitable spatial resolution should be chosen to reduce intra-pixel variability. Several studies have highlighted that the optimal pixel size is less than half the size of the smallest feature to map (Alavipanah et al. 2010; Garrigues et al. 2006; Hengl 2006).

2.2.1.2 Spectral resolution

When the aim is to detect objects on the earth's surface that appear similar through visual analysis of a remotely sensed image, spectral resolution is particularly important (Lee & Carder 2002). Spectral resolution is a measure of the ability of a sensor to resolve features into separate spectral bands on the electromagnetic spectrum (Campbell & Wynne 2011). Due to physical sensor constraints, there is a trade-off between spatial and spectral resolution (Key et al. 2001), and one needs to find a sensor with the best balance for the specific mapping objective (Ose, Corpetti & Demagistri 2016)

When using narrowly defined bands one can identify details not otherwise possible, such as differentiating between tree types, whereas with broader bands it is only possible to distinguish between land cover classes i.e. trees, grass, bare ground etc (Mutanga & Skidmore 2004; Underwood, Ustin & Ramirez 2007). While hyperspectral data have definite advantages when differentiating between similar features, it is also less widely available when compared to multispectral data, as currently, only airborne hyperspectral sensors exist. Consequently, data are captured mostly for just one point in time and such flight campaigns are costly. Additionally, more storage space is required which is exacerbated when spatial resolution needs to be fine as well (Cucci & Casini 2020). Hyperspectral data also contain redundancies and the data in all bands can often be represented using only a few bands, making it a time-intensive task (Ray et al. 2010).

2.2.1.3 Temporal resolution

Since the launch of multispectral sensors on satellites, a vast number of images were captured for any given location on the earth's surface. This is possible due to the orbit speed and continuous working of satellites, unlike sensors mounted on aeroplanes which require human effort every time imagery needs to be captured. The temporal resolution refers to the time it takes a satellite to revisit a position on the earth's surface (Campbell & Wynne 2011). Higher temporal resolution imagery is favourable, especially in tropical areas where cloud cover frequently prevents sensing of objects on the earth in the visible spectrum (Eberhardt et al. 2016). A high temporal resolution also enables more detailed monitoring of change over time (Small et al. 2017).

2.2.1.4 Radiometric resolution

Sensors used on Earth-imaging satellites vary in terms of imaging capabilities. The detail each pixel can store is influenced by how detailed the sensor can capture the real world. The radiometric resolution of a sensor is defined as its ability to capture varying levels of brightness (Campbell & Wynne 2011). This resolution is indicated by the bit depth of an image. As shown on the right in Figure 2.4, a one-bit raster would be a black and white image, where each pixel can contain one of two values. Satellite images are often comprised of eight or sixteen-bit pixels, being able to store number values between zero and 2^8 and zero and 2^{16} respectively per pixel. The optical sensors aboard Landsat 1 to 7 captured satellite imagery at 8-bit radiometric depth, whereas the newer Landsat 8 optical sensor captures data at 12-bits and is scaled to 16-bit datasets for Level 1 products (United States Geological Survey 2020a).

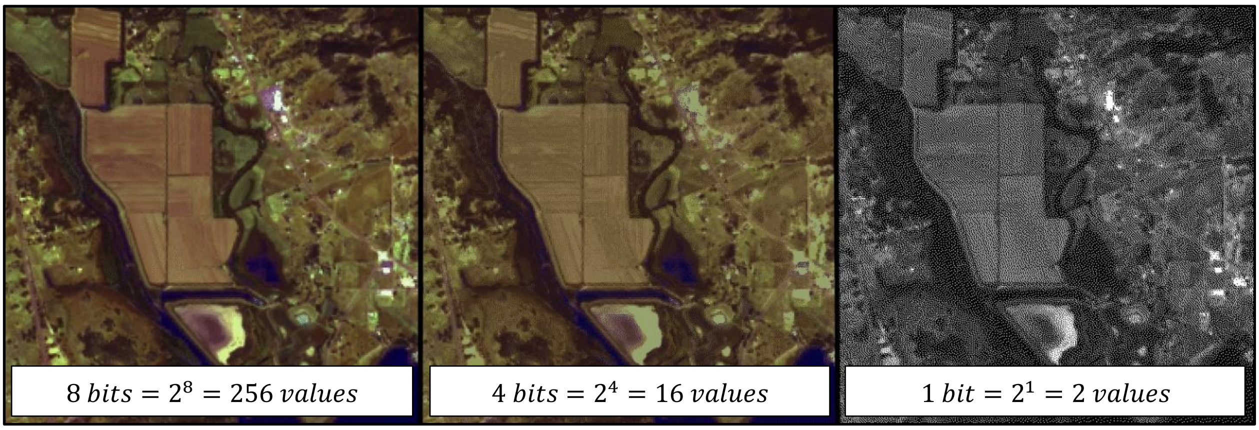

Figure 2.4 The effect of radiometric resolution on imagery

2.2.2 Active and passive sensors

Remote sensing platforms can capture data with or without the use of their own energy. In the case of multispectral sensors, such as Landsat, the sensor relies on the sun's energy reflected by objects on the earth's surface. With other types of remote sensing technology such as LiDAR (Light Detection and Ranging) and RADAR (Radio Detection and Ranging) the platform generates its own energy and does not rely on external sources of light (Campbell & Wynne 2011).

2.2.3 Spectral reflectance signature

The basis of vegetation mapping using remotely sensed imagery relies on the fact that different surface types reflect radiation differently in various spectral bands. When radiation, such as sunlight, strikes an object on the earth's surface, certain wavelengths of the spectrum are absorbed, while others are reflected. In the case of healthy vegetation, visible light – specifically red and blue – is strongly absorbed and near-infrared light is reflected (Campbell & Wynne 2011). The absorption of blue and red light is essential for the photosynthesis process (Kirkham 2014). A typical spectral signature of healthy vegetation is compared to water and soil in Figure 2.5.

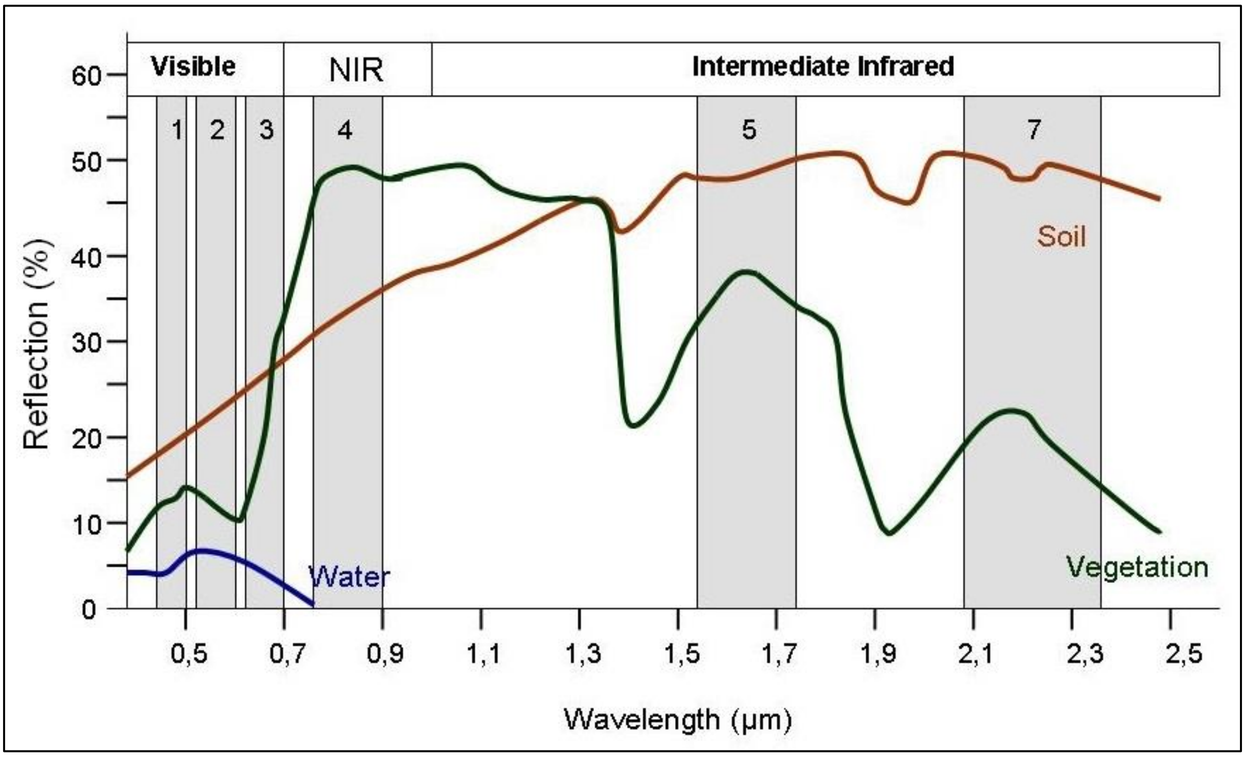

Figure 2.5 Spectral signature of vegetation (green), soil (red) and water (blue)

Adapted from: Siegmund & Menz (2005)

Spectral signatures of *Prosopis*, crops, water, bare ground, Karoo shrubs and trees were extracted from a Landsat image and are shown in Figure 2.6. These points were randomly sampled in the Northern Cape, South Africa to show how the spectral signature of plants varies from other land cover classes.

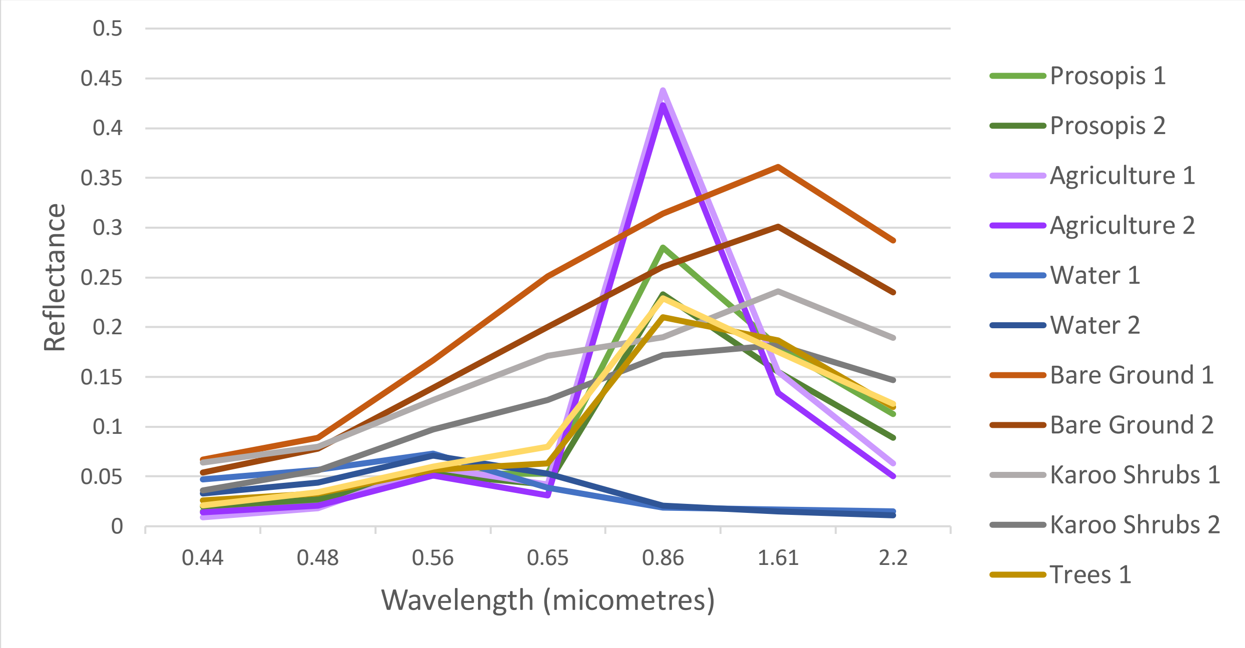

Figure 2.6 Sample spectral signatures of some land cover classes in the Northern Cape

For each land cover class, two samples are present. From this example, it is evident that the same land cover class will have some variation, but that the general trend should remain the same. The points on the graph represent the mean bandwidth of the Landsat 8 bands from band one to seven, namely coastal aerosol, blue, green, red, near-infrared, shortwave infrared 1 and shortwave infrared 2. The rapid change of vegetation from red to near-infrared is visible in the vegetation samples. This region is referred to as the red edge (Seager et al. 2005).

2.2.4 Spectral indices

A spectral index is a combination of spectral reflectance from two or more image bands where spectral differences between land cover classes are at a maximum (Jackson & Huete 1991). In general, the bands used to calculate indices are chosen such that one band decreases and the other increases with a cover increase in the land cover class(es) of interest. Vegetation indices are the most popular, but indices are available for mapping burnt areas, urban areas, water and geological features (Verstraete & Pinty 1996).

2.2.4.1 Normalised Difference Vegetation Index

One of the most-used vegetation indices is the normalised difference vegetation index (NDVI) (Carlson & Ripley 1997). It is calculated in Equation 2.1.

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \qquad \text{Equation 2.1}$$

where ρ_{NIR} is the near-infrared band value;

ρ_{red} is the red band value;

Values of the NDVI range from negative 1 to positive 1, with negative values mostly corresponding to water, values close to zero being bare ground, rocks and snow. Low positive values (up to ~0.4) correspond to shrubs and grasslands. High values indicate rainforests and dense growth (Campbell & Wynne 2011; Chen et al. 2017; Gandhi et al. 2015).

2.2.4.2 Normalised Difference Moisture Index

The Normalised Difference Moisture Index (NDMI) is sensitive to moisture levels in vegetation by utilizing the NIR and SWIR bands of the electromagnetic spectrum (Wilson & Sader 2002). It is less sensitive to atmospheric scattering effects than NDVI (Gao 1996). The SWIR reflectance values reflect changes in vegetation water content and the mesophyll of plant canopies, whereas the NIR reflectance is affected by leaf dry matter content and internal structure. This combination of bands remove the variations caused by leaf structure and only focuses on leaf water content (Ceccato et al. 2001). It is calculated by the formula in Equation 2.2.

$$NDMI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}} \qquad \text{Equation 2.2}$$

where ρ_{NIR} is the near-infrared band value;

ρ_{SWIR} is the shortwave infrared band value;

Similar to NDVI and other normalised indices, NDMI also varies between -1 and 1 with generally positive values for green vegetation and negative values for dry vegetation and bare soil (Gao 1996). The Normalised Difference Moisture Index is also known as the Normalised Difference Water Index (NDWI) and Normalised Burn Ratio (NBR) amongst others (Ji et al. 2011).

2.2.4.3 Modified Soil-Adjusted Vegetation Index

The Modified Soil-Adjusted Vegetation Index (MSAVI2) builds on the earlier Soil-Adjusted Vegetation Index (Huete 1988) by incorporating a self-adjusting soil factor in contrast to the manually set soil factor in the original implementation (Qi et al. 1994). Both MSAVI2 and the original SAVI was developed to reduce the soil background effect in the then newly developed NDVI. The equation for calculating the MSAVI is provided in Equation 2.3.

$$MSAVI2 = \frac{2\rho_{NIR} + 1 - \sqrt{(2\rho_{NIR} + 1)^2 - 8(\rho_{NIR} - \rho_{red})}}{2} \qquad \text{Equation 2.3}$$

where ρ_{NIR} is the near-infrared band value;

ρ_{red} is the red band value;

2.2.4.4 Surface Albedo

Unlike the other vegetation indices listed here, surface albedo is a physical parameter of the earth's surface with various factors contributing to it. Surface albedo refers to the ratio of the reflected to the incident solar radiation (Post et al. 2000). Amongst others, albedo is affected by human-induced land cover changes. Activities such as deforestation and agricultural expansion generally lead to increased albedo values, whereas afforestation reduces surface albedo (Zhai et al. 2015). Albedo values range between 0 and 1, with snow and bright bare soil have values close to 1 in contrast to water and dark surfaces which present albedo values close to 0 (Hereher 2017).

An approximation of albedo is used in remote sensing. Liang (2001) and Liang et al. (2003) applied Equation 2.4 to Landsat 7 imagery to derive an albedo image.

$$albedo = c_0 + c_1 r_1 + c_3 r_3 + c_4 r_4 + c_5 r_5 + c_7 r_7 \qquad \text{Equation 2.4}$$

where c is the constant values provided in Table 2.1;
r is the surface reflectance per band from Landsat imagery;

The same equation was applied by Hereher (2017) and Münch, Gibson & Palmer (2019) to Landsat 8 imagery as well, with the corresponding Landsat 8 bands being used.

Table 2.1 Constant values used for albedo calculation

Constant	$c0$	$c1$	$c3$	$c4$	$c5$	$c7$
Landsat 7		Band 1	Band 3	Band 4	Band 5	Band 7
Landsat 8		Band 2	Band 4	Band 5	Band 6	Band 7
Value	-0.0018	0.356	0.130	0.373	0.085	0.072

Source: Münch, Gibson & Palmer (2019)

2.2.5 Pre-processing

Before imagery can be used for analysis, it needs to be pre-processed to correct for radiometric and atmospheric inaccuracies (Young et al. 2017). This is an essential step to ensure that accurate values are extracted for correct object identification and to ensure changes identified between images are not caused by variables other than the study's target objects. Pre-processing also ensures that all data is in the correct format or projection and that pixel values are comparable.

2.2.5.1 Radiometric correction

The values stored in a raw satellite image are often referred to as digital numbers (Campbell & Wynne 2011). These values are not meaningful for analysis without being converted. The first conversion needed to make sense of digital numbers involves converting these values to radiance. Radiance is the amount of energy reaching the sensor and is measured in watts per steradian per square metre, abbreviated as $W \cdot sr^{-1} \cdot m^{-2}$ (Allen & Triantaphillidou 2011). This measurement includes atmospherically scattered light and the light reflected from the earth's surface may also be absorbed partially by the atmosphere.

To compensate for effects such as illumination intensity and direction, the orientation and position of the target on the earth's surface and the path of light through the atmosphere, atmospheric correction is necessary (Young et al. 2017). The sensor may also produce stripes on images due to sensor calibration problems or altogether leave gaps on images when a sensor experience mechanical problems (Chen et al. 2011). Collectively these pre-processing operations are referred to as radiometric correction.

The value obtained from the atmospheric correction of radiance values is called reflectance. It is expressed as the relative brightness of a surface as measured for a specific wavelength interval (Campbell & Wynne 2011). As it is a ratio, it is unitless. It is calculated by the formula provided in Equation 2.5 where $observed\ brightness$ refers to the brightness of light striking the target and $irradiance$ refers to the amount of light leaving the target.

$$reflectance = \frac{observed\ brightness}{irradiance} \qquad \text{Equation 2.5}$$

2.2.5.2 Cloud masking

When analysing remotely sensed imagery, clouds often partially or completely obstruct objects on the earth's surface. Furthermore, clouds also cast shadows on the ground which change the spectral reflectance from the objects in these areas (Zhu et al. 2018). This can lead to skewed results when analysing cloudy images. Several methods have been developed to detect cloud cover. Some cloud detection algorithms make use of pixel-by-pixel approaches, while others use neighbourhood functions such as standard deviation (Hagolle et al. 2010). Algorithms such as Fmask use thermal bands to detect clouds that are colder than the earth's surface (Zhu & Woodcock 2012) and are often used for Landsat and Sentinel multispectral imagery. Snow and clouds often have similar spectral signatures, but can be distinguished by using shortwave infrared bands (Hagolle et al. 2010).

When using Landsat 8 surface reflectance imagery, several quality assessment bands are included, namely sr_aerosol, pixel_qa and radsat_qa. These bands provide quality values that are expressed as either a confidence level or a boolean value. The values of sr_aerosol were classified using the Landsat Surface Reflectance Code (LaSRC) algorithm and are based on coastal aerosol band values and climate data from the Moderate Resolution Imaging Spectroradiometer (MODIS; U.S. Geological Survey 2019a). Pixels classified as high aerosol content are not recommended for use (U.S. Geological Survey 2019b).

The pixel_qa band fulfils the same purpose as sr_aerosol and sr_cloud_qa but was instead generated by the CFMask algorithm, which is derived from the Fmask algorithm (Foga et al. 2017; Zhu & Woodcock 2012). The radsat_qa band is a representation of which sensor bands were saturated during data capture, yielding unusable data. The values of pixel_qa, which is often used for pixel quality assessment, are tabulated in Table 2.2.

Table 2.2 Pixel quality attributes generated from the CFMask algorithm

Bit	Value	Description
0	Fill	No data values are present in pixel (1), 0 if image data is present.
1	Clear	0 if cloud bits are set, otherwise 1 (pixel clear of clouds).
2	Water	Pixel was identified as water (1).
3	Cloud shadow	High likelihood of cloud shadow present in pixel (1).
4	Snow & ice	High likelihood of snow or ice present in pixel (1).
5	Cloud	High likelihood of cloud present in pixel (1).
6,7	Cloud confidence	None (0), low (1), medium (2) or high (3) cloud confidence.
8,9	Cirrus confidence	None (0), low (1), medium (2) or high (3) cirrus confidence.
10	Terrain occlusion	This bit is set when the desired terrain is not visible from the sensor due to intervening terrain.

Source: Google Earth Engine (2020)

Similarly, surface reflectance products from Landsat 7 and earlier Landsat satellites also contain a band for cloud masking named sr_cloud_qa (U.S. Geological Survey 2019a). Although it is similar to that of Landsat 8, it was produced by a different algorithm, the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), and consequently, there may be small differences. Both Landsat 7 and 8 images also contain the pixel_qa and radsat_qa quality assessment bands.

2.2.5.3 Orthorectification

While radiometric correction alters pixel values and cloud masking excludes them, these pixels may not be in the correct location on the earth's surface. Orthorectification aims to transform a remotely sensed image to match a projection and maintain a constant scale across the image (Brown & Harder 2016). Landsat 7 and 8 Level-1 terrain and precision corrected (L1TP) imagery are already radiometrically calibrated and orthorectified using ground control points and a digital elevation model (DEM) to correct for relief displacement. This makes the imagery suitable for pixel-level time series analysis (Young et al. 2017).

2.2.5.4 Pan-sharpening

Multispectral imagery often contains a panchromatic band of higher spatial resolution, lower spectral resolution. This band can be fused, or pan-sharpened, with lower spatial, higher spectral resolution imagery. The combined output is then of both high spatial and spectral resolution (Zhang 2004).

Pan-sharpened imagery was not used in this study due to the loss of spatial properties when calculating vegetation indices Johnson (2014) and also to avoid possible errors with mismatched pixels (Pohl & Van Genderen 1998).

2.3 REMOTE SENSING FOR INVASIVE ALIEN PLANT MAPPING

Field mapping of the species' geographical extent and abundance is difficult over large and rugged areas. Remote sensing is known for its ability to map various plant features over large aerial extents and over repeat time steps while saving time and cost (Huang & Asner 2009).

2.3.1 Google Earth Engine platform

In December 2010 Google launched Earth Engine (GEE), a free cloud computing platform for planetary-scale analysis of remotely-sensed imagery (Gardner 2010). The platform provides access to freely available satellite imagery and other geospatial data sources in the cloud, eliminating the need to download these datasets. Additionally, Google also pre-processes the Landsat imagery available in its data archive using workflows provided by the United States Geological Survey, saving the user the time of conventional pre-processing workflows such as radiometric correction and orthorectification. The Landsat collection available on Earth Engine dates to the first image of Landsat 4, from August 1982. Should a dataset not be available on GEE, it can be ingested to the platform by the user (Gorelick et al. 2017).

Since the launch of Google Earth Engine, dozens of studies have used the platform for remote sensing analysis. A literature search with the keyword "Google Earth Engine" returned more than 200 results as of the end of 2019, with 82 publications using GEE in 2018 alone (Google Inc. 2019). Initial applications of Earth Engine have included mapping Mexican forests (Regalado 2010), crop mapping (Lemoine & Leo 2015; Lobell et al. 2015), soil mapping (Padarian, Minasny

& McBratney 2015), water body mapping (Xu & Bai 2015), woody vegetation mapping (Johansen, Phinn & Taylor 2015) and urban mapping (Patel et al. 2015).

More recently, GEE was used to monitor tiger habitat (Joshi et al. 2016), map malaria risk (Kurtzman 2014) and produce a global map of surface water dynamics from 1984 (Pekel et al. 2016). *Prosopis* invasions were also mapped in India on a single-date composite of both Landsat 8 and Sentinel 2 imagery using machine-learning classifiers including Classification and regression trees (CART), Random forest (RF) and Support vector machine (SVM) on the Google Earth Engine platform (Vanthof & Kelly 2017).

2.3.2 Satellite imagery

Most invasive species mapping projects covering large areas make use of remotely-sensed imagery (van den Berg, Kotze & Beukes 2013; Cohen, Yang & Kennedy 2010; Ng et al. 2017; Robinson, van Klinken & Metternicht 2008; Wakie et al. 2014; Wang et al. 2018). Two popular remote sensing satellite programmes which provide freely available remote sensing imagery include the Landsat and Sentinel programmes (Atzberger 2016; van den Berg 2010; van den Berg, Kotze & Beukes 2013; Meroni et al. 2017; Ng et al. 2017; Ng, Immitzer, et al. 2016; Wang 2006).

2.3.2.1 Moderate-resolution imagery

Sentinel 2 captures imagery with spatial resolutions up to ten metres and Landsat 7 and 8 up to 30 metres – the smallest object visible on these images would consequently have a dimension of ten square metres and 30 square metres respectively. While this is not nearly the size of a single *Prosopis* tree, the canopy cover can be estimated from the mixture of *Prosopis* trees and ground or other plants in a single pixel with an acceptable level of accuracy using field reference data (van den Berg 2010; Ng et al. 2017; Ng, Meroni, et al. 2016). Mbaabu et al. (2019) noted that satellite data captured at the optimal time of the year must be chosen to successfully identify and distinguish *Prosopis* from other species' spectral signatures.

2.3.2.2 Landsat 7 & 8 imagery

Currently, Landsat is considered as the standard imagery source for land cover classification over large areas and longer periods (Cohen & Goward 2004). This is due to its medium spatial resolution, high spectral resolution and the wide ground swath results in fewer images having to be processed for large areas.

The Landsat archive also dates to 25 July 1972 when the first Landsat 1 image was captured at 60m spatial resolution (NASA Earth Observatory 2012). Since the launch of Landsat 4 in 1982, which had an improved sensor, 30m spatial resolution images became available and a continuous archive of these 30m resolution images are available until the present (NASA 2019).

Landsat 5 captured images from August 1984 until January 2013 and Landsat 7 started acquiring imagery in April 1999 and at the time of writing it was still operational. The latest satellite in the Landsat programme, Landsat 8, started capturing imagery in March 2013 and was also still operational at the time of writing (NASA 2019). The data availability is also continuous except for Landsat 7 imagery having a sensor malfunction since 2003 which causes black lines in images. A chart of the Landsat constellation's image availability is shown in Figure 2.7, with the white line indicating the span of the sensor malfunction on the Landsat 7 satellite.

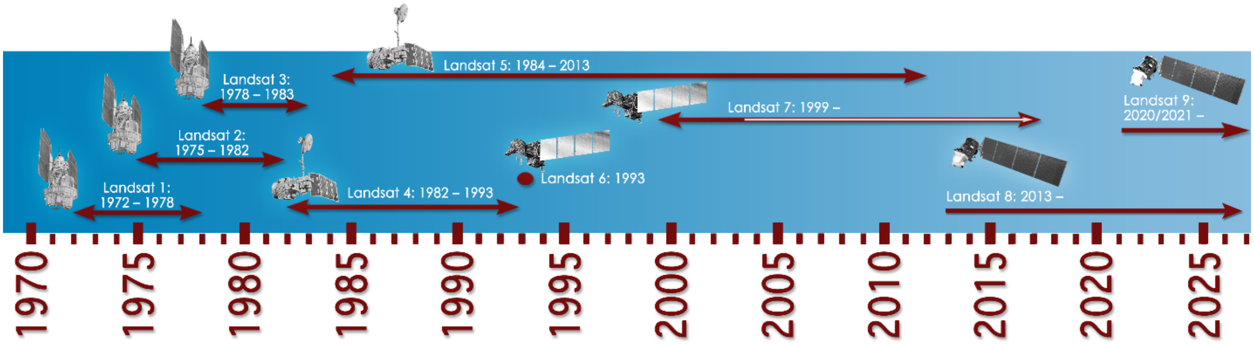

Figure 2.7 Landsat mission timeline Source: NASA (2019)

Since June 2003 the malfunction of the scan line corrector on Landsat 7 causes a partial loss of data in scenes captured by the sensor. Fortunately, with a pixel-composite approach commonly used when performing analysis on Google Earth Engine, the issue can be circumvented by combining pixels from different image acquisitions to form a complete image for each month.

From Table 2.3 it can be seen that both Landsat 7 and 8 have comparable spatial resolutions and spectral bands are more or less the same, allowing analysis from these satellites to be compatible. The bands for Landsat 7 and 8 are shown in Table 2.3 along with spectral and spatial resolution.

Table 2.3 Landsat 7 & 8 bands

#	Band Description	Platform	Sensor	Wavelength range (nm)	Spatial resolution (m)
1	Coastal Aerosol	Landsat 8	OLI	435 – 451	30
2	Blue	Landsat 8	OLI	450 – 510	30
1	Blue	Landsat 7	ETM+	450 – 520	30
3	Green	Landsat 8	OLI	530 – 590	30
2	Green	Landsat 7	ETM+	520 – 600	30
4	Red	Landsat 8	OLI	640 – 670	30
3	Red	Landsat 7	ETM+	630 – 690	30
5	Near-infrared (NIR)	Landsat 8	OLI	850 – 880	30
4	Near-infrared (NIR)	Landsat 7	ETM+	770 – 900	30

#	Band Description	Platform	Sensor	Wavelength range (nm)			Spatial resolution (m)
6	Shortwave-infrared (SWIR) 1	Landsat 8	OLI	1570	–	1650	30
5	Shortwave-infrared (SWIR) 1	Landsat 7	ETM+	1550		1750	30
10	Thermal Infrared (TIRS) 1	Landsat 8	OLI	10600		11190	100 resampled to 30
11	Thermal Infrared (TIRS) 2	Landsat 8	OLI	11500	–	12510	100 resampled to 30
6	Thermal	Landsat 7	ETM+	10400		12500	60 resampled to 30
7	Shortwave-infrared (SWIR) 2	Landsat 8	OLI	2110	–	2290	30
7	Shortwave-infrared (SWIR) 2	Landsat 7	ETM+	2090		2350	30
8	Panchromatic	Landsat 8	OLI	500	–	680	15
8	Panchromatic	Landsat 7	ETM+	520		900	15
9	Cirrus	Landsat 8	OLI	1363	–	1384	30

Source: United States Geological Survey (2015)

Landsat imagery is often used for large area land cover classification. Dong et al. (2016) used Landsat 8 OLI data to identify rice fields in North-Eastern Asia, which includes parts of China, North Korea, South Korea and Japan. Knorn et al. (2009) classified forested areas around the Carpathian mountains spanning across the Czech Republic, Slovakia, Poland, Ukraine, Hungary, and Romania totalling an area of about 185 000 km^2. Walker et al. (2010) mapped the Brazilian Amazon forest using Landsat and PALSAR data.

Several studies mapped invasive alien plants such as *Phragmites* and *Prosopis* using Landsat imagery (van den Berg 2010; van den Berg, Kotze & Beukes 2013; Liu et al. 2016; Mbaabu et al. 2019; Ng, Meroni, et al. 2016; Shiferaw et al. 2019; Vanthof & Kelly 2017). Of these studies, Van den Berg (2010) mapped *Prosopis* at time intervals for the Northern Cape from the 1980s and achieved an accuracy of 72%. Overall, accuracies of between 70 and 90% were achieved by these studies using Landsat for large area invasive plant mapping, indicating that Landsat is a sensible choice for mapping invasive alien plants over large areas.

A review by Gómez, White & Wulder (2016) highlighted that the use of pixel-based Landsat composites is one of the developments enabling progress in the optical remote sensing field. Tsai et al. (2018) mapped vegetation and land use using a multi-seasonal Landsat image composite. This minimized cloud and terrain issues. The authors grouped images by season to preserve seasonal vegetation signals. These composites were then reduced to a single image by taking the mean value of all pixels. Similarly, Azzari & Lobell (2017) produced land cover maps of Zambia by creating seasonal composites of Landsat 7 scenes by reducing seasonal images on their median pixel values.

With this study, the aim is to monitor *Prosopis* management using satellite imagery, compared to the distributional mapping and distributional mapping at set intervals of invasive alien plants often used in other studies imagery (van den Berg 2010; van den Berg, Kotze & Beukes 2013; Liu et al.

2016; Mbaabu et al. 2019; Ng, Meroni, et al. 2016; Shiferaw et al. 2019; Vanthof & Kelly 2017). While it is possible to evaluate a change in the distribution of an invasion at set intervals of ten years, for example, comparing two discrete classifications ten years apart would not meet the aims of this study, which is to comment on management effectiveness by analysing trends of regrowth and how it was affected by clearing.

