USING SPECTRAL AND TEXTURAL INFORMATION TO DETECT AND MAP *PARTHENIUM HYSTEROPHORUS L*. IN MTUBATUBA, SOUTH AFRICA

By

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DECLARATION

The study undertaken for this dissertation was in fulfilment of a Master in Science (MSc) Environmental Science and represents the original work of the author. Work taken from other authors or organizations is duly acknowledged within the text and reference list.

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DECLARATION – PUBLICATIONS

DETAILS OF CONTRIBUTION TO PUBLICATIONS that form part of and/or include research presented in this dissertation (includes publications in preparation and those that have been submitted, are in press or are published, and gives details of the contributions of each author to the experimental work and writing of each publication).

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The work was done by the first author under the guidance and supervision of the second and third authors.

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DEDICATION

A message to every person who wants to give up:

Don’t.

To my family:

Where would I be without you?

To myself:

My goodness, you are strong. You can accomplish anything you desire. You just needed the passion and the purpose. I’m glad you have found it.

PLAGIARISM DECLARATION

I, …………………………………………………. declare that;

1. The research presented in this dissertation is my original work, except where otherwise indicated.
2. This dissertation has not submitted for any examination or degree at any other university.
3. This dissertation does not contain other persons' data, graphs, pictures or any other information, unless acknowledged as being sourced from other persons.
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Signed: …………………………………..

TABLE OF CONTENTS

LIST OF FIGURES:

LIST OF TABLES:

ACRONYMS AND ABBREVIATIONS

ARI	Anthocyanin reflectance index
ENVI	Environment for Visualizing Images
ESA	European Space Agency
FLAASH	Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercube
GARI	Green atmospherically resistant vegetation index
GIS	Geographic Information Systems
GLCM	Grey-level co-occurrence measures
GLI	Green leaf index
GLOM	Grey-level occurrence measures
GPS	Global Positioning System
NGRDI	Normalized green red difference index
OLI	Operational Land Imager
PLS	Partial Least Squares
PLS-DA	Partial Least Squares-Discriminant Analysis
PPR	Normalized difference 550/450 plant pigment ratio
PVR	Normalized difference 550/650 photosynthetic vigour ratio
QGIS	Quantum GIS
REP	Red-edge position linear interpolation
SANSA	South African Space Agency

SGB	Stochastic Gradient Boosting
SPLS-DA	Sparse Partial Least Squares-Discriminant Analysis
SPOT	Satellite Pour l’Observation de la Terre
SR520/670	Simple ratio 520/670
SRMIR/Red	Simple ratio MIR/Red eisenhydroxid-index
WET	Tasselled cap wetness
WGS 1984 UTM	World Geodetic System 1984 Universal Transverse Mercator
YVIMSS	Tasselled cap yellow vegetation index MSS

UNITS OF MEASUREMENT

%	Percent
°C	Degrees Celsius
M	Metre
m^2	Square metre
nm	Nanometre
mm	Millimetre

ABSTRACT

Parthenium hysterophorus L. (parthenium) is an alien invasive species that has had severe environmental and human impacts in three continents. Sustainable management and control of the invasive species requires an understanding of its distribution and rate of spread. Our first study focuses on the use of spectral information of commercial sensor RapidEye and freely available Sentinel-2 imagery to detect parthenium and other land cover classes. Sentinel-2 outperformed RapidEye to classify most land cover classes, with an overall classification accuracy of 82% and 71%, respectively. This was likely due to the superior spectral resolution of Sentinel-2. However, RapidEye performed better when classifying parthenium, potentially due to the fact that there were some patches that were smaller than the Sentinel-2 spatial resolution. Nonetheless, Sentinel-2 represents a good opportunity to map larger parthenium stands and other land cover types. The second study focused on mapping parthenium using texture analysis and SPOT-6 imagery. It compared the mapping ability between the panchromatic and multispectral bands using the PLS-DA algorithm. The panchromatic band achieved a higher overall classification accuracy than the multispectral bands (77% and 73%, respectively). Furthermore, the panchromatic band achieved superior performance compared to multispectral bands for parthenium. This may be attributed to the higher spatial resolution of the panchromatic band as it has been shown that finer spatial resolution is beneficial in texture analysis. Overall texture analysis using SPOT 6 imagery was the most successful combination which allowed us to accurately map parthenium distribution.

Key words: *Parthenium hysterophorus L.*; alien invasive species; spectral; texture; Sentinel-2; SPOT; RapidEye; SGB; PLS-DA

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CHAPTER 1

1. INTRODUCTION

1.1. Background

Biological invasion poses a severe threat to biodiversity, second only to that of habitat destruction (Richardson & van Wilgen, 2004). The rapid increase in alien invasive species causes major species extinctions, resulting in homogenisation of fauna and flora throughout the world (Joshi *et al*., 2004). According to Singh (2005), an alien species is a non-native organism that occurs outside of their natural habitat and beyond their dispersal potential. Some species can become invasive when they establish quickly and out-compete native species (Singh, 2005). Some of the ways that invasive species impact their surrounding environment is by changing the functioning of ecosystems and their hydrology. They influence soil structure, soil profile, nutrient content, moisture and decomposition due to their distinct resource requirements, mode of resource acquisition and consumption that is different compared to native species. Invasive species therefore seriously hinder conservation and sustainability, while negatively impacting ecosystem goods and services (Singh, 2005). Human communities are also greatly impacted by invasive species, as they erode natural capital and threaten economic productivity (Richardson & van Wilgen, 2004). Thus, biological invasions are a global problem and will increase in severity due to global trade, travel and tourism (Singh, 2005). These vast ecological, economic and human consequences spark the need to hinder the spread of alien invasive species.

Parthenium hysterophorus L. is an herbaceous annual or biennial plant (Belz *et al*., 2009) that establishes and grows rapidly in new environments (Joshi *et al*., 2004; Singh *et al*., 2005). Each plant can produce an extensive seed bank (between 10 000-15000 viable seeds), capable of dispersing over great distances (Patel, 2011). Furthermore, it thrives in various environmental conditions, allowing it to colonize different habitats, including road sides, barren land, crop, and grazing lands (Dhileepan & Strathie, 2009; Nigatu *et al*., 2010; Kaur *et al*., 2014). It aggressively colonizes disturbed and degraded areas with exposed soils and low ground cover (Singh *et al*., 2005; Belz *et al*., 2009), which create open spaces for parthenium to invade. For instance, grazing lands are especially susceptible to invasion by parthenium, due to increased levels of disturbance caused by high livestock densities (Strathie *et al*., 2011). Parthenium can also cause an entire habitat change by replacing native vegetation, especially in grasslands, woodlands and flood plains (Dhileepan *et al*., 1996; Nigatu *et al*., 2010). Allelopathic properties of parthenium play a large role in inhibiting the growth and seed germination of surrounding vegetation, by releasing chemicals into the soil (Strathie *et al*., 2011). It can reduce agriculture and pasture productivity drastically, causing lower crop yields and grass biomass (Dhileepan *et al*., 1996; Patel, 2011); therefore causing huge economic losses.

Parthenium is regarded as the most dangerous terrestrial weed, attributed to its harmful impact on biodiversity and humans (Kaur *et al*., 2014). It contains a toxic substance named parthenin that has a significant health threat to animals and humans (Patel, 2011). The prolonged exposure of parthenium to humans can cause dermatitis, blisters, hay fever and bronchitis, amongst other symptoms (Dhileepan *et al*., 1996; Singh *et al*., 2005; Kelaniyangoda & Ekanayake, 2010; Patel, 2011; Strathie *et al*., 2011). Parthenium can form large stands, which animals may feed on. This can cause haemorrhaging and tissue damage of their internal organs (Kelaniyangoda & Ekanayake, 2010; Nigatu *et al*., 2010). A substantial amount of parthenium in the diet of cattle can result in death (Kaur *et al*., 2014).

Parthenium originated in Central and Southern America and has spread to Asia, Australia and Africa (Strathie *et al*., 2011). According to Nigatu *et al*. (2010), climate change and higher carbon dioxide in the atmosphere will further increase the invasion potential of parthenium, resulting in further expansion. Many countries in Africa have already been invaded by parthenium, including Mozambique, Swaziland, Zimbabwe and South Africa (Nigatu *et al*., 2010; Strathie *et al*., 2011). Parthenium was documented for the first time in 1880 in South Africa and became prevalent in the 1980s. It now widely populates Mpumalanga, North West and KwaZulu-Natal, subtropical north-eastern provinces of the country (Strathie *et al*., 2011). Studies conducted in South Africa have shown that there are extensive seed banks of up to 95 800 seeds/m^2 in some study sites, while other studies have indicated that seeds are capable of germinating within 24 hours under tunnel conditions (Strathie *et al*., 2011). These ecological properties of parthenium may have facilitated their extensive spread. It has even infiltrated protected areas and national parks such as the Kruger National Park and Hluhluwe-iMfolozi (Belz *et al*., 2009; Adkins & Shabbir, 2014), creating a threat to endangered plant and animal species. Furthermore, the economic impacts on South Africans have been substantial as many people make their living by livestock and agricultural farming (Mcconnachie *et al*., 2011).

Controlling parthenium via chemical or mechanical methods is expensive, especially for a developing country; hence manual labour of predominantly women and children is used, which is labour intensive, time-consuming and detrimental to health (Mcconnachie *et al*., 2011). The vast economic losses and environmental and health concerns in South Africa caused by parthenium has prompted the need to study parthenium invasion. First, however, we must focus on accurately mapping their distribution to determine the extent of the invasion, so that we make informed decisions on where and how to use limited resources.

Remote sensing has been successfully applied for the collection of data and mapping alien invasion and their impact (Joshi *et al*., 2004). Its synoptic view, multi-temporal coverage and cost-effectiveness are greatly beneficial in monitoring changes caused by alien invasive species (Joshi *et al*., 2004). Traditional methods of acquiring field data are expensive, labour-intensive, time consuming and in some cases, not practical (Bruzzone & Prieto, 2001; Turner *et al*., 2003; Ruiz- Gallardo *et al*., 2004). Remote sensing provides a convenient method to studying complex geographic terrain and ecosystems that are inaccessible (Joshi *et al*., 2004). Consistent and frequent imagery allows the detection and quantification of land cover changes (Joshi *et al*., 2004), which would be extremely useful for invasion mapping. Moreover, it is invaluable for monitoring an alien invasive species, such as parthenium, that has been spreading rapidly throughout continents.

Once we have identified our need for remote sensing, we need to determine the sensors that are most suited to our specific needs. There are a variety of remote sensing scanners that offer different spatial and spectral resolutions and are suited to different purposes. For example, multispectral scanners capture a few broad spectral bands of approximately one hundred nm wide (Joshi *et al*., 2004). They are useful for discriminating between broad land cover classes, for example forests, water and soil (Joshi *et al*., 2004). Conversely, hyperspectral scanners have narrower band widths (from a few nm to tens of nm) and many spectral bands (tens to several hundred) (Joshi *et al*., 2004) that aid in discriminating between more subtle differences, such as different species of vegetation (Adam *et al*., 2012). Even though hyperspectral imagery would seem like an ideal choice in most analyses, including invasion mapping, it suffers from a few severe limitations that hinder its extensive use, such as large data volumes, redundancy, multicollinearity and high expense (Dye *et al*., 2011). We therefore need to look at alternatives.

While there are many studies that have documented the ecology of parthenium and its numerous effects, there are very limited studies focusing on the spatial distribution and monitoring of alien invasive plants, including parthenium. However, these studies have been successful in mapping parthenium, which is an encouraging step towards consistent monitoring. For example, a study by Kganyago *et al*. (2018) mapped parthenium using OLI and SPOT 6 and FRAGSTATS with high accuracy, and showcased that SPOT 6 was more suited to delineating gaps and more accurately estimated patch sizes compared to OLI. Another recent study by Arogoundade *et al.* (2019) successfully mapped parthenium using Sentinel-2 in the MaxEnt environment, by combining environmental variables with remotely sensed data and also achieved high accuracy. These encouraging results show that monitoring parthenium is indeed possible, prompting us to further investigate the ability of affordable sensors to accurately map parthenium. We can further explore the strengths and weaknesses of each sensor to determine which provides better results; thereafter we may beneficially use these sensors for mass alien invasive monitoring across the globe. More specifically, in this study we would like to explore the mapping ability of new generation sensors. These sensors were developed in the recent years that attempt to merge the advantages of multispectral and hyperspectral imagery. This includes sensors such as WorldView-2, RapidEye and Sentinel (Omer *et al*., 2015). It has specifically focused on including strategically positioned bands, mainly within the red-edge region (Adelabu *et al*., 2014).