2.3.2.3 Sentinel 2 imagery

The Sentinel 2 mission consists of two satellites – Sentinel 2A was launched in June 2015 and Sentinel 2B in March of 2017. With a single satellite, the revisit period of the mission is 10 days and when imagery from both satellites are used, the revisit period is reduced to 5 days. Due to the satellite imagery of the Sentinel 2 mission only being available from 2015 onwards, Landsat was chosen due to its historical record of imagery, which overlaps completely with the clearing of *Prosopis*.

2.3.2.4 Very high-resolution imagery

In contrast to the freely available moderate to high-resolution imagery used in many remote sensing projects, there are very high-resolution satellite (VHR) imagery available which was shown to accurately map *Prosopis* in Eastern Africa (Ng et al. 2017). However, the use of very high-resolution satellite imagery is not feasible for mapping the study area, let alone the entire Northern Cape (372 889 km^2) in terms of cost, storage capacity needed, processing power and time required. Very high-resolution imagery is more suited for smaller areas of interest. Acquiring higher resolution imagery such as RapidEye, SPOT or aerial imagery from the Chief Directorate: National Geospatial Information (CD:NGI) for certain areas can assist with verification as these sensors capture imagery at five-metre spatial resolution or higher. Google Earth also provides high-resolution imagery and some historical imagery in some areas, although these historical are more readily available for larger cities and their surrounding areas.

2.3.3 Trend algorithms

To identify invasive alien plants such as *Prosopis* in satellite images, image classification algorithms are used. There are several different algorithms available and literature has shown some to be more suitable for invasive alien plant mapping than others. This section will review the algorithms for calculating the rate of spread to determine the management efficacy of *Prosopis*.

2.3.3.1 Analysing trends in the change of *Prosopis* abundance

Land surface change is often divided into three broad categories, namely intra-annual, inter-annual and abrupt change (Zhu & Woodcock 2014). In the case of intra-annual change, change is caused by vegetation phenology driven by seasonal patterns of environmental factors such as temperature and precipitation, whereas with inter-annual change the change is caused by climate variability, vegetation growth or gradual change in land management or land degradation. The latter form of change can occur over several years. In contrast to these gradual vegetation change events, abrupt change can occur in a single day due to events including deforestation, natural events such as floods and fire, and insects (Zhu & Woodcock 2014). Consequently, an algorithm used to evaluate the change of vegetation over time should capture all the above-mentioned factors – seasonality, trends and breaks.

There are two popular approaches to analyse a remote sensing time series to monitor changes in vegetation abundance over time. The first is to compare individual landcover maps of two different dates. An extension of this approach would be to use multiple two-date comparisons to extract a trend from an imagery time series (Kennedy, Yang & Cohen 2010). In this approach images of different dates would be treated as separate classifications – subtle or long-term variation in vegetation cover may be inseparable from background noise (Hicke et al. 2006; Logan, Régnière & Powell 2003).

Mbaabu et al. (2019) have used the first approach with a time series of Landsat satellite imagery to map *Prosopis* spread at stand level in the Baringo county in Kenya between 1988 and 2016 from individual image sets at intervals of seven years. Both wet and dry season imagery were used to assess the spread. The authors made use of the Random Forest (RF) machine learning algorithm for the classification of the invasion. Variables used for classification included the blue, green, red, near-infrared (NIR) and shortwave infrared (SWIR) bands as well as NDVI. Accuracies of above 90% were achieved by this study. K-fold cross-validation was done to assess the accuracy – given a limited set of training and validation samples, these samples are partitioned into folds ensuring that every sample will be used as both training and testing in the classification process.

The second approach addresses this problem by extracting spectral trajectories on a pixel-level of land cover change from yearly satellite imagery stacks.

2.3.4 Land-cover trend analysis algorithms

2.3.4.1 BFAST

The Breaks for Additive Season and Trend (BFAST) algorithm has been developed to identify long term trends and abrupt changes (breaks) in a remote sensing time series (Verbesselt, Hyndman, Newnham, et al. 2010). BFAST combines land cover change detection with the additive decomposition of the signal into trend, seasonal and noise components (Figure 2.8). The algorithm does this by iteratively fitting piecewise linear trend and seasonal models to a remote sensing time series. BFAST estimates the time and number of changes and characterizes change by its magnitude and direction. The algorithm was developed for detecting vegetation change in an offline mode, meaning not in real-time or near real-time.

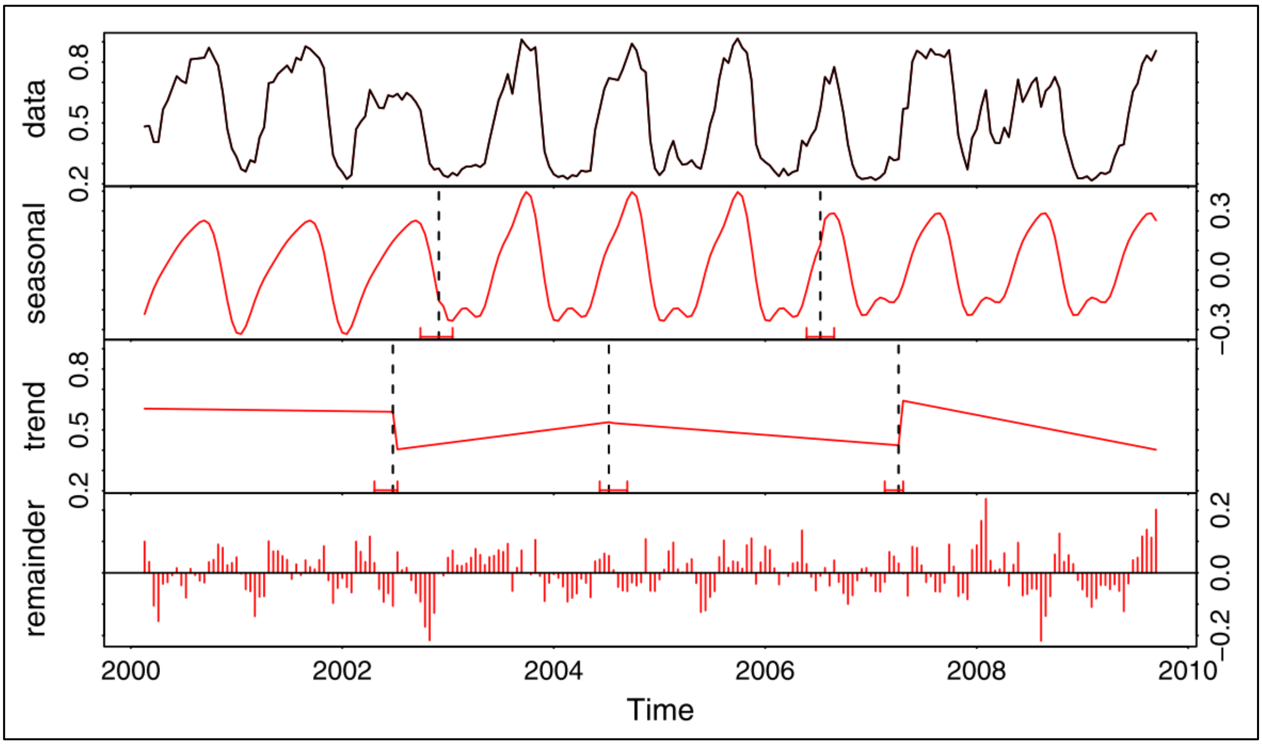

Figure 2.8 BFAST components: season, trend and remaining noise Source: (Verbesselt, Hyndman, Zeileis, et al. 2010)

BFAST is often used for forest disturbance detection, but some studies also covered other land cover change topics. The BFAST algorithm has been applied to Landsat time series for detecting forest change (Ng et al. 2017; Schachtschneider & February 2013; Schmidt et al. 2015), wetland change (Li et al. 2017), yearly vegetation change and greenness variation (Li et al. 2019) and land-use history (Dutrieux et al. 2016; Platt, Manthos & Amos 2018). Several BFAST applications using MODIS time series also exist including forest change (Grogan et al. 2016; Xulu et al. 2018), fire and flood detection (Watts & Laffan 2014) and fluctuations in lake water levels (Che et al. 2017).

BFAST has several user-adjustable parameters. One of its most prominent parameters, the *h* parameter, is calculated as the number of observations per segment divided by the length of the entire time series (Almeida et al. 2018). In other words, it determines the potential number of breaks that can be detected. It does this by controlling the minimal segment size between breaks. Consequently, lower *h* values result in a high number of breaks detected (and short trend segments) and vice versa.

As an example, let the time series used as input to BFAST cover 20 years with one observation per month. That would equate to 240 observations in total. An *h* parameter of 0.2 would mean that

$0.2 \times 240 = 36$ observations would be used to fit each linear segment. In this example, up to three breaks can be detected with segment lengths equating to 5 years each.

In a study by Watts & Laffan (2014) the parameters of BFAST were studied, including several different h values ranging from 0.14 to 0.33. While no exact h value exists for a given scenario, the study pointed out that using too large values of h, such as 0.33 in the case of the study by Watts & Laffan (2014), could lead to a disturbance event not being recorded at the time the event occurred in the real world or missed completely (Saxena et al. 2018). In contrast, using low h values could lead to false positives – in Watts & Laffan (2014) values of 0.14 caused additional unexplained breaks to be detected. The authors have also cautioned against using less than 30 observations per segment in regression analysis, while Lin et al. (2020) recommend at least 23 observations and use an h value of 0.17. Additionally, Verbesselt, Hyndman, Zeileis, et al. (2010) outlines how to implement recommendations by Bai & Perron (2003) concerning the fraction of data required between breaks. The authors have used an h value of 0.2 as a result. In a study by Li et al. (2019), an h value of 0.1 was used, as this value provided an acceptable number of breaks for their objective of identifying land cover change.

Other BFAST parameters include a seasonal model option, the maximum number of breaks and the maximum number of iterations. The seasonal model parameter specifies the model used to fit the seasonal component and detect significant phenological change (seasonal breaks). One of three options can be used for the seasonal model, namely “dummy”, “harmonic” and “none”. The authors note that “none” should only be used when no seasonality is observed i.e. no seasonal cycle to be modelled (Verbesselt, Zeileis & Hyndman 2015).

The “dummy” season-modelling option was first used by Verbesselt et al. (2010) and focuses on the detection of trend changes rather than temporal shifts in land surface phenology (Watts & Laffan 2014). The “harmonic” option fits a harmonic model to the seasonal trend. Verbesselt, Hyndman, Zeileis, et al. (2010) summarises three main advantages of the “harmonic” option over the “dummy” option. The authors note that the harmonic seasonal modelling is less prone to short-term data variations and noise, fewer observations are required for the multiple regression model used and it is easier to characterise phenological change using the amplitude and phase of the harmonic model.

The breaks parameter allows for setting the maximum number of breaks to be calculated. Saxena et al. (2018) note that in the event where the number of breaks detected by BFAST exceeds the number of breaks defined by the user (x), only the x most significant breaks will be detected. By default, the maximum number of breaks is defined by the h parameter (Verbesselt, Zeileis & Hyndman 2015).

The maximum number of iterations parameter of BFAST allow the specification of the maximum amount of iterations used for estimation of breakpoints in the seasonal and trend component. Awty-Carroll et al. (2019) have experimented with using up to 50 iterations for BFAST but concluded that five iterations were optimal for striking a balance between computational cost and an adequate number of outputs. In an implementation of BFAST by Almeida et al. (2018), only a single iteration was used.

2.3.4.2 BFAST Monitor

BFAST was later adapted and renamed BFAST Monitor (Verbesselt, Zeileis & Herold 2012). Unlike BFAST, BFAST Monitor does not separate seasonal and trend changes (Awty-Carroll et al. 2019). Instead, it constructs a stable season-trend model for an observed time (the history period) to model normal vegetation dynamics. After the historical period, new observations are compared to the stable history model in the monitoring period. A deviation from the stable model in the monitoring period will result in BFAST Monitor detecting a break.

As BFAST Monitor relies on a stable historical period to have a baseline to compare future observations to, it is unsuitable for this study where known periods that exhibit typical trends of areas with unmanaged *Prosopis* are not available to compare to periods when *Prosopis* were managed. Also, environmental factors such as precipitation events and periods of drought impact the study area significantly, making typical trends of unmanaged *Prosopis* hard to identify without detailed historical records of each site.

2.3.4.3 BFAST01

Another variant of the BFAST algorithm, BFAST01, was developed by De Jong et al. (2013). BFAST01 attempts to fit a suitable model to the data by choosing either a model with no or a single major breakpoint. The decision on whether or not a break should be detected relies on a significance test based on moving sums (MOSUMs) of ordinary least squares (OLS) residuals (OLS-MOSUM in short) or another user-specified test method (Verbesselt, Zeileis & Hyndman 2015). If the test detects a significant instability in the season-trend model, a breakpoint is estimated, and separate season-trend models are fit to the segments before and after the break. If the MOSUM test results are non-significant no break will be detected.

Although the two-segment model with one break potentially contains more breaks, the breakpoint identified by BFAST01 will be the most significant (De Jong et al. 2013; Tai-leung Chong 1995). BFAST01 is less sensitive to changes to a phenological pattern (season shifts or amplitude changes) and more sensitive to changes in trend. The authors advise interpreting results with caution when the breakpoint is near the start or end of the time series, as one of the segments, which a trend is based on, is very short (De Jong et al. 2013).

BFAST01 has been used for a range of applications including the analysis of the socioeconomic impact on vegetation productivity (Zhou et al. 2019), identification of ecosystem turning points (Bernardino et al. 2020) and for break detection in water-use efficiency (Horion et al. 2019).

In an interesting non-remote sensing use for BFAST01, Dupas et al. (2018) used the algorithm for analysing trends in the nitrogen and phosphorus levels in rivers in France using historical water tests over 46 years. Another alternative use for BFAST01 is illustrated in Camino-Serrano et al. (2016) where BFAST01 is used to detect breakpoints in dissolved organic carbon trends in forests in Europe. The BFAST01 analysis enabled the authors to remove time series affected by local disturbances (breaks) and to solely retain time series with monotonic trends.

BFAST01 parameters include options for harmonic order, regression formula, breakpoint test method, significance level for the test and bandwidth to name a few often used in research (Bernardino et al. 2020; Horion et al. 2019; Ma et al. 2019; Zhou et al. 2019).

The harmonic order parameter refers to the order of the harmonic term, which defaults to three if unspecified. As with BFAST Monitor, options for regression formulas include “trend and harmonic”, “trend” and “harmonic” where “trend” refers to a linear trend and “harmonic” refers to a harmonic season component. Bernardino et al. (2020) used the “trend” formula option for BFAST01 due to the absence of seasonality in their input time series while the authors opted to use default values for the remaining parameters. In a study by Ma et al. (2019) the “harmonic” seasonal model was used.

A sequence of tests for the null hypothesis of zero breaks is performed using the test method of choice, such as MOSUM, which is specified by the breakpoint test method parameter. Each test results in a decision of false for no break or true for a structural break. Test decisions are then aggregated to form a single decision. The significance level used in the test is specified by the significance level parameter provided to the BFAST01 algorithm. A significance level of 0.05 is often used (Horion et al. 2019; Ma et al. 2019; Zhou et al. 2019). The bandwidth parameter is passed on as the h parameter of the algorithm performing tests for structural change in the regression model (Verbesselt, Zeileis & Hyndman 2015).

CHAPTER 3: CHANGES IN THE COVER OF INVASIVE ALIEN *PROSOPIS* TREES OVER 20 YEARS AT SELECTED SITES IN THE NORTHERN CAPE PROVINCE, SOUTH AFRICA

3.1 ABSTRACT

Invasive alien plant management can be expensive, so scarce resources need to be used effectively to achieve control. One such invasive alien plant (*Prosopis*) which was planted to provide fodder for livestock, spreads rapidly and forms dense thickets, causing negative impacts which outweigh any benefits for landowners. Evaluating trends in the cover (biomass) of *Prosopis* over time can provide insights into the efficacy of different management methods.

Trends in *Prosopis* biomass were analysed using a Landsat remote sensing time series and the BFAST and BFAST01 trend algorithms to determine their suitability for detecting trends in the cover of *Prosopis* in the Northern Cape province and relating these to management effort (which included areas that were not managed at all). With both algorithms, several indices were also assessed, including NDVI, NDMI, MSAVI2 and surface albedo, to find the most suitable index for detecting *Prosopis* biomass best. A suitable sample size was determined to account for heterogeneity in managed sites while including smaller sites spanning only a few satellite imagery pixels too.

The indices varied in their suitability for detecting sudden changes (termed “breaks”) in *Prosopis* cover, and NDVI was selected as the best index in this regard. Results vary due to site heterogeneity and the number of pixels aggregated for analysis of a site, with more stable results obtained in more homogenous sites and when more pixels were used. Furthermore, results varied depending on the method of management, the number of treatments over time, and the amount of money spent per treatment episode. BFAST and BFAST01 produced similar results, but breaks detected by BFAST were more closely aligned to management inputs as more than one break could be detected per time series. Some breaks were possibly not related to management input because they occurred on both managed and unmanaged sites, and were likely related to environmental factors such as drought.

In areas with high variability in management effort within a single site, or when management spanned several years, results were inconclusive. When management was completed in a few months, the clearing of *Prosopis* was detected well using NDVI combined with BFAST and BFAST01. While varying results were observed, BFAST and BFAST01 proved to be suitable methods for vegetation change analysis and the detection of invasive alien plant management.

3.2 INTRODUCTION

Prosopis trees, native to north and central America, are invasive in South Africa. These invasive trees are managed by private landowners, sometimes in combination with government-funded control teams. Knowing how effective the *Prosopis* invasion in South Africa is being managed by these different groups and the effectiveness of a combination of these management efforts is important when planning management strategies to control the species. The Northern Cape Province has seen an alarming increase in *Prosopis* cover over the last 50 years (van den Berg, Kotze & Beukes 2013). Given that the Northern Cape spans an extensive area, it is not viable to send large teams out to map the occurrence and spread of *Prosopis*. Estimating cover using ground surveys can also be challenging and yield very subjective results. Furthermore, it is not possible to analyse the historical increase in cover with in-situ methods if the data was not captured in the past.

In an era where remotely-sensed imagery is becoming more accessible, analysis thereof offers new and improved methods to address ecological problems (Buchanan et al. 2015; Buchanan et al. 2009) including the mapping of invasive alien plant species (Cord, Klein & Dech 2010; Huang & Asner 2009). Multispectral imagery has been used before to map the *Prosopis* invasion in the Northern Cape (van den Berg 2010), but existing research does not consider the effectiveness of management in reducing the extent of the *Prosopis* invasion in the Northern Cape province.

In this chapter phenological trend analysis algorithms are compared and applied to a time series of multispectral imagery to evaluate the effectiveness of control of *Prosopis* by comparing areas that have been subjected to different management regimes over the past 20 years. The purpose of this chapter is to present the results of mainly three analyses that were performed, namely a) the selection of suitable vegetation index to detect *Prosopis* cover (biomass) changes, b) the selection of an appropriate number of pixels to achieve reliable breaks with the tested algorithms and c) test of best performing algorithm to identify *Prosopis* clearing (using the optimum number of pixels).

3.3 MATERIALS AND METHODS

3.3.1 Study area

This study was conducted on sections of individual farms around the towns of Carnarvon and Vanwyksvlei in the Northern Cape Province of South Africa (Figure 3.1). The Northern Cape is the largest of nine provinces in South Africa and covers 372 889 km^2, about a third of the country's total surface area. The province falls in the arid and semi-arid zone of the country and has an extremely low population density of approximately three people per square kilometre (Statistics

South Africa 2012). *Prosopis* invasions and degradation from overstocking, in addition to a recent drought, are key pressures in the area (Jordaan 2012; Van der Spuy 2019).

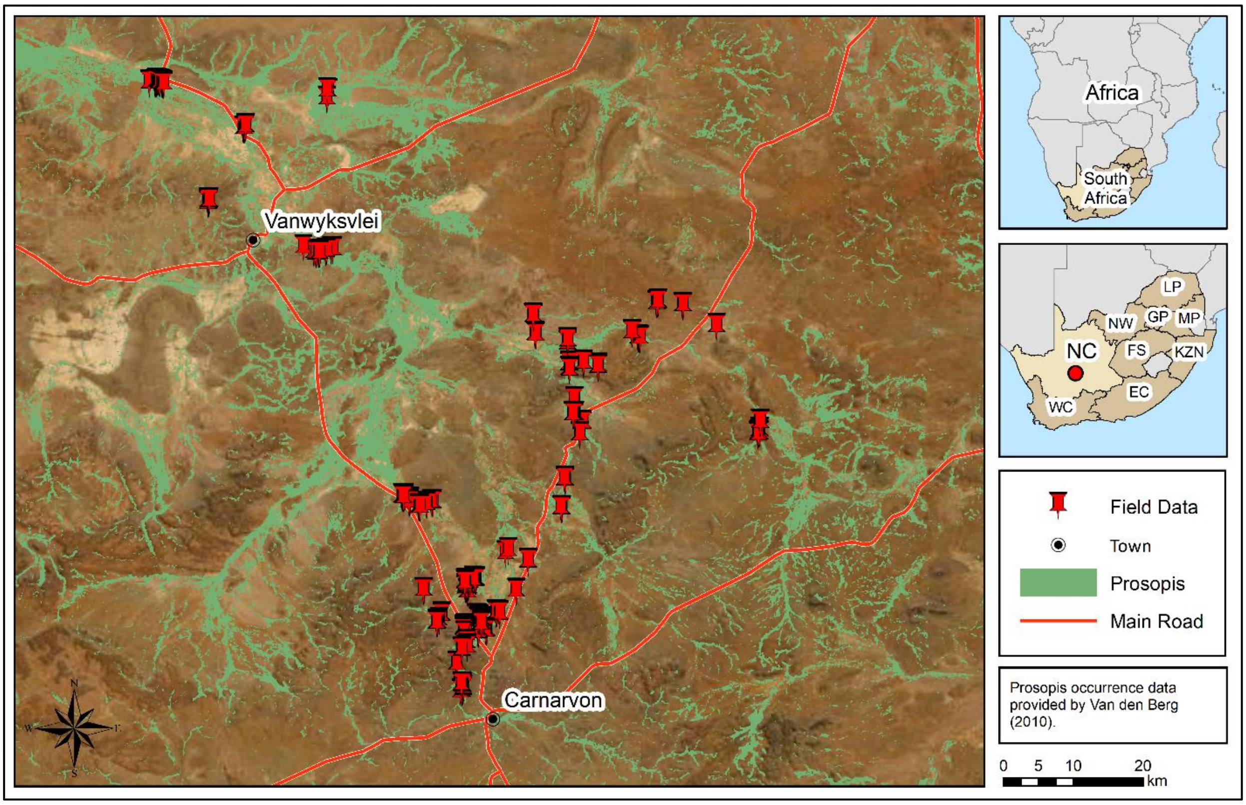

Figure 3.1 Study sites around Carnarvon and Vanwyksvlei

All study sites fall within the Nama Karoo biome (Rutherford, Mucina & Powrie 2006), characterised by short, shrubby vegetation of low cover. The study area is dominated by about four types of soils. These soil types include brown and reddish soils with a marked clay accumulation in low-lying areas, shallow soils with minimal development in higher areas and red dune sand intrusions towards the northern parts of the area (Department of Agriculture, Land Reform and Rural Development 2018).

The economy in this area is mostly agriculturally driven (Statistics South Africa 2000). In terms of *Prosopis* management, only small areas were treated by the government-funded Working for Water (WfW) programme. Some private landowners have also attempted to clear their properties, but clearing records have generally not been documented in great detail.

3.3.2 Data acquisition

Data used in this study mainly include a remote sensing time series of Landsat surface reflectance imagery and field data collected during a field trip to the study sites, which consist of questionnaires, coordinates of sites and several photos per site.

3.3.2.1 Field data

Initial field data were collected in April 2019 during a field trip to the Northern Cape. To reduce the diversity of soil types and biomes, the study area was limited to the area between Carnarvon and Vanwyksvlei. The area falls within a single biome, the Nama Karoo, and covers two bioregions: the Bushmanland bioregion and Upper Karoo bioregion (Rutherford, Mucina & Powrie 2006). A significant number of sites that had been cleared by WfW are also found in the area. The selection of this area was based on the relative homogenous environment across all sites, the presence of government-managed sites, and the considerable invasions of *Prosopis* trees in the area.

Due to the national COVID-19 lockdown, field data collection was interrupted and this necessitated the use of a digital questionnaire and email correspondence to collect further data. Data collection at sites between Carnarvon and Vanwyksvlei commenced in May and June 2020 utilizing digital questionnaires with interactive maps, where participants could indicate areas where they managed *Prosopis,* as well as where Working for Water had conducted management operations and areas where no management was done.

In a subsequent step, the coordinates collected from the questionnaires were used for ground-truthing. Areas defined by the coordinates were assigned to one of four categories:

1. *Prosopis* cleared by Working for Water with follow-up clearing by the landowner or land manager between 1995 and 2020.
2. *Prosopis* cleared by Working for Water with no follow-up by the farmer between 1995 and 2020.
3. *Prosopis* cleared by the landowner or land manager between 1995 and 2020.
4. No *Prosopis* clearing was done by either party between 1995 and 2020.

The digital questionnaires were developed on the KoBoToolbox platform, a free and open-source suite of tools for field data collection (KoBoToolbox 2018). The questionnaire (Appendix A; Figure 3.2) consisted of a single bilingual (English and Afrikaans) interactive form which was shared with participants via email. They could then complete the form on a computer or mobile device in their own time and then return the completed questionnaire.

Useful background knowledge of sites was provided by the participants who completed the questionnaires and additional data was recorded with follow-up communication. Questions and locations regarding unmanaged areas were included in the questionnaire to obtain control areas for comparison with areas where *Prosopis* was managed.

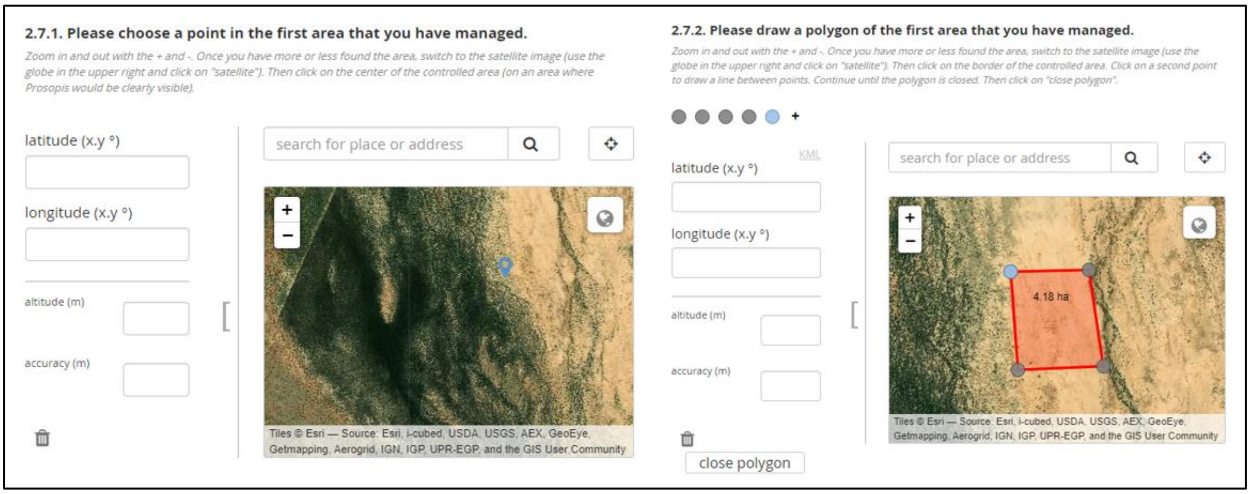

Figure 3.2 An extract from the first questionnaire used for field data collection. For the full questionnaire, see Appendix A.

A final field trip was undertaken in October 2020 to verify *Prosopis* clearing site locations, dates of clearing and other clearing-related information. A total of 23 landowners and managers were interviewed. Before interviews were conducted, a consent form to participate in the research, as well as a COVID-19 screening form, were completed.

A general interview form was completed for each farmer where questions focused on the general state of *Prosopis* management on the property. The purpose was also to ascertain how knowledgeable the interviewee was on all *Prosopis* management done in the study period, between 1995 and 2020. At this stage, interviews that would not be beneficial for the project could also be flagged and further site-specific interviews would not be conducted. One such example would be if an area of less than $30m^2$ were cleared – it would be unlikely that changes would be detected with such a small footprint using 30m-resolution Landsat satellite imagery. Another condition for the removal of an interview from the study was if the management of *Prosopis* on the farm did not fall within the time frame set by the study period, being from 1995 to 2020.

On each property individual interviews were completed for the same four site categories used during the digital interviews in May and June of 2020. At each site, the category of management was captured along with the dates of management and up to four coordinates. For one of the coordinates, a photo was taken in each main direction (north, east, south and west) to help with feature identification later. Up to three additional photos were also taken in cases where specific areas or features needed to be illustrated.

The KoBoCollect Android application was used for field data collection during the October 2020 trip. The web-based forms (on KoBoToolbox – see Appendix A) used during the digital interview phase was synchronised to be used offline on the mobile phone as reception is scarce between Carnarvon and Vanwyksvlei. The mobile phone that was used had a global navigation satellite system (GNSS) receiver capable of using positioning from the GPS, GLONASS and BeiDou satellite constellations, ensuring quick positioning with a precision of at least five metres. A few screenshots of the field questionnaires can be seen in Figure 3.3.

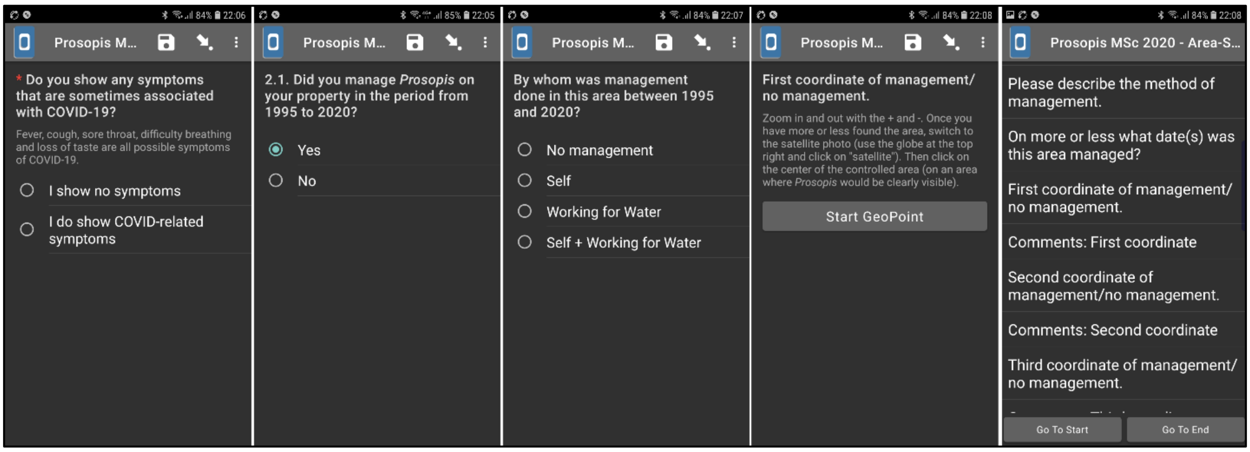

Figure 3.3 Screenshots of the various field questionnaires

In addition to the data collected via the application, additional aerial photos were also acquired using a drone if weather and time allowed. The aerial photos assist with understanding the density of the invasion and were specifically useful in areas with impenetrable *Prosopis* thickets where only a side-view is possible without knowledge of what the invasion looks like behind the "wall" of *Prosopis* visible from outside (Figure 3.4).

Figure 3.4 *Prosopis* thicket viewed from the side (left) and from above using the drone (right)

In total, about 145 sites were visited for which interviews were completed, although the actual total unique areas will be less due to more than one form occasionally being completed per area if it was a significantly large area that required more photos or there were differences within the area that needed to be recorded. Of these initial unfiltered 145 site forms, 52 were managed privately, 56 by Working for Water, five by Working for Water with follow-up done by the landowner, and 32 sites that were not managed at all in the study period.

Data captured during the fieldwork was further filtered afterwards. Extremely small managed sites, sites where management effects were negligible, where the canopy cover of *Prosopis* was low before management or where insufficient field data were available, were removed from the dataset as management cannot be detected using the satellite imagery used in the study, or if data is lacking, it cannot be compared to known management data. After the sites were filtered, the number of usable sites was 82 (Table 3.1).

Table 3.1 *Prosopis* management sites used in the study

#	Category	Count
1	*Prosopis* cleared by Working for Water with follow-up clearing by the landowner or land manager between 1995 and 2020	2
2	*Prosopis* only cleared by Working for Water with no follow-up by the landowner between 1995 and 2020	24
3	*Prosopis* only cleared by landowner or land manager between 1995 and 2020	21
4	No management between 1995 and 2020	35
	Total	82

The sites were expanded from a single coordinate per site to up to 20 coordinates per site for large areas. These coordinates were aligned with the locations of pixel centres of Landsat imagery to minimise mixed pixels being selected for analysis (Figure 3.5). The relevant Google Earth Engine code can be seen in Appendix B.

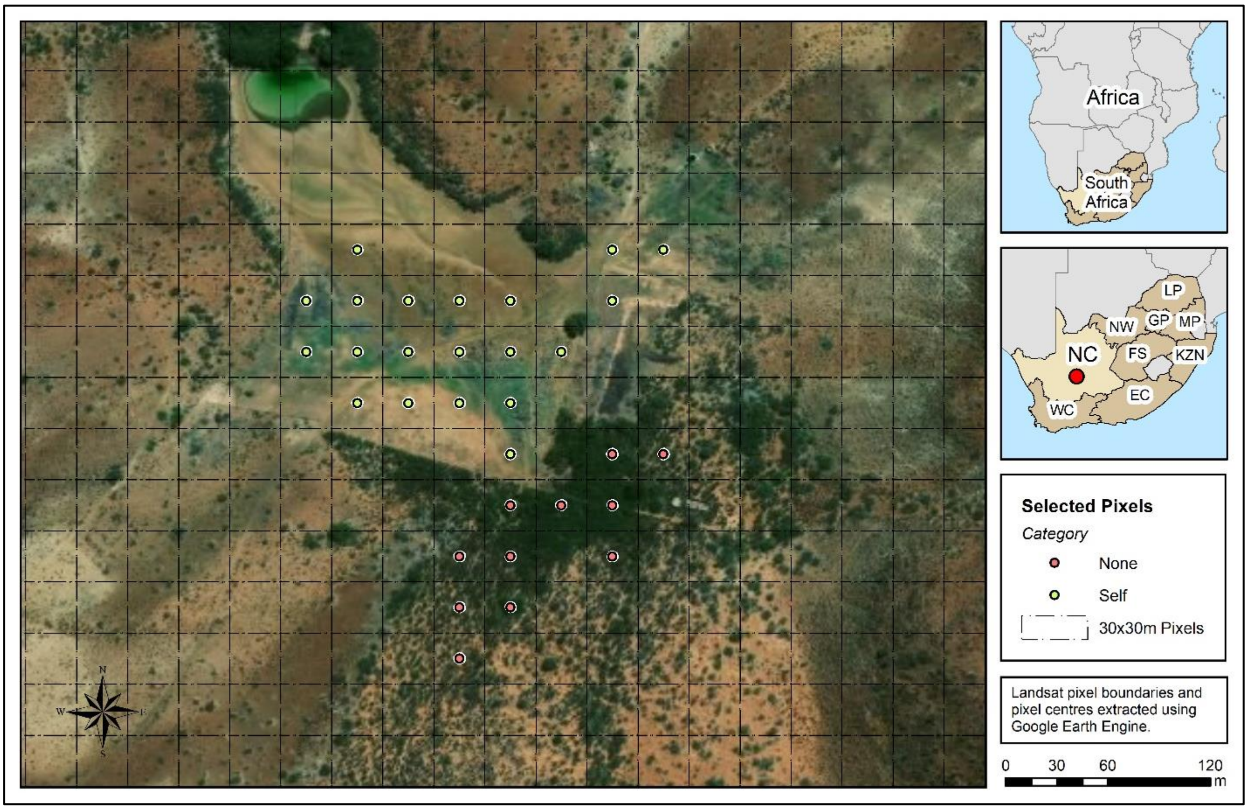

Figure 3.5 Selected Landsat pixel centres of two neighbouring sites – farmer-managed and unmanaged

3.3.2.2 Remote sensing data

3.3.2.2.1 Sensors

A suitable spatial resolution should be chosen to reduce intra-pixel variability. Several studies have highlighted that the optimal pixel size is less than half the size of the smallest feature to map (Alavipanah et al. 2010; Garrigues et al. 2006; Hengl 2006). In the case of this study, the smallest feature that should ideally be visible is a *Prosopis* tree. While several sensors exist that can capture satellite imagery at resolutions in the same proportion of a *Prosopis* tree, these images are often prohibitively expensive and require ample storage space when covering several sites over a larger area.

Two popular remote sensing satellite programmes which provide freely available remote sensing imagery include the Landsat and Sentinel programmes (Atzberger 2016; van den Berg 2010; van den Berg, Kotze & Beukes 2013; Meroni et al. 2017; Ng et al. 2017; Ng, Immitzer, et al. 2016; Wang 2006). Due to the limited availability of Sentinel-2 imagery (2015 until present), Landsat imagery was selected for this study.

Imagery from Landsat 7 and 8 was used in this research due to the amount of usable time series data available from the Landsat programme dating back beyond the start of the period used in this study. New images are currently still being captured by both Landsat 7 and 8, with Landsat 7 collecting imagery from January 1999 and Landsat 8 from April 2013. The temporal resolution for Landsat 7 and 8 respectively is 16 days, but when the data from the sensors are used together that is reduced to 8 days due to the image acquisition dates of these two satellites being offset by 8 days. A summary of sensor bands, their wavelengths and spatial resolutions is shown in Table 3.2.

Table 3.2 Landsat 7 & 8 bands

#	Band Description	Platform	Sensor	Wavelength range (nm)			Spatial resolution (m)
1	Coastal Aerosol	Landsat 8	OLI	435	–	451	30
2	Blue	Landsat 8	OLI	450	–	510	30
1	Blue	Landsat 7	ETM+	450		520	30
3	Green	Landsat 8	OLI	530	–	590	30
2	Green	Landsat 7	ETM+	520		600	30
4	Red	Landsat 8	OLI	640	–	670	30
3	Red	Landsat 7	ETM+	630		690	30
5	Near-infrared (NIR)	Landsat 8	OLI	850	–	880	30
4	Near-infrared (NIR)	Landsat 7	ETM+	770		900	30
6	Shortwave-infrared (SWIR) 1	Landsat 8	OLI	1570	–	1650	30
5	Shortwave-infrared (SWIR) 1	Landsat 7	ETM+	1550		1750	30
10	Thermal Infrared (TIRS) 1	Landsat 8	OLI	10600		11190	100 resampled to 30
11	Thermal Infrared (TIRS) 2	Landsat 8	OLI	11500	–	12510	100 resampled to 30
6	Thermal	Landsat 7	ETM+	10400		12500	60 resampled to 30
7	Shortwave-infrared (SWIR) 2	Landsat 8	OLI	2110	–	2290	30
7	Shortwave-infrared (SWIR) 2	Landsat 7	ETM+	2090		2350	30
8	Panchromatic	Landsat 8	OLI	500	–	680	15
8	Panchromatic	Landsat 7	ETM+	520		900	15
9	Cirrus	Landsat 8	OLI	1363	–	1384	30

Source: United States Geological Survey (2015)

Unfortunately, Landsat 7 suffered the loss of its scan line corrector (SLC) on May 31st 2003 which lead to a loss of about 22% of each image due to missing bands. However, when aggregated with other Landsat 7 or 8 images, this problem can be circumvented mostly. It must be noted that Landsat 7 acquisitions were temporarily suspended from 31 May 2003 and resumed on 17 September 2003 after an investigation into the SLC loss was complete (United States Geological Survey 2020b). Several other issues of Landsat 7 are known which may lead to periods without data from the specific sensor (United States Geological Survey 2019a).

Clouds often partially or completely obstruct objects on the earth's surface. Furthermore, clouds also cast shadows on the ground which change the spectral reflectance from the objects in these areas (Zhu et al. 2018), which can lead to skewed results. Several methods have been developed to detect cloud cover, including pixel-by-pixel approaches and neighbourhood functions such as standard deviation (Hagolle et al. 2010). Algorithms like Fmask use thermal bands to detect clouds colder than the earth's surface (Zhu & Woodcock 2012) and are often used for Landsat and Sentinel multispectral imagery. While snow and clouds often have similar spectral signatures, they can be distinguished by using shortwave infrared bands (Hagolle et al. 2010).

When using Landsat surface reflectance imagery, several quality assessment bands are included, namely sr_aerosol (sr_cloud_qa for Landsat 7 and earlier Landsat satellites), pixel_qa and radsat_qa. These bands provide quality values that are expressed as either a confidence level or a boolean value. The values of sr_aerosol are classified using the Landsat Surface Reflectance Code (LaSRC) algorithm in the case of Landsat 8 and for Landsat 7 and earlier the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) are used. Pixels classified as high aerosol content are not recommended for use (U.S. Geological Survey 2019b).

The pixel_qa band fulfils the same purpose as sr_aerosol and sr_cloud_qa but was instead generated by the CFMask algorithm, which is derived from the Fmask algorithm (Foga et al. 2017; Zhu & Woodcock 2012). The radsat_qa band is a representation of which sensor bands were saturated during data capture, yielding unusable data.

The Google Earth Engine (GEE) platform was used for data extraction from the Landsat 7 and 8 Tier 1 collections. The surface reflectance products of all three Landsat satellites were used as these products were already corrected for atmospheric and geometric errors as provided by the United States Geological Survey (2019b). Additionally, cloud masking was implemented using the pixel_qa band values provided with the satellite imagery.

3.3.2.2.2 Indices

The Normalised Difference Vegetation Index (NDVI; Rouse et al. 1973) was used due to its wide use for monitoring vegetation presence in several environments (Carlson & Ripley 1997). Values of the NDVI range from -1 to 1, with negative values mostly corresponding to water, values close to zero being bare ground, rocks and snow. Low positive values (up to ~0.4) often correspond to shrubs and grasslands. High values indicate rainforests and dense growth (Campbell & Wynne 2011; Chen et al. 2017; Gandhi et al. 2015), also used to isolate *Prosopis* presence (Eckert et al. 2020; Kyuma et al. 2016; Shiferaw et al. 2019).

In addition to NDVI, the Normalised Difference Moisture Index (NDMI; Wilson & Sader 2002), the Modified Soil-Adjusted Vegetation Index (MSAVI2; Qi et al. 1994) and surface albedo (Post et al. 2000) were also used for a comparison of results. Based on these results, NDVI was selected as it outperformed the other indices and was often used with *Prosopis* detection and mapping from satellite imagery (Atzberger 2016; Kyuma et al. 2016; Shiferaw et al. 2019; Vidhya, Vijayasekaran & Ramakrishnan 2017; Wakie et al. 2014).

3.3.2.3 Additional sources

To aid in the process of site selection, historical imagery on the Google Earth Pro software (Google Inc. 2005) was used to verify clearing locations, approximate dates, and intensity. Google Earth imagery was often used to approximate the year of *Prosopis* clearing, in instances where participants could not provide exact dates or locations. Due to the remote location of the study area, satellite images on Google Earth are not updated as often as areas around large cities and this meant the images on Google Earth were often separated by a few years making exact estimation of clearing dates impossible. Despite this, Google Earth imagery often proved to be helpful when no clearing dates were known.

In the case of a site cleared by Working for Water, the expected clearing dates correspond to the year in which the clearing of the site was completed. These details are recorded in a database kept by Working for Water, namely the Water Information Management System (WIMS). Records include, amongst others, details such as the area cleared, date(s) when clearing was completed, and financial details related to the clearing. It should be noted that due to the clearing often spanning several months, the break detected by BFAST01 could be found a year before the expected break as the WIMS database only records the date when management ended.

3.3.3 Trend analysis

Trends in the biomass of *Prosopis* were analysed using the BFAST (Verbesselt, Hyndman, Newnham, et al. 2010) and BFAST01 (De Jong et al. 2013) algorithms, which map the seasonal changes in vegetation biomass and how these change over years.

3.3.3.1 Overview of trend algorithms

BFAST combines land cover change detection with the additive decomposition of the signal into trend, seasonal and noise components. The algorithm does this by iteratively fitting piecewise linear trend and seasonal models to a remote sensing time series. BFAST has several user-adjustable parameters. One of its most prominent parameters, the h parameter, is calculated as the number of observations per segment divided by the length of the entire time series (Almeida et al. 2018). It is important to note that any number of breaks can be detected by the BFAST algorithm, depending on the h parameter.

In contrast, BFAST01 attempts to fit a suitable model to the data by choosing either a model with no break or a single major breakpoint, meaning it will either detect a single break or no break at all. The decision on whether or not a break should be detected relies on a significance test based on moving sums (MOSUMs) of ordinary least squares (OLS) residuals (OLS-MOSUM in short) or another user-specified test method (Verbesselt, Zeileis & Hyndman 2015). If the test detects a significant instability in the season-trend model, a breakpoint is estimated, and separate season-trend models are fit to the segments before and after the break. If the MOSUM test results are non-significant no break will be detected. BFAST01 is less sensitive to changes to a phenological pattern (season shifts or amplitude changes) and more sensitive to changes in trend.

Another variant of BFAST, BFAST Monitor, was excluded from this study. It is unsuitable for this study as BFAST Monitor relies on a stable historical period to have a baseline to compare future observations to and known periods that exhibit typical trends of areas with unmanaged *Prosopis* are not available to compare to periods when *Prosopis* were managed. Also, environmental factors such as precipitation events and periods of drought impact the study area significantly, making typical trends of unmanaged *Prosopis* hard to identify without detailed historical records of each site.

3.3.3.2 Evaluating the impact of several variables on results

To avoid mixed pixels, the points used as input to BFAST and BFAST01 were placed on Landsat pixel centroids on pixels that had a more or less homogenous composition. Due to the lack of clearing present in the study area before 2000, only a time series spanning Landsat 7 and 8 imagery from 1999 until 2020 was analysed in this study.

Four vegetation indices were compared to determine which detected *Prosopis* abundance the best. The indices tested included NDVI, NDWI, MSAVI2 and surface albedo. These indices were tested for four single pixels per site for two sites, one managed by Working for Water and one managed by the landowner. Single pixels were used to exclude all changes unrelated to changing the vegetation index.

Furthermore, the effect of micro-niche variation within a site on the performance of the trend analysis results was tested by variably randomly selecting three to ten pixels for all managed sites, and then calculating the BFAST01 breaks over ten iterations with the replacement of samples/pixels (meaning the same pixel could be included in more than one iteration). This approach of randomly selecting pixels in multiple iterations is similar to how ensemble classification methods such as Random Forest work (Breiman 2001). In cases where breaks correspond between iterations, there is a higher chance of an actual break related to clearing being detected rather than a break by chance with the selection of particular pixels.

Based on initial results from testing the impact of sample size and site heterogeneity, five pixels were chosen per site. While a minimum of three pixels was considered for statistical purposes, results indicated that the effect of differences between samples causes breaks in the trend which are not indicative of the overall site state. Increasing the number of pixels used per site meant that samples used in the time series would be lost. When using five samples per site, only 14 additional sites of the 82 total sites when three pixels are used, are lost – leaving 68 sites. These pixels were grouped to ensure the effect of mixed pixels and differences in management are minimised in the time series data.

Subsequently, five sets of five randomly selected pixels from each site present in the study were analysed using both BFAST and BFAST01. The majority break for these five sets of results per site was noted. This provided a more robust result. The workflow for a single iteration of BFAST and BFAST01 algorithms can be seen in Figure 3.6.

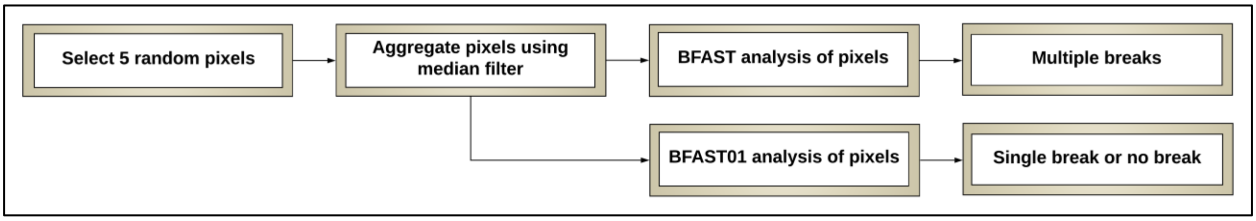

Figure 3.6 Workflow of a single iteration of the BFAST and BFAST01 analysis

First, the five randomly selected pixels were aggregated using a median filter. BFAST analysis would then be able to produce multiple breaks determined by the h parameter. An h parameter of 0.1 was used as it would be possible for BFAST to detect a break about every two years. This was calculated based on the knowledge that each pixel consists of approximately 250 images (one composite image per month between 1999 and 2020). The number of observations multiplied by the h parameter equals the minimum length of a trend line before a new break can be detected. In this case, this was approximately 25 months (250×0.1).

In the analysis of BFAST01, managed sites were paired with their closest unmanaged site to be able to compare trends from both. The objective of this was to evaluate whether some breaks can be attributed to environmental factors if they were observed in both the managed and unmanaged sites in a pair.

3.3.3.3 BFAST and BFAST01 implementation

A modified implementation of BFAST and its variants, originally developed by Almeida et al. (2018), was used. It utilises the Google Earth Python API to obtain a remote sensing time series which is then analysed using the “bfast” and “bfast01” functions in the “bfast” package in R (Verbesselt, Zeileis & Hyndman 2015). The implementation in R allows for the exploration of all historical surface reflectance data from the 7 and 8 datasets provided in the Earth Engine Data Catalog. After a single or multiple coordinates are selected, the data for those pixel(s) are acquired from Google Earth Engine through the GEE Python API, after which it is pre-processed with the

CFMask filter (Foga et al. 2017; Zhu & Woodcock 2012) to mask cloudy pixels. Vegetation indices are also created in this step. A simplification of the process can be seen in Figure 3.7.

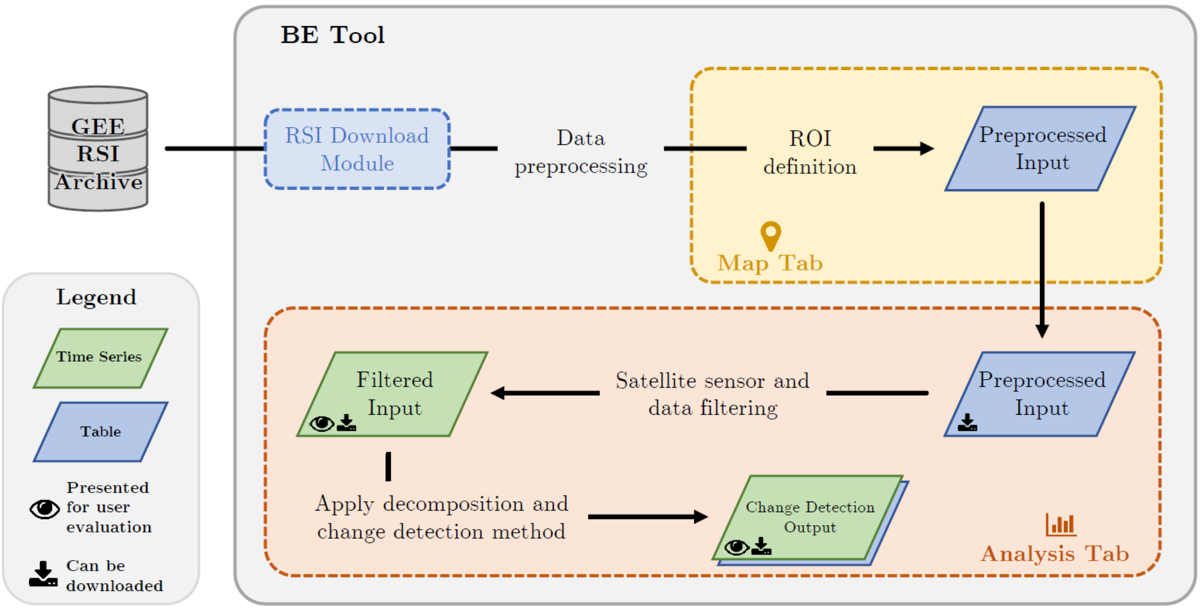

Figure 3.7 Architectural overview of the BFAST application. Source: Almeida et al. (2018)

3.4 RESULTS

3.4.1 Impact of vegetation index on the detection of phenological trends

Four different vegetation indices were applied to the BFAST algorithm to evaluate if notable differences could be detected. The vegetation indices tested include the Normalised Difference Vegetation Index (NDVI), Normalised Difference Moisture Index (NDMI), Modified Soil-Adjusted Vegetation Index (MSAVI2) and surface albedo.

Only breaks indicating a decrease in vegetation cover are noted (possibly a *Prosopis* clearing event). This corresponds to a decrease in NDVI, NDMI and MSAVI2 and an increase in surface albedo. Analysis to select a suitable vegetation index was done on all managed sites. A summary of the results is presented in Table 3.3, with the full set of results available in Appendix F.

Table 3.3 Comparison of expected breaks in the cover of *Prosopis* due to management intervention, and breaks detected by BFAST for selected pixels (numbered 1 to 4) in two sites (5.1 and 19.4) using the Normalised Difference Vegetation Index, Normalised Difference Moisture Index, Modified Soil-Adjusted Vegetation Index and surface albedo

Site ID	Managed By	Expected Break (from WfW or land manager)	Pixel ID	NDVI	NDMI	MSAVI2	Surface Albedo
19.4	Working for Water	1. ± 2002 2. ± 2013	1	2016 2017	2016 2017	2016 2017	None

Site ID	Managed By	Expected Break (from WfW or land manager)	Pixel ID	NDVI	NDMI	MSAVI2	Surface Albedo
		3. ± 2018	2	2017	2017 2018	None	2017
			3	2017	2017	2017	2017
			4	2017 2018	2016 2018	2017 2018	2017
5.1	Farmer	2012 – 2016 (estimate)	1	2014	2015 2016 2018	2014	None
			2	2014	2014 2016 2018	2014	2014 2016
			3	2014	2014 2016 2018	None	None
			4	2014	2014 2018	2014	None

From site 19.4, a recurring break that occurs throughout is the 2017 break, which likely corresponds to clearing done by Working for Water. For site 5.1 the 2014 break is most likely representing the clearing done by the farmer due to its frequent occurrence across indices. From both sites, NDVI mostly produced a single break matching an expected break. MSAVI2 produced results remarkably similar to that of NDVI, only deviating from the NDVI result in cases where it failed to detect a break at all. NDMI produced more breaks overall, although those breaks mostly aligned with the NDVI and MSAVI2 results. The results from surface albedo mostly matched NDVI in cases where it was able to detect breaks. Surface albedo provided the weakest results of the four indices compared, as it failed to detect breaks in 50% of the performed tests in Table 3.3.

NDVI was able to consistently produce a break in the year that clearing took place and did not introduce additional breaks as NDMI did or missed breaks like MSAVI2. Additionally, NDVI also performs well in detecting small vegetation cover changes in arid environments (Funghi et al. 2020; Shiferaw et al. 2019). Based on the comparison of the four indices, NDVI was selected to be used on the remaining analyses in this study.

3.4.2 Impact of sample size and field site heterogeneity on the detection of phenological trends

The results of the five sites used to evaluate the effect of varying the number of pixels used in the time series, as well as the effect of differences in site heterogeneity, are summarised in Table 3.4. The expected break for each cleared site is provided from information provided by Working for Water or the farmer, as well as the break which BFAST01 produced most often through the ten iterations for each sample size. Additional breaks which occurred during the ten iterations are also noted with their frequency.

Table 3.4 Impact of sample size and site heterogeneity on trend detection using BFAST01 over ten iterations

Site ID	Managed By	Expected Break (from WfW or land manager)		Number of pixels used in time series							
				3	4	5	6	7	8	9	10
19.4	Working for Water	1. ± 2002 2. ± 2013 3. ± 2018	Majority	2017	2017	2017	2017	2017	2017	2017	2017
			Majority %	90%	70%	100%	100%	100%	100%	100%	100%
			Other	2014	2012	-	-	-	-	-	-
			Other %	10%	30%	-	-	-	-	-	-
19.1	Working for Water	1. ± 2001 2. ± 2013 3. ± 2018	Majority	2010	2013	2013	2013	2013	2013	2013	2013
			Majority %	40%	60%	60%	50%	60%	70%	90%	90%
			Other	2010 2013	2010 2014	2010 2014	2010 2014	2010	2010	2010	2010
			Other %	30% 30%	30% 10%	20% 20%	40% 10%	40%	30%	10%	10%
1.1	Farmer	± 2015 (estimate)	Majority	2017	2017	2017	2017	2017	2017	2017	2017
			Majority %	80%	100%	100%	100%	100%	100%	100%	100%
			Other	2015	-	-	-	-	-	-	-
			Other %	20%	-	-	-	-	-	-	-
5.1	Farmer	2012 – 2016 (estimate)	Majority	2007	2007	2007	2007	2007	2007	2007	2007
			Majority %	60%	60%	80%	100%	100%	100%	90%	90%
			Other	2013 2016	2014 2016 2017	2014	-	-	-	2014	2017

Site ID	Managed By	Expected Break (from WfW or land manager)		Number of pixels used in time series							
				3	4	5	6	7	8	9	10
					2020						
			Other %	30% 10%	10% 10% 10% 10%	20%	-	-	-	10%	10%
5.2	None	-	Majority	2016	2002	2002 2016	2002	2002 2016	2002	2002	2002
			Majority %	60%	70%	40% 40%	70%	40% 40%	60%	50%	80%
			Other	2015 2002 2020	2015 2016	2015					
			Other %	20% 10% 10%	20% 10%	20%					

In the case of a site cleared by Working for Water, the expected clearing dates correspond to the year in which the clearing of the site was completed as indicated in the WIMS database. As clearing often spans several months, the break detected by BFAST01 could be found a year before the expected break as the WIMS database does not record the date when management started, only when it ended.

With farmer-cleared sites, there is no general rule of thumb for how long clearing will take, and this mostly depends on the method used, as well as the purpose of clearing and the financial standing of the farmer. These purposes of clearing can be categorised into five broad categories, namely, to clear the entire farm, to clear and maintain some parts of the farm in an uninvaded state, to only prevent the spread of *Prosopis* to new areas, to prevent the establishment of *Prosopis* on farms currently free of it and to confine clearing to areas of strategic importance such as roads, fences and water points. As an example, when a farmer clears an area of *Prosopis* around areas of strategic importance, clearing will often be intermittent and take place whenever access is restricted to these areas by *Prosopis*. Also, clearing using an excavator and bulldozer (as was done by some farmers) will see an area cleared in a significantly shorter time than when clearing is done with manual labour. Lastly, the funding dedicated to the clearing of *Prosopis* differ from farmer to farmer and this will affect the speed of clearing operations.

None of the private landowners in this study kept highly detailed records of clearing, and as a result, rough estimates were often provided for areas cleared by farmers. These estimates could therefore be inaccurate regarding the year of clearing, the exact location and area cleared, the method used, and the cost. To minimise the effect of incorrect data on matching breaks to clearing, all breaks within a window of two years before or after the date indicated by management records were considered to be the same. This was done for both farmer- and WfW-managed sites.

The two Working for Water sites in Table 3.4 (19.1 and 19.4) share some trends with the farmer-managed site 1.1, concerning the number of pixels at which results (percentage of times the same year of management action is identified) stabilised. The major breaks remain relatively consistent for these three sites when increasing the number of samples used in the time series. Sites 19.1 and 19.4 were mechanically cleared with multiple labourers over a relatively short period – likely less than six months. The farmer-cleared area (1.1) was cleared using a bulldozer and excavator in less than a month, and the result stabilizes at fewer pixels selected. As mentioned previously, the dates provided by farmers are very rough estimates in contrast to the dates provided by Working for Water in their WIMS database. This could explain the farmer indicating a clearing date of 2015 for this site (1.1), whereas a major break is consistently observed only two years later in 2017.

Notably, the expected dates of clearing in the case of the two Working for Water sites differ considerably from the majority of breaks found for these sites. This might be due to several factors, including errors in the capturing of boundaries areas demarcated for clearing, or only partial clearing of the demarcated area. In site 19.1, only the clearing of 2013 is evident. In site 19.4 the break observed in 2017 is observed in almost all cases, with breaks only being detected in 2012 and 2014 when less than five observations are used, which might indicate only partial clearing of the site in those years.

What is interesting to note is what happens to the trend line in site 19.4 after the break with the inclusion of different pixels. There is one area in which fieldwork found that water accumulates slightly, so the regrowth in those pixels will be much higher compared to the other pixels, such that results are strongly impacted depending on whether these “waterlogged” pixels are included in a particular iteration. In Figure 3.8 five observations are used in the time series, of which three observations fall in the dense regrowth area.

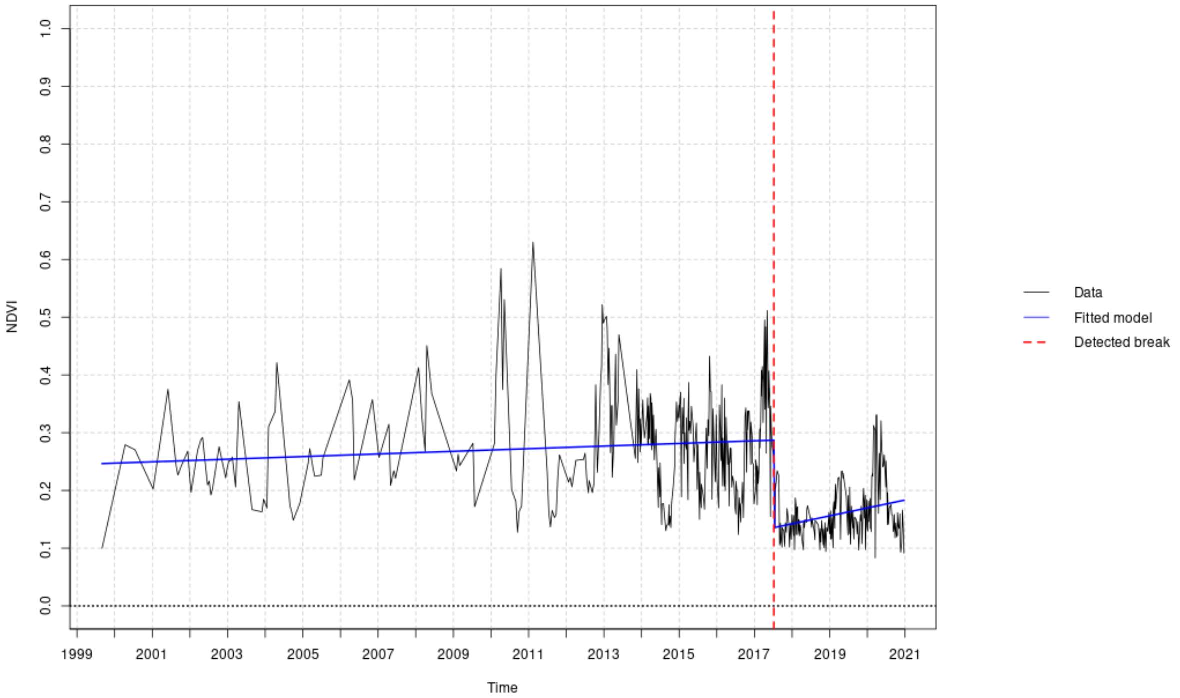

Figure 3.8 *Prosopis* regrowth in site 19.4 with the inclusion of pixels where water had accumulated

This particular selection of pixels causes the high rate of regrowth observed between 2017 and 2020, which is not visible in Figure 3.9 where only one pixel is selected from the area with dense regrowth.

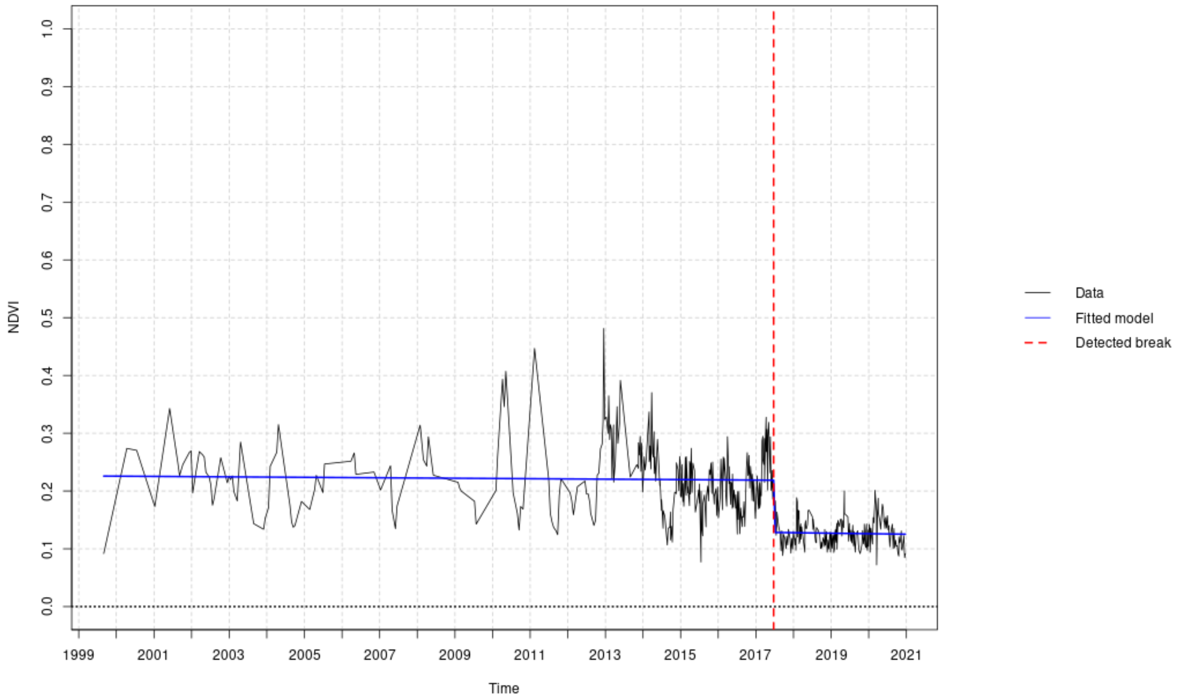

Figure 3.9 *Prosopis* regrowth in site 19.4 with fewer pixels included where water had accumulated

In an oblique aerial photo of the site (Figure 3.10) the area where rainfall water accumulates and extraordinarily strong regrowth is seen, is outlined in green, with the entire cleared area outlined in red.