Sentinel-2 has attracted a lot of attention within the remote sensing community, due to its open access and free imagery. One of its pioneering features is three spectral bands situated in the red-edge and two in the short-wave infrared region, proven to be particularly useful in vegetation analysis (Immitzer *et al*., 2016). Furthermore, it has a minimum revisit time of approximately 5 days (van der Werff & van der Meer, 2016), which could offer unprecedented opportunities to track short-term changes (Kussul *et al*., 2017). The draw-back of Sentinel-2 imagery is that the spatial resolution ranges from 10 to 60 metres (Lefebvre *et al.*, 2016), which is quite coarse for detecting land cover that is heterogeneous. However, it is more beneficial to work with free imagery due to limited resources, especially in developing countries; hence it is necessary to compare the capabilities between free and commercial sensors of similar spectral and spatial characteristics. RapidEye is a commercial sensor that is comparable to Sentinel-2 in terms of spectral and spatial resolution. RapidEye has a spatial resolution of 5 m and four spectral bands, including a red-edge band. Research has shown that the red-edge band, specifically, picks up subtle differences between vegetation, therefore has been useful in grassland mapping and detecting change in land cover (Gärtner *et al*, 2016). These two sensors offer a great opportunity to detect alien invasive species, such as parthenium, especially due to its distinct physiological characteristics as compared to other species. Stochastic gradient boosting (SGB) was the classification method used to make land cover classes from RapidEye and Sentinel-2 imagery in our first study. It was chosen due to the substantially higher accuracies it produced, compared to common parametric and other boosting methods. As this method is popular with radar or very high resolution sensors, but is limited for medium and high resolution sensors (Dube *et al*., 2015), it is necessary to understand its performance using coarser spatial resolution. This will enable us to exploit free imagery to our maximum benefit if results are satisfactory. Furthermore, SGB has not been used often in ecological applications (Chirici *et al*., 2013; Filippi *et al*., 2014) and to our knowledge has not been used for the detection of parthenium, hence prompting its investigation.

Image texture is an alternative to using spectral information. Texture is determined by the spatial arrangement of grey tones within an image (Franklin *et al*., 2000) and can be described based on how smooth or coarse the features are within the image (Chica-Olmo & Abarca-Hernandez, 2000). However the terms "smooth" and "coarse" tends to be very subjective, therefore quantitative approaches were invented for objective texture description (Chica-Olmo & Abarca-Hernandez, 2000). It can also be analysed computationally using remote sensing imagery. The combination of texture and spectral information has been shown to provide more accurate classification results than spectral information alone (Wulder *et al*., 1998; Mariz *et al.*, 2009). However, texture is dependent on the spatial resolution of imagery, with coarser spatial resolution negatively affecting classification results. Consequently, it is important to use very high spatial resolution imagery. SPOT 6 is an operationally free sensor that offers very high resolution in the panchromatic band (1.5 m) and high resolution in four multispectral bands (6 m) (Oumar, 2016), each of which is sensitive to different land covers characteristics. The in-expense and superior spatial resolution of SPOT 6 images is extremely beneficial for research and other purposes, especially in financially-constrained countries like South Africa. For this reason, SPOT 6 imagery was chosen for the second study to conduct texture analysis, which may be useful in detecting alien invasive herbaceous species, such as parthenium. The method used to create land cover classes (including parthenium) was the Partial Least Squares-Discriminant Analysis (PLS-DA). The PLS-DA is a partial least squares regression (Pérez-

Enciso & Tenenhaus, 2003) that decomposes explanatory variables into a few latent components, while retaining the most important information (Peerbhay *et al*., 2014; Lenhardt *et al*., 2015). It is extremely useful for analyses that have many explanatory variables, such as spectral bands or texture parameters, hence it was chosen for this study.

1.2. Research problem

The extensive damage of parthenium to biological systems and humans on a global scale triggers the crucial need to map this species so that we may understand its extent and thereafter propose mitigation measures in line with this understanding. The rapid spread across different countries and continents calls for a need for up-to-date information on the distribution of parthenium. To date, methods of mapping alien invasive species have been very limited, with manual data collection methods being labour-intensive, expensive and impractical for large and inaccessible areas. Accurate mapping of alien invasive species, such as parthenium, requires enough spatial and spectral detail to differentiate it from other land cover, while also being affordable and accessible to resource-constrained countries.

The following research problems were identified:

I. The availability of accessible and affordable sensors with adequate spatial resolution to detect and map erratic parthenium patches in resource limited countries.
II. The affordability of sensors with adequate spectral resolution or strategically positioned bands that is able to differentiate between spectrally similar land cover classes.
III. Mapping of parthenium is difficult using multispectral sensors due to the limited information that broad bands provide, hence it is important to investigate alternate imagery analysis.

1.3. Scope of the study

Remote sensing provides an inexpensive, innovative and efficient method to map alien invasive species, which consumes far less time. Different types of remote sensors are available, with commercial sensors providing better mapping capabilities, such as higher spatial and/or spectral resolution. Detecting smaller patches of land cover becomes challenging using freely available imagery, such as LANDSAT, that has coarser spatial resolution. However, the new generation of sensors that have recently been released may provide a solution to this. Sentinel-

2 is new generation sensor that has high spectral resolution (13 spectral bands) that would greatly aid subtle class discrimination. This is particularly useful when differentiating between parthenium and the surrounding natural vegetation. The one drawback is its coarse spatial resolution (10-60 m). On the other hand, RapidEye is a commercial sensor with high spatial resolution of 5 m, but a low spectral resolution of 5 bands. These two sensors provide an interesting ground for comparison to map parthenium due to patch sizes being similar in size to RapidEye and Sentinel-2 pixel size. Investigating their strengths and weaknesses will be an outstanding way to decide if investing limited resources in commercial sensors is necessary and worthwhile for a particular project.

Due to spectral confusion with co-existing vegetation or an imprecise overlay of the GPS points with the pixels on the image, sensors with even finer spatial resolution may be necessary to map parthenium. Furthermore, another limitation to mapping parthenium is its small patch sizes and erratic growth patterns, which makes accurate mapping more difficult. Consequently SPOT 6, which is an operationally free sensor that provides very high spatial resolution imagery in the panchromatic band, was chosen for the second study. Furthermore, spectral analyses may be of limited value for discriminating between different vegetation types, due to their similar spectral qualities and the inadequate spectral resolution of multispectral sensors. Thus, alternate imagery analyses should be considered to determine which is more successful for parthenium detection. For these reasons, texture analysis was used in the second study, which makes use of grey tonal variations and patterns in an image, and has shown good results in vegetation mapping. It was used in conjunction with the PLS-DA algorithm to create land cover classes of parthenium and the surrounding land cover. Limitations whilst carrying out the study included lack of many large parthenium stands to sample and time constraints in taking out wide-spread sample points of each land cover class.

1.4. Aims and objectives

With this background understanding, this dissertation has the following aim and objectives.

The aim of this study was to investigate the ability of spectral and textural information of multispectral remote sensing imagery to map *Parthenium hysterophorus L.* (parthenium) and the surrounding land cover. The specific objectives were as follows:

I. To compare the ability of new generation multispectral sensors: Sentinel-2 and RapidEye to detect parthenium and the surrounding land cover using spectral information and SGB algorithm

II. Evaluate the ability of texture analysis to map parthenium and the surrounding land cover using the PLS-DA algorithm and SPOT 6 imagery

1.5. Research questions

This dissertation addresses the following research questions:

I. Which multispectral sensor detects parthenium and the surrounding land cover with the highest classification accuracy between Sentinel-2 and RapidEye?

II. Are multispectral or panchromatic bands of SPOT 6 more efficient at detecting and map parthenium and the surrounding land cover using texture analysis?

1.6. Outline of dissertation

This dissertation consists of four distinct chapters. It is structured around two main chapters, namely chapter two and three, which constitute publishable papers. These will be submitted to peer-reviewed journals for publication. Both chapters have detailed information on the literature review, study area and methodology, therefore this introductory chapter does not include this information.

Chapter Two compares the ability of new generation multispectral sensors, Sentinel-2 and RapidEye, to detect *Parthenium hysterophorus L.* and other land cover classes using the stochastic gradient boosting algorithm. Vegetation indices were computed and used as predictor variables along with the spectral bands. The most significant predictor variables were determined and ranked for importance towards classification.

Chapter Three focuses on using texture analysis to map *Parthenium hysterophorus L.* and other land cover classes. The texture analysis was run using grey-level occurrence and grey-level co-occurrence measures. Thereafter, the PLS-DA ensemble was used to classify the image into land cover classes. The texture variables with the most influence during the classification process were chosen using the variable importance (VIP) method.

Chapter Four is a synthesis chapter, providing a summary of the entire study. The overall aims and objectives are revisited, highlighting the important findings and conclusions. This chapter further looks into the limitations of the study, furthermore presenting future recommendations.

CHAPTER 2

2. COMPARING THE ABILITY OF SENTINEL-2 AND RAPIDEYE TO DETECT ALIEN INVASIVE SPECIES *PARTHENIUM HYSTEROPHORUS L.* USING SPECTRAL INFORMATION

2.1. Abstract

Parthenium (*Parthenium hysterophorus L.*) is an alien invasive plant species that has had devastating impacts throughout the world, including biological homogenisation, animal and human health effects and substantial economic loss. Invasion has occurred in three continents, including Africa, where it has placed pressure on livelihoods, resulting in the need to monitor parthenium distribution. Recent technological advances in GIS and remote sensing have proven beneficial for tracking alien invasion, creating extensive opportunities for inexpensive monitoring. Due to financial constraints in South Africa, it is more beneficial to use free imagery, rather than commercial imagery, hence it is necessary to compare the capabilities between them and assess the benefits of using each. For this reason, this study compared commercial sensor RapidEye with freely available Sentinel-2 using their spectral bands and vegetation indices to discriminate between parthenium and the surrounding land cover. Sentinel-2 achieved a higher overall classification accuracy than RapidEye (82% and 71%, respectively). Sentinel-2 outperformed RapidEye in classifying most land cover types, despite its lower spatial resolution, which may be attributed to the superior spectral resolution of Sentinel-2. However, RapidEye outperformed Sentinel-2 for the classification of parthenium. Considering that some patches of parthenium were smaller than the spatial resolution of Sentinel-2, it can be deduced that the finer spatial resolution of RapidEye resulted in a higher accuracy for parthenium. Overall, the results suggest an opportunity to utilize freely available Sentinel-2 imagery to detect and map plant invasive species, which is a major advantage for resource-constrained countries in Africa.

Key words: *Parthenium hysterophorus L.*; alien invasive species; Sentinel-2; RapidEye; high resolution; multispectral; SGB

2.2. Introduction

Parthenium hysterophorus L. (hereafter referred to as parthenium) is one of the world's most devastating and hazardous alien invasive plant species (Singh, 2005). It has the ability to rapidly establish itself in a new environment, out-compete native species (Joshi *et al*., 2004; Singh, 2005), and effectively disperse over vast distances (Patel, 2011). Furthermore, it can thrive in a variety of environmental conditions, therefore colonizing a wide range of habitats, such as crop and grazing lands, road sides, barren land and riparian habitats (Dhileepan & Strathie, 2009; Nigatu *et al*., 2010; Kaur *et al*., 2014). Parthenium is regarded as the most hazardous terrestrial weed attributed to its harmful impact on the health of biodiversity and humans (Kaur *et al*., 2014). Parthenium contains a toxic substance named parthenin that has a significant health threat to animals and humans (Patel, 2011). When present in large stands, animals such as cattle sometimes feed on it, causing haemorrhaging and tissue damage of their internal organs (Kelaniyangoda & Ekanayake, 2010; McConnachie *et al*., 2011; Kaur *et al*., 2014). Prolonged exposure to this plant can cause several health issues among humans, for example contact dermatitis, blisters, hay fever and bronchitis, amongst other symptoms (Dhileepan *et al*., 1996; Singh, 2005; Kelaniyangoda & Ekanayake, 2010; Patel, 2011; Strathie *et al*., 2011). Additionally, parthenium can result in huge economic losses by reducing agriculture and pasture productivity, thereby causing lower crop yields and grass biomass (Dhileepan *et al*., 1996; Patel, 2011).

The invasive plant originated in Central and Southern America (Singh, 2005; Kelaniyangoda & Ekanayake, 2010; Nigatu *et al*., 2010; Strathie *et al*., 2011) and has since spread around three other continents, namely Africa, Asia and Australia (Tefera, 2002; Nigatu *et al*., 2010; Patel, 2011). Its tropical origin allows it to be more invasive in warmer climates (Patel, 2011); consequently, studies have shown that a large part of sub-Saharan Africa has the potential for being highly affected by parthenium invasion in upcoming years due to climate change (Strathie *et al*., 2011; Kaur *et al*., 2014). Many countries in Africa have already been invaded, including Ethiopia, Mozambique, Swaziland, Zimbabwe and South Africa (Nigatu *et al*., 2010; Strathie *et al*., 2011). Parthenium was first documented in KwaZulu-Natal, South Africa in 1880 (Belz *et al*., 2009; Retief *et al*., 2013). It has infiltrated protected areas and national parks such as the Kruger National Park and Hluhluwe-iMfolozi (Belz *et al*., 2009; Adkins & Shabbir, 2014), where it could threaten endangered plant and animal species. The economic impacts on

South Africans have been substantial as many earn their living from livestock and agricultural farming (Mcconnachie *et al*., 2011). Furthermore, milk and meat products from affected animals are not suitable for human consumption (Kelaniyangoda & Ekanayake, 2010; Patel, 2011), further increasing economic losses. The vast economic losses and environmental and health concerns in South Africa caused by parthenium has prompted the need to study parthenium invasion.