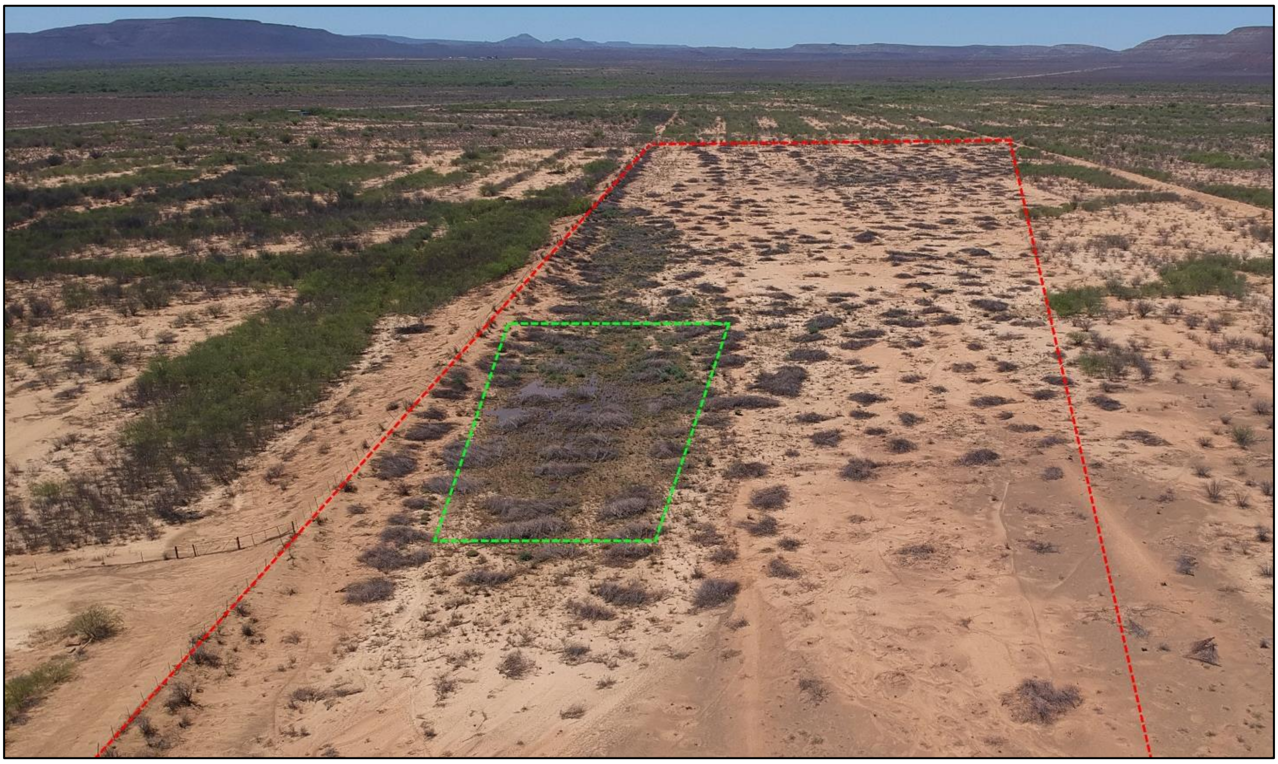

Figure 3.10 An aerial view of site 19.4 (red) with dense regrowth visible (green). Dead branches were piled by Working for Water, but never removed and are also visible.

3.4.3 Effect of *Prosopis* clearing

The effect of *Prosopis* clearing was tested on all sites with five pixels or more (24 sites cleared by WfW, 14 farmer sites and two sites where both parties managed *Prosopis*). Additionally, the analysis also included 28 unmanaged sites to be able to compare breaks exhibited in managed sites with those in unmanaged sites.

Two sets of results were produced to investigate the effect of clearing: BFAST01 with NDVI and BFAST also with NDVI as the indicator of biomass. For all sets of results, five iterations were used (with five randomly selected pixels each time). The full set of BFAST and BFAST01 results from all 40 managed sites can be seen in Appendices C and D respectively. BFAST01 results of unmanaged sites are available in Appendix E.

3.4.3.1 BFAST01

A summary of the results of the BFAST01 algorithm with NDVI used as input for all managed sites can be seen in Table 3.5. Results were condensed from five sets of results per site (200 BFAST01 graphs), each of which had its own break as different pixels were randomly selected by the implementation of BFAST01. Breaks that occurred most of the time were termed "major breaks" and breaks that occurred less frequently are referred to as "minor breaks".

Table 3.5 Summary of break detections from all managed sites analysed with BFAST01 and NDVI, with and without the inclusion of minor breaks – i.e. breaks which did not occur most of the time during iterative analysis of sites.

	Managed by	Total Sites	Detection Success #	Detection Success %
Using only major break	Farmer	14	3	21%
	WfW	24	9	38%
	Both	2	2	100%
Major and minor breaks	Farmer	14	8	57%
	WfW	24	15	63%
	Both	2	2	100%

Of the 40 managed sites, better management detection success rates are observed for Working for Water sites. The inclusion of minor breaks improves detection success rates on both WfW and farmer-managed sites. Of the 40 managed sites, 25 were matched to management records. The results in Table 3.5 are available in full detail in Appendix D.

To illustrate specific results better, the same five sites used to demonstrate the impact of sample size and field site heterogeneity on the detection of phenological trends were included in more detail in Table 3.6. The trend in *Prosopis* biomass before the break and after the break is noted, as well as the trend during the break. When *Prosopis* clearing is done, the expectation is that a decrease will be observed during the break i.e. a high NDVI value before the break followed by a lower NDVI value immediately after the break. The trend after the break may also indicate regrowth.

Table 3.6 Extract of results from selected pixels from Landsat 7 and 8 using BFAST01 with NDVI.

Area	Managed By	Expected Break (from WfW or land manager)	Observed Breaks	Trend Before Break	Trend During Break	Trend After Break
19.4	Working for Water	4. ± 2002 5. ± 2013 6. ± 2018	2017 (60%)	Steady	Decrease	Steady
			2012 (40%)	Steady	Increase	Decrease
19.1	Working for Water	1. ± 2001	2010 (60%)	Increase	Decrease	Decrease

Area	Managed By	Expected Break (from WfW or land manager)	Observed Breaks	Trend Before Break	Trend During Break	Trend After Break
		2. ± 2013 3. ± 2018	2013 (40%)	Increase	Decrease	Increase
1.1	Farmer	± 2015 (estimate)	2017 (80%)	Variable	Decrease	Variable
			2015 (20%)	Increase	Decrease	Decrease
5.1	Farmer	2012 – 2016 (estimate)	2007 (80%)	Decrease	Increase	Decrease
			2014 (20%)	Decrease	Decrease	Increase
5.2	None	-	2002 (100%)	Increase	Decrease	Increase

The two areas managed by WfW (19.1 and 19.4) both have indications that breaks are successfully detected. In site 19.4, the observed break in 2017 is highly likely the same as the expected break of 2018 due to records not specifying when clearing has commenced. This is also further emphasised by the clear unambiguous break observed in 2017 on a plot of the time series data (Figure 3.8 and Figure 3.9). The break observed for the second Working for Water site indicates a majority break in 2010 (Figure 3.11).

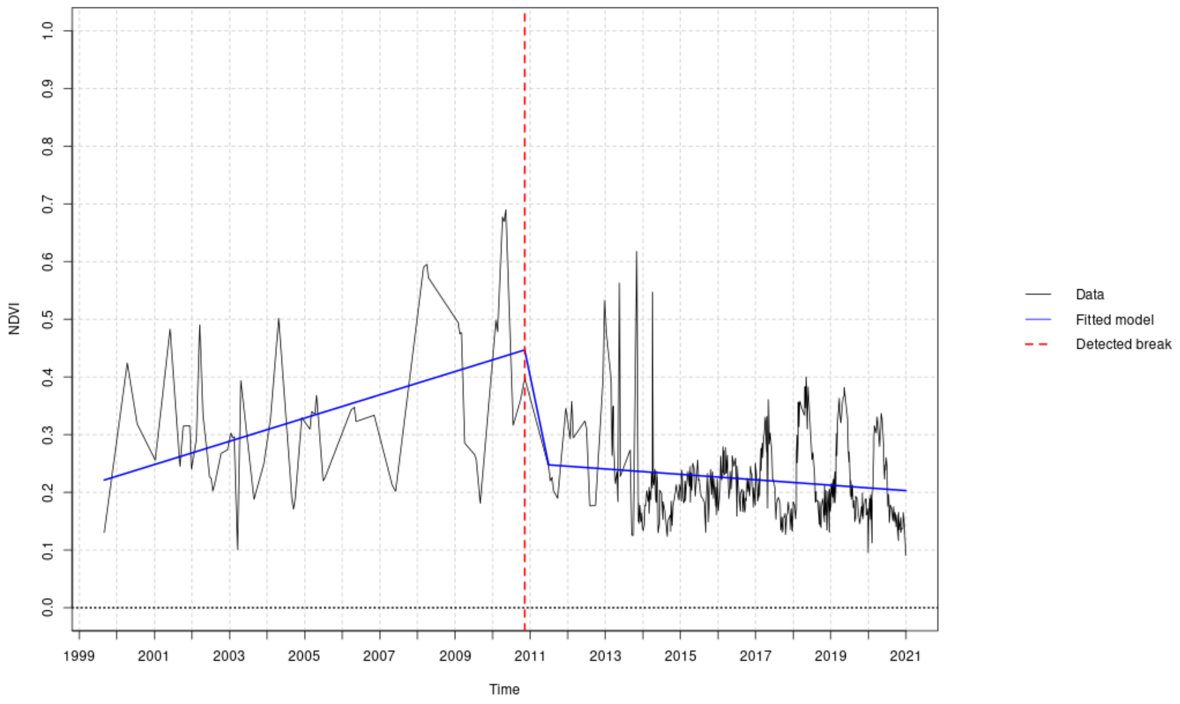

Figure 3.11 Break identified by BFAST01 at the end of 2010 in site 19.1

While the majority break is observed in 2010, when visually inspecting the time series graphs a break of 2013 would be expected as only in 2013 does the annual growth peaks stabilise at a lower NDVI value (Figure 3.12). In this case, the minority break likely corresponds to the expected break (provided by WfW) in 2013.

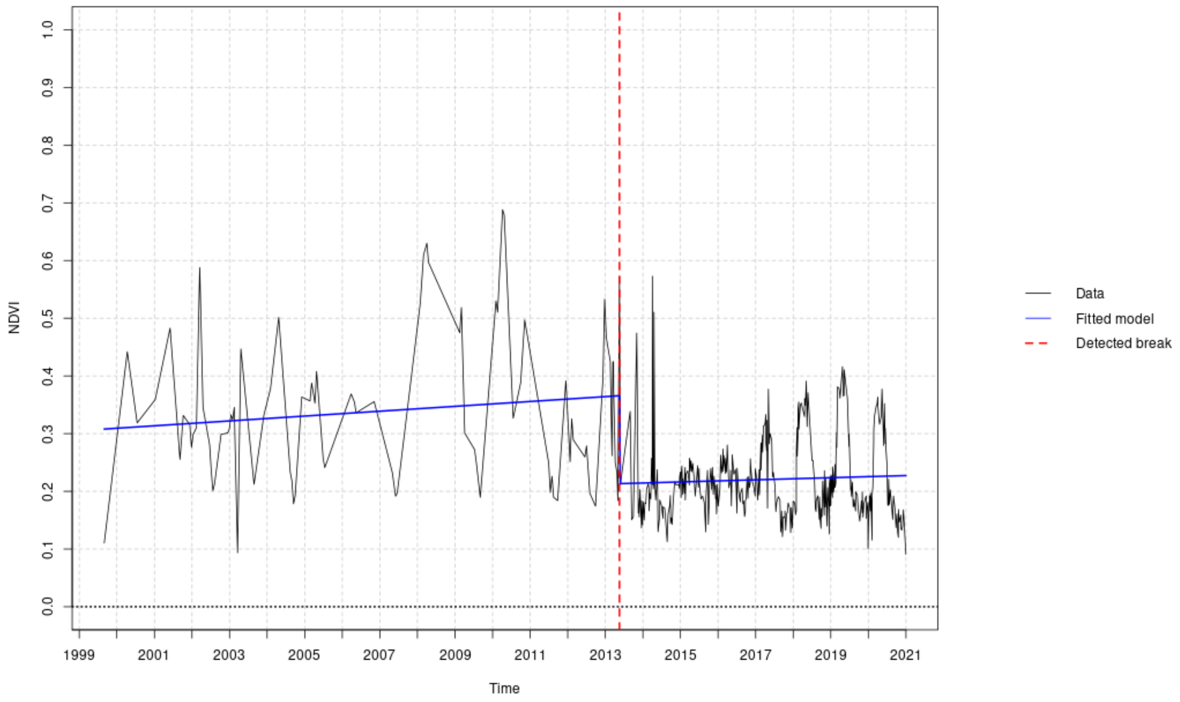

Figure 3.12 Break identified by BFAST01 in 2013 in site 19.1

Similar results were observed when using MSAVI2 instead of NDVI to model *Prosopis* biomass (Table 3.7). Breaks correspond mostly with those observed when using NDVI, although some sites with large differences between pixels of the same site introduce new breaks, which is likely due to the variability in those sites. It is important to note that the time series exhibit the same trends for NDVI and MSAVI2 when the same break is detected, pointing to similarities between these two indices.

Table 3.7 Extract of results from selected pixels from Landsat 7 and 8 using BFAST01 with MSAVI2. Breaks in bold were not present when using BFAST01 with NDVI.

Area	Managed By	Expected Break (from WfW or land manager)	Observed Breaks	Trend Before Break	Trend During Break	Trend After Break
19.4	Working for Water	1. ± 2002 2. ± 2013 3. ± 2018	2017 (60%)	Steady	Decrease	Increase
			2012 (20%)	Decrease	Increase	Decrease
			2014 (20%)	Increase	Decrease	Decrease
19.1	Working for Water	1. ± 2001 2. ± 2013 3. ± 2018	2010 (100%)	Increase	Decrease	Variable
1.1	Farmer	± 2015 (estimate)	**2020 (60%)**	Decrease	Increase	Decrease
			2017 (20%)	Increase	Decrease	Increase

Area	Managed By	Expected Break (from WfW or land manager)	Observed Breaks	Trend Before Break	Trend During Break	Trend After Break
			2019 (20%)	Steady	Decrease	Increase
5.1	Farmer	2012 – 2016 (estimate)	2007 (40%)	Decrease	Increase	Decrease
			2012 (40%)	Increase	Decrease	Decrease
			2016 (20%)	Decrease	Increase	Decrease
5.2	None	-	2002 (60%)	Increase	Decrease	Increase
			2015 / 2016 (40%)	Decrease	Increase	Decrease

Unmanaged sites were also analysed using BFAST01 to compare each managed site to the closest unmanaged site and inspect overlaps in the dates of breaks detected between these sites. In total, of the 25 sites that were matched to records of management by comparing years of management in records with years when breaks were identified by BFAST01, 13 sites had breaks that matched their unmanaged paired site. This does not necessarily mean that the breaks in these sites cannot be attributed to management, but there is a possibility that some of the breaks in these sites might be due to environmental causes if the break is also found in the unmanaged paired site. Paired managed and unmanaged sites can be seen in Appendices D and E.

3.4.3.2 BFAST

An h value of 0.1 was selected for BFAST, as there was a total of approximately 250 observations (one per month) which was used as input to BFAST for break detection. Setting $h = 0.1$ meant that each segment can have a duration of 25 months before a new break (and segment) can start. A value of more than 0.1 did shift breaks from their real date of occurrence or completely miss them when it was tested with h values of 0.125, 0.15 and 0.2.

A summary of the results of the BFAST algorithm with NDVI used as input for all managed sites can be seen in Table 3.8. Results were condensed from five sets of results per site where different pixels were used, with results from each iteration having their own set of breaks ranging between zero and seven breaks per site. Only breaks that occurred most frequently were included due to the number of breaks per iteration of a site.

Table 3.8 Summary of break detections from all managed sites analysed with BFAST and NDVI.

	Managed by	Total Sites	Detection Success #	Detection Success %
Using only major break	Self	14	7	50%
	WfW	24	12	50%
	Both	2	2	100%

The detection success rate of sites managed by farmers is equal to those for Working for Water. Overall, detection success rates are higher than those observed with BFAST01 when using only the major break, but lower when also considering other breaks (Table 3.5). The results in Table 3.8 are available in full detail in Appendix C.

To highlight specific results, the same subset of results used in Table 3.6 are tabulated in more detail in Table 3.9.

Table 3.9 Extract of results from selected pixels from Landsat 7 and 8 using BFAST with NDVI.

Area	Managed By	Expected Break (from WfW or land manager)	Observed Breaks	Trend Before Break	Trend During Break	Trend After Break
19.4	Working for Water	1. ± 2002 2. ± 2013 3. ± 2018	2017 (100%)	Increase	Decrease	Variable
19.1	Working for Water	1. ± 2001 2. ± 2013 3. ± 2018	2011 (100%)	Increase	Decrease	Decrease
1.1	Farmer	± 2015 (estimate)	2017 (40%)	Increase	Decrease	Decrease
			2014 (20%)	Increase	Decrease	Decrease
			2011 (20%)	Decrease	Increase	Decrease
			2006 (20%)	Increase	Increase	Decrease
5.1	Farmer	2012 – 2016 (estimate)	2011 (60%)	Decrease	Decrease	Decrease
			2016 (40%)	Decrease	Increase	Decrease
5.2	None	-	1998 / 2002 / 2007 / 2015 (100%)	-	-	-

For site 19.4, the 2017 break was constantly observed with all five iterations of BFAST, confirming the majority break observed using BFAST01 and NDVI (Table 3.6), as well as BFAST01 and MSAVI2 (Table 3.7). A similar observation can be made regarding the break seen in 2010 for site 19.1 – it also agrees very well with the break observed as the majority break in previous analyses (Table 3.6 and Table 3.7). Site 1.1 has shown erratic results, but the majority break still agrees with BFAST01 results for the same site. Surprisingly, the results for site 5.1 might point toward clearing detected starting in 2011, with a downwards trend afterwards (Figure 3.13).

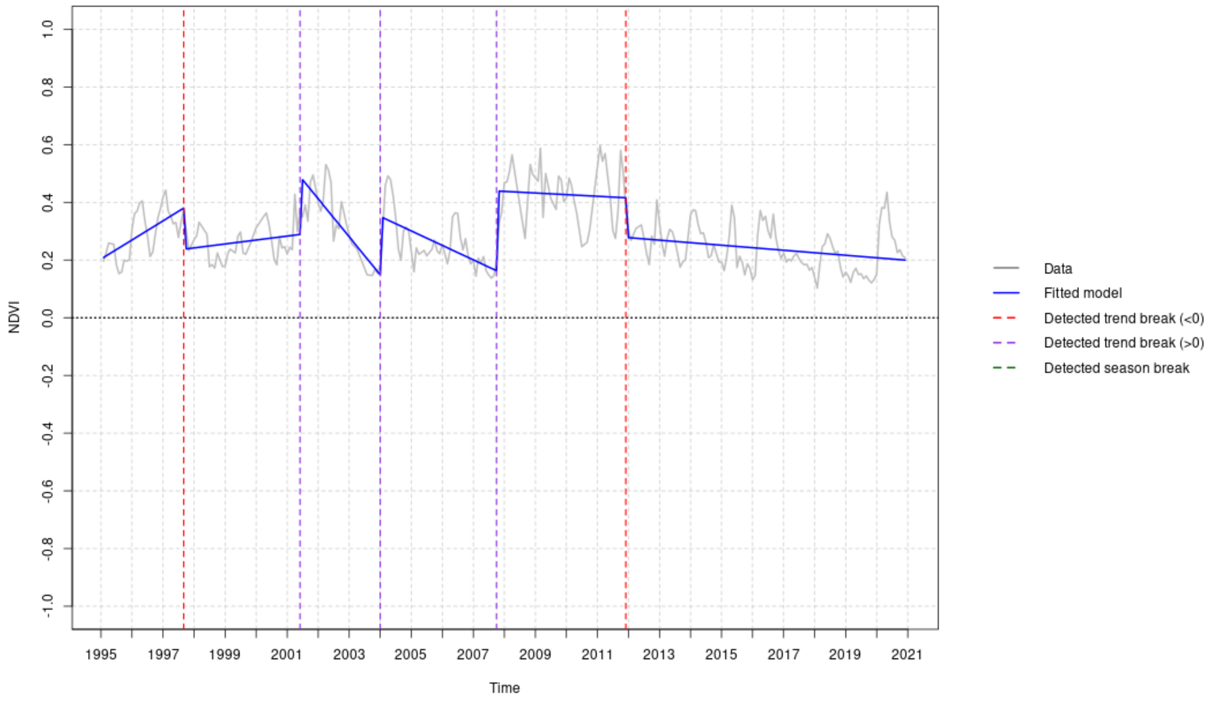

Figure 3.13 A notable reduction in NDVI is visible at the 2011 break produced by BFAST using NDVI (site 5.1).

Less predictable results were seen for this site with BFAST01 analysis (Figure 3.14). It must be stressed that the landowner of this site approached clearing over about five years whenever time and funding was available. This led to clearly visible breaks on Google Earth imagery between 2012 and 2016, but when more pixels are aggregated for analysis the resulting loss of data variation causes BFAST01 to miss existing breaks.

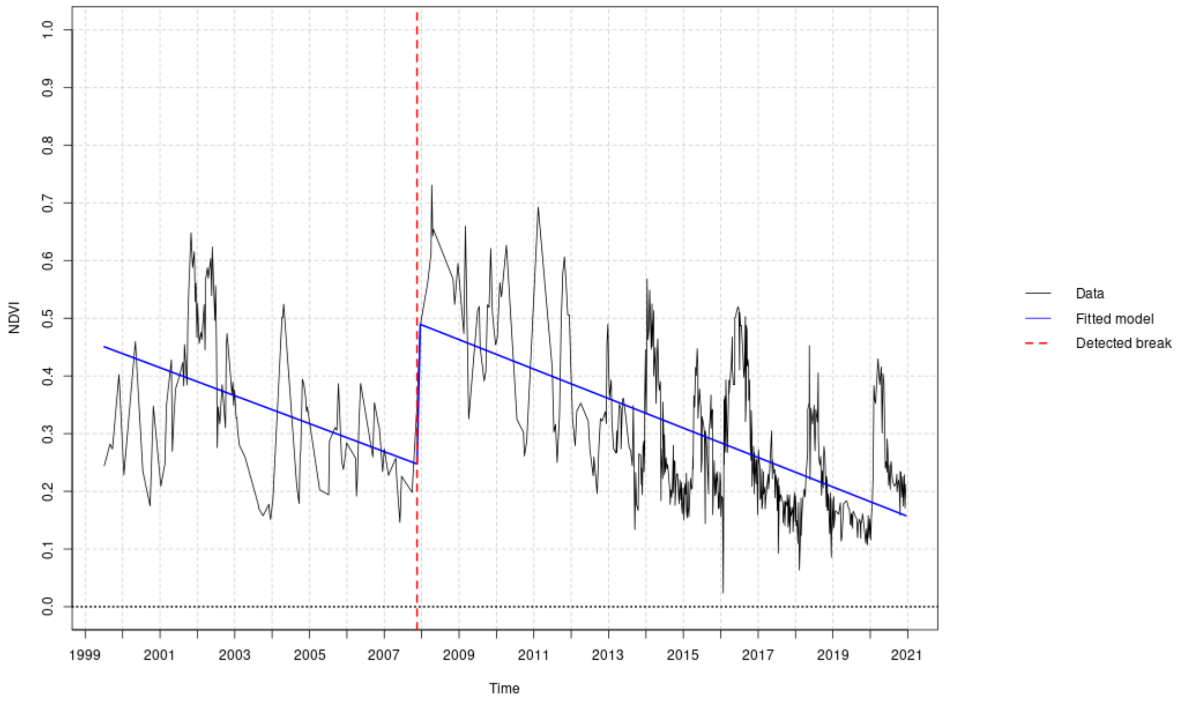

Figure 3.14 Break identified by BFAST01 in late 2007 in site 5.1

3.5 DISCUSSION

This study used changes observed in the biomass of *Prosopis* in combination with the trend analysis algorithms, BFAST and BFAST01, to identify changes in cover of invasive alien *Prosopis* trees. This method differs from the classical multi-temporal pre- and post-event(s) classification approaches making use of a few satellite images, typically reflecting the situation in selected points in time (i.e. selected years), providing no information on how vegetation cover has changed (i.e. increased or decreased) in between the observed points in time (Mbaabu et al. 2019). While both methods have advantages and disadvantages, the method used in this study provides almost continuous information (with a monthly interval) on the amount of living biomass, thus enabling the estimation of clearing dates from satellite imagery when an exact date is not known.

Firstly, different vegetation indices were compared to select a suitable index to use with the BFAST and BFAST01 trend analysis algorithms. BFAST can detect multiple breaks over a period, with the number and occurrence of breaks defined by the h parameter. Based on literature review, a value of 0.1 was chosen for the h parameter (Lin et al. 2020; Saxena et al. 2018; Verbesselt, Hyndman, Newnham, et al. 2010; Watts & Laffan 2014; Zhou et al. 2019). BFAST01 only detects the most significant break and did not have additional parameters like BFAST which had an impact on the location of breaks. Both algorithms were able to detect breaks in trends expected due to management action of clearing *Prosopis*. As expected, BFAST were able to detect more breaks when compared to the major breaks of BFAST01. This can be attributed to the ability of BFAST to detect more than one break per site. This property also contributed to many unexplained breaks being detected in addition to expected breaks, making evaluating results from BFAST more time-consuming than with BFAST01. In cases where breaks were evidently visible on satellite imagery after a clearing event, the break detected by BFAST01 would often correspond to one of the breaks detected by BFAST for that site. In a few cases, BFAST01 detected breaks not detected by BFAST, despite BFAST being able to detect multiple breaks per site. This might be due to the choice of the *h* parameter of BFAST, which was set to 0.1, which limited break detections to one break every two years.

Before the effects of management could be detected, a vegetation index was to be selected for use by both BFAST and BFAST01. NDVI, NDWI, MSAVI2 and surface albedo were evaluated on all sites using BFAST and their resulting breaks were compared against each other, and to data that was collected during fieldwork. NDVI and MSAVI2 performed similarly, except in some cases where MSAVI2 failed to detect some breaks detected by NDVI. When using BFAST with NDMI, more breaks were consistently detected, which often did not match with clearing data on record. Surface albedo failed to detect breaks in 50% of the sites analysed, which might be due to the relatively small changes in albedo in cases where NDVI exhibit larger fluctuations. Subsequently, NDVI was chosen for the rest of the analysis in this chapter.

With a vegetation index selected, the area of each site to be used as input required standardisation - some sites consisted of only a single pixel, whereas other sites often consisted of more than ten pixels. Different vegetation growth patterns could be observed in individual pixels, within a site cleared by management action, due to environmental and human factors, such as the availability of water to sustain growth (Figure 3.10) as well as the duration of clearing of *Prosopis* trees. Three to ten pixels were selected (per study site for a subset of five sites) over ten iterations with replacement and analysed using BFAST01 to determine the sample size to use.

It was found that with different management methods and paces of *Prosopis* clearing, results stabilised at a different number of pixels used for the study site. In cases where management was done over a short period (e.g. six months or less), fewer pixels were required to obtain a stable result and clearing dates could be accurately retrieved by the methods used in this study. In sites where longer periods of management were seen, more variability was observed. Five pixels were consequently selected as the number of pixels to use per site for further analyses.

Furthermore, the intent of clearing and funding available per year also had influences on how well the methods could detect clearing. For instance, the method accurately retrieved clearing dates for WfW sites cleared within six months, whereas sites that were cleared by farmers over several years, as time and funding were available, made it challenging for the algorithm to identify a clear break in the phenology trend. The method may have potential as a tool for confirming the extent of clearing by WfW in the short term.

In sites with more inherent heterogeneity observed on the ground between pixel locations, results did not stabilise to the point where a single break could easily be identified as the majority with confidence. A good example of this is site 5.1 where the landowner managed a relatively small area over about five years, resulting in pixels that were partially cleared at times and only fully cleared a year or more later. It was also observed that in sites unequal rates of *Prosopis* regrowth can occur which can affect regrowth trends observed after clearing with the inclusion of different pixels per study site.

Variable soil and drainage patterns influenced *Prosopis* regrowth within the same site. This was well-observed in site 19.4 where a portion of the site had regrown, after clearing, to form moderately dense *Prosopis* stands while other areas remained almost bare. As some sites are made up of only a few pixels, five pixels per site were selected to balance the exclusion of sites with fewer pixels with the increase in stability seen when increasing the number of pixels. In some sites with high variability between pixels, using more than five pixels lead to losses of pixel information as the median pixel value is used for analysis.

Finally, this study compared two trend algorithms, BFAST and its variant BFAST01, to analyse the changes in *Prosopis* cover over 21 years at all managed sites in the study to determine if and how well the effect of clearing could be observed using remote sensing.

After elimination of sites that did not consist of at least five pixels or which did not have the required metadata such as robust estimates of dates or boundaries of clearing, 40 managed sites remained. Of these 40 sites (Appendix C and D), 24 were managed by Working for Water (WfW), 14 by landowners and only two sites were managed by both parties. A management detection success was defined as a break that has occurred within two years of the indicated date of clearing and having a decreasing trend during the time of the break. This was done as landowners could not always remember the exact date (or year) of the clearing and because clearing in such cases often took place over a number of years, such that a two-year leeway was deemed to provide a suitable window of temporal detection.

For BFAST01, with only the major break taken into account, i.e. the break that occurs most throughout the five iterations per site over the 21-year time series, the management detection success of WfW sites is 38%, compared to 21% for sites managed by landowners and 100% for the two sites managed by both parties. When breaks other than the major break was taken into consideration, these figures increased to 63% for WfW-managed sites and 57% for sites managed by landowners.

The increase in the management detection success rate when minor breaks are included suggests that the variation found in sites have a greater effect on results than expected. With the selection of five random pixels per site for each iteration where breaks were calculated, the variation between pixels in some sites led to a situation where different breaks were recorded for each iteration. In sites 21.9 and 23.1 this can be seen where no majority break was recorded, but instead five different breaks throughout the iterations.

When BFAST results are evaluated, overall management detection success rates are 50% for both WfW- and landowner-managed sites and stays at 100% for the two sites managed by both parties. While these figures are somewhat lower than those seen with BFAST01 when including all minor breaks too, this drop in the detection success rate is expected as several sites only showed increasing breaks. This can be due to the way the BFAST break and trend line fitting was done, which depend on the h parameter. Several of the sites which only showed increasing breaks had many short breaks every two or more years. This problem of overfitting was often seen when a seasonal growth spike caused a break.

With BFAST01, cleared sites were also compared to uncleared sites to determine if they have similarities that can be used to isolate breaks caused by natural causes such as rainfall, drought and other external variations. This was not attempted with BFAST, as the latter can detect several breaks which complicates matching managed and unmanaged breaks. Each managed site was paired with the closest unmanaged site covered with *Prosopis*. From a comparison between managed and unmanaged sites, of the 25 sites that were matched to records of management by comparing years of management in records with years when breaks were identified by BFAST01, 13 sites (52%) had breaks that matched their unmanaged paired site. This does not necessarily mean that the breaks in these sites cannot be attributed to management, but there is a possibility that some of the breaks in these sites might be due to environmental causes if the break is also found in the unmanaged paired site. This might indicate the complexity of using phenological trend analysis in areas that have less distinct seasonal patterns and highly variable inter-annual conditions.

Overall, BFAST and BFAST01 were able to successfully detect management of *Prosopis*, albeit with varying results depending on the method, its parameters and several management-related factors. The current methods performed better with sites managed by Working for Water than sites managed by private landowners, possibly due to the more rapid clearing taking place at WfW managed sites, leading to less mixed pixels which are partially cleared.

Future research can build on the methods and results of this study by evaluating the ability of additional trend analysis algorithms such as Landsat-based detection of Trends in Disturbance and

Recovery (LandTrendr) and Continuous Change Detection and Classification (CCDC) to detect invasive alien plant clearing. The LandTrendr algorithm can provide landcover change information on an annual time scale, which might capture less variation due to seasonality and other unexplained changes the methods in this study are susceptible to – in particular the effect of seasonal growth spikes causing overfitting of trend lines. The CCDC algorithm is a multivariate approach, meaning it is capable of using all spectral bands available to detect changes in land cover, unlike univariate approaches like BFAST and BFAST01 which was used in this study.

To improve results in situations where management progressed slowly and differed between pixels, a pixel-based approach that also deals with the spatial aspect of the break can be considered. One such approach is the BFAST Spatial algorithm, which evaluates each pixel present in the input using BFAST Monitor and outputs a raster indicating breaks and their magnitudes with all pixels per site included in the analysis. This might provide better insight into what areas within a site were best cleared without having to randomly pick and aggregate pixels to find the average trends within each managed site.

3.6 CONCLUSION

This chapter used changes observed in the biomass of *Prosopis* in combination with the trend analysis algorithms, BFAST and BFAST01, to identify changes in the cover of invasive alien *Prosopis* trees. Four indices were compared as input, namely the Normalised Difference Vegetation Index (NDVI), the Modified Soil-Adjusted Vegetation Index (MSAVI2), the Normalised Difference Moisture Index (NDMI) and surface albedo, as well as the effect of varying the input sample size, was also evaluated.

Of the four vegetation indices that were compared in terms of whether their estimation of *Prosopis* biomass as input to the BFAST algorithm produced noticeable differences, NDVI was selected as the indicator of *Prosopis* biomass for the rest of the study as it provided a balanced number of breaks when used with BFAST. MSAVI2 performed remarkably similar to NDVI but missed some breaks detected when using NDVI, and NDMI produced several extra breaks not observed with other indices. Surface albedo missed most breaks other vegetation indices could detect, likely due to its very flat response observed to changes in *Prosopis* biomass.

Using the median aggregate of fewer pixels in the analysis resulted in more accurate *Prosopis* biomass trends representing the pixels involved but does not provide a broader picture of the entire site, which was managed, whereas when more pixels were included, the spectral data representing *Prosopis* biomass were lost in most cases due to heterogeneity between pixels. As a result, a sample size of five pixels was used to attempt to capture management efforts even in sites with high heterogeneity, which is likely caused by factors such as slow clearing or variable water availability within a site.

When using BFAST and BFAST01 with NDVI to detect *Prosopis* management intervention, *Prosopis* clearing was overall better detected in sites managed by Working for Water than in sites managed by private landowners, which can be attributed to several differences, including funding and purpose of clearing - which ultimately affects the rate of clearing. WfW sites are generally cleared over a few months, while landowner cleared sites were generally cleared over a number of years, which leads to sites with highly heterogenous pixels and differences between pixels as biomass is not removed uniformly over a short period of time. In cases where management was rapid and where the stakeholder completely cleared the area of *Prosopis*, clear breaks were found where they were expected based on interview data.

To summarise, while *Prosopis* management was less accurately detected than expected, results in this chapter have shown that *Prosopis* management detection using Landsat imagery is possible given sufficient background data, and that current analysis methods proved to be more suitable for detecting management by Working for Water than for landowner-managed sites. In retrospect, an analysis of a smaller sample size could have provided more accurate break detection, albeit at the cost of losing a sense of management for the entire site.

CHAPTER 4: AN ASSESSMENT OF THE EFFECTIVENESS OF ATTEMPTS TO CONTROL *PROSOPIS* TREES IN THE NORTHERN CAPE PROVINCE, SOUTH AFRICA

4.1 ABSTRACT

Prosopis trees are alien to South Africa, and since their introduction in the 1880s have become invasive, specifically in the Northern Cape Province, where they covered an estimated 1.5 million hectares in 2007. These trees have had significant negative impacts on biodiversity, groundwater resources, and grazing capacity.

Until the 1960's the planting of *Prosopis* was actively encouraged through government subsidies and extension programmes. *Prosopis* trees were later declared as invasive species, but due to their perceived value, only seed-feeding biological control agents were introduced to assist with control. At the start of the 21st century, various stakeholders finally agreed that the negative impacts outweighed any positive benefits, and it was finally agreed that more damaging biological control agents should be sought.

In 1995 the South African government initiated the Working for Water program to assist land managers in their attempts to bring alien plant invasions under control. Invasive alien plant management in the Northern Cape is focused almost exclusively on *Prosopis*. Working for Water has spent approximately ZAR 580 million (adjusted for inflation to 2021 values and with project overheads included) on *Prosopis* management across South Africa, based on WfW records of contracts awarded to clearing teams since 1998, but *Prosopis* invasions are increasing despite this significant spending.

In this study, I conducted structured interviews with 17 landowners whose farms were invaded by *Prosopis* trees and examined the outcomes of control on the ground to establish farmers' attitudes towards *Prosopis*, to document perceived benefits and impacts, and whether state support through Working for Water improved the effectiveness of controlling *Prosopis*. In addition, a remote sensing time series from 1999 to 2020 was analysed using the BFAST and BFAST01 trend analysis algorithms to assess whether these algorithms could be useful for monitoring management activities and resultant trends.

Farmers all recognised that *Prosopis* trees had both advantages and disadvantages. More than half of the farmers identified fodder for livestock as an advantage, and less than a quarter also mentioned that shade and firewood were beneficial. On the other hand, farmers identified twice as many disadvantages than advantages associated with *Prosopis*, of which water usage and loss of grazing capacity were most frequently mentioned. Farmers were almost unanimous in agreeing

that they would like to eradicate *Prosopis* from their farms, but in reality, they had to set lesser goals for themselves depending on their financial standing, with some simply being unable to afford any form of control.

The farmer survey included farms where control had been carried out either by the farmer or by Working for Water. It was found that relatively good progress was made towards achieving control on demarcated sites when the farmers carried out the control themselves, while sites treated by Working for Water generally showed poor progress. Only two sites could be located where the treatments were conducted by both the farmer and Working for Water, so the effectiveness of joint control could not be assessed. I conclude by suggesting that scarce funds for the control of *Prosopis* are probably too thinly spread to be effective, and that management could improve if funds were to be focussed on fewer, high-priority sites. In addition, attempts to identify effective and lethal biological control agents should be intensified, as they arguably offer the only realistic chance of controlling *Prosopis* over large areas.

4.2 INTRODUCTION

Prosopis species (mesquite) are leguminous thorny trees that are drought-resistant with deep taproots. *Prosopis* trees are alien to South Africa and were introduced in the 1880s from their native range in south-central America to provide benefits such as fodder and shade for livestock (Pasiecznik et al. 2001). *Prosopis* trees are aggressive invaders that can form dense, impenetrable thickets which are of very little value (Bekele et al. 2018; Mwangi & Swallow 2005; Shackleton et al. 2015b). At least six species of *Prosopis* are found in South Africa, and the invasive population constitutes a hybrid swarm which is the second most widespread invasive alien tree genus in South Africa, after Australian trees and shrubs in the genus *Acacia* (Henderson 2007).

Prosopis is most abundant in the arid Northern Cape Province, where it covered an estimated 1.5 million hectares in 2007 (of which about 160 000 ha were very dense stands), with the potential to invade up to 8 million hectares in this province alone (van den Berg 2010). Between 1974 and 2007 *Prosopis* increased in range by approximately 7.4% per year (Wise, van Wilgen & Le Maitre 2012).

Invasive *Prosopis* trees have had significant negative impacts on biodiversity, groundwater resources, and grazing capacity. These impacts included decreases in the abundance and diversity of dung beetles (Steenkamp & Chown 1996), birds (Dean et al. 2002), and indigenous plants (Schachtschneider & February 2013; Shackleton et al. 2015a). The capacity of invaded rangelands to support livestock decreased by 34% when *Prosopis* cover was above 15%, to 100% when sites became fully invaded (Ndhlovu, Milton-Dean & Esler 2011). Dense invasions also significantly reduce groundwater levels and result in the mortality of indigenous trees (Dzikiti et al. 2017; Dzikiti et al. 2015; Fourie et al. 2007; Schachtschneider & February 2013). Similar impacts have been noted in other parts of Africa, including impacts on indigenous vegetation (Linders et al. 2019), water resources (Shiferaw et al. 2021), and indigenous mammals (Kebede & Coppock 2015). Research by Muller et al. (2017) has demonstrated that West African villages with *Prosopis* invasions can support more mosquitoes, increasing the risk of contracting malaria. Although *Prosopis* trees can arguably provide benefits in the form of fodder, shade and firewood, these benefits are exceeded by the cost of negative impacts when invasions become more widespread (Wise, van Wilgen & Le Maitre (2012).

Until the 1960's the planting of *Prosopis* was encouraged by the government due to its ability to grow in very dry conditions. This was done through subsidies and extension programmes (Poynton 1990). In the Northern Cape, native trees are scarce, and local people valued the shade and fuelwood that *Prosopis* trees provided (Zachariades, Hoffmann & Roberts 2011). *Prosopis* pods are also high in sugar, carbohydrates and protein, making them useful as a source of fodder (Choge et al. 2007).

In the years between the 1960s and 1980s, *Prosopis* increasingly became recognised as a problem and was declared an invasive species in 1983 (Henderson & Harding 1992). Biological control in the form of seed-feeding insects that target *Prosopis* was introduced in the 1980s (Impson, Moran & Hoffmann 1999). Due to the perceived value of *Prosopis*, biological control was restricted to seed-feeding agents (Moran, Hoffmann & Zimmermann 1993). Three workshops involving a wide range of stakeholders were held to address the problem between 2001 and 2019. During the first meeting in 2001, it was agreed that the negative impacts of *Prosopis* outweighed any benefits and that the introduction of flower-bud and flower-feeding insects, in addition to seed-feeders, would be justified. The biological control programme was consequently expanded to investigate agents that prevent the pods from reaching maturation. A later meeting in 2004 suggested that agents that attack the vegetative parts of the plant should also be considered, and further prospects for additional biological control agents were discussed at a meeting in 2019. Currently, potential agents that damage the growth of the plants are being considered, in response to the observation that there is no other route to the successful control of *Prosopis* in South Africa (Kleinjan et al. in press).

In 1995, South Africa's newly-elected democratic government initiated a program to assist land managers, both government and private, in their attempts to bring alien plant invasions under control in the areas for which they were responsible (Koenig 2009; van Wilgen & Wannenburgh 2016). South African legislation requires landowners to control listed invasive alien species on their land. Private landowners are simply expected to pay for the control of listed invasive species on their land even though they may not have been responsible for the introduction of the species in the first place (this has been called a "faultless liability" by Lukey & Hall (2020)). The central government has thus sought to provide assistance to both private and state landowners in the form of teams of workers who can clear invasive alien species. The workers are drawn from the ranks of disadvantaged people in mainly rural areas, where unemployment is rampant. It has been possible to justify expenditure on this program (dubbed "Working for Water", hereafter WfW) because it addresses multiple goals by providing developmental opportunities, alleviating unemployment, and dealing with an important environmental problem.

WfW is often depicted in the literature as a program that is responsible for managing invasive species in South Africa (Turpie, Marais & Blignaut 2008; Zimmermann, Moran & Hoffmann 2004). This is not accurate, because (as explained above) WfW simply assists landowners who are in turn legally responsible for control. In reality, however, almost all of the funding that is available for control originates from WfW. This funding has been available since 1995 and currently amounts to over ZAR 1 billion annually (Zengeya & Wilson 2020). Funding is granted by WfW subject to non-negotiable operating rules, for example, labour-intensive methods are compulsory, pay scales are pre-determined, and each intervention requires signing a short-term contract for clearing a particular area. The programme is nonetheless by far the most influential intervention for managing invasive species at a national level.

WfW's performance indicators are formulated in terms of project inputs (money spent and people employed) or immediate outputs (hectares cleared), rather than desired outcomes (reductions in the cover and density of *Prosopis*, and ecosystem restoration) (van Wilgen & Wannenburgh 2016). There are thus no monitoring data that could be used to assess the effectiveness of the program.

Invasive alien plant management in the Northern Cape is focused almost exclusively on *Prosopis* (van Wilgen et al. 2012). WfW spent approximately ZAR 580 million (adjusted for inflation to 2021 values and with project overheads included), based on WfW records of contracts awarded to clearing teams since 1996. Despite this, research suggests that that *Prosopis* invasions are increasing at an exponential rate. Van den Berg (2010) found that the extent of *Prosopis* in the Northern Cape grew from about 77 000 condensed hectares in 1990 to 360 000 "condensed" hectares[1] in 2007 – an increase of 363% over 17 years. Henderson & Wilson (2017) also estimated that the range occupied by *Prosopis glandulosa* increased by 280% (from 40 to 112 quarter degree grid cells) between 2000 and 2016, and that *Prosopis* hybrids simultaneously increased by 23%

[1] A condensed ha is the equivalent area occupied at a canopy cover of 100% (i.e. 50% cover on 10 ha = 5 condensed ha).

(from 390 to 481 quarter degree grid cells). Several studies have suggested that a different approach to the management of *Prosopis* in the Northern Cape would be needed if *Prosopis* were to be effectively controlled (Shackleton et al. 2017; van Wilgen et al. 2012; Wise, van Wilgen & Le Maitre 2012).

In this study, I conducted structured interviews with 17 landowners whose farms were invaded by *Prosopis* trees and examined the outcomes of control on the ground. On these farms, the landowners either funded the control themselves or relied on WfW teams to do the control; in some cases, both approaches were used. The goal was to establish farmer's attitudes towards *Prosopis*, to document perceived benefits and impacts, and to establish the goals of control and the methods employed. My interests also included whether or not state support from WfW improved the effectiveness of controlling *Prosopis*.

4.3 METHODS

4.3.1 Site selection

This study was conducted on 19 farms, owned by 17 farmers, in the Northern Cape Province, selected in a relatively homogenous bioregion between the towns of Carnarvon and Vanwyksvlei (Figure 4.1). This area falls within the Nama Karoo and Succulent Karoo biomes, characterised by largely treeless landscapes with low mean annual rainfall (100 – 400 mm; Rutherford, Mucina & Powrie 2006).

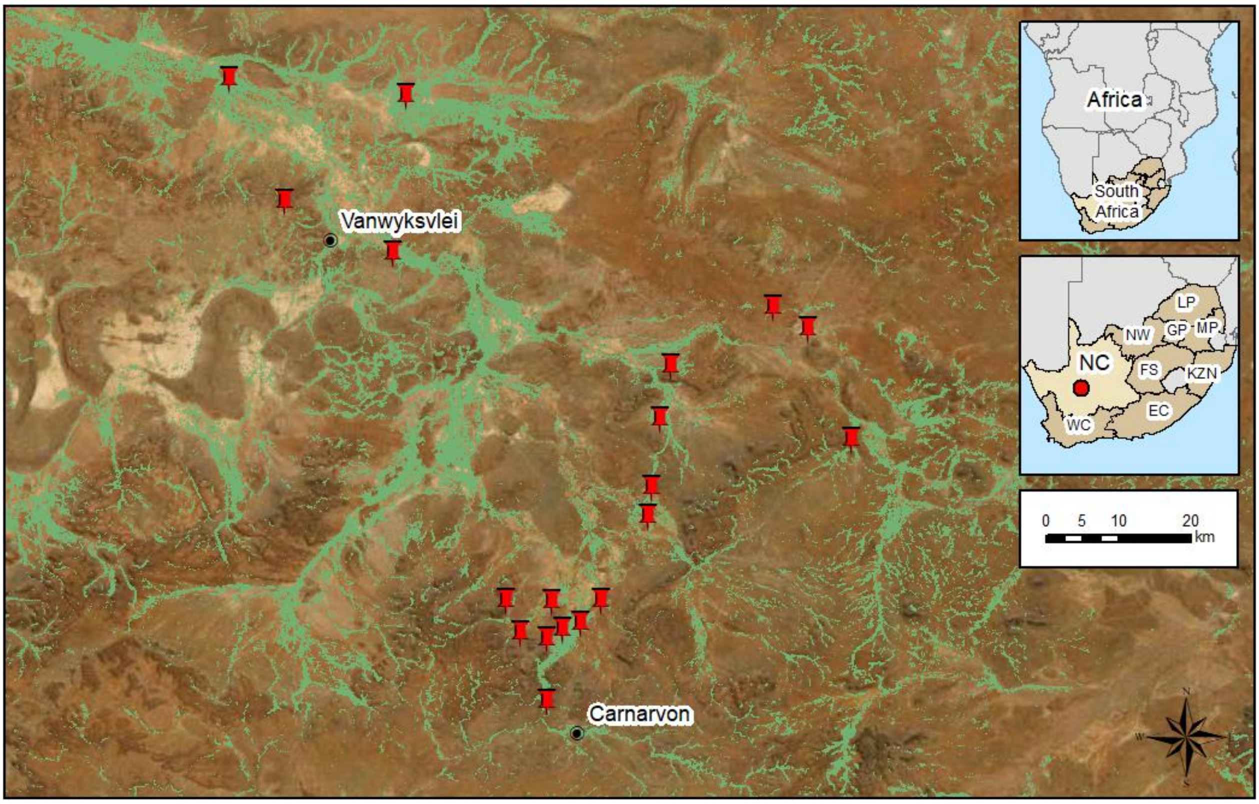

Figure 4.1 Location of farms (red pins) on which the approaches to, and effectiveness of, management of invasive *Prosopis* trees was surveyed in the Northern Cape. Areas shaded in green show the distribution of *Prosopis* invasions as mapped by Van den Berg (2010).

I included farms where the management of *Prosopis* over the past 25 years could be categorised into one of the following categories: (1) management by the farmer only; (2) management by Working for Water only; (3) a combination of management by Working for Water and the farmer; and (4) areas where no attempt had been made to manage *Prosopis*. On each farm, several sites were selected to establish the management approaches and to assess their effectiveness (Table 4.1).

Table 4.1 The number of farms, and sites within farms, on which the approaches to, and effectiveness of, management of invasive *Prosopis* trees was surveyed in the Northern Cape. The area under management was based on contract records from Working for Water or was indicated by the farmer. The area where there was no management was examined on five 30 x 30 m pixels per site.

Treatment history	Number of farms	Number of sites	Total area under management (ha)
Management by Working for Water only	7	24	760.93
Management by farmer only	11	14	101.24
Management by both Working for Water and farmer	2	2	52.15
No management	13	28	12.6
Totals	19	68	941.45

4.3.2 Trends in the cover of *Prosopis*

A remote sensing time series for the period between 1999 and 2020 were analysed using the BFAST and BFAST01 algorithms (Verbesselt, Hyndman, Newnham, et al. 2010) to detect breaks in vegetation cover in the time series, which could be related to management intervention. In both algorithms, the Normalised Difference Vegetation Index (NDVI) was used as the vegetation index used to indicate changes in *Prosopis* biomass. First, five pixels were randomly selected within each site, including sites managed by farmers, WfW, both farmers and WfW and also unmanaged sites. The median NDVI value of these five pixels was used as the input to the BFAST and BFAST01 trend algorithms. This process of randomly selecting five pixels and producing results using both algorithms was repeated five times, to be able to account for differences between pixels in a site. In the case of BFAST, with specific algorithm parameters set, a break in the time series can be detected about every two years if the change deviates significantly from previous values. With BFAST01, only a single break can be detected.

4.3.3 Information on control efforts

Information on *Prosopis* management efforts was obtained from two sources. First, in the case of farms where Working for Water had been active, a spatial database of control operations was available, which provided data on the location and extent of the area subjected to control treatments, the date(s) of the treatment(s), the cost of the treatment(s), the number of people employed, and whether the treatment was an initial clearing or a follow-up action. I adjusted amounts spent by WfW on each site for each year to 2021 values for South African Rands (ZAR; 1 USD = ~ 15 ZAR) to account for inflation, by using annual inflation rates (Statistica 2021). Secondly, I conducted an initial survey on farms around 6300 km of roads in April 2019. I used this information to select 19 farms that covered a range of management approaches for further study. Each of these farms was visited in October 2020. I conducted structured interviews on each farm, in which the owners were asked about attitudes, goals of management, methods used, challenges faced and, where appropriate, whether the assistance provided by the state's WfW programme had assisted in the achievement of goals. The full set of questions asked is provided in Appendix A. I also inspected several sites on each farm, where management had been carried out to assess effectiveness on the ground (Table 4.1).

At each site, I classified the outcome as either good (a marked reduction in cover, or elimination of *Prosopis* from the whole site), limited (reductions in cover on some parts of the site, but not on others), or poor (increases in cover and density on the site). I also categorised trends in the cover of *Prosopis* as either increasing (an increasing trend in the remote sensing time series), decreasing (a decreasing trend in the remote sensing time series), or steady (no change in the remote sensing time series).

4.4 RESULTS

4.4.1 Management effort and outcomes

The survey included 14 sites that were managed by the farmer only, 24 sites that were managed by Working for Water only, and two sites that were managed jointly by the farmer and Working for Water. Working for Water spent a total of 7 745 person-days on these 26 sites, at a total cost of ZAR 2 745 236 (adjusted to 2021 values) on *Prosopis* management that covered 761 ha. This amounts to ZAR 3 607 and 10.18 person-days per hectare over the period of the management. The amount of money spent by farmers is not known, as they did not keep any records, although at least one farmer spent ZAR 346 870 on hiring a bulldozer to clear about 29 ha of land.

Field inspections of the sites revealed that relatively good progress was made when the farmers carried out the control themselves, while sites treated by Working for Water generally showed poor progress (Figure 4.2). I was only able to locate two sites where the treatments were conducted by both the farmer and Working for Water, and no clear pattern could be deduced. Examination of remotely-sensed data suggested that cover had mainly decreased when areas were managed by the farmer alone and that areas managed by Working for Water resulted in decreasing, steady or increasing cover in about equal proportions (Figure 4.3). For the 28 unmanaged sites, a consistent cover was exhibited in 12 sites, with almost the same number of sites showing an increase and decrease in cover, at 9 and 7 sites respectively. However, I suspect that many of the sites where remote sensing indicated a gradual decrease in cover over years would have been due to severe drought (between about 2014 and 2021) that would have resulted in the loss of leaves and an inability of the sensor to detect *Prosopis* trees.

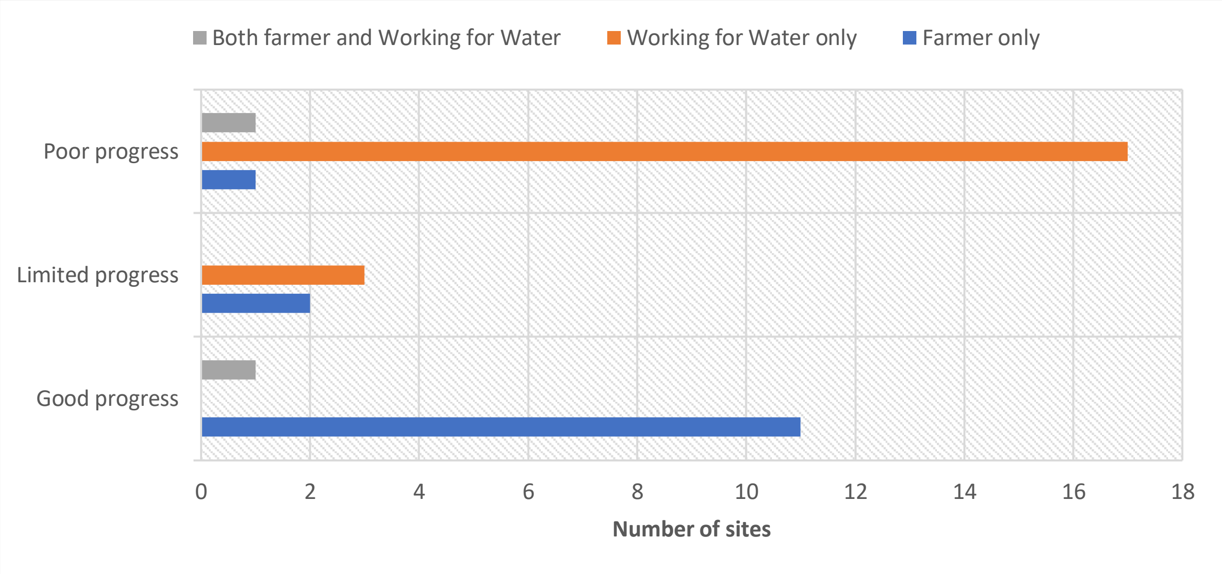

Figure 4.2 Comparison of progress towards the goals of reducing the cover of *Prosopis* invasions managed by farmers only, Working for Water only, or both parties, at 40 sites in the Northern Cape.

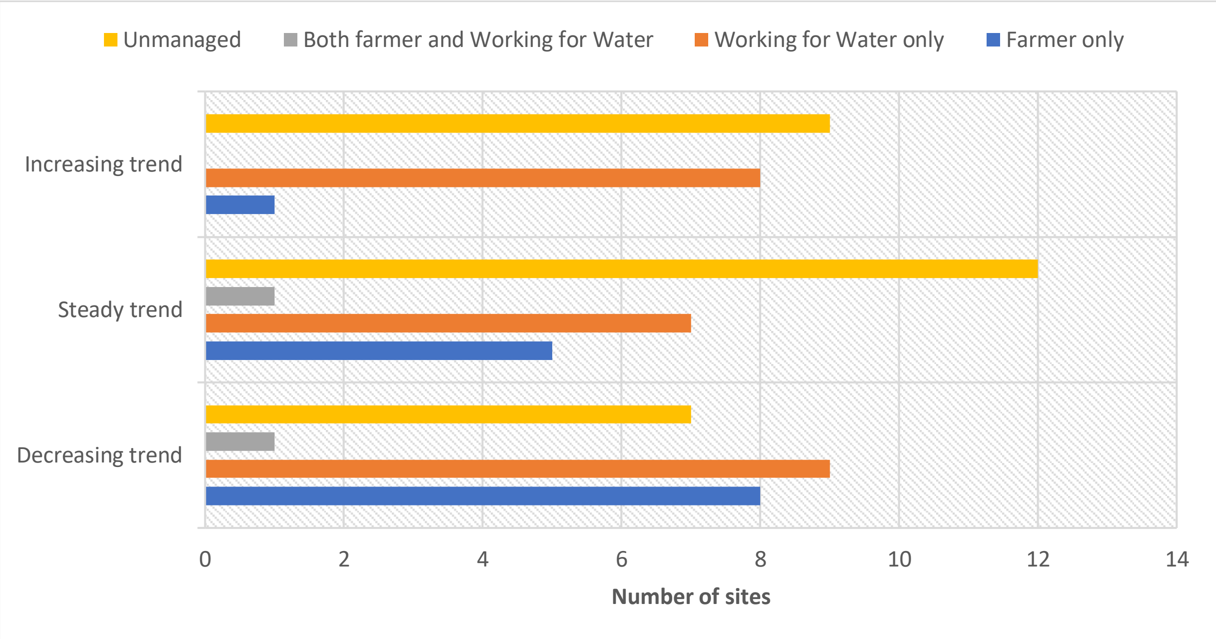

Figure 4.3 Comparison of trends in *Prosopis* unmanaged, managed by farmers only, Working for Water only, and both parties, at 68 sites in the Northern Cape.

4.4.2 Information gathered from farmers

4.4.2.1 Farmers attitudes towards *Prosopis*

Farmers interviewed all acknowledged that *Prosopis* trees had both advantages and disadvantages. More than half of the farmers identified fodder for livestock as an advantage, with a relatively small number of farmers also mentioning shade and firewood as additional advantages (Table 4.3). Thirteen farmers identified no advantages at all on their property.

It is understandable that in some cases *Prosopis* trees can be viewed as beneficial. Given the natural vegetation type and frequent droughts, *Prosopis* pods can sustain livestock through periods where farmers would otherwise have to purchase fodder.

The second most-mentioned advantage of *Prosopis* was the shade it provides. The only other tall tree found in the study area is the Karee tree (*Searsia lancea*), but it is uncommon. Temperatures frequently exceed 35°C in summer and without *Prosopis* trees, livestock would have to compete for shade under very few if any trees. With this scarcity of trees, wood is also scarce in the area and *Prosopis* wood is thus important to local people. In one case the abundance of *Prosopis* on a farm led to the farm being sold for half the price asked for neighbouring farms. This allowed another farmer to buy the farm and supplement fodder for his livestock.

Farmers identified twice as many disadvantages than advantages associated with *Prosopis* (Table 4.2). The most frequently mentioned disadvantage was the significant water use by *Prosopis*, leading to a reduction in groundwater and surface water. Related to this was the fact that *Prosopis* roots often caused blockages of boreholes if they were close to the borehole. The presence of *Prosopis* trees also displaced natural vegetation that would otherwise have provided good grazing for livestock. Farmers also mentioned allelopathic effects on natural vegetation as a result of tannins in the plant.

Prosopis is known to form dense thickets and farmers noted that these thickets make parts of the farm inaccessible for management. In addition, livestock was unable to reach water points when *Prosopis* thickets become too dense. For certain livestock, such as angora goats, *Prosopis* can be deadly when the long hair of the goats become trapped in *Prosopis* thickets. The dense thickets also provide cover to predators such as jackals (*Canis mesomelas*) and caracals (*Felis caracal*). Some farmers also indicated that they have seen an increase in stock theft in areas with *Prosopis* thickets because of the good cover it provides.

Table 4.2 Advantages and disadvantages of *Prosopis* that were identified during interviews with 17 farmers in the Northern Cape Province

	Nature of advantage or disadvantage	Number of farmers who mentioned the advantage or disadvantage	Notes
Advantages	Fodder	13	Livestock utilise the pods, but not leaves
	Shade	3	Shade is valuable as the area is hot in summer
	Wood	3	Used as firewood
	Enable the purchase of land by reducing the price	1	*Prosopis* is mostly unwanted and reduces the property value significantly. This could be advantageous to

			one party, but disadvantageous to the other.
Disadvantages	Groundwater and surface water reduction	17	Additional effort, for example, drilling to deeper depths, is required to secure sufficient water to support livestock production
	Blocking of boreholes by roots	2	Increases maintenance costs and reduces the viability of stock farming
	Displaces native vegetation and grazing	16	Results in serious shortages of fodder for livestock
	Tannins and allelopathy	6	Retards the growth of native vegetation that provides grazing
	Access to areas for management, as well as access by livestock to water points	7	Can lead to increased management costs or mortality in livestock
	Mortality of livestock	2	Angora goats become entangled in thorny *Prosopis* thickets and die
	Provides cover for predators	3	*Prosopis* trees provide cover for jackals and caracals that prey on livestock
	Provides cover to stock thieves	2	Stock theft has been noted to increase where dense invasions of *Prosopis* have established

Only one of the 17 farmers regarded *Prosopis* as entirely beneficial on their property in the short-term, while 11 farmers indicated that *Prosopis* was entirely disadvantageous, and five were ambivalent, recognising a mixture of advantages and disadvantages. All farmers said they would like to see *Prosopis* eradicated in the long term, while one considered the trees to be advantageous in the short term, but likely to become a problem in the more distant future.

4.4.2.2 Goals of management on farms

Interviews with farmers suggested that six potential goals were considered (Table 4.3). The goals that were adopted were dependent on the farmer's financial standing, the extent of invasions, and the perceived value of the benefits or impacts of *Prosopis*. Note that sometimes a farmer identified different goals for different areas on the farm, based on factors such as the density of the invasion.

Table 4.3 Goals of management of *Prosopis* that were identified during interviews with 17 farmers in the Northern Cape Province

Goal of management	Number of farmers who had adopted the goal	Situations where the goal is appropriate
Clear the entire farm	3	Farmers with sufficient resources to manage significant areas of *Prosopis* trees continuously, often with workers solely appointed to clear *Prosopis*.

Goal of management	Number of farmers who had adopted the goal	Situations where the goal is appropriate
Clear and maintain some parts of the farm in an uninvaded state	3	Farms where *Prosopis* clusters have become extremely dense so that farmers abandon clearing efforts in those areas and focus on clearing sparsely invaded areas. Some farms along fence lines that provide an identifiable break between invaded areas and those targeted for clearing.
Prevent the spread of *Prosopis* to new areas	3	*Prosopis* invasions observed during the field trips were often most dense in low-lying areas with ample water. Farmers often opt to leave these very dense areas and remove individual *Prosopis* trees when they appear in uninvaded areas to prevent new thickets from forming.
Prevent the establishment of *Prosopis* on farms where it is not yet present	2	Some farms are uninvaded and often these farmers put the effort in to keep the farm *Prosopis*-free as these farmers have seen the negative effects of *Prosopis* on nearby farms.
Confine clearing to areas of strategic importance such as roads, fences, and water points	7	When farmers are not in a financial position to do large-scale clearing of *Prosopis*, or if they believe the plant has more advantages than disadvantages, they only focus on clearing strategic areas such as roads, fences, and water points. At least one farmer did intensive removal of *Prosopis* around water points when livestock started struggling to access the water in herds.
Simply allow invasions to continue	2	This is often the case when the farm is completely covered in *Prosopis* and where it would be more affordable to sell the farm and buy an uninvaded farm as a few farmers commented.

4.4.2.3 Methods employed by farmers

Most farmers used mechanical control methods in combination with chemical control, either funded by themselves or in combination with assistance provided by Working for Water (Table 4.4). Some used chemical control only, while others resorted to the use of earth-moving equipment, especially where large trees had to be removed.