Traditionally, alien invasion data was collected using ground-based surveys, very high spatial resolution aerial photography or manual processing of photography (Müllerová *et al*., 2013). The utility of these traditional methods, such as field surveys have shown remarkable capability in mapping and managing alien invasive species. Although this approach has been proven accurate, it is associated with serious challenges such as cost, time, limited coverage of remote and inaccessible areas and is labour intensive (Bruzzone & Prieto, 2001; Turner *et al*., 2003; Ruiz- Gallardo *et al*., 2004). However, the emergence of remote sensing and GIS has proven an efficient and powerful method to track alien invasion (Heilman, 2002; Ruiz- Gallardo *et al*., 2004; Otukei & Blaschke, 2010), whilst being inexpensive, less time consuming and more accurate (Rawat & Kumar, 2015). It is particularly useful for coverage of large geographical areas, with repetitive coverage providing the ability for tracking changes (Dube *et al*., 2017). Remote sensing has been used successfully for alien invasion monitoring in a number of studies, for example Ustin *et al*., (2002), Fuller (2005), Hamada *et al*. (2007) and Asner *et al*., (2008). Most case studies explore shrub and tree species, however monitoring of herbaceous species (for example, parthenium) is only possible when enough spatial and/or spectral detail of imagery is provided (Müllerová *et al*., 2013). Furthermore, the species needs to be sufficiently distinct from surrounding vegetation or land cover, form dense stands or be large enough for detection (Müllerová *et al*., 2005; Jones *et al*., 2011). Generally, hyperspectral information was used as it is difficult to detect herb species, with uncommon use of panchromatic and multispectral data (Müllerová *et al*., 2013). However, hyperspectral data has its own set of drawbacks, including expense, data redundancy, large correlation between bands and difficulty in analysing large datasets (Mutanga *et al*., 2012). Furthermore, hyperspectral imagery has limited availability and cannot be utilized often in resource-strained areas like South Africa (Dube *et al*., 2017). Other remote sensing datasets that are affordable, readily available and have strategically positioned bands such as multispectral imagery (Dube *et al*., 2017) should therefore be considered for monitoring of parthenium.

Recently, a new generation of satellites were introduced with high spatial and temporal resolution, for example WorldView-2, WorldView-3, RapidEye and Sentinel-2 (Omer *et al*., 2015). Improvement in these sensors has focused on including strategically positioned broad bands, mostly within the red-edge region (Adelabu *et al*., 2014). The red edge band provides crucial and sensitive measurements of plant characteristics, including chlorophyll and leaf area index, that are unavailable in pre-existing multispectral sensors, for example Landsat and SPOT (Dube *et al*., 2017). Sentinel-2 is an innovative sensor that offers freely available imagery with high spatial resolution (between 60 and 10 metres) and 13 multispectral broad bands, which ranges from the visible to short-wave infrared region (Lefebvre *et al*., 2016; Navarro *et al*., 2017). The most pioneering feature of this sensor is the three spectral bands situated in the red-edge and two in the short-wave infrared region, proven to be particularly useful in vegetation analysis (Immitzer *et al*., 2016). It has a wide swath and a revisit time of minimum five days owing to twin satellites (Van Der Werff & Van Der Meer, 2016). The frequent coverage of Sentinel-2 and free data access offers unprecedented opportunities to capture landscape changes in the short-term (Kussul *et al*., 2017), providing the ability to track and monitor phenomena such an alien plant invasion. A limitation to Sentinel-2 imagery is that the spatial resolution is too coarse for detection of small patches of a certain land cover type, hence finer spatial resolution would be preferred. As free imagery reduces financial constraints, it is important to compare Sentinel-2 to a commercial sensor of finer spatial resolution to understand the benefits of using each sensor and make informed decisions.

RapidEye is the first multispectral commercial sensor with a red-edge band and a high temporal and spatial resolution (Kross *et al*., 2015). It has a spatial resolution of 5 metres and 5 multispectral broad bands. The RapidEye constellation consists of five satellites that have a temporal resolution of up to one day and a relatively wide swath of 77 km (Kross *et al*., 2015). It has commonly been utilized for grassland mapping and detection of land cover change (Gärtner *et al*, 2016). RapidEye and Sentinel-2 are comparable based on their spectral and spatial resolution, with the most significant difference being that Sentinel-2 is freely available, whereas RapidEye is a commercial sensor. To our knowledge, there are limited studies that have investigated parthenium detection using multispectral imagery, despite its large threat to the environment and society; hence it is imperative to find suitable sensors for accurate and affordable detection and mapping. Consequently, this study aims to compare the capability of Sentinel-2 and RapidEye imagery in land cover classification, specifically focusing on parthenium. The specific objectives are to: 1) determine the most important spectral bands and vegetation indices used to detect parthenium and other land cover using RapidEye and Sentinel-2 imagery; 2) determine the sensor with the highest classification accuracy, particularly focusing on parthenium.

2.3. Materials and Methods

2.3.1. Study site and data collection

The study site is situated in the north-eastern municipality of Mtubatuba, alongside the coastline of KwaZulu-Natal, South Africa (Figure 2.1). Mtubatuba is in close proximity to Hluhluwe and Umfolozi Game Reserves and Lake St Lucia. The climate is warm and temperate with an average temperature of 21.7 ^{o} C and an annual average rainfall of 967 mm. The vegetation consists of savanna, natural forests, agriculture and plantations. Other land uses consist of ecotourism, low and high residential areas. Shapefiles used to map the location were provided by the University of KwaZulu-Natal, Pietermaritzburg, Geography department. The imagery of the study site was captured by RapidEye at 5 m spatial resolution.

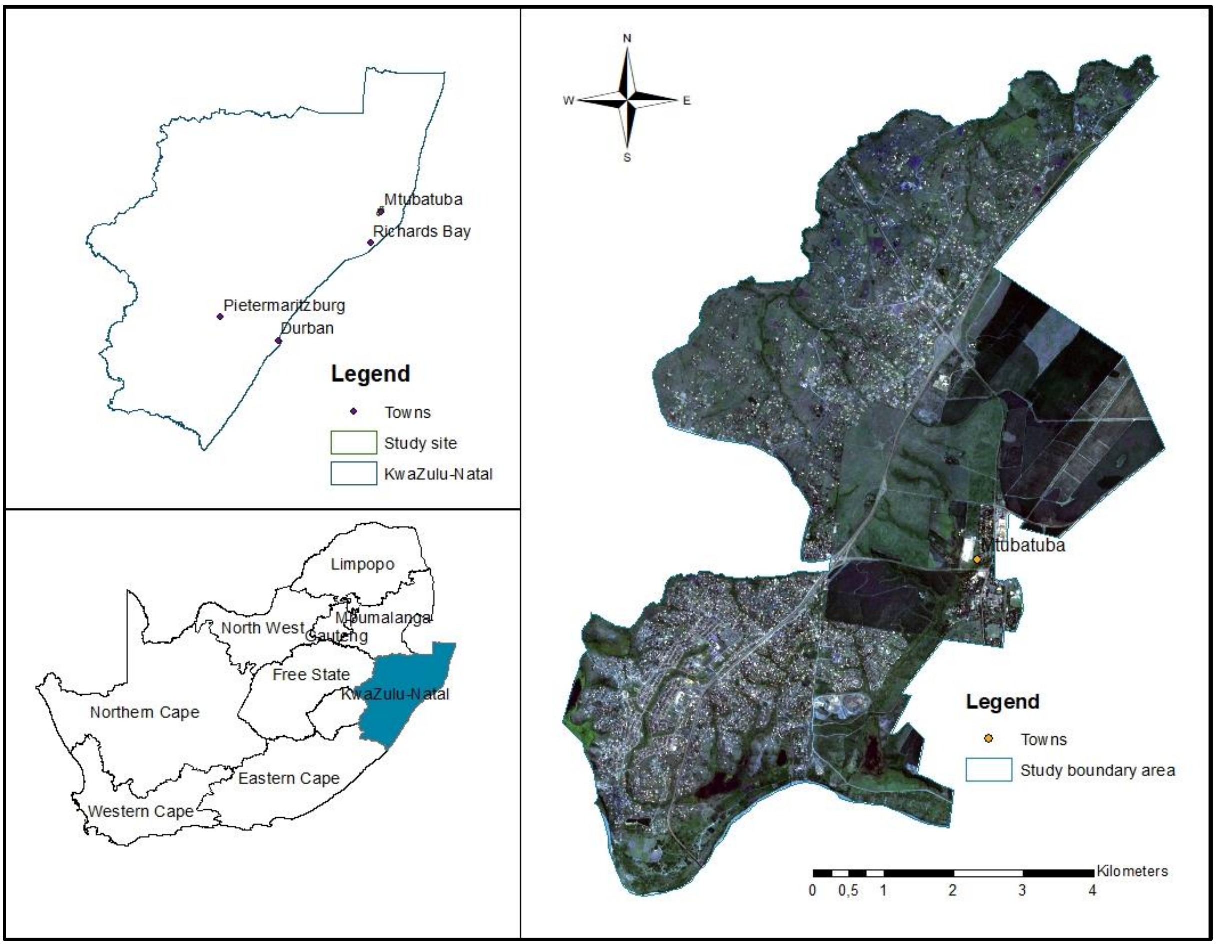

Figure 2.1: Location of the study site in Mtubatuba, KwaZulu-Natal, South Africa.

Data collection occurred in the field in late February 2018, in summer. GPS locations of land cover classes were captured using a differentially corrected Trimble GeoXT handheld GPS receiver. Nine land use covers were selected, namely parthenium, grass, natural forest/vegetation, commercial forest, agriculture, bare soil, buildings, roads and water. GPS points for parthenium were taken in patches greater than 10 m² so that they would be detectable by Sentinel and RapidEye sensors (with a spatial resolution of 10 m² and 5 m², respectively). However, due to a limited amount of large parthenium patches, some GPS points were taken in patches that were less than 10 m². Fifty GPS points of parthenium were taken in the field. Ten pre-determined points using purposive sampling from Google Earth 7.3.2.5776 for each of the eight remaining classes were located in the field and verified. The other points for each class (approximately 50) were taken from Google Earth 7.3.2.5776 that provides very high resolution satellite imagery using purposive sampling based on our knowledge of the area. This was compared with the Sentinel-2 and RapidEye images for any discrepancies due to differences in field date to acquisition date. Class distribution of all collected GPS points are shown in Table 2.1.

Table 2.1: Class distribution of GPS points

Class	Number of GPS points
Agriculture	60
Bare soil/pathways	60
Buildings	60
Commercial forest	60
Grass	60
Natural forest	56
Parthenium	50
Roads	60
Water	60

2.3.2. Satellite imagery

2.3.2.1. RapidEye

Two RapidEye scenes dating 21st of March 2018 were downloaded from Planet™, which is sponsored by the German Federal Ministry of Economy and Energy (Dube *et al*., 2017). RapidEye imagery contains 5 spectral bands, each with 5 m spatial resolution. The bands include blue (440-510 nm), green (520-590 nm), red (630-685 nm), red edge (690-730 nm) and near-infrared (760-850 nm) (Dube *et al*., 2017). Orthoproduct images were chosen, where sensor and geometric corrections were already applied. The images were pre-processed for radiometric calibration in ENVI 4.3, using FLAASH (Fast Line-of-sight Atmospheric Analysis of Hypercubes). The images were projected using WGS 1984 UTM. The two scenes were mosaicked in ArcMap 10.4 to create one image for the analysis. A shapefile was created using the GPS points collected and used to extract reflectance values for each land cover class from the RapidEye image.

2.3.2.2. Sentinel-2

Sentinel-2 comprises of 13 spectral bands, which span the visible to shortwave infrared regions of the electromagnetic spectrum (Lefebvre *et al*., 2016; van der Werrf & van der Meer, 2016). Four 10 metre bands ensure continuity with other sensors of similar spatial resolution, such as Landsat-8 and SPOT 5. Six, 20 metre bands enhance land cover classification and three 60 metre bands are used for atmospheric correction. Due to their coarse spatial resolution and their main use in atmospheric corrections, these 60 metre bands (bands 1, 9 and 10) were not used for the analysis. One Sentinel-2B scene covering the study area was downloaded for the 23rd of February 2018 from the European Space Agency's (ESA) Sentinel Scientific Data Hub, which provides free access to Sentinel-2 imagery. It was pre-processed using the semi-classification plugin in QGIS. The spatial resolution ranged from 10 to 20 metres, therefore it was homogenized to 10 m using nearest neighbour resampling. Like the RapidEye image, reflectance values for each land cover class were extracted from the image to create a model of the investigated land cover types.