Table 4.4 Methods of *Prosopis* management that were identified during interviews with 17 farmers in the Northern Cape Province

Method employed	Approach	Number of farmers using the method
Manual labour-intensive clearing combined with chemical control, funded by the farmer alone	*Prosopis* trees are cut down, either with hand or electrical saws, and stumps are afterwards treated with herbicide such as Garlon diluted with diesel.	6
Manual labour-intensive clearing combined with chemical control, with initial clearing done by Working for Water	Initial clearing work is done by Working for Water. Often the cost of initial clearing is the prohibitive factor and once initial clearing is done, it is relatively easy to keep the area free of *Prosopis*.	2
Chemical control only	Apply herbicide to the stem or spray the tree with a foliar herbicide to leave the dead tree standing upright. According to participants who mentioned this, there are two advantages. Firstly, *Prosopis* trees can be quite thorny and cause punctures to vehicle tyres. Leaving the branches on the tree also leaves the thorns above the ground level where vehicle tyres run. Secondly, some farmers said that *Prosopis* seeds dormant in the ground are more likely to germinate when a large *Prosopis* tree is cut down and the ground is exposed to sunlight. Aerial spraying was not done by any participants in the area, but some of them indicated that they might consider aerial spraying if it was	*2*

Method employed	Approach	Number of farmers using the method
	affordable enough in areas where *Prosopis* trees are very densely spaced.	
Manual clearing using earth-moving equipment	On farms where money is less of a constraint to intensive management, mechanical clearing involving excavators and bulldozers has been used. The method followed is generally to remove large trees which have strong root networks with an excavator and then use a bulldozer to flatten smaller trees and push all *Prosopis* trees onto heaps where they are burned. This method is far less time-consuming than cutting trees by hand, but it costs significantly more per hectare than manual labour.	3
Biological control	No farmer in the study introduced biological agents to their farms, but some indicated that they could see signs of damage to pods caused by beetles, most likely introduced to the area by previous governmental and research efforts to slow the spread of *Prosopis*.	0

None of the farmers who took part in the study kept detailed records of the cost of management. In cases where records were kept, these were aggregated across farms, and it was not possible to obtain precise costs for each area cleared. The fact that farmers mostly use their regular farmworkers to clear *Prosopis* and to attend to other tasks without differentiating between them essentially means that the labour effort spent on control alone could not be estimated.

Farmers could sometimes provide a rough estimate of costs, or at least an estimate of person-days spent on clearing, which tools were used and how much herbicide was used in a year. When farmers made use of heavy machinery such as bulldozers and excavators for clearing, those costs were recorded as they constituted a significant single expense.

A recent drought in the study area had an impact on how farmers spend their income and *Prosopis* management was halted mostly for the period between 2016 and 2020 due to this extensive drought that resulted in substantially less income. This had the effect that *Prosopis* continued to spread, albeit more slowly than would have been the case in wetter years. While the drought also stunted *Prosopis* growth somewhat, most farmers indicated that they believed *Prosopis* management would become a priority when rainfall increased again.

Farmers were also asked about what they regarded as the most effective way of managing *Prosopis*, irrespective of constraints such as effort and costs. Most farmers agreed that continuous management would be needed. If funds were not limiting, they indicated that they would carry out uninterrupted management for at least 20 years. Most farmers said that realistically this would require funding beyond what they would ever be capable of spending, and often cost more per hectare than the hectare of land is worth.

Some farmers also pointed out that, to have the maximum effect, *Prosopis* would need to be controlled in the correct growing phase. Lastly, farmers with dense invasions on their property said that they believed that aerial spraying could assist with initial clearing in areas where *Prosopis* stands are impenetrable on ground level.

4.5 DISCUSSION AND CONCLUSION

Prosopis trees are aggressively invasive, and although they do have some advantages, I found general agreement that any such advantages are outweighed by negative impacts. While all farmers would therefore like to see *Prosopis* trees eradicated from their lands, effective control appears to be largely beyond their means, except for removal in small areas or in rare cases where the farmer has sufficient personal resources. The government's programme for assisting farmers by providing state-funded control teams does not appear to have been effective, as in most cases progress towards achieving effective control using these teams alone has been poor. On the other hand, control projects that were funded by the farmers themselves, without state assistance, tended to be more successful.

Perhaps the best solution would be for Working for Water to carry out the initial clearing, and to have this followed up by the farmer. This is certainly the intent of the Working for Water programme, but I was not able to locate sufficient examples of these combinations to assess whether this was working in practice. However, the fact of the matter is that Working for Water, although well-funded, has far too little funding to reverse the spread of *Prosopis* across the entire Northern Cape. Although the programme invests around 100 000 person-days per year on the control of *Prosopis* in South Africa (about 85% of it in the Northern Cape), it is still only able to reach less than 4% of the invaded area every year, and invasions continue to spread (van Wilgen et al. 2012).

WfW has spent around ZAR 580 million on *Prosopis* management since the inception of the programme. However, indications are that the level of funding is dropping (Zengeya and Wilson 2020). The drop in spending is due to recent drastic cuts in the budget of WfW, and a change in priorities. WfW, therefore, faces the same challenges as farmers and cannot adhere to best practices concerning continuous follow-up, often resulting in cleared areas becoming re-invaded. It is thus clear that a change in strategy will be needed if *Prosopis* invasions are to be brought under control. In the first place, the available scarce funding will need to be focussed on priority areas where the goals of management can be met through the implementation of adequate and sustained partnerships between government-funded assistance and farmers. Clearly, a program of random and intermittent funding of individual projects will not be effective and may even be counter-productive. The criteria for deciding on priority areas, and the form and content of defensible and transparent collaborative agreements will still have to be agreed on. Secondly, and more importantly, the only sustainable solution will probably have to come from effective biological control, if suitable agents can be found. It has taken a long time to finally reach a consensus that lethal biological control agents will be acceptable. While there is no guarantee that such agents will be found, investing in research to locate and assess potential agents would appear to be the best way to use scarce funding to potentially bring a significant environmental threat under control.

CHAPTER 5: DISCUSSION AND CONCLUSION

This chapter summarises the findings of this research. Firstly, the aims and objectives are revisited, followed by a discussion of the main findings and limitations of the study and lastly suggestions are made for future research. Finally, *Prosopis* management is discussed at a broader scale followed by the conclusions that can be drawn from this research.

5.1 REVISITING THE AIMS AND OBJECTIVES

This study aimed to compare and apply multispectral satellite imagery and trend analysis algorithms to evaluate the effectiveness of the management of *Prosopis* by comparing areas that have been subjected to different management regimes in the Northern Cape over the past 20 years. The study was motivated by the importance of insights into the efficacy of different management methods employed to manage *Prosopis*. These trees are alien to South Africa, and they became invasive following their introduction in the 1880s, specifically in the Northern Cape Province, where they covered an estimated 1.5 million hectares in 2007 in a province of about 37 million hectares.

Before the 1990s *Prosopis* in the Northern Cape was relatively unmanaged, except for some individual farmers who targeted specific areas where it was deemed to be a problem. By 1995, the South African government initiated a program to assist land managers in their attempts to bring alien plant invasions under control. This program, called Working for Water (WfW), has since spent approximately ZAR 580 million (adjusted for inflation to 2021 values) on *Prosopis* management across South Africa, based on WfW records of contracts awarded to clearing teams since 1998. Despite this significant spending, *Prosopis* invasions are increasing.

My first research objective was to carry out a literature review to become familiar with past and current techniques used to assess the *Prosopis* invasion and to identify suitable trend analysis strategies (Chapter 2). A review of the history of *Prosopis* trees, their uses, problems and spread over time highlighted the extent of the problem, not only in South Africa but globally. The species is able to spread so successfully due to the lack of co-evolved natural enemies (e.g. insects and pathogens) which retard their spread in their native range. Negative impacts of *Prosopis* were identified as, among others, negative impacts on biodiversity, groundwater resources, and grazing capacity, including decreases in the abundance and diversity of dung beetles, birds, indigenous plants, decreases in the ability of rangelands to support livestock and reductions in groundwater levels. Existing research highlighted that, although *Prosopis* trees can provide benefits in the form of fodder, shade and firewood, these benefits are exceeded by the cost of negative impacts when invasions become more widespread.

Literature pointed to several remote sensing methods used to assess changes in the biomass of invasive alien plants, with two methods often used, namely image classifications of two or more scenes at different dates and analysis of trends in the full stack of imagery available, often reduced using a mean or median filter to create a composite scene. The latter method was selected for use in this study, utilizing two similar algorithms, BFAST (Breaks for Additive Season and Trend) and BFAST01. Imagery from both the Sentinel and Landsat satellite constellations were often used in literature due to their medium spatial resolution and relatively high temporal resolutions. For this research, imagery from Landsat 7 and 8 was used, as Sentinel imagery does not fully cover the duration of the study. Landsat imagery also has a collection of spectral bands which is often used in research to create vegetation indices for improved biomass detection, such as Normalised Difference Vegetation Index (NDVI), Normalised Difference Moisture Index (NDMI), Modified Soil-Adjusted Vegetation Index (MSAVI2) and surface albedo.

For the second research objective, farms with *Prosopis*, that have been subjected to different management regimes, were selected and field data were obtained through interviews, participatory mapping, and examination of sites in the field. Initial fieldwork conducted in the Northern Cape during two separate trips in 2019 narrowed the study area down to the region between the towns of Carnarvon and Vanwyksvlei, where the *Prosopis* invasion has a long history, with a cluster of management sites grouped in a relatively small area. This region also falls within the Nama Karoo biome characterised by short, shrubby vegetation of low cover, which assisted remote sensing analysis as most trees in the area could be assumed as *Prosopis* with high certainty.

In 2020 during a third field trip to the final selected study area, structured interviews were conducted with 17 landowners whose farms were invaded by *Prosopis* trees. Additionally, several sites per farm were inspected and selected for remote-sensing analysis, with inputs from farmer interviews and a database kept by Working for Water gathered as a baseline for the comparison of trend analysis results.

In Chapter 3, the third objective – to analyse remote sensing time series algorithms to estimate the change in abundance of the *Prosopis* invasion on selected farms – was addressed. Trends in *Prosopis* biomass were analysed using a Landsat 7 and 8 remote sensing time series and the BFAST and BFAST01 trend algorithms were applied to determine their suitability for detecting trends in the cover of *Prosopis* in the Northern Cape Province and relating these to management effort. With both algorithms, several indices were also assessed, including the NDVI, NDMI, MSAVI2 and surface albedo, to find the most suitable index for detecting *Prosopis* biomass in the study area. A suitable sample size of five pixels per site was determined through experimentation to account for heterogeneity within sites, while still including smaller sites spanning only a few satellite imagery pixels. BFAST and BFAST01 produced similar results but breaks detected by BFAST were more closely aligned to management inputs.

In Chapter 4, the effect of management actions on the abundance of the *Prosopis* invasion in the Northern Cape was assessed (objective four). The structured interviews with farmers (objective two), the Working for Water database and trends observed in sites (Chapter 3) were used as input to analyse *Prosopis* management efficacy. Farmers all recognised that *Prosopis* trees had both advantages and disadvantages. More than half of the farmers identified fodder for livestock as an advantage, and less than a quarter also mentioned that shade and firewood were beneficial. On the other hand, farmers identified twice as many disadvantages than advantages associated with *Prosopis*, of which water usage and loss of grazing capacity were most frequently mentioned. Farmers were almost unanimous in agreeing that they would like to eradicate *Prosopis* from their farms, but in reality, they had to set lesser goals for themselves depending on their financial standing, with some simply being unable to afford any form of control. It was found that relatively good progress was made towards achieving control on demarcated sites when the farmers carried out the control themselves, while sites treated by Working for Water generally showed poor progress.

The fifth and last objective was collectively addressed in both Chapters 3 and 4 and is summarised in Section 5.2 of this chapter.

5.2 MAIN FINDINGS AND VALUE OF THE RESEARCH

In chapter 3, NDVI, NDMI, MSAVI2 and surface albedo were compared and NDVI was selected as vegetation index for further analysis as it detected breaks most often and agreed best with management records obtained during fieldwork. It should be noted that the results obtained from using MSAVI2 matched well with that of NDVI, but in some cases, it missed breaks that NDVI could detect. NDMI introduced many unknown breaks, which were unmatched by the other indices, possibly as it is more sensitive to small microvariations in plant moisture than NDVI. Trend lines produced by surface albedo were flatter than those observed with the other indices and consequently, it missed most breaks detected by other indices. The results observed when using NDVI matches the observation made by existing research that NDVI performs well in detecting small vegetation cover changes in arid environments (Funghi et al. 2020; Shiferaw et al. 2019).

Further, an analysis of sample size and its effect on the results of the trend analysis algorithms were conducted. Sample sizes used in the analysis ranged from three pixels, up to and including ten pixels used per site to detect breaks in vegetation growth. More stable results were obtained in more homogenously managed sites i.e. sites that were cleared in a short time with the same level of management applied throughout the site, as well as when more pixels were used. Using the median NDVI value of fewer pixels resulted in different breaks being observed with each iteration of BFAST and BFAST01 when a different set of managed pixels were used. To maintain a balance between analysing the overall management done in a site and including variations due to differing environmental conditions throughout the site, five pixels were randomly selected, the median monthly NDVI value obtained and used as input for BFAST and BFAST01. Similar to the concept of the Random Forest algorithm (Breiman 2001), five iterations of analysis, each with five randomly selected pixels, were performed for each site.

The results in Chapter 3 further demonstrated that analysis of a remote sensing time series using the BFAST and BFAST01 trend analysis algorithms can be used to detect management of invasive *Prosopis* trees in the Northern Cape Province. It was observed that the success of matching a break in growth, as well as the growth trends observed, varied due to environmental heterogeneity found within a site, such as more thorough clearing in some parts of a site or part of a site becoming flooded at times. Of the 40 managed sites, better management detection success rates (38%) were observed for Working for Water sites when compared to farmer-managed sites (21%). The inclusion of minor breaks (breaks which did not occur the most frequently when comparing the outcome of five sets of samples) improved detection success rates on both WfW and farmer-managed sites, reaching 57% and 63% respectively. Of the 40 managed sites, 25 had breaks that were matched to management records.

The duration of management, that is the time taken to clear a site, which could be several years, likely had the greatest effect on the overall lower management detection success rate observed on sites managed by farmers. Unlike Working for Water-managed sites, farmers often manage sites as funds and time become available, and from interviews it was apparent that clearing sometimes spanned several years, leading to a slow and very gradual downwards trend, which was often not detected using BFAST and BFAST01. These trend algorithms did prove to be very effective in sites managed by earth-moving machinery where *Prosopis* trees were removed in a matter of days, being present one month and completely absent the next. Similarly, sites managed by dedicated teams, who use manual labour to remove *Prosopis* trees in a relatively short time, such as Working for Water, was also in most cases detected with the trend analysis algorithms.

In Chapter 4, the management effectiveness of *Prosopis* was analysed for the same sites used in Chapter 3. To understand the reasons behind management, interview responses were first summarised. From the results, it was observed that all 17 farmers recognised that *Prosopis* trees had both advantages and disadvantages. More than half of the farmers identified fodder for livestock as an advantage, and less than a quarter also mentioned that shade and firewood were beneficial. On the other hand, farmers identified twice as many disadvantages than advantages associated with *Prosopis*, of which water usage and loss of grazing capacity were most frequently mentioned. Farmers were almost unanimous in agreeing that they would like to eradicate *Prosopis* from their farms, but in reality, they had to set lesser goals for themselves depending on their financial standing, with some simply being unable to afford any form of control.

The results further suggested that farmers would consider one or more of six potential goals (see Table 4.3), depending on their financial standing, the extent of invasions, and the perceived value of the benefits or impacts of *Prosopis*. Farmers often had multiple goals for different areas of a farm. The goal most often mentioned was to confine clearing to areas of strategic importance such as roads, fences, and water points, with only two farmers having no goal of management.

Clearing methods used by farmers varied, also based on affordability, with manual labour-intensive clearing combined with chemical control being the most common method of management. It was found that relatively good progress was made towards achieving control on demarcated sites when the farmers carried out the control themselves, while sites treated by Working for Water generally showed poor progress. Only two sites where the treatments were conducted by both the farmer and Working for Water could be located, so the effectiveness of joint control could not be assessed.

5.3 LIMITATIONS AND RECOMMENDATIONS

This research provides a good foundation for *Prosopis* management detection in the arid areas of South Africa using Landsat satellite imagery and the BFAST and BFAST01 trend analysis algorithms. However, the study has some limitations, which are addressed here.

As seen from the BFAST and BFAST01 results, detection of growth breaks due to management is limited to areas where management made a significant difference in a short amount of time. Future research can evaluate the ability of additional trend analysis algorithms such as Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) and Continuous Change Detection and Classification (CCDC) to detect invasive alien plant clearing that occurs over longer time periods, such as over a number of years. The LandTrendr algorithm can provide land cover change information on an annual time scale, which might capture less variation due to seasonality and other unexplained changes the methods in this study are susceptible to. The CCDC algorithm is a multivariate approach, meaning it can use all spectral bands available to detect changes in land cover, unlike univariate approaches like BFAST and BFAST01 which was used in this study.

To improve results in situations where management differed between pixels within a site, a pixel-based approach that also deals with the spatial aspect of the break can be considered, instead of selecting the median of five pixels within a site as was done in this study. One such approach is the BFAST Spatial algorithm (Gao et al. 2019), which evaluates each pixel present in the input using BFAST Monitor and outputs a raster indicating breaks and their magnitudes with all pixels per site included in the analysis. This might provide better insight into what areas within a site were best cleared without having to randomly pick and aggregate pixels to find the average trends within each managed site.

The absence of accurate dates of management obtained through interviews with farmers also contributed to additional uncertainty in the cross-verification of management events, as farmers often guessed a year in which management took place and mostly had no way of providing accurate costs of management. The database provided Working for Water data also contained inconsistencies, such as missing dates and costs of management. Future research on *Prosopis* management detection, should, if possible, collect field data and interview responses before and during clearing episodes.

A severe drought also occurred during the last half of the study period (between about 2014 and 2021), and this would have resulted in the loss of leaves of some trees and consequently a decrease in growth trend reported by BFAST and BFAST01. Some sites did indicate a gradual decrease in seasonal peaks from about 2013, but the drought was taken into account when interpreting breaks followed by such a gradual decrease.

Lastly, this study only examined a relatively small number of sites covering less than 1000 hectares in total, which is a very small percentage of the total *Prosopis* invasion in the Northern Cape. The methods presented in this study are well-suited to be expanded to a larger scale, provided sufficient field data is available for verification. Recent research done by Mbaabu et al. (2019) was able to successfully monitor the spread of *Prosopis* in Kenya through several discrete Random Forest classified images, and while their methods and goals differed from those of this study, an additional land cover change map could provide useful data (given a large number of validation data points) to further assess and spatially visualise trends in the Northern Cape *Prosopis* invasion.

5.4 CONCLUSIONS

The research presented in this thesis had the goal of comparing and applying multispectral satellite imagery and trend analysis algorithms to evaluate the effectiveness of the management of *Prosopis* by comparing areas that have been subjected to different management regimes in the Northern Cape over the past 20 years. The aim of the research was achieved by five objectives listed in Chapter 1, Section 5, of which all were met.

From the analysis of a remote sensing time series management of *Prosopis* was detected and this research provides a baseline for a feasible monitoring framework to evaluate the effectiveness of management. While management detection success rates were lower than initially expected, the BFAST and BFAST01 trend algorithms combined with NDVI values from Landsat 7 and 8 imagery proved to be well-suited for thorough clearing in a short time, as is often done by Working for Water with large teams which manually clear a site, or in the case of farmers which can afford to use earth-moving equipment to clear dense *Prosopis* thickets completely in a short period.

While there are some success stories where *Prosopis* was brought under control on farms, at a broader scale the problem is out of hand. Firstly, it seems that the available scarce funding will need to be focussed on priority areas where the goals of management can be met through the implementation of adequate and sustained partnerships between government-funded assistance and farmers. In other words, limited funds should not be diluted to a point where they become thinly spread and outcomes ineffective. This observation, based on outcomes observed in this study, agrees with observations made by van Wilgen et al. (2016). Secondly, a concerted effort to find effective biological control agents needs to be made, which, if effective, could vastly increase the effectiveness of clearing operations.

The findings of this study provide valuable insights into methods that can be used to assess the efficacy of *Prosopis* management in an arid region. Further, it shows that the current success of the management of *Prosopis* is variable and that a unified approach is required where all stakeholders work together to find solutions to the environmental problem.

40 100 words

REFERENCES

Agricultural Research Council 2014. Mesquite/Prosopis : Prosopis species (Fabaceae) [online]. Available from: http://www.arc.agric.za/arc-ppri/Pages/Mesquite-Prosopis.aspx [Accessed 3 July 2019].

Alavipanah SK, Matinfar HR, Emam AR, Khodaei K, Bagheri RH & Panah AY 2010. Criteria of selecting satellite data for studying land resources. *Desert (2008-0875)* 15, 2: 83–102. [online]. Available from: http://search.ebscohost.com/login.aspx?direct=true&db=aph&AN=59622589&site=ehost-live&scope=site

Allen E & Triantaphillidou S 2011. Light theory. In Allen E & Triantaphillidou SBT-TM of P (Tenth E (eds) *The Manual of Photography*, 19–42. Oxford: Focal Press. [online]. Available from: http://www.sciencedirect.com/science/article/pii/B978024052037710002X

Almeida AE, Menini N, Verbesselt J & De Torres RS 2018. *BFAST Explorer: An effective tool for time series analysis*. International Geoscience and Remote Sensing Symposium (IGARSS). Institute of Electrical and Electronics Engineers Inc.: 4913–4916.

Alston G 1914. The screw-bean: a useful shrub. *Agricultural Journal of the Union of South Africa* 7: 119–120.

Atzberger C 2016. *Modeling of prosopis yield and above ground biomass based on very high resolution Sentinel-2 satellite imagery in Turkana, Kenya*.

Awty-Carroll K, Bunting P, Hardy A & Bell G 2019. An evaluation and comparison of four dense time series change detection methods using simulated data. *Remote Sensing* 11, 23.

Azzari G & Lobell DB 2017. Landsat-based classification in the cloud: An opportunity for a paradigm shift in land cover monitoring. *Remote Sensing of Environment* 202: 64–74. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0034425717302237 [Accessed 22 May 2019].

Bai J & Perron P 2003. Computation and analysis of multiple structural change models. *Journal of Applied Econometrics* 18, 1: 1–22.

Bekele K, Haji J, Legesse B & Schaffner U 2018. Economic impacts of Prosopis spp. invasions on dryland ecosystem services in Ethiopia and Kenya: Evidence from choice experimental data. *Journal of Arid Environments* 158: 9–18. [online]. Available from: https://doi.org/10.1016/j.jaridenv.2018.07.001

van den Berg E 2010. Detection, quantification and monitoring Prosopis spp. in the Northern Cape Province of South Africa using Remote Sensing and GIS. North-West University. [online]. Available from: https://repository.nwu.ac.za/handle/10394/4377 [Accessed 28 September 2018].

van den Berg E, Kotze I & Beukes H 2013. *Detection, Quantification and Monitoring of Prosopis in the Northern Cape Province of South Africa using Remote Sensing and GIS*. 2.*South African Journal of Geomatics* 2 [online]. Available from: http://www.sajg.org.za/index.php/sajg/article/view/66

Bernardino PN, De Keersmaecker W, Fensholt R, Verbesselt J, Somers B & Horion S 2020. Global-scale characterization of turning points in arid and semi-arid ecosystem functioning. *Global Ecology and Biogeography* , January 2019: 1–16.

Breiman L 2001. *Random Forests*. 45 [online]. Available from: https://link.springer.com/content/pdf/10.1023%2FA%3A1010933404324.pdf [Accessed 26 August 2018].

Brown C & Harder C 2016. *The ArcGIS imagery book : new view, new vision*.

Buchanan GM, Brink AB, Leidner AK, Rose R & Wegmann M 2015. Advancing terrestrial conservation through remote sensing. *Ecological Informatics* 30, April 2010: 318–321. [online]. Available from: http://dx.doi.org/10.1016/j.ecoinf.2015.05.005

Buchanan GM, Nelson A, Mayaux P, Hartley A & Donald PF 2009. Delivering a Global, Terrestrial, Biodiversity Observation System through Remote Sensing. *Conservation Biology* 23, 2: 499–502.

Bullock E 2018. Continuous Degradation Detection (CODED) Documentation [online]. Available from: https://coded.readthedocs.io/en/latest/index.html [Accessed 3 January 2020].

Camino-Serrano M, Graf Pannatier E, Vicca S, Luyssaert S, Jonard M, Ciais P, Guenet B, Gielen B, Peñuelas J, Sardans J, Waldner P, Etzold S, Cecchini G, Clarke N, GaliÄ Z, Gandois L, Hansen K, Johnson J, Klinck U, Lachmanová Z, Lindroos AJ, Meesenburg H, Nieminen TM, Sanders TGM, Sawicka K, Seidling W, Thimonier A, Vanguelova E, Verstraeten A, Vesterdal L & Janssens IA 2016. Trends in soil solution dissolved organic carbon (DOC) concentrations across European forests. *Biogeosciences* 13, 19: 5567–5585.

Campbell JB & Wynne RH 2011. *Introduction to Remote Sensing*. Fifth. New York: Guilford Press. [online]. Available from:

http://public.eblib.com/choice/publicfullrecord.aspx?p=843851

Carlson TN & Ripley DA 1997. On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sensing of Environment* 62, 3: 241–252. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0034425797001041 [Accessed 10 March 2019].

Ceccato P, Flasse S, Tarantola S, Jacquemoud S & Grégoire JM 2001. Detecting vegetation leaf water content using reflectance in the optical domain. *Remote Sensing of Environment* 77, 1: 22–33.

Che X, Yang Y, Feng M, Xiao T, Huang S, Xiang Y & Chen Z 2017. Mapping Extent Dynamics of Small Lakes Using Downscaling MODIS Surface Reflectance. *Remote Sensing* 9, 1: 82. [online]. Available from: http://www.mdpi.com/2072-4292/9/1/82 [Accessed 27 May 2020].

Chen B, Xiao X, Li X, Pan L, Doughty R, Ma J, Dong J, Qin Y, Zhao B, Wu Z, Sun R, Lan G, Xie G, Clinton N & Giri C 2017. A mangrove forest map of China in 2015: Analysis of time series Landsat 7/8 and Sentinel-1A imagery in Google Earth Engine cloud computing platform. *ISPRS Journal of Photogrammetry and Remote Sensing* 131: 104–120. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S092427161730285X [Accessed 22 May 2019].

Chen J, Zhu X, Vogelmann JE, Gao F & Jin S 2011. A simple and effective method for filling gaps in Landsat ETM+ SLC-off images. *Remote Sensing of Environment* 115, 4: 1053–1064. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0034425710003482 [Accessed 16 May 2019].

Choge SK, Pasiecznik NM, Harvey M, Wright J, Awan SZ & Harris PJC 2007. Prosopis pods as human food, with special reference to Kenya. *Water SA* 33, 3: 419–424. [online]. Available from: http://dx.doi.org/10.4314/wsa.v33i3.49162

Chuvieco E 2018. *Fundamentals of Satellite Remote Sensing*. Boca Raton: CRC Press.

Cohen WB, Yang Z & Kennedy R 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync - Tools for calibration and validation. *Remote Sensing of Environment* 114, 12: 2911–2924. [online]. Available from: https://doi.org/10.1016/j.rse.2010.07.010 [Accessed 30 January 2019].

Cohen WB & Goward SN 2004. Landsat's Role in Ecological Applications of Remote Sensing.

BioScience 54, 6: 535–545. [online]. Available from: https://doi.org/10.1641/0006-3568(2004)054[0535:LRIEAO]2.0.CO

Conway E 1997. *An Introduction to Satellite Image Interpretation*. Baltimore: Johns Hopkins University Press. [online]. Available from: http://books.google.com/books?id=iGrHsr2U8p0C

Cord A, Klein D & Dech S 2010. Remote sensing time series for modeling invasive species distribution: A case study of Tamarix spp. in the US and Mexico. *Modelling for Environment's Sake: Proceedings of the 5th Biennial Conference of the International Environmental Modelling and Software Society, iEMSs 2010* 2: 1404–1411.

Cucci C & Casini A 2020. Hyperspectral imaging for artworks investigation. In *Data Handling in Science and Technology*, 583–604. Elsevier Ltd.

Davis R 2020. In drought-ravaged Northern Cape, government assistance may be too little, too late. *Daily Maverick* [online]. Available from: https://www.dailymaverick.co.za/article/2020-01-22-in-drought-ravaged-northern-cape-government-assistance-may-be-too-little-too-late/

Dean WRJ, Anderson MD, Milton SJ & Anderson TA 2002. Avian assemblages in native Acacia and alien Prosopis drainage line woodland in the Kalahari, South Africa. *Journal of Arid Environments* 51, 1: 1–19. [online]. Available from: https://doi.org/10.1006/jare.2001.0910

Department of Agriculture Land Reform and Rural Development 2018. Comprehensive Atlas V2.1 [online]. Available from: http://daffarcgis.nda.agric.za/Comp_Atlas_v2/ [Accessed 24 February 2021].

Department of Water Affairs and Forestry 2005. *South African Groundwater Resource Assessment, Phase II*.

Dong J, Xiao X, Menarguez MA, Zhang G, Qin Y, Thau D, Biradar C & Moore B 2016. Mapping paddy rice planting area in northeastern Asia with Landsat 8 images, phenology-based algorithm and Google Earth Engine. *Remote Sensing of Environment* 185: 142–154. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S003442571630044X [Accessed 22 May 2019].

Drusch M, Del Bello U, Carlier S, Colin O, Fernandez V, Gascon F, Hoersch B, Isola C, Laberinti P, Martimort P, Meygret A, Spoto F, Sy O, Marchese F & Bargellini P 2012. Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services.

Remote Sensing of Environment 120: 25–36. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0034425712000636 [Accessed 9 March 2019].

Dupas R, Minaudo C, Gruau G, Ruiz L & Gascuel-Odoux C 2018. Multidecadal Trajectory of Riverine Nitrogen and Phosphorus Dynamics in Rural Catchments. *Water Resources Research* 54, 8: 5327–5340.

Dutrieux LP, Jakovac CC, Latifah SH & Kooistra L 2016. Reconstructing land use history from Landsat time-series: Case study of a swidden agriculture system in Brazil. *International Journal of Applied Earth Observation and Geoinformation* 47: 112–124.

Dzikiti S, Ntshidi Z, Le Maitre DC, Bugan RDH, Mazvimavi D, Schachtschneider K, Jovanovic NZ & Pienaar HH 2017. Assessing water use by Prosopis invasions and Vachellia karroo trees: Implications for groundwater recovery following alien plant removal in an arid catchment in South Africa. *Forest Ecology and Management* 398, August: 153–163. [online]. Available from: https://doi.org/10.1016/j.foreco.2017.05.009

Dzikiti S, Schachtschneider K, Naiken V, Gush M, Moses G & Le Maitre DC 2013. Water relations and the effects of clearing invasive Prosopis trees on groundwater in an arid environment in the Northern Cape, South Africa. *Journal of Arid Environments* 90: 103–113. [online]. Available from: https://doi.org/10.1016/j.jaridenv.2012.10.015

Dzikiti S, Ntshidi Z, Bugan RDH, Le Maitre DC, Mazvimavi D, Schachtschneider K, Gush MB & Jovanovic NZ 2015. *Comparative use of groundwater by invasive alien Prosopis spp and co-occurring indigenous V. karroo in a semi-arid catchment*. 14th biennial Ground Water Division Conference And Exhibition, 21-23 September 2015, Muldersdrift, South Africa. [online]. Available from: https://www.researchgate.net/publication/284340414 [Accessed 1 May 2019].

Eberhardt IDR, Schultz B, Rizzi R, Sanches IDA, Formaggio AR, Atzberger C, Mello MP, Immitzer M, Trabaquini K, Foschiera W & Luiz AJB 2016. Cloud cover assessment for operational crop monitoring systems in tropical areas. *Remote Sensing* 8, 3: 1–14.

Eckert S, Hamad A, Kilawe CJ, Linders TEW, Ng W, Mbaabu PR, Shiferaw H, Witt A & Schaffner U 2020. Niche change analysis as a tool to inform management of two invasive species in Eastern Africa. *Ecosphere* 11, 2.

Evans J 2019. “We are going to lose our land”: Sutherland farmers pleading for help amid 6-year drought [online]. Available from: https://www.news24.com/SouthAfrica/News/we-are-going-to-lose-our-land-sutherland-farmers-pleading-for-help-amid-6-year-drought-

20190418 [Accessed 13 July 2019].

Foga S, Scaramuzza PL, Guo S, Zhu Z, Dilley RD, Beckmann T, Schmidt GL, Dwyer JL, Joseph Hughes M & Laue B 2017. Cloud detection algorithm comparison and validation for operational Landsat data products. *Remote Sensing of Environment* 194: 379–390. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0034425717301293?via%3Dihub [Accessed 1 August 2019].

Fourie F, Mbatha K, Verster H & Van Dyk G 2007. *The effect of vegetation (Prosopis sp.) on groundwater levels in Rugseer River, Kenhardt, South Africa*. Groundwater and Ecosystems, XXXV IAH Congress: 8. [online]. Available from: http://www.dwaf.gov.za/wfw/docs/Fourieetal2002.pdf [Accessed 28 September 2018].

Funghi C, Heim RHJ, Schuett W, Griffith SC & Oldeland J 2020. Estimating food resource availability in arid environments with Sentinel 2 satellite imagery. *PeerJ* 2020, 5: 1–19.

Gandhi GM, Parthiban S, Thummalu N & Christy A 2015. *Ndvi: Vegetation Change Detection Using Remote Sensing and Gis - A Case Study of Vellore District*. Procedia Computer Science. Elsevier.: 1199–1210.

Gao B 1996. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment* 58, 3: 257–266. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0034425796000673 [Accessed 14 August 2019].