2.3.3. Data Analysis

A variety of vegetation indices were computed using RapidEye and Sentinel-2 bands. Stochastic gradient boosting (SGB) was used for the classification analysis. The data used for analysis included GPS points and their respective land cover. The data was split into 70% for training the classifier and 30% for testing the accuracy of the classification. According to Adelabu *et al*. (2015), the 70-30% split produced the lowest mean standard error and consequently produced the highest accuracy. Spectral bands and their respective vegetation indices for each sensor were ranked for their importance in the classification process. The highest accuracy for each sensor was chosen based on the lowest number of predictor variables (consisting of both raw spectral bands and derived vegetation indices). Thereafter, the model was optimized using the random search method to improve the classification accuracies. Random search tunes algorithm parameters using a sample from a random distribution and a fixed number of iterations; thereafter a model is created and evaluated based on the combination of chosen parameters. The final accuracies were taken after model optimization. All analysis was run in a python environment.

2.3.3.1. Vegetation Indices

Earth's features reflect, absorb and transmit electromagnetic energy in various amounts depending on the type of material and condition (Prabhakar *et al*., 2012). These amounts change with different wavelengths, which enables different features to be distinguished. Remote sensing systems measure spectral reflectance, which is the portion of incident energy that is reflected. Vegetation indices are a radiation-based measurement which is calculated from spectral reflectance captured by remote sensors (Prabhakar *et al*., 2012). Vegetation indices help to minimize external factors that cause reflectance variability and hence inaccuracies. They enhance spectral signals of green vegetation and reduce spectral noise caused by soil background, atmospheric influences and sensor viewing and sun angle (Dube *et al*., 2017). Vegetation indices are created by applying a mathematical operation using two or more spectral bands from a sensor. A variety of vegetation indices were computed for RapidEye and Sentinel-2 (38 and 88, respectively) to improve classification accuracy by enhancing the signals given off by individual classes, thereby increasing the separability between classes.

2.3.3.2. Stochastic Gradient Boosting

Stochastic gradient boosting (SGB) is a supervised classification method that involves a hybrid between bagging and boosting procedures (Lawrence *et al*., 2004; Moisen *et al*., 2006; Chirici *et al*., 2013). Many regression or classification trees are built from pseudo residuals, using a random subset of the dataset, which produces an improvement in the model (Moisen *et al*., 2006). Using a small fraction of the training dataset increases the prediction accuracy and computational speed, and avoids over-fitting. The combined effect of the model reduces its sensitivity to inaccurate training data and places emphasis on incorrectly classified training data that is closest to the correct classification, instead of the worst classified data (Lawrence *et al*., 2004). Therefore, SGB produces substantially higher accuracies than other boosting methods. Good performance has been achieved using SGB for remote sensing applications in comparison to common parametric methods for land use/cover classification (Chirici *et al*., 2013). Tree-based ensemble approaches were popular in studies using radar or very high-spatial resolution sensors, but have been limited for medium and high-spatial resolution sensors (Dube *et al*., 2015). Very high-spatial resolution data is expensive; therefore the accuracy of SGB for land use/cover classification using readily available data from medium-high spatial resolution sensors should be tested. Only a few ecological and forestry applications using the SGB method have been investigated based on remote sensing data (Chirici *et al*., 2013; Filippi *et al*., 2014). To our knowledge, SGB has previously not been used for the detection and classification of parthenium.

2.3.3.3. Accuracy Assessment

An accuracy assessment is used to test the accuracy of the classification results produced by the algorithm, compared to the verified ground truth data (Lewis & Brown, 2001). The training dataset is used to train the algorithm used for the classification, whereas the test dataset is used to produce classification accuracies. The accuracy of each land cover class produced by the algorithm can be evaluated using the user and producer accuracy (Belgiu & Csillik, 2018). The user accuracy is the probability that a pixel belongs to a specific class assigned by the classifier and the producer accuracy represents the probability of a certain class being classified correctly (Royimani *et al.*, 2019). The overall accuracy is determined by the percentage of correctly classified samples to the total number of test data samples. The remaining percentage is referred to as overall disagreement, which can be divided into quantity and allocation disagreement, which is argued to be more informative than the kappa statistic (Warrens, 2015). Quantity disagreement is the difference between the comparison and reference map which is caused by the imperfect proportion of categories (Warrens, 2015). Allocation disagreement is the difference between comparison and reference map, caused by the imperfect spatial allocation of categories. These accuracies provide a measure of error to determine how useful the classification results are.

2.3.4. Results

In theory, each class being detected should have a unique spectral reflectance signature that changes throughout the electromagnetic spectrum. The change in spectral reflectance for each class throughout sensor bands can be represented in spectral curves. Spectral curves are important to determine how similar or dissimilar classes are, to know if they are separable using that specific sensor. According to the spectral curve for RapidEye (Figure 2.2), showcasing all investigated land cover classes; there is spectral similarity in blue (B), green (G) and red-edge (RE) between classes, with some overlap in reflectance. However, there is a widening between individual spectral curves of most classes within red (R) and near-infrared (NE), increasing separability between classes. This indicates that the red and near-infrared regions are important for land cover classification. However, there is a lot of spectral overlap between grass and parthenium throughout their spectral curves, signifying that it is difficult to distinguish between the two classes, hence reducing classification accuracy.

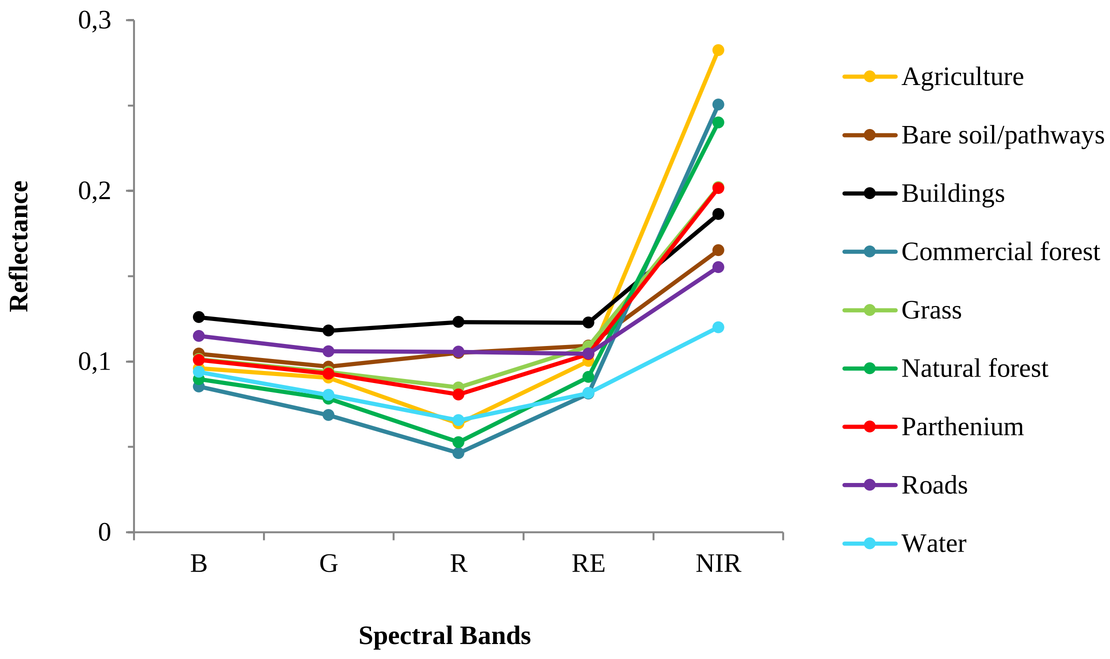

Figure 2.2: Spectral reflectance of land cover classes for RapidEye.

Figure 2.3 illustrates the spectral curve of land cover classes for Sentinel-2. A fair amount of overlap between classes is evident for spectral bands blue (B), green (G), red (R), and red-edge 1 (RE1), mostly representing the visible region of the electromagnetic spectrum. Shortwave infrared 1 (SW1) and shortwave infrared 2 (SW2) also show some spectral similarity between classes, but less than bands 2-5. Conversely, there is more spectral separability between land cover classes in red-edge 3 (RE3), near-infrared (NE) and near-infrared narrow (NIN), indicating that the region between the visible and shortwave infrared is more valuable for class differentiation. One important finding is that parthenium seems to be more easily distinguishable from other classes in the Sentinel-2 spectral curve, rather than RapidEye, suggesting that Senintel-2 should in theory attain higher classification accuracy.

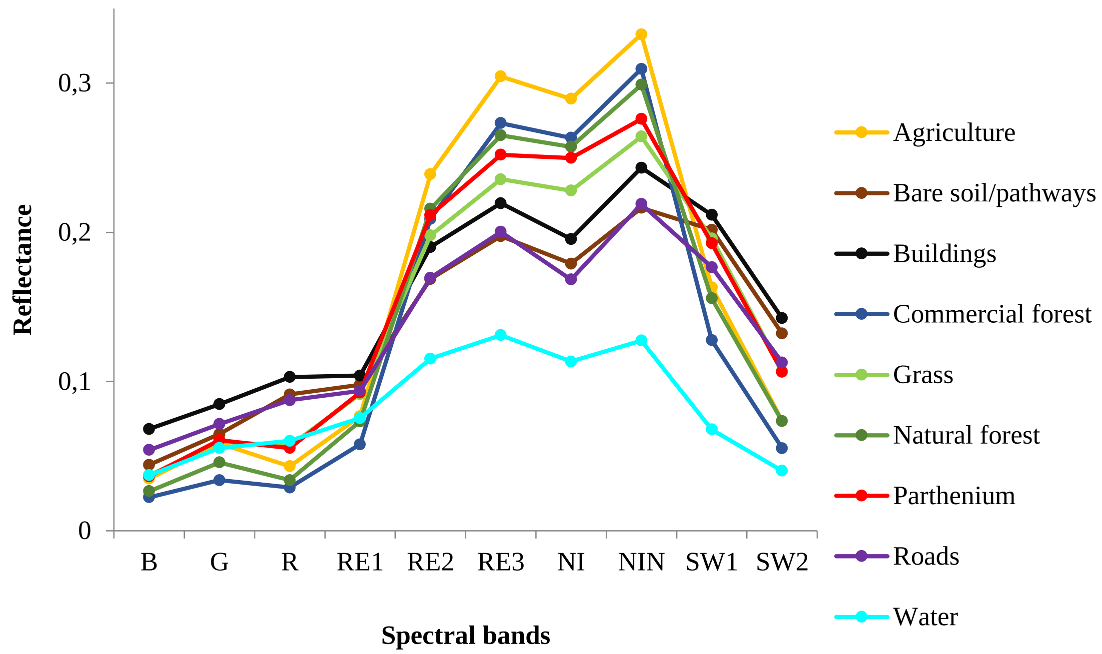

Figure 2.3: Spectral reflectance of land cover classes for Sentinel-2.

The eight most important bands and indices (variables) for the classification of the RapidEye image were chosen, which attained an overall accuracy of 68.99%. The 8 most important variables were blue, red, Green leaf index (GLI), Normalized green red difference index (NGRDI), Norm R (also referred to as Norm R), Normalized difference 550/450 plant pigment ratio (PPR), Normalized difference 550/650 photosynthetic vigour ratio (PVR) and Green atmospherically resistant vegetation index (GARI). After the model was optimized, the overall classification accuracy increased to 71%, with an allocation disagreement of 23% and a quantity disagreement of 6%. According to Table 2.2, water and commercial forest achieved the highest producer accuracy (93% and 89%, respectively), while commercial forest, water and agriculture achieved the highest user accuracy (89%, 78% and 78%, respectively). The lowest producer accuracy was bare soil/pathways and grass (52% and 60%, respectively); the lowest user accuracy was parthenium, roads and buildings (60%, 61% and 61%, respectively). Despite the low user accuracy for parthenium, it achieved a high producer accuracy of 82%.

Table 2.2: User and producer accuracy for various land cover classes for RapidEye.

	Producer Accuracy (%)	User Accuracy (%)
Agriculture	78	78
Bare soil/pathways	52	72
Buildings	65	61
Commercial forest	89	89
Grass	60	67
Natural forest	71	71
Parthenium	82	60
Roads	65	61
Water	93	78

Allocation disagreement: 23%; Quantity disagreement: 6%; Overall accuracy: 71%

Sentinel-2 had an overall accuracy of 82% and an allocation and quantity disagreement of 12% and 6%, respectively. Fourteen spectral bands and vegetation indices provided the most importance towards the model. The allocation and quantity disagreement was 12% and 6%, respectively. The 14 most important variables were band blue, green, red, near-infrared, shortwave infrared 1, shortwave infrared 2, Simple ratio 520/670 (SR520/670), Simple ratio MIR/Red eisenhydroxid-index (SRMIR/Red) and Red-edge position linear interpolation (REP), Tasselled cap wetness (WET), Tasselled cap yellow vegetation index MSS (YVIMSS), Anthocyanin reflectance index (ARI), Alt and Norm NIR. The user and producer accuracy ranged between 56-100% and 67-100%, respectively (Table 2.3). Commercial forest and water achieved the highest producer accuracy (both 100%), while water and bare soil/pathways achieved the highest user accuracy (both 100%). Grass and parthenium achieved both the lowest user and producer accuracy (67% and 67%; 56% and 53%, respectively). Furthermore, the sensitivity analysis for RapidEye showed that the red edge, near-infrared and green band ranked 25th, 36th and 19th, respectively out of 43 raw bands and vegetation indices. Red-edge 2 and red-edge 3 of Sentinel-2 ranked 10th and 29th out of 98 raw bands and vegetation indices.

Table 2.3: User and producer accuracy for various land cover classes for Sentinel-2.

	Producer Accuracy (%)	User Accuracy (%)
Agriculture	76	89
Bare soil/pathways	86	100
Buildings	78	78
Commercial forest	100	89
Grass	67	56
Natural forest	81	76
Parthenium	67	53
Roads	81	94
Water	100	100

Allocation disagreement: 12%; Quantity disagreement: 6%; Overall accuracy: 82%

A comparison of the producer accuracy between Sentinel-2 and RapidEye shows that Sentinel-2 outperformed RapidEye for most classes, except agriculture and parthenium (Figure 2.4). Figure 2.5, illustrating the user accuracy of Sentinel-2 and RapidEye, shows a similar trend, where Sentinel-2 out-performed RapidEye for all land cover classes, except for grass and parthenium. Sentinel-2 increased the average classification accuracy by approximately 10% for most land cover classes. However, RapidEye had a higher user and producer accuracy for parthenium, specifically.

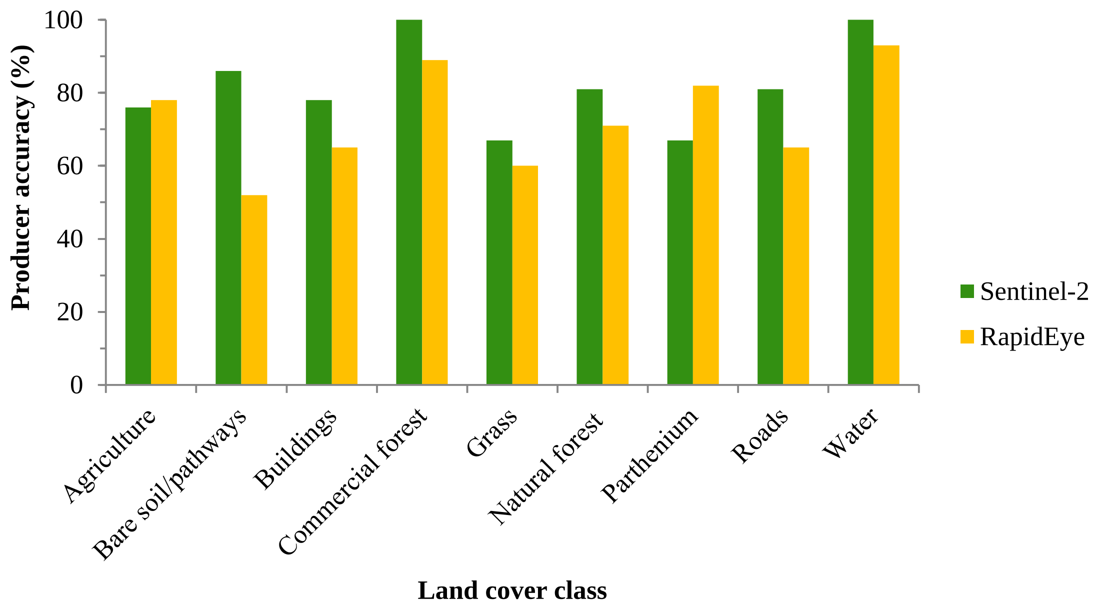

Figure 2.4: Producer accuracy for Sentinel-2 and RapidEye.

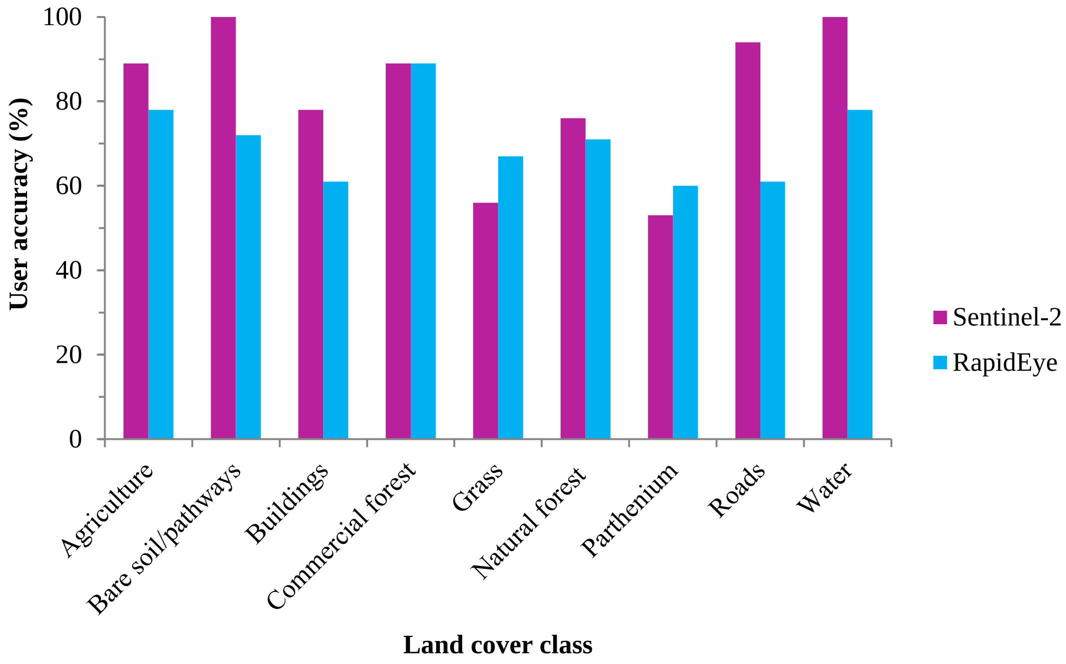

Figure 2.5: User accuracy for Sentinel-2 and RapidEye.

2.4. Discussion

This investigation focused on comparing the capability of Sentinel-2 and RapidEye in detecting *Parthenium hysterophorus L.* and the surrounding land cover using spectral bands and vegetation indices. The stochastic gradient boosting algorithm was used for the classification.

RapidEye is the first multispectral commercial sensor developed with a red-edge band (Kross *et al*., 2015) intended to capture important spectral information not available in the visible region of the electromagnetic region. This is particularly true for capturing differences in vegetation. Horler *et al.* (1983), have stated that changes in chlorophyll is evident within the red-edge region, due to the inflection point where there is a rapid transition between reflectance in the red and near-infrared region. Chlorophyll causes major absorption broadening, shifting the red-edge towards longer wavelengths, at approximately 680 nm in the electromagnetic spectrum; whereas low chlorophyll concentration would result in a shift toward shorter wavelengths. For this reason, the sensitive red-edge region would be considered as potentially important for the discrimination between vegetation types, including grass, forests and alien invasive species. However, in our study we found that the red-edge band was only present in 1 out of 6 of the most important RapidEye vegetation indices used for the classification analysis.

Sensitivity analysis also indicates that the red-edge band ranked 25th out of 43 bands and indices, confirming its poor performance in class discrimination. Furthermore, the spectral curve for RapidEye indicates a high overlap between classes in the red-edge region; therefore it may not have been able to effectively capture marked differences between land cover types. This is supported by the fact that the red-edge band of RapidEye was ranked 25th out of a combination of 43 raw bands and vegetation indices that were analysed on their importance in the classification.

Sentinel-2 displayed a similar trend as RapidEye, with the visible region and first red edge band showing some spectral overlap between classes. However, red-edge band 2/ 3, near-infrared and near-infrared narrow showed a greater ability to distinguish between classes. It should be noted that the band range for the red-edge band/s for RapidEye and Sentinel differ, i.e. RapidEye is 690-730 nm, while the three red-edge bands for Sentinel-2 range from 694-714 nm (red-edge), 731-749 nm (red-edge 2) and 768-796 nm (red-edge 3). This is important to highlight to understand the wavelengths and bands that are important for class discrimination. RapidEye red-edge band has a similar spectral range to Sentinel-2 red-edge and both bands show a higher level of spectral overlap for various classes, which may result in difficulty in distinguishing between land cover classes. However, red-edge 2 and red-edge 3 for Sentinel-2 began showing more separability between classes and were ranked 10th and 29th out of 98 bands and indices in the sensitivity analysis. Furthermore, the near-infrared band of RapidEye (760-850 nm) also shows more separability between classes and it is interesting to note that the spectral range of red-edge 3 of Sentinel-2 is captured within the broader near-infrared RapidEye band and show similar results. A study by Kganyago *et al*. (2018) found that Operational Land Imager's (OLI) shortwave infrared bands were important for parthenium and land cover discrimination. Furthermore, Curran (1989) stated that the organic compounds found in leaves, such as cellulose, lignin and starch, cause minor and broad absorption features between 0.4-2.4 μm of the electromagnetic spectrum, which includes the shortwave infrared region and may provide some insight into its importance for class discrimination (Curran, 1989). In our study, the shortwave infrared bands show some significance for land cover discrimination, however less than the red-edge and near-infrared region. This implies that a specific spectral range is more important to differentiate between vegetation and land cover classes, i.e. in this study 704 to 881 nm (red-edge to near-infrared narrow of Sentinel-2) of the electromagnetic spectrum.

Sentinel-2 achieved an overall classification accuracy of 82%, an allocation disagreement of 12% and a quantity disagreement of 6%, while RapidEye achieved an overall classification accuracy of 71%, an allocation disagreement of 23% and a quantity disagreement of 6%. Sentinel-2 outperformed RapidEye during the classification analysis for most land cover classes. Even though Sentinel-2 has a coarser spatial resolution (between 10 to 20 m^2 used in this study) compared to RapidEye (5 m^2), Sentinel-2 has a higher spectral resolution (13 bands) compared to RapidEye (5 bands). Spectral curves have shown that Sentinel-2 captures more spectral discrepancies between classes than RapidEye, which likely improved its ability to distinguish between land cover classes. The use of vegetation indices created from spectral bands may have also enhanced the signals given off by land cover classes, further improving separability. Moreover, Hsieh *et al*. (2001) states that high spatial resolution imagery may be able to provide more information for detailed observation of vegetation than coarse resolution imagery, however higher spatial resolution may not necessarily increase classification accuracy. This is because smaller pixel sizes may fail to capture the spectral characteristics of a specific class, which increases the variability within a class and reduces the statistical separability between different classes (Yu *et al*., 2006). This results in a reduction of classification accuracy for pixel-based classification methods (Yu *et al*., 2006).

Parthenium achieved the lowest classification accuracy for RapidEye and Sentinel-2, which could be attributed to the mixed pixel problem, which is an innate problem in raster imagery. Parthenium tends to grow in stands; however some stands where GPS points were taken were smaller than 10 m^2, due to a low number of areas with larger parthenium stands. This could have caused the reflectance signal for parthenium to be distorted by surrounding land cover, hence reducing classification accuracy. A similar finding was reported by Kganyago *et al*. (2018) who mapped parthenium and broad land cover classes using SPOT 6 and Landsat OLI using a similar methodology. They found that SPOT 6 outperformed OLI slightly, which was likely due to the coarser spatial resolution of OLI that was unable to capture smaller patches of parthenium and resulted in the spectral signature being overwhelmed by soil background reflectance, co-existing vegetation and other broad land cover classes. Grass also achieved a low accuracy for both sensors and the spectral curves shows that it is spectrally similar to parthenium. Furthermore, parthenium tends to grow amongst grass at the study site, thereby causing more spectral confusion during acquisition. Huang & Asner (2009) support this statement by stating that alien invasive species tend to be hidden between natural vegetation, making it difficult to discern. This problem could potentially be overcome by capturing images in different seasons, where spectral differences may be evident between grass and parthenium. According to Müllerová *et al*. (2013), it is difficult to detect herbaceous species using multispectral data, which may explain low accuracies for grass and parthenium. Species also need to be sufficiently distinct from surrounding vegetation/land cover for easy detection (Jones *et al*., 2011). Multispectral sensors have limited ability in distinguishing land covers that are spectrally similar, due to their generally low spatial and spectral resolution that may be incapable of capturing subtle, yet significant, spectral differences (Dube *et al*., 2017).