Gao Y, Quevedo A, Szantoi Z & Skutsch M 2019. Monitoring forest disturbance using time-series MODIS NDVI in Michoacán, Mexico. *Geocarto International* 0, 0: 1–17. [online]. Available from: https://doi.org/10.1080/10106049.2019.1661032

Gardner T 2010. Google unveils satellite platform to aid forest efforts - Reuters [online]. Available from: https://www.reuters.com/article/us-climate-google/google-unveils-satellite-platform-to-aid-forest-efforts-idUSTRE6B13RK20101202 [Accessed 29 July 2019].

Garrigues S, Allard D, Baret F & Weiss M 2006. Quantifying spatial heterogeneity at the landscape scale using variogram models. *Remote Sensing of Environment* 103, 1: 81–96. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0034425706001210 [Accessed 17 July 2019].

GIS Geography 2018. Why the Atmospheric Window Matters in Earth Science [online].

Available from: https://gisgeography.com/atmospheric-window/ [Accessed 11 September 2019].

Gómez C, White JC & Wulder MA 2016. Optical remotely sensed time series data for land cover classification: A review. *ISPRS Journal of Photogrammetry and Remote Sensing* 116: 55–72. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0924271616000769 [Accessed 25 July 2019].

Google Earth Engine 2020. USGS Landsat 8 Surface Reflectance Tier 1 - Bands [online]. Available from: https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C01_T1_SR#bands [Accessed 23 February 2021].

Google Inc. 2019. Google Earth Engine

Google Inc. 2005. Google Earth [online]. Available from: https://www.google.com/earth/index.html [Accessed 28 February 2021].

Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D & Moore R 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment* 202: 18–27. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0034425717302900 [Accessed 14 May 2019].

Grogan K, Pflugmacher D, Hostert P, Verbesselt J & Fensholt R 2016. Mapping Clearances in Tropical Dry Forests Using Breakpoints, Trend, and Seasonal Components from MODIS Time Series: Does Forest Type Matter? *Remote Sensing* 8, 8: 657. [online]. Available from: http://www.mdpi.com/2072-4292/8/8/657 [Accessed 28 May 2020].

Hagolle O, Huc M, Pascual DV & Dedieu G 2010. A multi-temporal method for cloud detection, applied to FORMOSAT-2, VENµS, LANDSAT and SENTINEL-2 images. *Remote Sensing of Environment* 114, 8: 1747–1755. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0034425710000908#bib3 [Accessed 22 July 2019].

Harding GB 1988. The genus Prosopis as an invasive alien in South Africa. University of Port Elizabeth.

Henderson L 2007. Invasive, naturalized and casual alien plants in southern Africa: a sum-mary based on the Southern African Plant Invaders Atlas (SAPIA). *Bothalia* 37, 2: 215–248.

[online]. Available from: http://abcjournal.org/index.php/ABC/article/view/322 [Accessed 25 February 2019].

Henderson L & Harding G 1992. *Mesquite*.*Farming in South Africa*

Henderson L 1991. Invasive alien woody plants of the Northern Cape. *Bothalia* 21, 2: 177–189. [online]. Available from: https://doi.org/10.4102/abc.v21i2.885 [Accessed 28 September 2018].

Henderson L & Wilson JRU 2017. Changes in the composition and distribution of alien plants in South Africa: An update from the Southern African Plant Invaders Atlas. *Bothalia* 47, 2: 1–26. [online]. Available from: https://doi.org/10.4102/abc.v47i2.2172

Hengl T 2006. Finding the right pixel size. *Computers and Geosciences* 32, 9: 1283–1298.

Hereher ME 2017. Retrieving spatial variations of land surface temperatures from satellite data–Cairo region, Egypt. *Geocarto International* 32, 5: 556–568. [online]. Available from: http://dx.doi.org/10.1080/10106049.2016.1161077

Hicke JA, Logan JA, Powell J & Ojima DS 2006. Changing temperatures influence suitability for modeled mountain pine beetle (Dendroctonus ponderosae) outbreaks in the western United States. *Journal of Geophysical Research: Biogeosciences* 111, 2: 1–12.

Horion S, Ivits E, De Keersmaecker W, Tagesson T, Vogt J & Fensholt R 2019. Mapping European ecosystem change types in response to land-use change, extreme climate events, and land degradation. *Land Degradation and Development* 30, 8: 951–963.

Huang C-Y & Asner GP 2009. Applications of remote sensing to alien invasive plant studies. *Sensors (Basel, Switzerland)* 9, 6: 4869–4889. [online]. Available from: https://www.ncbi.nlm.nih.gov/pubmed/22408558

Huete AR 1988. A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment* 25, 3: 295–309.

Impson FAC, Moran VC & Hoffmann JH 1999. A review of the effectiveness of seed-feeding bruchid beetles in the biological control of mesquite, Prosopis species (Fabaceae), in South Africa. *African Entomology Memoir* 1: 81–88.

Jackson RD & Huete AR 1991. Interpreting vegetation indices. *Preventive Veterinary Medicine* 11, 3–4: 185–200. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0167587705800042 [Accessed 26 July 2019].

Ji L, Zhang L, Wylie BK & Rover J 2011. On the terminology of the spectral vegetation index

(NIR - SWIR)/(NIR+SWIR). *International Journal of Remote Sensing* 32, 21: 6901–6909.

Johansen K, Phinn S & Taylor M 2015. Mapping woody vegetation clearing in Queensland, Australia from Landsat imagery using the Google Earth Engine. *Remote Sensing Applications: Society and Environment* 1: 36–49. [online]. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2352938515000051 [Accessed 14 May 2019].

Johnson B 2014. Effects of Pansharpening on Vegetation Indices. *ISPRS International Journal of Geo-Information* 3, 2: 507–522.

De Jong R, Verbesselt J, Zeileis A & Schaepman ME 2013. Shifts in global vegetation activity trends. *Remote Sensing* 5, 3: 1117–1133.

Jordaan AJ 2012. Drought risk reduction in the Northern Cape. University of the Free State.

Joshi AR, Dinerstein E, Wikramanayake E, Anderson ML, Olson D, Jones BS, Seidensticker J, Lumpkin S, Hansen MC, Sizer NC, Davis CL, Palminteri S & Hahn NR 2016. Tracking changes and preventing loss in critical tiger habitat. *Science advances* 2, 4: e1501675. [online]. Available from: http://www.ncbi.nlm.nih.gov/pubmed/27051881 [Accessed 29 July 2019].

Kebede AT & Coppock DL 2015. Livestock-Mediated Dispersal of Prosopis juliflora Imperils Grasslands and the Endangered Grevy’s Zebra in Northeastern Ethiopia. *Rangeland Ecology & Management* 68, 5: 402–407. [online]. Available from: https://doi.org/10.1016/j.rama.2015.07.002

Kennedy RE, Yang Z & Cohen WB 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr - Temporal segmentation algorithms. *Remote Sensing of Environment* 114, 12: 2897–2910. [online]. Available from: https://doi.org/10.1016/j.rse.2010.07.008 [Accessed 30 January 2019].

Key T, Warner TA, McGraw JB & Fajvan MA 2001. A Comparison of Multispectral and Multitemporal Information in High Spatial Resolution Imagery for Classification of Individual Tree Species in a Temperate Hardwood Forest. *Remote Sensing of Environment* 75, 1: 100–112. [online]. Available from: https://www.sciencedirect.com/science/article/pii/S0034425700001590 [Accessed 15 September 2019].

Kirkham MB 2014. Structure and Properties of Water. In Kirkham MBBT-P of S and PWR (Second E (ed) *Principles of Soil and Plant Water Relations*, 27–40. Boston: Academic Press. [online]. Available from:

http://www.sciencedirect.com/science/article/pii/B9780124200227000033

Kleinjan CA, Hoffmann JH, Heystek F, Ivey P & Kistensamy Y Developments and prospects for biological control of Prosopis (Leguminosae) in South Africa. *African Entomology*.

de Klerk JN 2004. *Bush Encroachment in Namibia*. [online]. Available from: http://www.the-eis.com/data/literature/Bush Encoachment in Namibia_deKlerk2004_1.pdf [Accessed 4 July 2019].

Knorn J, Rabe A, Radeloff VC, Kuemmerle T, Kozak J & Hostert P 2009. *Land cover mapping of large areas using chain classification of neighboring Landsat satellite images*.

KoBoToolbox 2018. KoBoToolbox - Data collection tools for challenging environments [online]. Available from: https://www.kobotoolbox.org/ [Accessed 25 February 2021].

Koenig R 2009. Unleashing an Army to Repair Alien-Ravaged Ecosystems. *Science* 325, 5940: 562 LP – 563. [online]. Available from: http://science.sciencemag.org/content/325/5940/562.abstract

Kurtzman L 2014. UCSF, Google Earth Engine Making Maps to Predict Malaria | UC San Francisco [online]. Available from: https://www.ucsf.edu/news/2014/09/116906/ucsf-google-earth-engine-making-maps-predict-malaria [Accessed 29 July 2019].

Kyuma RK, Wahome RG, Kinama JM & V OW 2016. Temporal relationship between climate variability, Prosopis juliflora invasion and livestock numbers in the drylands of Magadi, Kenya. *African Journal of Environmental Science and Technology* 10, 4: 129–140. [online]. Available from: http://www.academicjournals.org/AJEST [Accessed 30 January 2021].

Lee Z & Carder KL 2002. Effect of spectral band numbers on the retrieval of water column and bottom properties from ocean color data. *Applied Optics* 41, 12: 2191. [online]. Available from: https://www.osapublishing.org/abstract.cfm?URI=ao-41-12-2191 [Accessed 15 September 2019].

Lemoine G & Leo O 2015. *Crop mapping applications at scale: Using Google Earth Engine to enable global crop area and status monitoring using free and open data sources*. 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE.: 1496–1499. [online]. Available from: http://ieeexplore.ieee.org/document/7326063/ [Accessed 29 July 2019].

Li D, Lu D, Li N, Wu M & Shao X 2019. Quantifying annual land-cover change and vegetation greenness variation in a coastal ecosystem using dense time-series Landsat data. *GIScience and Remote Sensing* 56, 5: 769–793.

Li D, Lu D, Wu M, Shao X & Wei J 2017. Examining Land Cover and Greenness Dynamics in Hangzhou Bay in 1985–2016 Using Landsat Time-Series Data. *Remote Sensing* 10, 2: 32. [online]. Available from: http://www.mdpi.com/2072-4292/10/1/32 [Accessed 27 May 2020].

Liang S 2001. Narrowband to broadband conversions of land surface albedo I algorithms. *Remote Sensing of Environment* 76, 2: 213–238.

Liang S, Shuey CJ, Russ AL, Fang H, Chen M, Walthall CL, Daughtry CST & Hunt R 2003. Narrowband to broadband conversions of land surface albedo: II. Validation. *Remote Sensing of Environment* 84, 1: 25–41.

Lin Y, Zhang L, Wang N, Zhang X, Cen Y & Sun X 2020. A change detection method using spatial-temporal-spectral information from Landsat images. *International Journal of Remote Sensing* 41, 2: 772–793. [online]. Available from: https://doi.org/10.1080/01431161.2019.1648905

Linders TEW, Schaffner U, Eschen R, Abebe A, Choge SK, Nigatu L, Mbaabu PR, Shiferaw H & Allan E 2019. Direct and indirect effects of invasive species: Biodiversity loss is a major mechanism by which an invasive tree affects ecosystem functioning. *Journal of Ecology* 107, 6: 2660–2672.

Liou K 2007. Thermal Infrared Radiation Transfer in the Atmosphere. In Liou KN (ed) *An Introduction to Atmospheric Radiation*, 116–168. Academic Press. [online]. Available from: http://www.sciencedirect.com/science/article/pii/S0074614202800195

Liu X, Zhang A, Wang H & Liu H 2016. Using multi-remote sensing data to assess Phragmites invasion of the Detroit river international wildlife refuge. *World Journal of Engineering* 13, 1: 44–52. [online]. Available from: http://www.emeraldinsight.com/doi/10.1108/WJE-02-2016-016

Lobell DB, Thau D, Seifert C, Engle E & Little B 2015. A scalable satellite-based crop yield mapper. *Remote Sensing of Environment* 164: 324–333. [online]. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0034425715001637 [Accessed 29 July 2019].

Logan JA, Régnière J & Powell JA 2003. Assessing the impacts of global warming on forest pest dynamics. *Frontiers in Ecology and the Environment* 1, 3: 130–137.

Lukey P & Hall J 2020. Biological Invasion Policy and Legislation Development and Implementation in South Africa. In van Wilgen BW Measey J Richardson DM Wilson JR & Zengeya TA (eds) *Biological Invasions in South Africa*, 515–551. Cham: Springer

International Publishing. [online]. Available from: https://doi.org/10.1007/978-3-030-32394-3_18

Ma J, Xiao X, Miao R, Li Y, Chen B, Zhang Y & Zhao B 2019. Trends and controls of terrestrial gross primary productivity of China during 2000-2016. *Environmental Research Letters* 14, 8.

Mack RN, Ruiz GM & Carlton JT 2003. Global plant dispersal, naturalization, and invasion: pathways, modes, and circumstances. *Invasive species: vectors and management strategies*: 3–30.

Martin-Gallego P, Aplin P, Marston C, Altamirano A & Pauchard A 2020. Detecting and modelling alien tree presence using Sentinel-2 satellite imagery in Chile's temperate forests. *Forest Ecology and Management* 474: 118353.

Maundu P, Kibet S, Morimoto Y, Imbumi M & Adeka R 2009. Impact of prosopis juliflora on Kenya's semi-arid and arid ecosystems and local livelihoods. *Biodiversity* 10, 2–3: 33–50. [online]. Available from: https://doi.org/10.1080/14888386.2009.9712842 [Accessed 27 January 2019].

Mbaabu PR, Ng WT, Schaffner U, Gichaba M, Olago D, Choge S, Oriaso S & Eckert S 2019. Spatial Evolution of Prosopis Invasion and its Effects on LULC and Livelihoods in Baringo, Kenya. *Remote Sensing* 11, 1217. [online]. Available from: http://www.mdpi.com/2072-4292/11/10/1217 [Accessed 22 March 2019].

Meroni M, Ng WT, Rembold F, Leonardi U, Atzberger C & Gadain H 2017. Mapping Prosopis juliflora in west Somaliland with Landsat 8 satellite imagery and ground information. *Land Degradation & Development* 28: 494–506. [online]. Available from: https://doi.org/10.1002/ldr.2611

Moran VC, Hoffmann JH & Zimmermann HG 1993. Objectives, constraints, and tactics in the biological control of mesquite weeds (Prosopis) in South Africa. *Biological Control* 3, 1: 80–83.

Muller GC, Junnila A, Traore MM, Traore SF, Doumbia S, Sissoko F, Dembele SM, Schlein Y, Arheart KL, Revay EE, Kravchenko VD, Witt A & Beier JC 2017. The invasive shrub Prosopis juliflora enhances the malaria parasite transmission capacity of Anopheles mosquitoes: A habitat manipulation experiment. *Malaria Journal* 16, 1: 1–9. [online]. Available from: https://doi.org/10.1186/s12936-017-1878-9

Münch Z, Gibson L & Palmer A 2019. Monitoring effects of land cover change on biophysical drivers in rangelands using albedo. *Land* 8, 2: 1–25.

Mutanga O & Skidmore AK 2004. Narrow band vegetation indices overcome the saturation problem in biomass estimation. *International Journal of Remote Sensing* 25, 19: 3999–4014.

Mwangi E & Swallow B 2005. *Invasion of Prosopis juliflora and local livelihoods: Case study from the lake Baringo area of Kenya*.*World Agroforestry Center* [online]. Available from: http://hdl.handle.net/10535/4277

NASA 2019. A Landsat Timeline [online]. Available from: https://landsat.gsfc.nasa.gov/a-landsat-timeline/ [Accessed 25 July 2019].

NASA Earth Observatory 2012. First of Three Million [online]. Available from: https://earthobservatory.nasa.gov/images/78623/first-of-three-million [Accessed 25 July 2019].

Ndhlovu T, Milton-Dean SJ & Esler KJ 2011. Impact of Prosopis (mesquite) invasion and clearing on the grazing capacity of semiarid Nama Karoo rangeland, South Africa. *African Journal of Range and Forage Science* 28, 3: 129–137. [online]. Available from: https://doi.org/10.2989/10220119.2011.642095

Ng WT, Immitzer M, Floriansitz M, Vuolo F, Luminari L, Adede C, Wahome R & Atzberger C 2016. *Mapping Prosopis spp. within the Tarach water basin, Turkana, Kenya using Sentinel-2 imagery*.Neale CMU & Maltese A (eds). International Society for Optics and Photonics. [online]. Available from: https://doi.org/10.1117/12.2241279 [Accessed 22 November 2018].

Ng WT, Mbaabu PR, Einzmann K, Immitzer M, Atzberger C & Eckert S 2017. Assessing the potential of Sentinel-2 and Pléiades data for the detection of Prosopis and Vachellia spp. in Kenya. *Remote Sensing* 9, 1: 74. [online]. Available from: https://doi.org/10.3390/rs9010074 [Accessed 22 November 2018].

Ng WT, Meroni M, Immitzer M, Böck S, Leonardi U, Rembold F, Gadain H & Atzberger C 2016. Mapping Prosopis spp. with Landsat 8 data in arid environments: Evaluating effectiveness of different methods and temporal imagery selection for Hargeisa, Somaliland. *International Journal of Applied Earth Observation and Geoinformation* 53: 76–89. [online]. Available from: https://doi.org/10.1016/j.jag.2016.07.019

Ose K, Corpetti T & Demagistri L 2016. Multispectral Satellite Image Processing. In Baghdadi N & Zribi M (eds) *Optical Remote Sensing of Land Surface: Techniques and Methods*, 58–

124. Elsevier. [online]. Available from: http://www.sciencedirect.com/science/article/pii/B9781785481024500028

Padarian J, Minasny B & McBratney AB 2015. Using Google's cloud-based platform for digital soil mapping. *Computers & Geosciences* 83: 80–88. [online]. Available from: https://linkinghub.elsevier.com/retrieve/pii/S009830041530008X [Accessed 29 July 2019].

Pasiecznik NM, Felker P, Harris PJC, Harsh LN, Cruz G, Tewari JC, Cadoret K & Maldonado LJ 2001. *The Prosopis juliflora - Prosopis pallida Complex: A Monograph*. Coventry, UK: HDRA.

Patel NN, Angiuli E, Gamba P, Gaughan A, Lisini G, Stevens FR, Tatem AJ & Trianni G 2015. Multitemporal settlement and population mapping from Landsat using Google Earth Engine. *International Journal of Applied Earth Observation and Geoinformation* 35: 199–208. [online]. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0303243414001998 [Accessed 22 May 2019].

Pekel J-F, Cottam A, Gorelick N & Belward AS 2016. High-resolution mapping of global surface water and its long-term changes. *Nature* 540: 418. [online]. Available from: https://doi.org/10.1038/nature20584

Platt R V., Manthos D & Amos J 2018. Estimating the Creation and Removal Date of Fracking Ponds Using Trend Analysis of Landsat Imagery. *Environmental Management* 61, 2: 310–320. [online]. Available from: http://dx.doi.org/10.1007/s00267-017-0983-4

Pohl C & Van Genderen JL 1998. Multisensor image fusion in remote sensing: Concepts, methods and applications. *International Journal of Remote Sensing* 19, 5: 823–854. [online]. Available from: https://doi.org/10.1080/014311698215748

Post DF, Fimbres A, Matthias AD, Sano EE, Accioly L, Batchily AK & Ferreira LG 2000. Predicting Soil Albedo from Soil Color and Spectral Reflectance Data. *Soil Science Society of America Journal* 64, 3: 1027–1034. [online]. Available from: http://doi.wiley.com/10.2136/sssaj2000.6431027x [Accessed 25 August 2020].

Poynton RJ 1990. The Genus Prosopis in Southern Africa. *South African Forestry Journal* 152, 1: 62–66. [online]. Available from: https://www.tandfonline.com/action/journalInformation?journalCode=tsfs20 [Accessed 2 December 2020].

Qi J, Chehbouni A, Huete AR, Kerr YH & Sorooshian S 1994. A modified soil adjusted vegetation index. *Remote Sensing of Environment* 48, 2: 119–126.

Ray SS, Jain N, Miglani A, Singh JP, Singh AK, Panigrahy S & Parihar JS 2010. Defining optimum spectral narrow bands and bandwidths for agricultural applications. *Current Science* 98, 10: 1365–1369.

Regalado A 2010. New Google Earth Engine - ScienceInsider [online]. Available from: https://web.archive.org/web/20130501203438/http://news.sciencemag.org/scienceinsider/2010/12/new-google-earth-engine.html [Accessed 29 July 2019].

Ren G, Zhao Y, Wang J, Wu P & Ma Y 2021. Ecological effects analysis of Spartina alterniflora invasion within Yellow River delta using long time series remote sensing imagery. *Estuarine, Coastal and Shelf Science* 249, June 2020.

Robinson TP, van Klinken RD & Metternicht G 2008. Spatial and temporal rates and patterns of mesquite (Prosopis species) invasion in Western Australia. *Journal of Arid Environments* 72, 3: 175–188. [online]. Available from: https://doi.org/10.1016/j.jaridenv.2007.05.011

Rouse JW, Haas RH, Schell JA & Deering DW 1973. *Monitoring vegetation systems in the Great Plains with ERTS*. Proceedings of the Third ERTS Symposium: 309–317.

Rutherford MC, Mucina L & Powrie LW 2006. Biomes and bioregions of southern Africa. In Mucina L & Rutherford MC (eds) *The vegetation of South Africa, Lesotho and Swaziland.*, 30–51. South African National Biodiversity Institute.

Saxena R, Watson LT, Wynne RH, Brooks EB, Thomas VA, Zhiqiang Y & Kennedy RE 2018. Towards a polyalgorithm for land use change detection. *ISPRS Journal of Photogrammetry and Remote Sensing* 144: 217–234.

Schachtschneider K & February EC 2013. Impact of Prosopis invasion on a keystone tree species in the Kalahari Desert. *Plant Ecology* 214, 4: 597–605. [online]. Available from: https://doi.org/10.1007/s11258-013-0192-z

Schmidt M, Lucas R, Bunting P, Verbesselt J & Armston J 2015. Multi-resolution time series imagery for forest disturbance and regrowth monitoring in Queensland, Australia. *Remote Sensing of Environment* 158: 156–168.

Seager S, Turner EL, Schafer J & Ford EB 2005. Vegetation's Red Edge: A Possible Spectroscopic Biosignature of Extraterrestrial Plants. *Astrobiology* 5, 3: 372–390. [online]. Available from: https://doi.org/10.1089/ast.2005.5.372

Shackleton RT, Le Maitre DC, van Wilgen BW & Richardson DM 2015a. The impact of invasive alien Prosopis species (mesquite) on native plants in different environments in South Africa. *South African Journal of Botany* 97: 25–31. [online]. Available from:

https://doi.org/10.1016/j.sajb.2014.12.008

Shackleton RT, Le Maitre DC, van Wilgen BW & Richardson DM 2017. Towards a national strategy to optimise the management of a widespread invasive tree (Prosopis species; mesquite) in South Africa. *Ecosystem Services* 27, August 2016: 242–252. [online]. Available from: https://doi.org/10.1016/j.ecoser.2016.11.022

Shackleton RT, Le Maitre DC, van Wilgen BW & Richardson DM 2015b. Use of non-timber forest products from invasive alien prosopis species (mesquite) and native trees in South Africa: Implications for management. *Forest Ecosystems* 2, 16. [online]. Available from: https://doi.org/10.1186/s40663-015-0040-9

Shiferaw H, Alamirew T, Dzikiti S, Bewket W, Zeleke G & Schaffner U 2021. Water use of Prosopis juliflora and its impacts on catchment water budget and rural livelihoods in Afar Region, Ethiopia. *Scientific Reports* 11, 1: 2688. [online]. Available from: https://doi.org/10.1038/s41598-021-81776-6 [Accessed 7 March 2021].

Shiferaw H, Schaffner U, Bewket W, Alamirew T, Zeleke G & Teketay D 2019. Modelling the current fractional cover of an invasive alien plant and drivers of its invasion in a dryland ecosystem. *Nature Scientific Reports* 9, 1576. [online]. Available from: https://doi.org/10.1038/s41598-018-36587-7 [Accessed 10 February 2019].

Siegmund A & Menz G 2005. Fernes nah gebracht - Satelliten- und Luftbildeinsatz zur Analyse von Umweltveränderungen im Geographieunterricht. *Geographie und Schule* 27, 154: 2–10, S. 49.

Small C, Okujeni A, Van der Linden S & Waske B 2017. Remote sensing of urban environments. In *Comprehensive Remote Sensing*, 96–127. Elsevier.

Smit GN 2005. Tree thinning as an option to increase herbaceous yield of an encroached semi-arid savanna in South Africa. [online]. Available from: http://www.biomedcentral.com/1472-6785/5/4 [Accessed 13 July 2019].

Van der Spuy M 2019. Noord-Kaap: Drie distrikte tot rampgebiede verklaar [online]. Available from: https://www.netwerk24.com/landbou/Nuus/noord-kaap-drie-distrikte-tot-rampgebiede-verklaar-20190712 [Accessed 13 July 2019].

Statistica 2021. Inflation Rate: South Africa [online]. Available from: https://www.statista.com/statistics/370515/inflation-rate-in-south-africa/

Statistics South Africa 2012. *Census 2011.Census 2011 Statistical release – P0301.4*

Statistics South Africa 2000. *Employment trends in agriculture in South Africa*. 1st ed. Lestrada-

Jefferis J (ed). Pretoria: Statistics South Africa. [online]. Available from: http://www.nda.agric.za

Steenkamp HE & Chown SL 1996. Influence of dense stands of an exotic tree, Prosopis glandulosa Benson, on a savanna dung beetle (Coleoptera: Scarabaeinae) assemblage in southern Africa. *Biological Conservation* 78, 3: 305–311. [online]. Available from: https://doi.org/10.1016/S0006-3207(96)00047-X

Tai-leung Chong T 1995. Partial parameter consistency in a misspecified structural change model. *Economics Letters* 49, 4: 351–357.

Tsai YH, Stow D, Chen HL, Lewison R, An L & Shi L 2018. Mapping vegetation and land use types in Fanjingshan National Nature Reserve using google earth engine. *Remote Sensing* 10, 6.

Turpie JK, Marais C & Blignaut JN 2008. The working for water programme: Evolution of a payments for ecosystem services mechanism that addresses both poverty and ecosystem service delivery in South Africa. *Ecological Economics* 65, 4: 788–798.

U.S. Geological Survey 2019a. Landsat 4-7 Surface Reflectance (LEDAPS). , May.

U.S. Geological Survey 2019b. Landsat 8 Surface Reflectance Code (LASRC) Poduct Guide. , May: 40.

Underwood EC, Ustin SL & Ramirez CM 2007. A comparison of spatial and spectral image resolution for mapping invasive plants in coastal California. *Environmental Management* 39, 1: 63–83.

United States Geological Survey 2020a. Landsat 8 [online]. Available from: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-8 [Accessed 22 February 2021].

United States Geological Survey 2020b. Landsat 7 Maneuvers [online]. Available from: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-7-maneuvers [Accessed 20 November 2020].

United States Geological Survey 2019a. Landsat Known Issues [online]. Available from: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-known-issues [Accessed 27 February 2021].

United States Geological Survey 2019b. Landsat Surface Reflectance [online]. Available from: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-surface-reflectance [Accessed 27 February 2021].

United States Geological Survey 2015. What are the band designations for the Landsat satellites? [online]. Available from: https://www.usgs.gov/faqs/what-are-band-designations-landsat-satellites

Vanthof VR & Kelly REJ 2017. *Mapping prosopis juliflora invasion within rainwater harvesting structures in India using Google Earth Engine*. 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE.: 1115–1118. [online]. Available from: http://ieeexplore.ieee.org/document/8127152/ [Accessed 10 March 2019].

Verbesselt J, Hyndman R, Newnham G & Culvenor D 2010. Detecting trend and seasonal changes in satellite image time series. *Remote Sensing of Environment* 114, 1: 106–115. [online]. Available from: http://dx.doi.org/10.1016/j.rse.2009.08.014

Verbesselt J, Hyndman R, Zeileis A & Culvenor D 2010. Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. *Remote Sensing of Environment* 114, 12: 2970–2980.

Verbesselt J, Zeileis A & Herold M 2012. Near real-time disturbance detection using satellite image time series. *Remote Sensing of Environment* 123: 98–108. [online]. Available from: http://dx.doi.org/10.1016/j.rse.2012.02.022

Verbesselt J, Zeileis A & Hyndman R 2015. Package 'bfast.' [online]. Available from: https://cran.r-project.org/web/packages/bfast/bfast.pdf

Verstraete MM & Pinty B 1996. Designing optimal spectral indexes for remote sensing applications. *IEEE Transactions on Geoscience and Remote Sensing* 34, 5: 1254–1265.

Vidhya R, Vijayasekaran D & Ramakrishnan SS 2017. Mapping invasive plant Prosopis juliflora in arid land using high resolution remote sensing data and biophysical parameters. *Indian Journal of Geo Marine Sciences* 46, June: 1135–1144. [online]. Available from: http://nopr.niscair.res.in/handle/123456789/42009 [Accessed 29 January 2019].

Wakie TT, Evangelista PH, Jarnevich CS & Laituri M 2014. Mapping current and potential distribution of non-native Prosopis juliflora in the Afar region of Ethiopia. *PLoS ONE* 9, 11: 112854. [online]. Available from: https://doi.org/10.1371/journal.pone.0112854

Walker WS, Stickler CM, Kellndorfer JM, Kirsch KM & Nepstad DC 2010. Large-Area Classification and Mapping of Forest and Land Cover in the Brazilian Amazon: A Comparative Analysis of ALOS/PALSAR and Landsat Data Sources. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 3, 4: 594–604.

Wang D, Wan B, Qiu P, Su Y, Guo Q & Wu X 2018. Artificial mangrove species mapping using

Pléiades-1: An evaluation of pixel-based and object-based classifications with selected machine learning algorithms. *Remote Sensing* 10, 2: 294. [online]. Available from: https://doi.org/10.3390/rs10020294

Wang L 2006. *Invasive Species Spread Mapping Using Multi-Resolution Remote Sensing Data*. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. XXXVII: 135–142. [online]. Available from: http://www.isprs.org/proceedings/XXXVII/congress/2_pdf/1_WG-II-1/23.pdf [Accessed 28 September 2018].

Watts LM & Laffan SW 2014. Effectiveness of the BFAST algorithm for detecting vegetation response patterns in a semi-arid region. *Remote Sensing of Environment* 154, 1: 234–245.

van Wilgen BW, Fill JM, Baard J, Cheney C, Forsyth AT & Kraaij T 2016. Historical costs and projected future scenarios for the management of invasive alien plants in protected areas in the Cape Floristic Region. *Biological Conservation* 200: 168–177. [online]. Available from: http://dx.doi.org/10.1016/j.biocon.2016.06.008

van Wilgen BW, Forsyth GG, Le Maitre DC, Wannenburgh A, Kotzé JDF, van den Berg E & Henderson L 2012. An assessment of the effectiveness of a large, national-scale invasive alien plant control strategy in South Africa. *Biological Conservation* 148, 1: 28–38. [online]. Available from: http://dx.doi.org/10.1016/j.biocon.2011.12.035

van Wilgen BW & Wannenburgh A 2016. Co-facilitating invasive species control, water conservation and poverty relief: Achievements and challenges in South Africa's Working for Water programme. *Current Opinion in Environmental Sustainability* 19: 7–17. [online]. Available from: http://dx.doi.org/10.1016/j.cosust.2015.08.012

Wilson EH & Sader SA 2002. Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment* 80, 3: 385–396.

Wise RM, van Wilgen BW & Le Maitre DC 2012. Costs, benefits and management options for an invasive alien tree species: The case of mesquite in the Northern Cape, South Africa. *Journal of Arid Environments* 84: 80–90. [online]. Available from: https://doi.org/10.1016/j.jaridenv.2012.03.001

Xu H & Bai Y 2015. *Evaluation of urban lake evolution using Google Earth Engine - A case study of Wuhan, China*. 2015 Fourth International Conference on Agro-Geoinformatics (Agro-geoinformatics). IEEE.: 322–325. [online]. Available from: http://ieeexplore.ieee.org/document/7248087/ [Accessed 29 July 2019].

Xulu S, Peerbhay K, Gebreslasie M & Ismail R 2018. Drought influence on forest plantations in Zululand, South Africa, using MODIS time series and climate data. *Forests* 9, 9: 1–15.

Young NE, Anderson RS, Chignell SM, Vorster AG, Lawrence R & Evangelista PH 2017. A survival guide to Landsat preprocessing. *Ecology* 98, 4: 920–932. [online]. Available from: https://esajournals.onlinelibrary.wiley.com/doi/pdf/10.1002/ecy.1730 [Accessed 23 July 2019].

Zachariades C, Hoffmann JH & Roberts AP 2011. Biological Control of Mesquite (Prosopis Species) (Fabaceae) in South Africa. *African Entomology* 19, 2: 402–415. [online]. Available from: http://www.bioone.org/doi/abs/10.4001/003.019.0230 [Accessed 16 January 2019].