The superior performance of Sentinel-2 over RapidEye for land cover classification is extremely beneficial to the remote sensing community, by providing free imagery that could potentially attain good results for a variety of applications, including alien plant species detection. Even though Sentinel-2 achieved less than satisfactory results for parthenium and grass, it can still be considered a viable means for detecting alien invasion. Particularly, parthenium was more easily separated from other classes in the spectral curves using Sentinel-2 rather than RapidEye, indicating that other factors may have reduced classification accuracy. Possibly the sizes of the parthenium patches were not large enough to be detected by the coarser resolution Sentinel-2, but were able to be detected by the finer resolution RapidEye. Results can be improved by focusing on larger stands of parthenium (if available) and increasing the number of GPS points for each class. With a larger pixel size, such as with Sentinel-2, it also has to be understood that there will sources of error in each pixel, as it is not often that each pixel contains only one land cover class. Hence, sensors sometimes cannot detect smaller patches of parthenium, which will create a discrepancy between invasion in real life and that which can be detected by a sensor. There is a level of inaccuracy which has to be accepted when dealing with classification based on pixels due to the generalization in each pixel. However, remote sensing remains a practical method for alien invasion mapping that is steadily improving with innovative technology, even for herbaceous species like parthenium. It provides an efficient and fast method to monitor alien invasive species, especially to track the areas that are heavily invaded and areas that can potentially be rehabilitated before extensive damage. Sentinel-2 can therefore be considered a suitable alternative to RapidEye for land cover and parthenium detection.

2.5. Conclusion

This study compared the ability of commercial sensor RapidEye and freely available Sentinel-2 in detecting the alien invasive species *Parthenium hysterophorus L.* and surrounding land cover using spectral bands and vegetation indices. We found that:

- Sentinel-2 attained a higher overall accuracy of 82% and RapidEye achieved 71%. The allocation disagreement was 12% and 23% and the quantity disagreement was both 6% for Sentinel-2 and RapidEye, respectively.
- Sentinel-2 outperformed RapidEye for most land cover classes. However, RapidEye achieved a higher accuracy than Sentinel-2 for parthenium. Since spectral curves show that Sentinel-2 provided a greater separability between classes, including parthenium, we have deduced that spatial resolution played a role in reducing the classification accuracy.
- Sentinel-2 achieved reasonable results that can be improved by focusing on greater patches of parthenium during data collection.
- Sentinel-2 can therefore be considered a suitable alternative to RapidEye. The feasibility of using free and efficient Sentinel-2 imagery for alien invasive mapping creates a plethora of opportunities for invasion monitoring to help us deal with contemporary environmental problems.

2.6. Link to next chapter

The chapter above has shown the ability of Sentinel-2 imagery in detecting *Parthenium hysterophorus L.* using spectral bands and vegetation indices. However, studies have also recommended the use of image texture in detecting and mapping invasive alien species. Therefore, the next chapter focuses on the ability of image texture in detecting and mapping Parthenium hysterophorus.

CHAPTER 3

3. COMPARING THE ABILITY OF PANCHROMATIC AND MULTISPECTRAL SPOT-6 BANDS TO DETECT AND MAP *PARTHENIUM HYSTEROPHORUS L.* USING IMAGE TEXTURE ANALYSIS

3.1. Abstract

Parthenium hysterophorus L. (parthenium) is a devastating weed that is spreading rapidly throughout five continents, including Africa. Its climatic niche ranges between temperate and subtropical regions and it is suited to warmer climates, hence its invasion in most continents. Reasons for its rapid spread include rapid growth, allelopathy and extensive seed banks of parthenium. Moreover, globalization of markets, travel and tourism has enhanced the spread. Parthenium can drastically reduce agriculture and pasture productivity by outgrowing these species, which in turn impacts livestock production. This poses severe ecological and economic challenges in poverty stricken countries. Traditionally, information on plant distribution was collected using impractical, time-consuming and expensive methods. Remote sensing has revolutionized the collection of landscape feature data in recent years, making plant distribution studies more efficient. This study investigates the use of operationally free SPOT-6 imagery to map parthenium and associated land cover. Specifically, it utilized texture analysis to compare the mapping capability of 1.5 metre panchromatic and 6 metre multispectral SPOT-6 imagery. The Partial Least Squares-Discriminant Analysis (PLS-DA), a combination of a partial least squares regression and a classification technique, was used to classify the images and the VIP score was used to determine the significant predictor variables. The panchromatic band achieved higher user accuracy than multispectral bands for parthenium (64% and 56%, respectively) and a higher overall classification accuracy (77% and 73%, respectively). The results have indicated that the panchromatic band is more useful in mapping land cover distribution, including parthenium. Spatial resolution has been shown to be a crucial factor in texture analysis, with higher spatial resolution providing a better representation of features on the ground and producing textures for land covers that are distinguishable from one another. The panchromatic band was especially useful in being able to detect and map small patches of parthenium, which are more common than large stands; therefore improving the representation of remote sensing images to features on the ground.

Key words: *Parthenium hysterophorus L.*; SPOT-6; alien invasive species; texture; pan-chromatic; multi-spectral; high-spatial resolution; PLS-DA

3.2. Introduction

Parthenium hysterophorus L. (hereafter referred to as parthenium) is a toxic alien invasive weed that is spreading rapidly throughout Asia, Africa and America (Singh, 2005; Kaur *et al*., 2014). Its prolific seed production, allelopathic effects, strong competitiveness against natural vegetation and crops, and fast-spreading ability (Joshi *et al*., 2004; Singh, 2005) are among the top characteristics that make parthenium a worldwide threat to biodiversity, the economy and society. The toxicity of parthenium negatively affects human and animal health (Patel, 2011), for example causing respiratory problems and dermatitis in humans (Dhileepan *et al*., 1996; Singh, 2005; Kelaniyangoda & Ekanayake, 2010; Patel, 2011; Strathie *et al*., 2011) and internal bleeding and potentially death in animals (Nigatu *et al*., 2010; McConnachie *et al*., 2011; Kaur *et al*., 2014). Its presence has been notable in South Africa since the 1980s, specifically in KwaZulu-Natal, Mpumalanga and the North West (Belz *et al*., 2009; Strathie *et al*., 2011), where it is observed growing in large, impenetrable stands. Parthenium tends to invade disturbed areas, for example roadsides and areas where vegetation has been removed (Singh, 2005; Belz *et al*., 2009), thereby easily out-competing surrounding natural vegetation and crops. For this reason, South Africans have suffered huge financial losses as a result of the reductions in crop yields and grass biomass that sustain livestock (Dhileepan *et al*., 1996; Patel, 2011). Further financial loss results from tainted meat and milk, animal health problems and livestock death caused by parthenium (Kelaniyangoda & Ekanayake, 2010; Patel, 2011; Strathie *et al*., 2011; Kaur *et al*., 2014). The devastating effects of parthenium have sparked an urgency to eradicate the weed; however, first and foremost it is essential to map and monitor its distribution so that decision makers are able to make informed decisions regarding eradication.

Remote sensing is an innovative technology that has been successful in many applications, such as forest inventory (Holmström & Fransson, 2003), land cover classification (Yuan *et al*., 2005), change detection (El-Kawy *et al*., 2011), biomass estimation (Li *et al*., 2019) and chlorophyll content estimation (Zarco-Tejada *et al*., 2019). It has also been particularly useful in tracking and mapping biological invasion and has consequently received considerable interest (Gairola *et al*., 2013). Its synoptic view, multi-temporal coverage and cost-effectiveness are greatly beneficial in monitoring changes caused by invasive species (Joshi *et al*., 2004). The popularity of remote sensing has been motivated by the limitations of traditional methods of collecting data, for example aerial photography (McRoberts & Tomppo, 2007) and field survey (Oumar, 2016). Collection of data in-field is expensive, labour-intensive, time consuming and in some cases, not practical, especially on a larger geographic scale (Bruzzone & Prieto, 2001; Turner *et al*., 2003; Ruiz- Gallardo *et al*., 2004). Remote sensing offers a useful approach to studying remote and complex environments (Joshi *et al*., 2004; Rawat & Kumar, 2015), for example mountainous areas. Consistent and frequent imagery allows the detection of vegetation and land cover changes and the ability to quantify these rates of change (Joshi *et al*., 2004). A significant advantage of using remote sensing imagery is that it can provide more information than can be attained by conventional methods (Franklin *et al*., 2000), for example its ability to capture information in the near-infrared and short-wave infrared region of the electromagnetic spectrum. This is extremely beneficial because the spectral reflectance of vegetation experiences marked and interesting changes within these regions, which helps us decipher between different types of vegetation and even species. One drawback of using remote sensing lies in the expectation of similar or even superior accuracy of data as compared to analogue methods (Franklin *et al*., 2000). Spectral information is frequently utilized for mapping alien invasive species and has achieved reasonable to good classification results (Peerbhay *et al*., 2015; Tarantino *et al*., 2019). However, according to literature, texture analysis could improve the results achieved by spectral analysis, offering an intriguing avenue to pursue alien invasion studies.

Texture is a rich source of information that can be exploited due to the arrival of increasingly higher spatial resolution imagery from airborne and satellite platforms (Franklin *et al*., 2001). Texture is a complex visual pattern made up of sub-patterns that have, among others, a specific colour, brightness and slope, which can be put into similar groupings (Materka & Strzelecki, 1998). It reveals information on the structural arrangement of features and their spatial relationship with objects within the surrounding environment (Chica-Olmo & Abarca-Hernandez, 2000). Texture analysis thereby aids in photointerpretation by allowing us to differentiate between different land cover types using the variation between patterns found for each type (Chica-Olmo & Abarca-Hernandez, 2000). According to Clausi & Yue (2004), texture is a significant characteristic that would aid in the interpretation of automated or semi-automated digital images. Texture analysis has been effectively used in many remote sensing studies for a variety of land cover analysis, such as Hay *et al*. (1996), Coburn & Roberts (2004) and Dobrowski *et al*. (2008).

Classification results of texture analysis are dependent on spatial resolution (Hay *et al*., 1996; Wulder, 1998); therefore it is necessary to select a sensor with very high spatial resolution. Hyperspectral sensors provide very high spatial resolution, however they are expensive and have many spectral bands which offer redundant information. For this reason, we need to investigate multispectral sensors that are affordable and can provide us with the necessary features needed. SPOT 6 is an operationally free sensor with a very high spatial resolution panchromatic band (1.5 m) and high resolution multispectral bands (6 m). It has a low spectral resolution, which prevents large data volumes from being produced with the texture analysis; hence it was an ideal choice for this study.

For the analysis, a classification algorithm is required to create categorical classes for land cover discrimination. Popular algorithms include Maximum Likelihood Classifier and Random Forest. However, in this study we chose Partial Least Squares-Discriminant Analysis (PLS-DA) due to the high number of predictor variables investigated and its ability to reduce data dimensionality and maximize prediction accuracy (Pérez-Enciso & Tenenhaus, 2003; Cavender-Bares *et al*., 2016). A study by Peerbhay *et al*., (2013) successfully discriminated between six spectrally similar commercial species and effectively dealt with a complex hyperspectral and computational challenging dataset; therefore rendering it a robust and efficient algorithm.

With this contextual understanding, our study aims to evaluate the capability of texture analysis to effectively classify and map *Parthenium hysterophorus L*. and the surrounding land cover. The specific objectives were to: 1) perform texture analysis on a 1.5 m panchromatic and 6 m multispectral SPOT 6 image, 2) compare and determine the better performance between panchromatic and multispectral SPOT 6 imagery and create land cover classes using the PLS-DA algorithm, and 3) determine the variables with the most significant influence on the classification analysis.

3.3. Methods

3.3.1. Study Site

The study site is situated in Mtubatuba, a small town to the north of Richards Bay (Figure 3.1). It is 28 km away from St Lucia and in close proximity to iSimangaliso Wetland Park and Hluhluwe Imfolozi Game Reserve. The area receives an average rainfall of approximately 967 mm per annum; with a warm and temperate climate averaging at 21.7° C. Land uses of the study area consists of mainly plantations (sugar cane and commercial farming), agriculture, cattle farming, eco-tourism and residential areas.

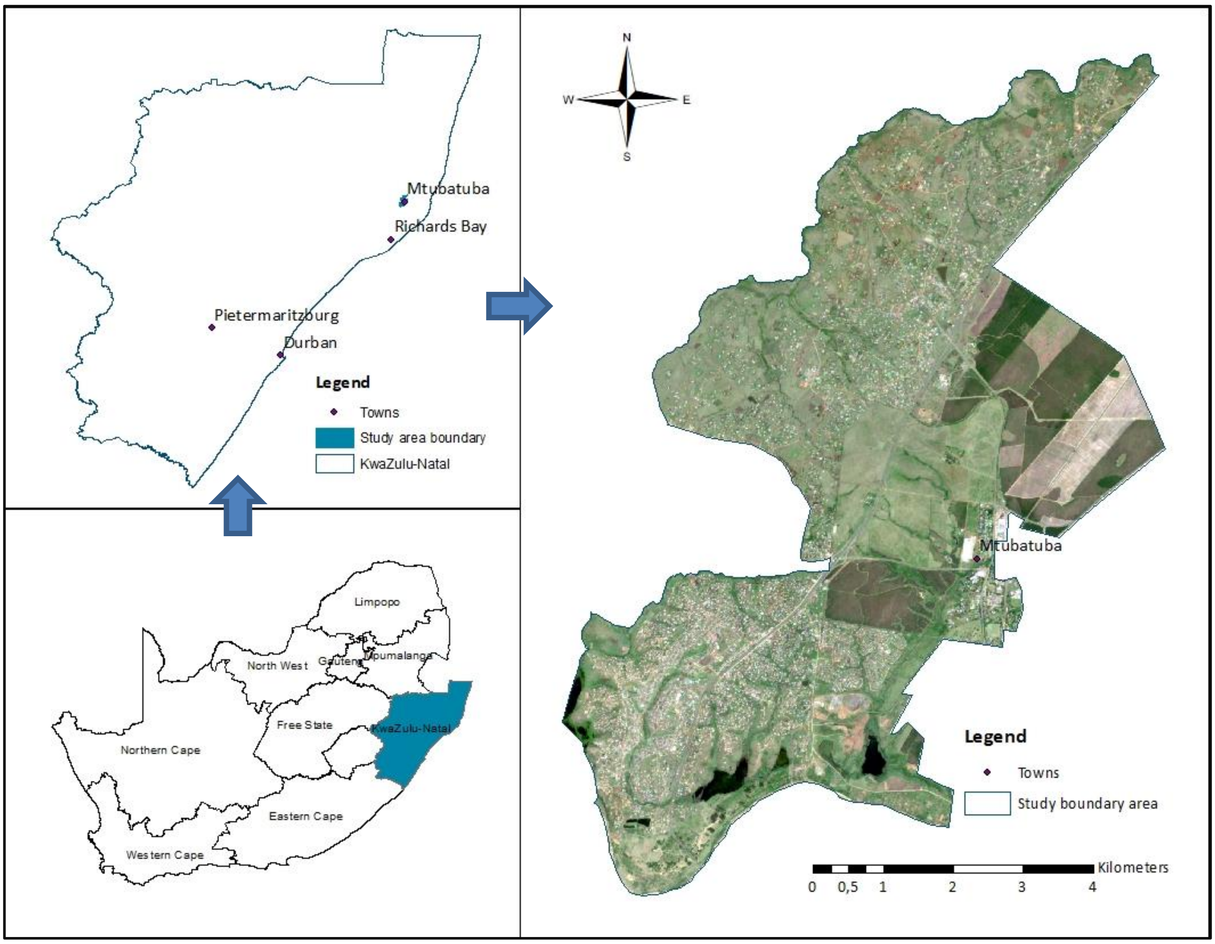

Figure 3.1: Location of study site in Mtubatuba, KwaZulu-Natal, South Africa.

3.3.2. Data Collection

Field data was collected in the summer of 2018, in late February. Nine land cover classes were predetermined to classify the area, namely: grass, commercial forest, natural forest, agriculture, parthenium, bare soil/pathways, buildings, roads and water. GPS locations were taken using a differentially corrected Trimble GeoXT handheld GPS receiver according to each land cover type. GPS points of parthenium were taken in patches greater than 10 m^2 to capture information within the 6 m^2 pixels of SPOT 6 multispectral bands, therefore enhancing detection ability. However, patches of parthenium greater than 10 m^2 were limited; therefore some GPS points were taken in patches less than 10 m^2. Fifty GPS points were taken of parthenium in the field. Ten GPS points each of the remaining 8 classes were predetermined using purposive sampling in Google Earth 7.3.2.5495 and were located using the GPS and verified in-field. Approximately 50 other GPS points were taken from Google Earth 7.3.2.5495 using purposive sampling points for the 8 remaining classes, excluding parthenium, and compared to the SPOT 6 image for any possible changes. Class distribution of all collected GPS points are shown in Table 3.1.

Table 3.1: Class distribution of GPS points

Class	Number of GPS points
Agriculture	60
Bare soil/pathways	60
Buildings	60
Commercial forest	60
Grass	60
Natural forest	56
Parthenium	50
Roads	60
Water	60

3.3.3. Image Acquisition

A SPOT-6 image, including the panchromatic band, was acquired from South African Space Agency (SANSA) who provides free images on an operational basis for November 2017, as this was the only available image closest to the field date. This sensor was chosen due to the very high spatial resolution of the panchromatic band (1.5 m). SPOT-6 consists of four 6-metre spectral bands, namely, blue (450-520 nm), green (530-590 nm), red (625-695 nm) and near-infrared (760-890 nm) (Oumar, 2016). The images were already ortho-rectified by SANSA and were atmospherically corrected in ENVI 4.3. using the Fast Line-of-Sight Atmospheric Hypercubes (FLAASH) algorithm to obtain top of canopy reflectance. Thereafter, the multispectral and panchromatic images were mosaicked in ArcMap 10.4 separately to form one image covering the study site.

3.3.4. Statistical Analysis

3.3.4.1. Image Texture Extraction

Texture is the complex visual patterns of grey tones in an image, which is characterized by among others: colour, shape and brightness (Pathak & Barooah, 2013). Texture analysis is achieved using mathematical procedures that extract information of the spatial patterns of grey tones within an image (Pathak & Barooah, 2013). The texture analysis was done on the SPOT 6 panchromatic and multispectral bands using ENVI 4.3. software. Texture images were computed using only the 3 x 3 moving window to capture the small patches of parthenium. This study used occurrence and co-occurrence texture parameters, also referred to as first- and second-order texture parameters, respectively and defined as follows. Grey-level occurrence measures (GLOM) use pixel intensities within a processing window and do not take into consideration spatial dependency between pixels (St-Louis *et al*., 2006; Hlatshwayo *et al*., 2019). Five filters are used for GLOM, namely: data range, mean, entropy, skewness and variance, defined in Table 3.2. Grey-level co-occurrence measures (GLCM) include spatial dependency to characterize texture with eight filters, namely: contrast, correlation, entropy, mean, dissimilarity, homogeneity, second moment and variance (Hlatshwayo *et al*., 2019). Definitions and formulas can be found in Table 3.3. Thereafter land cover GPS points were extracted from the texture images using zonal statistics in ArcMap 10.4.

Table 3.2: Formulas and equations characterizing grey-level occurrence measures (GLOM)

Parameter	Formula	Description
Mean	$Mean = \frac{\sum_k X_k}{k}$	The average spectral reflectance values within each window (Lottering & Mutanga, 2012).
Data range	$max\{X\} - min\{X\}$	Difference between highest and lowest pixel values (St-Louis *et al*., 2006)
Entropy	$\sum_{i=0}^{M-1} p(i) log_2[p(i)]$	Measures the randomness of the image texture (Alvarenga *et al*., 2007)
Skewness	$\mu_{3=\sigma^{-3}} \sum_{i=0}^{M-1} (i-\mu)^3 p(i)$	A measure of how skew the histrogram is about the mean (Materka & Strzelecki, 1998).
Variance	$\frac{\sum(xij - M)^2}{m-1}$	A measure of the deviation of intensity values from the mean (Materka & Strzelecki, 1998)

Table 3.3: Formulas and equations characterizing grey-level co-occurrence measures (GLCM)

Parameter	Formula	Description
Contrast	$\sum_{i,j=0}^{M-1} P_{i,j}(i-j)^2$	A measure of the local variability within a texture image (Alvarenga *et al.*, 2007)
Correlation	$\sum_{i,j=0}^{M-1} P_{i,j}\left[\frac{(i-\mu_i)(i-\mu_j}{(\sigma_i^2)(\sigma_j^2)}\right]$	Local grey-level dependency on a texture image (Alvarenga *et al.*, 2007)
Dissimilarity	$\sum_{i,j=0}^{M-1} P_{i,j}\lvert i-j\rvert$	Measures the variation of grey-level pairs within an image (Gebejes & Huertas, 2013)
Homogeneity	$\sum_{i,j=0}^{M-1} \frac{P_{i,j}}{1+(i-j)^2}$	Measures the uniformity of the non-zero values within the GLCM (Gebejes & Huertas, 2013)
Mean	$\mu_i = \sum_{i,j=0}^{M-1} i(P_{i,j})$ $\mu_j = \sum_{i,j=0}^{M-1} j(P_{i,j)}$	Average intensity level of the texture examined (Materka & Strzelecki, 1998)
Second Moment	$\sum_{i,j=0}^{M-1} P_{i,j^2}$	Measures local homogeneity (Yuan *et al.*, 1991)
Variance	$\sigma_i^2 = \sum_{i,j=0}^{M-1} P_{i,j}(i-\mu)^2$ $\sigma_j^2 = \sum_{i,j=0}^{M-1} P_{i,j}(i-\mu_j)^2$	A measure of the deviation of intensity values from the mean (Materka & Strzelecki, 1998)

Entropy	$\sum_{i,j=0}^{M-1} P_{i,j}(-\ln P_{i,j})$	Measures the randomness of the image texture (Alvarenga *et al*., 2007)

3.3.4.2. PLS-DA

PLS-DA is a classification method that combines a partial least squares regression with the discriminatory ability of a classification technique (Ballabio & Consonni, 2013). It specifically aims to reduce data dimensionality, effectively deal with multicollinearity and maximize prediction accuracy (Pérez-Enciso & Tenenhaus, 2003; Cavender-Bares *et al*., 2016). Furthermore, it reduces model over-fitting, suppresses background effects (Peerbhay *et al*., 2013) and is useful for analysis that includes missing data (Pérez-Enciso & Tenenhaus, 2003). The PLS-DA includes a set of binary variables that describes the categorical variable (*Y*) on a set of predictor variables (*X*) (Pérez-Enciso & Tenenhaus, 2003). The algorithm decomposes explanatory variables (texture parameters in this study) into a few intermediate latent components, which retain majority of the necessary information and are used to predict the dependent class variable of new samples (Lenhardt *et al*., 2015; Peerbhay *et al*., 2014). The aim of the PLS algorithm is dimension reduction so that a set of response variables can be related to a set of predictor variables (Pérez-Enciso & Tenenhaus, 2003). It is particularly useful as it helps us understand data patterns and allows graphical visualization (Ballabio & Consonni, 2013). The number of PLS components used in the model is determined using the tenfold cross-validation (CV) method (Lenhardt *et al*., 2015). The optimal number of components is chosen by systematically adding them to the PLS-DA model and calculating the corresponding CV error. The lowest CV error, and consequently optimum number of components, is achieved once the addition of components increases the CV error and no longer improves the model. The "plsda" function (Pérez-Enciso and Tenenhaus, 2003) in R statistical package version 3.1.3 (R Development Core Team 2015) was used to run the PLS-DA algorithm in this study.

The PLS-DA does not provide a method to determine the most useful parameters to be used for the final classification (Menze *et al.*, 2009). However, a preliminary variable selection is essential for PLS-DA to obtain meaningful results (Pérez-Enciso & Tenenhaus, 2003). The VIP method has been used effectively to determine the most important parameters for the classification analysis (Cécillon *et al.*, 2008; Peerbhay *et al.*, 2014). The VIP score is used to rank explanatory variables according to their significance and selects them prior to the classification to achieve optimum results (Peerbhay *et al.*, 2014). The VIP scores were calculated as follows:

$$\mathrm{VIP}_k = \sqrt{K \sum_{a=1}^{A} [(q_a^2\, t_a^T t_a\,)(w_{ak}/\|w_k\|^2)] / \sum_{a=1}^{A} (q_a^2 t_a^T t_a)}$$

where VIP_k is the importance of the k'th parameter in the PLS-DA model with a defining the number of components, K is the total number of parameters, w_{ak} is the corresponding loading weight of the k'th waveband in the a'th PLS-DA component, t_a, w_a, and q_a are the a'th column vectors.

Variables with a VIP score of >1 were identified as important, because the average of squared VIP scores is equal to 1. The PLS-DA model was run using the most important VIP parameters, which was thereafter used for the classification. The "vip" function in R statistical package version 3.1.3 (R Development Core Team 2015) was used to run the VIP in this study.

3.3.4.3. Classification Accuracy Assessment

The dataset was randomly split using 70% for training and 30% for validation of the model. This process was repeated a 100 times using different compositions of training and validation samples to account for variation in the data. The results from the classification were represented in a confusion matrix, which is based on the validation dataset. There are various accuracy measures that can be used to summarize a confusion matrix. Map-level accuracy is generally determined by the correctly classified proportion of units. The opposite of this is the overall disagreement (Warrens, 2015). Quantity and allocation disagreement is a more recent measure of accuracy that decomposes the overall disagreement into two types of disagreement; it is argued to be more informative than the kappa statistic, which merely states the correctly classified proportion of units (Warrens, 2015). Quantity disagreement calculates the difference between the reference and comparison map caused by the slight discrepancy in the proportions of categories (Pontius & Millones, 2011). Allocation disagreement is the difference between the reference and comparison map caused by the slight discrepancy in the spatial allocation of categories, given the proportions of categories in both the reference and comparison maps. These two types of disagreement help us to explain the reasons behind the disagreement found in the confusion matrix, which can be used to understand the sources of error (Pontius & Millones, 2011).