Zhai J, Liu R, Liu J, Huang L & Qin Y 2015. Human-Induced Landcover Changes Drive a Diminution of Land Surface Albedo in the Loess Plateau (China). *Remote Sensing* 7, 3: 2926–2941. [online]. Available from: http://www.mdpi.com/2072-4292/7/3/2926 [Accessed 28 July 2020].

Zhang Y 2004. Understanding Image Fusion Existing image fusion techniques. *Photogrammetric Engineering & Remote Sensing* , June: 657–661. [online]. Available from: http://scenesharp.com/wp-content/uploads/2016/11/Pub_2_Highlight_Article.pdf

Zhou Y, Zhang L, Xiao J, Williams CA, Vitkovskaya I & Bao A 2019. Spatiotemporal transition of institutional and socioeconomic impacts on vegetation productivity in Central Asia over last three decades. *Science of the Total Environment* 658: 922–935. [online]. Available from: https://doi.org/10.1016/j.scitotenv.2018.12.155

Zhu Z, Qiu S, He B & Deng C 2018. Cloud and Cloud Shadow Detection for Landsat Images: The Fundamental Basis for Analyzing Landsat Time Series. In Weng Q (ed) *Remote Sensing Time Series Image Processing*, Boca Raton: CRC Press. [online]. Available from: https://doi.org/10.1201/9781315166636

Zhu Z & Woodcock CE 2014. Continuous change detection and classification of land cover using all available Landsat data. *Remote Sensing of Environment* 144: 152–171.

Zhu Z & Woodcock CE 2012. Object-based cloud and cloud shadow detection in Landsat imagery. *Remote Sensing of Environment* 118: 83–94. [online]. Available from: https://www-sciencedirect-com.ez.sun.ac.za/science/article/pii/S0034425711003853 [Accessed 22 July 2019].

Zimmermann HG, Moran VC & Hoffmann JH 2004. Biological control in the management of invasive alien plants in South Africa, and the role of the Working for Water programme. *South African Journal of Science* 100, 1–2: 34–40.

Zimmermann HG 1991. Biological control of mesquite, Prosopis spp. (Fabaceae), in South Africa. *Agriculture, Ecosystems & Environment* 37, 1–3: 175–186. [online]. Available from: https://www.sciencedirect.com/science/article/pii/016788099190145N [Accessed 2 July 2019].

Zengeya T & Wilson JR (eds) 2020. *The status of biological invasions and their management in South Africa in 2019*. South African National Biodiversity Institute.

APPENDICES

APPENDIX A

Fieldwork questionnaires

GENERAL QUESTIONS (1 PER FARM)

1. Background

1.1. How long have you been on this farm?

1.2. Do you know how *Prosopis* ended up on your farm?

1.3. Do you view *Prosopis* as an advantage or problem?

1.3.1. Why do you view *Prosopis* as such?

2. Management by farmer

2.1. Did you manage *Prosopis* on your property in the period from 1995 to 2020?

2.2. Did you manage a fairly large area (more than a 30m x 30m block)?

2.3. Have you managed once or more than once? Or is it an ongoing effort without any concrete dates of management?

2.3.1. Will you please expand with a reason for your answer in 2.3?

2.4. Please describe your purpose with the management of *Prosopis* on your farm.

2.5. How much does the management cost you annually in terms of labour (person-days), herbicide, equipment, transport and so on?

2.6. How many areas do you manage on your farm?

3. Management by Working for Water (Government)

3.1. Did Working for Water (government) carry out any *Prosopis* management on your farm between 1995 and 2020?

3.2. Did Working for Water do any *Prosopis* management on your farm in areas where you did not also control *Prosopis*?

3.2.1. How many such areas (managed by Working for Water only) are on your farm?

3.3. Do you have any areas where both you and Working for Water did *Prosopis* management in the same area?

3.3.1. How many such areas (managed by Working for Water and you) are on your farm?

4. Areas of no management

4.1. Do you have *Prosopis* on your property that was NOT controlled between 1995 and 2020?

4.1.2. How many such areas (no management) are on your farm?

5. Farmer's opinion

5.1. Do you think that the current management by you is successful?

5.1.1. Why do you feel that way?

5.2. Do you think that the current management by Working for Water (without your follow-up) is successful?

5.2.1. Why do you feel that way?

5.3. Do you think the current combination of management by you and Working for Water is successful?

5.3.1. Why do you feel that way?

5.4. What suggestions do you have for better management?

5.5. Would you, if you had the choice, choose a farm with or without *Prosopis*?

SITE-SPECIFIC QUESTIONS (1 PER SITE)

1. Background

1.1. By whom was management done in this area between 1995 and 2020?

1.2. What was the purpose of management in this area?

2. Details of management

2.1. What was the purpose of management in this area?

2.2. Please describe the method of management.

2.3. How much does the management in this area cost you annually (or per cleaning if it was once) in terms of labour (person-days), herbicide, equipment, transport and so on?

2.4. On more or less what date(s) was this area managed?

3. Your opinion

3.1. Do you think that the management in this area is successful?

3.2. Why do you feel that way?

APPENDIX B

Script to extract Landsat pixel boundaries and centres using Google Earth Engine

```
var L8_SR = ee.ImageCollection("LANDSAT/LC08/C01/T1_SR"),
    L7_SR = ee.ImageCollection("LANDSAT/LE07/C01/T1_SR"),
    L5_SR = ee.ImageCollection("LANDSAT/LT05/C01/T1_SR"),

    ACTIVE_IMAGERY = L8_SR,

    START_DATE = '2020-05-01',
    END_DATE = '2021-06-10',

    EMPTY = ee.Image().byte();

Map.setCenter(LONGITUDE, LATITUDE, 10);

var region = Pts_All_Merge_Buffer_1km; // the ROI

var randomisePixel = function(image) { // prevents neighbouring pixels with similar values from
merging together
  var randomImage = ee.Image.random();
  var randomPix = image.select(['B4']).multiply(randomImage).rename('random');
  return image.addBands(randomPix);
};

//Select Landsat image
var image = ACTIVE_IMAGERY
  .filterBounds(region).map(randomisePixel).select(['random']).max();

  var imageOriginal = ACTIVE_IMAGERY
  .filterBounds(region).select(['B4']).median();

  var samplePts = image.sample({
  region: region,
  scale: 30, //scale of image to get centroid of every pixel
  geometries: true
});

var imagePoly = image.toInt().reduceToVectors({
  reducer: ee.Reducer.countEvery(),
  geometry: region,
  scale: 30
});

var AddXY = function(feature) {
  var lon = feature.geometry().coordinates().get(0);
```

```
  var lat = feature.geometry().coordinates().get(1);
  return feature.set({lat: lat, lon: lon});
};

var samplePtsAddedXY = samplePts.map(AddXY)
print(samplePtsAddedXY.first())
Map.addLayer(imagePoly)
Map.addLayer(samplePtsAddedXY)

Export.table.toDrive({
  collection: samplePtsAddedXY,
  description: 'samplePts',
  folder: 'GEE_2020',
  fileFormat: 'SHP'
})

Export.table.toDrive({
  collection: imagePoly,
  description: 'imagePoly',
  folder: 'GEE_2020',
  fileFormat: 'SHP'
})
```

APPENDIX C

BFAST results of all managed sites

Summary of breaks detected in *Prosopis* growth using five iterations of BFAST using different pixels within each site. Breaks marked using an asterisk (*) correspond to management records. Trends in *Prosopis* biomass are recorded as increasing in biomass (↑), decreasing in biomass (↓) and remaining steady (→). Breaks with a very slight increase in biomass during the duration of the break, followed by a decrease can also indicate a break due to clearing and was included.

#	Category	Recorded Management Year	Decreasing Breaks		Trends in Biomass		
			Year	Occurrence	Before	During	After
1.1	Self	2015*	2017*	100%	↑	↓	→
5.1	Self	2012 - 2016	Only increasing breaks detected				
6.1	WfW	2002* 2005	2002*	80%	↑	↓	↑
6.2	WfW	2001* 2002 2005	2001*	80%	↑	↓	↑
6.3	WfW	2001* 2002 2005	2001*	60%	↑	↓	↓
6.4	Both	**WfW:** 2001 2008 2003* 2005 2010* **Farmer:** 2011 - 2014	2002* 2011* 2014	100% 60% 60%	↑ ↑ ↑	↓ ↓ ↓	↑ ↑ →
8.1	Self	± 2013 Single unspecified follow-up	2002	60%	↑	↓	↓
8.2	Self	2015	2002	80%	↑	↓	↓
9.1	Self	± 2010 - 2020 annually	2002 2011*	80% 20%	↑ ↑	↓ ↓	↑ ↓
10.2	Self	± 2014	2002	40%	↑	↓	↓
11.2	Self	2004/2005 Annual follow-up until 2010	2002 2007* 2011 2014	40% 60% 40% 40%	↑ ↑ ↑ ↑	↓ ↓ ↓ ↓	↑ ↑ ↑ ↓
11.3	Self	2007 2020	Only increasing breaks detected				
11.5	Self	2006/2007	Only increasing breaks detected				
13.3	WfW	2002 2007	Only increasing breaks detected				

#	Category	Recorded Management Year	Decreasing Breaks		Trends in Biomass		
			Year	Occurrence	Before	During	After
14.1	WfW	2007	2014	100%	↑	↓	↑
15.1	Self	2010* 2016	2002 2006 2010*	20% 20% 20%	↑ ↑ ↑	↓ ↓ ↓	↓ ↓ ↓
16.1	WfW	2011 2016	Only increasing breaks detected				
16.2	WfW	2006 2016	Only increasing breaks detected				
16.3	WfW	2006* 2017*	2008* 2014 2018*	80% 80% 80%	↑ ↑ ↓	↓ ↓ ↑	↑ ↓ ↓
16.4	WfW	2006	Only increasing breaks detected				
16.5	WfW	2006	Only increasing breaks detected				
16.7	WfW	2006 2017	Only increasing breaks detected				
17.6	WfW	2006	Highly variable - breaks do not match between iterations				
17.7	WfW	2006	2002 2014	40% 40%	↑ ↑	↓ ↓	↑ ↓
17.8	WfW	2006	2002 2014	40% 40%	↑ ↑	↓ ↓	↑ ↓
18.7	Self	± 2000 - 2016	2002 2010 2014*	20% 60% 60%	↑ ↑ ↑	↓ ↓ ↓	↑ ↑ ↓
19.1	WfW	2001* 2013* 2018	2001* 2014*	20% 80%	↑ ↓/↑	↓ ↑/↓	↑ →
19.2	WfW	2001* 2013 2018*	2001* 2018*	60% 60%	↑ →	↓ ↓	→ ↓
19.3	Self	2018	2001 2013	40% 80%	↑ ↑	↓ ↓	→ ↓
19.4	WfW	2002 2013* 2018*	2013* 2017*	20% 100%	↑ ↑	↓ ↓	↓ ↑/→
19.5	WfW	2001* 2013*	2001* 2014*	100% 100%	↑ ↓	↓ ↑	↑ ↓
19.8	WfW	2016 - 2017	Only increasing breaks detected				
20.1	Self	2018*	2018*	20%	↑	↓	↓
21.1	Both	**WfW:** 2004* 2006* 2008* **Farmer:** 2016 – 2020	2003* 2006* 2008* 2011 2013/4	60% 20% 20% 20% 60%	↑ ↑ ↑ ↑ ↑	↓ ↓ ↓ ↓ ↓	↑ ↑ ↑ ↑ ↓

#	Category	Recorded Management Year	Decreasing Breaks		Trends in Biomass		
			Year	Occurrence	Before	During	After
21.4	WfW	2003 2005 2008	2013	60%	↑	↓	↓
21.6	WfW	2003 2008*	2006 2008*	20% 20%	↑ ↑	↓ ↓	↑ ↑
21.7	WfW	2003* 2008	2003*	100%	↑	↓	↑
21.8	WfW	2003* 2008	2003*	100%	↓	↓	↑
21.9	WfW	2003* 2008	2003* 2013	60% 40%	↑ ↑	↓ ↓	↑ ↓
23.1	Self	Before 2011	2006* 2013	100% 100%	↑ ↑	↓ ↓	↑ ↓

APPENDIX D

BFAST01 results of all managed sites

Summary of breaks detected in *Prosopis* growth using five iterations of BFAST01 using different pixels within each site. Breaks marked using an asterisk (*) correspond to management records. Uncleared sites nearby were paired with the managed sites below to identify breaks that occur in both managed and unmanaged sites. If a break occurs in both sites, it can be attributed to something other than management.

#	Category	Recorded Management Year	Uncleared Pair(s)	Matches Uncleared Pair(s)	Most Frequent Break		Other Breaks	
					Year	Occurrence	Year	Occurrence
1.1	Self	2015*	12.1	Yes – 2015*	2017*	80%	2015*	20%
5.1	Self	2012 - 2016	5.2	No	2007	80%	2014*	20%
6.1	WfW	2002 2005	5.2	No	2012	100%	N/A	N/A
6.2	WfW	2001 2002 2005	5.2	No	2017	80%	2020	20%
6.3	WfW	2001 2002 2005*	5.2	No	2017	60%	2007* 2012	20% 20%
6.4	Both	**WfW:** 2001 2008 2003* 2005 2010* **Farmer:** 2011 - 2014	5.2	Yes – 2002*	2012*	80%	2002*	20%
8.1	Self	± 2013* Single unspecified follow-up	8.3	Yes – 2012*/13*	2012*	60%	2002 2013*	20% 20%
8.2	Self	2015	8.4	Yes – 2012	2012	80%	2002	20%
9.1	Self	± 2010 - 2020 annually	9.2	No	2020	40%	2002	20%
10.2	Self	± 2014*	10.1	No	2005	40%	2007 2012* 2003	20% 20% 20%
11.2	Self	2004/2005* Annual follow-up until 2010	11.4	No	2017	80%	2002*	20%
11.3	Self	2007* 2020	11.4	No	2017	80%	2007*	20%
11.5	Self	2006/2007	11.6	No	2002	100%	N/A	N/A

#	Category	Recorded Management Year	Uncleared Pair(s)	Matches Uncleared Pair(s)	Most Frequent Break		Other Breaks	
					Year	Occurrence	Year	Occurrence
13.3	WfW	2002 2007	13.1	Yes – 2018	2018	40%	2020	40%
14.1	WfW	2007	18.1	Yes – 2014	2014	80%	2020	20%
15.1	Self	2010 2016	15.2	No	2002	100%	N/A	N/A
16.1	WfW	2011* 2016*	17.4	No	2012*	80%	2015*	20%
16.2	WfW	2006 2016*	17.4	Yes – 2017*/18*	2018*	80%	2017*	20%
16.3	WfW	2006 2017*	17.4	Yes – 2017*/18*	2018*	80%	2017*	20%
16.4	WfW	2006	17.4	No	2014	100%	N/A	N/A
16.5	WfW	2006	17.4	Yes – 2018	2012	40%	2014 2018	40% 20%
16.7	WfW	2006 2017*	17.4	Yes – 2017*	2017*	60%	2012	40%
17.6	WfW	2006*	17.4	Yes – 2007*	2014	80%	2007*	20%
17.7	WfW	2006	17.4	No	2014	100%	N/A	N/A
17.8	WfW	2006	17.4	No	2014	100%	N/A	N/A
18.7	Self	± 2000 - 2016	18.6	Yes – 2014*/15*	2015*	80%	2014*	20%
19.1	WfW	2001 2013* 2018	17.1	Yes – 2010/13*	2010	60%	2013*	40%
19.2	WfW	2001 2013 2018*	17.1	No	2018*	80%	2016*	20%
19.3	Self	2018	17.1	Yes – 2012	2012	100%	N/A	N/A
19.4	WfW	2002 2013* 2018*	17.1	Yes – 2012	2017*	60%	2012*	40%
19.5	WfW	2001 2013*	17.1	Yes – 2013*	2013*	100%	N/A	N/A
19.8	WfW	2016 - 2017	17.1	No	2009	100%	N/A	N/A
20.1	Self	2018	20.5	Yes – 2012/15	2015	60%	2012	40%
21.1	Both	**WfW:** 2004 2006 2008 **Farmer:** 2016 – 2020*	17.4	No	2016*	40%	2010 2012	40% 20%
21.4	WfW	2003 2005 2008*	17.4	No	2010*	80%	2016	20%

#	Category	Recorded Management Year	Uncleared Pair(s)	Matches Uncleared Pair(s)	Most Frequent Break		Other Breaks	
					Year	Occurrence	Year	Occurrence
21.6	WfW	2003 2008*	17.4	No	2016	80%	2010*	20%
21.7	WfW	2003 2008*	17.4	Yes – 2007*	2012	80%	2007*	20%
21.8	WfW	2003 2008*	17.4	Yes – 2007*	2009*	80%	2007*	20%
21.9	WfW	2003 2008*	17.4	Yes – 2007*/17/18	Variable	N/A	2007* 2010* 2012 2017 2018	20% 20% 20% 20% 20%
23.1	Self	Before 2011	18.1	Yes – 2012	Variable	N/A	2005* 2007* 2010* 2012 2019	20% 20% 20% 20% 20%

APPENDIX E

BFAST01 results of unmanaged sites

Summary of breaks detected in *Prosopis* growth using five iterations of BFAST01 using different pixels within each site. Can be used against Appendix D to see managed-unmanaged site pairs.

#	Most Frequent Break		Other Breaks	
	Year	Occurrence	Year	Occurrence
4.1	2016	80%	2020	20%
5.2	2002	100%	N/A	N/A
8.3	2012	100%	N/A	N/A
8.4	2012	80%	2007	20%
8.5	2012	100%	N/A	N/A
9.2	2019	40%	2018	60%
9.3	2020	80%	2002	20%
10.1	2020	100%	N/A	N/A
11.1	2016	60%	2014 2018	20% 20%
11.4	2012	60%	2014	40%
11.6	2018	60%	2012	40%
12.1	2017	80%	2014	20%
12.2	2020	60%	2019	20%
13.1	2017	80%	2012	20%
15.2	2018	100%	N/A	N/A
15.4	2018	80%	2006	20%
15.5	2020	80%	2002	20%
17.1	2012	100%	N/A	N/A
17.4	2019	80%	2005	20%
18.1	2014	100%	N/A	N/A
18.3	2014	100%	N/A	N/A
18.5	2014	100%	N/A	N/A
18.6	2014	100%	N/A	N/A
20.4	2019	100%	N/A	N/A
20.5	2014	100%	N/A	N/A

#	Most Frequent Break		Other Breaks	
	Year	Occurrence	Year	Occurrence
20.6	2014	100%	N/A	N/A
20.7	2019	60%	2004 2012	20% 20%
20.11	2012	40%	2015 2013	40% 20%

APPENDIX F

Vegetation index comparison using BFAST for all managed sites

#	Category	Recorded Management Year	Pixel ID	NDVI	NDMI	MSAVI2	Surface Albedo
1.1	Self	2015	1	2010 2014 2017	2010 2014 2017	2010 2014 2017	None
			2	2002 2010 2013	None	2002 2010	2016
			3	2002 2010 2013 2017	2002 2009	2002	None
			4	2010 2017	2004 2006 2010 2017	2010 2014 2017	None
5.1	Self	2012 - 2016	1	2014	2015 2016 2018	2014	None
			2	2014	2014 2016 2018	2014	2014 2016
			3	2014	2014 2016 2018	None	None
			4	2014	2014 2018	2014	None
6.1	WfW	2002 2005	1	None	None	None	2003
			2	None	2002	2002 2010 2014	2003
			3	2002 2011 2013	2002	2002 2011 2014	None
			4	2010 2014	2002	2002 2010 2014	2003
6.2	WfW	2001 2002 2005	1	2001 2017	2001 2008 2011 2017	2001	None
			2	2001 2017	None	2001 2017	None
			3	2001	None	2001	None
			4	2001 2018	None	2001 2017	None

6.3	WfW	2001 2002 2005	1	2001	2001	2001	2003
			2	2001 2012 2014	2001 2012 2014	2001 2012 2014	2009
			3	2001	2001	2001	2013
			4	2001	2001	2001 2012 2014	None
6.4	Both	**WfW:** 2001 2008 2003 2005 2010 **Farmer:** 2011 - 2014	1	2001	2001	2001	None
			2	2002 2015	2015	2002 2015	2015
			3	2002	2001 2014	2001	2002
			4	2002	2002 2014	2002	2002 2015
8.1	Self	± 2013 Single unspecified follow-up	1	2002	2001	2002	2002
			2	2002	2001	2002	2002 2015
			3	2002	2002	2002	2011
			4	2002	2002	2002	2002
8.2	Self	2015	1	2002	2001	2002	2002
			2	2002	2001	2002	2002
			3	2002	2001	2002	2002 2016
			4	2002	2001	2002	2002
9.1	Self	± 2010 - 2020 annually	1	2002	2002	2002	2002
			2	2002	2002	2002	2002 2004 2018
			3	2002	2002 2005 2011 2013	2002	2002
			4	2002	2002	2002	2002
10.2	Self	± 2014	1	2002 2009 2011 2013	2002 2011 2013	2002 2008 2011 2013	2005 2008 2011 2013 2015
			2	None	2002 2014	2002	2010
			3	2004 2006 2008	2002	2002	2006 2009 2015
			4	2002	2002	2003	None

			1	2004 2007	2002 2007	2005 2007	2007
			2	None	2014	None	None
11.2	Self	2004/2005 Annual follow-up until 2010	3	2002 2007	2002 2007 2010	2002 2005 2007 2010 2014	2007 2015
			4	2002 2007	None	None	2016
			1	2001	2002 2018	2002 2015 2018	None
11.3	Self	2007 2020	2	None	2004 2006 2008 2011 2013	2002	None
			3	2001	2018	None	None
			4	2001 2018	2002 2018	2001 2018	None
			1	None	2001 2007	2002 2004	None
			2	2001 2008 2011 2014	2001 2008 2011 2013	2001 2008 2011 2014	None
11.5	Self	2006/2007	3	2001 2011 2014	2001 2018	2001 2018	None
			4	2001 2008 2011 2014	2001 2008 2011 2013	2001 2008 2011 2014	2002
			1	2008	2011 2014	2008	None
			2	2008	None	None	None
13.3	WfW	2002 2007	3	None	2011 2013	2002 2008	None
			4	2002 2008	2011 2013	None	2001 2012
			1	2014	2014	2001 2008 2011 2014	None
14.1	WfW	2007	2	2014	2003 2006 2008 2011 2018	2014	None
			3	2001 2014	2001 2006	2001 2011 2014	None

					2011 2014		
			4	2014 2018	2006 2008 2018	2011 2014 2018	None
15.1	Self	2010 2016	1	2004 2015	None	2015	2003 2010
			2	2002	2002 2007 2009	2002	2002
			3	None	2002 2004 2006 2009	2016	2010
			4	2004	2002 2004 2006	None	2003 2009
16.1	WfW	2011 2016	1	None	None	None	None
			2	None	None	None	None
			3	2009 2011 2013	2008 2011 2013	2009 2011 2013	None
			4	2009 2011 2013	None	2009 2011 2013	None
16.2	WfW	2006 2016	1	2005 2008 2011 2013	2001 2009 2011 2013	2005 2008	None
			2	2005 2008 2011	2005 2008 2011	None	2003 2006
			3	None	None	None	2006
			4	2014	2011	None	2003 2006
16.3	WfW	2006 2017	1	None	2014	None	None
			2	None	2002 2014	2010 2014	None
			3	2006 2008 2014	None	2006 2008 2014	None
			4	2006 2008 2014	None	None	None
16.4	WfW	2006	1	2005 2014	2006 2008 2011 2014	2006 2008 2011 2014	2003 2006 2017
			2	None	None	None	None
			3	2006 2008	None	None	None

				2011 2014			
			4	None	None	None	None
16.5	WfW	2006	1	2014	2011 2014	2011 2014	2002
			2	None	None	2011 2014	None
			3	2006 2008	None	2006 2008 2010 2013	None
			4	None	2001	None	None
16.7	WfW	2006 2017	1	2008 2011 2014 2017	2008 2011	2009 2011 2014	2002
			2	2008 2011 2014 2017	2009 2011 2014 2017	2008 2011 2014	None
			3	2017	2002 2008 2011 2013	None	2010
			4	2006 2008 2011 2013	2003 2009 2011 2013	None	None
17.6	WfW	2006	1	2008 2010 2014	2014	2004 2008 2010 2014	None
			2	None	2014	2014	None
			3	None	None	2004 2008 2010	None
			4	2004 2008 2010	None	2004 2008 2010	None
17.7	WfW	2006	1	2002 2010 2014	2002 2014	2002 2014	None
			2	2002 2010 2014	2002 2014	2002 2014	None
			3	2002 2010 2014	2002 2014	2002 2014	None
			4	2002 2008 2010 2014	2002 2014	2002 2014	2009 2012 2017

17.8	WfW	2006	1	2002 2008 2010	2002 2008 2010	2002 2008 2010	None
			2	2002 2010 2014	2014	2002 2008 2010 2014	2017
			3	2010 2014	2010 2014	2008 2010 2014	None
			4	None	2002 2006	None	None
18.7	Self	± 2000 - 2016	1	2014	2002 2004 2006 2010 2015 2017	2014	None
			2	2002 2010 2014	2002 2004 2006 2010 2015 2018	2002 2015 2017	2012
			3	2003 2011 2014	2014	2011 2014	2001
			4	2004 2006 2014	2004 2006 2010 2015 2018	2010 2015 2018	2001
19.1	WfW	2001 2013 2018	1	2007 2009 2014	2006 2009 2011 2014	2005 2009 2011 2014	None
			2	None	2004	2004	None
			3	2001	2001	2001	None
			4	None	2001	None	2013
19.2	WfW	2001 2013 2018	1	2001 2004 2006 2013 2017	2001 2004 2006	None	None
			2	2001	2001	2001	None
			3	2001 2004 2006	2001 2004 2006	2001 2004	None
			4	2001	2001	2001	2007
19.3	Self	2018	1	2001 2011	2001 2011	2001	2007
			2	2001	2001 2010	2001	2007 2010 2018

			3	2001 2009 2011 2013	2001 2009 2011 2013	2001	2007 2011
			4	2001 2008 2011 2013	2001 2008 2013	2001	None
19.4	WfW	2002 2013 2018	1	2016 2017	2016 2017	2016 2017	None
			2	2017	2017 2018	None	2017
			3	2017	2017	2017	2017
			4	2017 2018	2016 2018	2017 2018	2017
19.5	WfW	2001 2013	1	2002	2001	2002 2010 2013	2003
			2	2003 2006 2011 2013	2003 2008 2011 2013	2003 2006 2010 2013	None
			3	None	2001	None	2003
			4	None	2001	2001	None
19.8	WfW	2016 - 2017	1	2002 2011 2013	2001 2011 2013	2001	2003 2006 2017
			2	2001 2013	2001 2011 2013	2001 2011 2013	None
			3	2001	2001 2011 2013	2001	None
			4	2001 2011 2013	2001 2011 2013	2001	2017
20.1	Self	2018	1	2003 2006 2010 2015 2018	2003 2006 2010 2015 2018	2003 2006 2015 2018	2018
			2	2003 2006 2010 2018	2002 2016 2018	2003 2006 2010 2018	2012 2018
			3	None	2003 2006 2018	2003 2006	2018
			4	2003 2006 2015 2018	2003 2006 2015 2018	2003 2005 2018	2018

21.1	Both	**WfW:** 2004 2006 2008 **Farmer:** 2016 – 2020	1	2008 2011 2013	2001 2008 2011 2013	2001 2008 2011 2013	None
			2	2008 2011 2013	2008 2011 2013	2008 2011 2013	None
			3	2004 2008 2011 2013	2001 2008 2011 2013	2002 2008 2011 2013	None
			4	2008 2011 2013	2001 2011 2013	2008 2011 2013	None
21.4	WfW	2003 2005 2008	1	2011 2013	2001	2011 2013	None
			2	None	None	2004 2006	2018
			3	2008 2011 2013	2009 2011 2013	2004 2006 2008 2011 2013	None
			4	None	None	2004 2006	2018
21.6	WfW	2003 2008	1	2003	None	2011 2013	2018
			2	2004 2006 2008	2004 2006 2008	None	None
			3	2004 2006	2004 2006 2011 2013	2004 2006 2011 2013	None
			4	2004 2006 2008	None	None	None
21.7	WfW	2003 2008	1	2003 2010 2013	2003 2006 2008 2011 2013	2003 2010 2013	None
			2	2003 2006 2008	2003	2003 2010 2013	None
			3	2003	2003	2003	None
			4	2003 2010	2003	2003 2010 2013	None
21.8	WfW	2003 2008	1	2003	2003 2011 2013	2003	None

			2	2003	2003 2011 2013	2003	None
			3	2003	None	None	None
			4	2003	None	2003	None
21.9	WfW	2003 2008	1	2003	2003 2011 2013	None	None
			2	2004 2006	None	None	None
			3	2004 2006	2003 2011 2013	None	None
			4	None	2003 2006	None	None
23.1	Self	Before 2011	1	None	2001 2011 2013	None	None
			2	None	2001	None	None
			3	None	2001 2006 2008 2011 2013	None	None
			4	None	2001 2006 2008 2011 2013	2008 2010 2013	None

APPENDIX G

Management action summary of managed sites

Site	Manage ment	Area *ha*	Labour *person days*	Cost *ZAR*	Treat ments	Method	Growth break	Growth trend	Progress
1.1	Self	29.15	No data	346 870	2	Excavator	Sudden, 2 years before farmer's record	Decrease	Good
5.1	Self	2.08	180	No data	4	Cut down	Gradual, matches record	Decrease	Good
6.1	WfW	14.01	520.12	118 475	4	Cut down	No clear break	Increase	Poor
6.2	WfW	17.31	401.2	123 420	4	Cut down	No clear break	Steady	Poor
6.3	WfW	17.53	313.56	89 535	4	Cut down	No clear break	Steady	Poor
6.4	Both	33.93	709.13	245 939	5	Cut down	WfW break observed	Steady	Good
8.1	Self	9.89	100	30 427	2	Spray	Gradual	Decrease	Good
8.2	Self	13.91	No data	No data	1	Spray	No clear break	Steady	Limited
9.1	Self	10.63	900	194 226	5	Cut down	No clear break	Steady	Good
10.2	Self	6.48	240	59 167	1	Pour herbicide over	No clear break	Decrease	Good
11.2	Self	7.39	No data	No data	4	Cut down	No clear break	Decrease	Good
11.3	Self	4.14	No data	No data	2	Cut down	Gradual	Decrease	Good
11.5	Self	5.65	No data	No data	1	Cut down	No clear break	Decrease	Good
13.3	WfW	71.62	1 131.6	226 783	6	Cut down	No clear break	Steady	Poor
14.1	WfW	106.7	98.16	30 171	1	Cut down	Clear break, wrong year	Steady	Limited
15.1	Self	1.11	No data	No data	2	Cut down	Clear break, wrong year	Increase	Poor
16.1	WfW	87.71	716.74	197 277	2	Cut down	Gradual	Decrease	Limited
16.2	WfW	37.11	626.84	167 773	2	Cut down	Gradual	Increase	Poor
16.3	WfW	38.23	347.17	90 264	1	Cut down	Gradual	Increase	Poor
16.4	WfW	65.88	303.05	98 223	1	Cut down	Clear break, wrong year	Increase	Poor
16.5	WfW	53.36	330.83	107 067	1	Cut down	Gradual	Increase	Poor

16.7	WfW	38.23	347.17	90 264	1	Cut down	Gradual	Increase	Poor
17.6	WfW	38.93	272.51	88 988	1	Cut down	No clear break	Steady	Poor
17.7	WfW	26.46	322.81	97 043	1	Cut down	Clear break, wrong year	Decrease	Poor
17.8	WfW	31.26	300.1	92 612	1	Cut down	Clear break, wrong year	Steady	Poor
18.7	Self	7.22	No data	No data	10	Cut down	Sudden break, matches farmer's date	Steady	Limited
19.1	WfW	16.03	1 088.86	168 580	3	Cut down	Gradual	Decrease	Poor
19.2	WfW	16.03	1 088.86	168 580	3	Cut down	Sudden, matches a date provided	Decrease	Limited
19.3	Self	1.74	No data	No data	1	Excavator	Gradual	Decrease	Good
19.4	WfW	16.58	699.61	97 167	3	Cut down	Sudden break, matches a date provided	Decrease	Limited
19.5	WfW	24.94	902.97	153 091	2	Cut down	Sudden, matches a date provided	Steady	Poor
19.8	WfW	38.96	636.08	597 027	1	Cut down	Gradual	Decrease	Poor
20.1	Self	0.63	No data	No data	1	Excavator	Clear break, wrong year	Steady	Good
21.1	Both	18.22	379.81	124 491	3	Cut down	Gradual	Decrease	Poor
21.4	WfW	8.98	430.98	71 059	4	Cut down	No clear break	Decrease	Poor
21.6	WfW	4.56	131.92	29 930	2	Cut down	No clear break	Decrease	Poor
21.7	WfW	4.56	131.92	29 930	2	Cut down	No clear break	Steady	Poor
21.8	WfW	6.54	43.17	10 487	2	Cut down	Steady	Decrease	Poor
21.9	WfW	6.54	43.17	10 487	2	Cut down	No clear break	Increase	Poor
23.1	Self	1.22	No data	No data	No data	Cut down	No clear break	Steady	Good