Finally the best texture results were chosen between the 1.5 metre panchromatic and 6 multispectral images. These were used to map parthenium and the surrounding land cover classes using the PLS-DA algorithm. The basic procedure followed in the methodology section is illustrated in Figure 3.2.

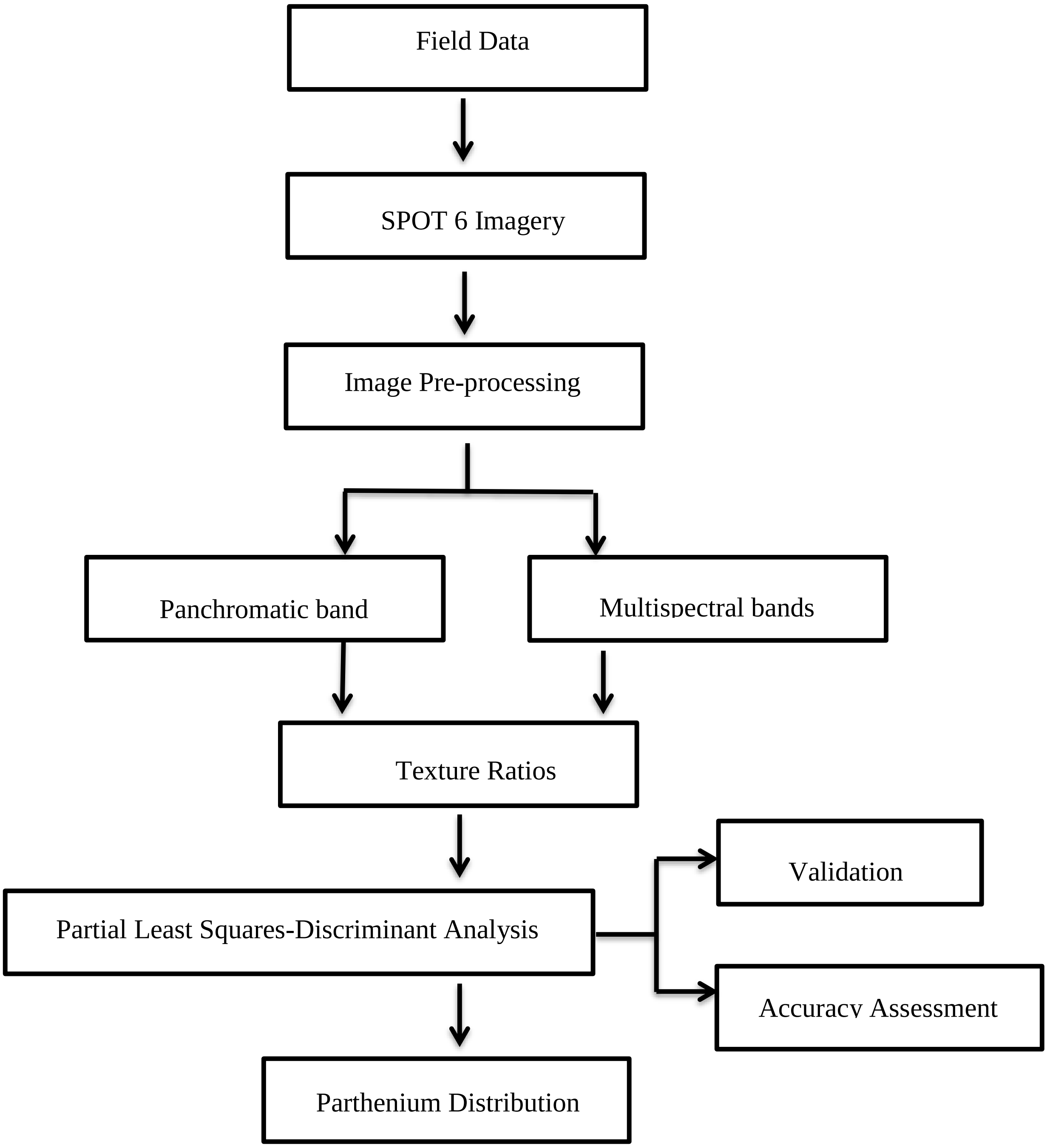

Figure 3.2: Summary of procedure followed in methodology.

3.4. Results

3.4.1. PLS-DA

The PLS-DA model for the multispectral bands was optimized using the number of components with the lowest error. According to Figure 3.3, the CV error significantly decreased from 74.14% to 35.8% from the 1^{st} to the 20^{th} component. The lowest CV error achieved was 27.56%

using 10 latent components, which were used to develop the model and thereafter VIP scores for the texture parameters were calculated. VIP selected 17 out of 52 texture parameters that were the most significant and were further used for model development.

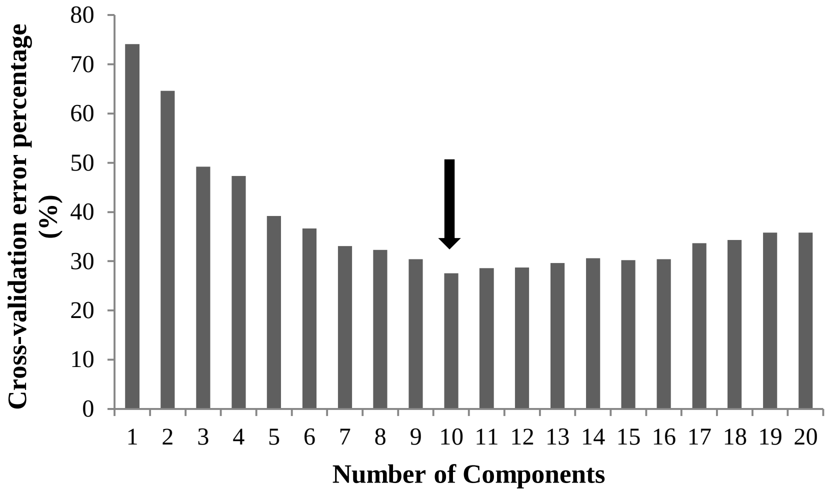

Figure 3.3: Testing the ability of each PLS-DA component to discriminate features using image texture parameters computed from multispectral data. Lowest error based on the training (n = 368) dataset was established using the tenfold cross validation. The arrow indicates that the 10th component had the lowest error.

The CV error for the panchromatic band ranged from 60.14% to 34.8% from the 1st to the 20th component (Figure 3.4). The lowest CV error was achieved with 8 components at 23.31%. These 8 components were used to develop the model. VIP selected 8 texture parameters out of a total of 13 for the panchromatic image that where the most significant for model development.

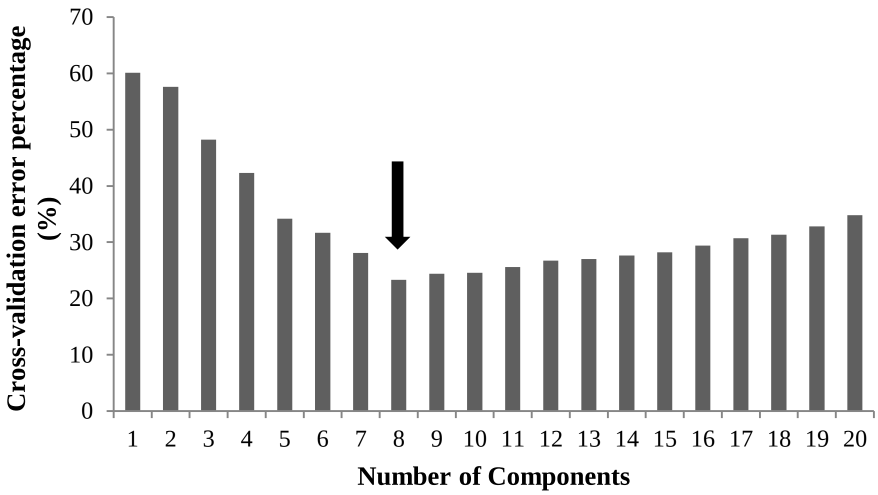

Figure 3.4: Testing the ability of each PLS-DA component to discriminate features using image texture parameters computed from the panchromatic data. Lowest error based on the training (n = 368) dataset was established using the tenfold cross validation. The arrow indicates that the 8^{th} component had the lowest error.

3.4.2. Parameter Frequencies

Figure 3.5 illustrates the frequency of selected texture parameters for the panchromatic and multispectral bands used in the PLS-DA model. Figure 3.5a shows that band 4 (near-infrared) was selected more frequently and most effective toward the classification, and band 1 (blue) the least frequent. Co-occurrence played a more significant role towards the analysis than occurrence for both panchromatic and multispectral bands; therefore was selected more often for model development (Figure 3.5b). Seven texture parameters are shown in Figure 3.5c, of which the most frequently selected, were mean, correlation and homogeneity for both panchromatic and multispectral bands, containing the majority of information.

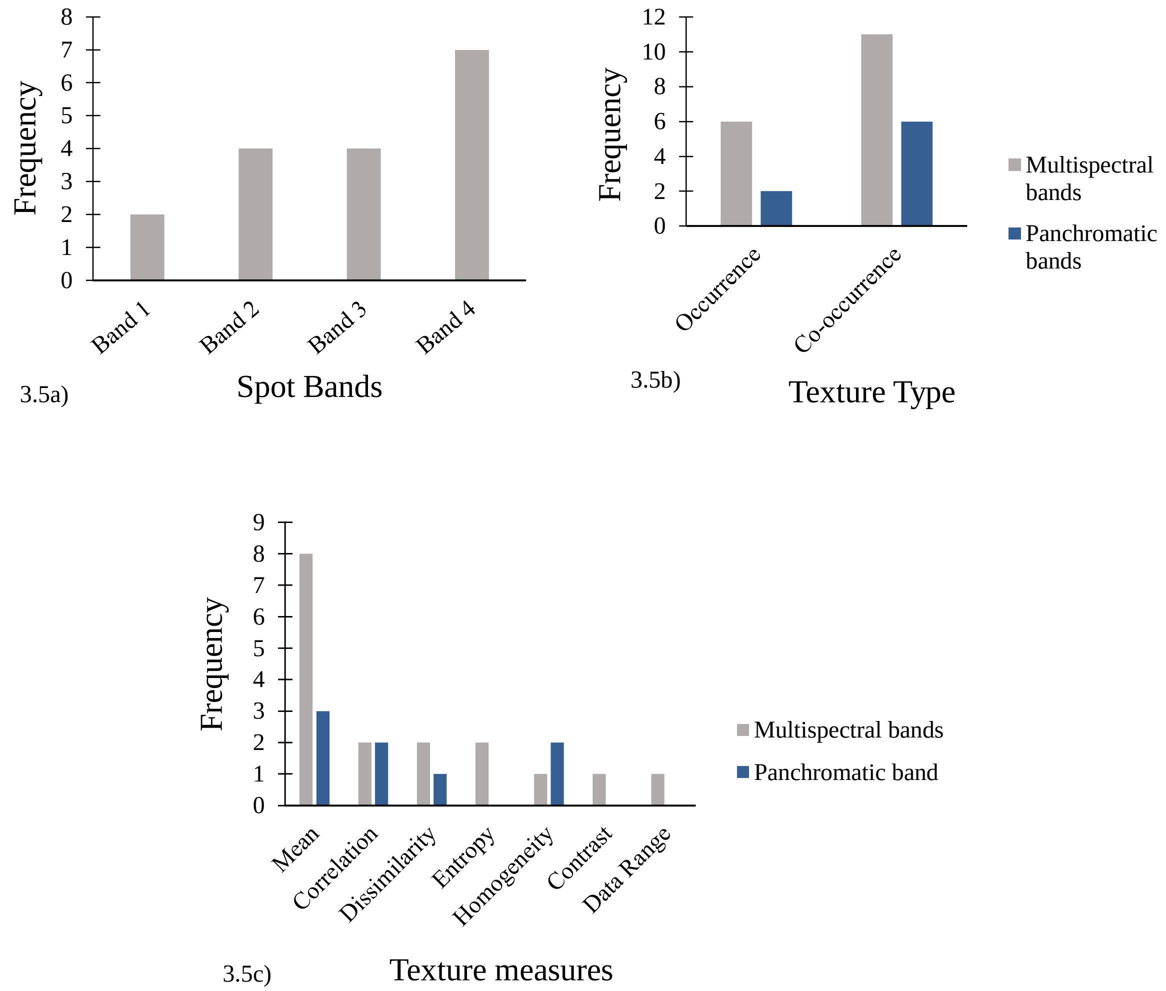

Figure 3.5 Frequency of selected parameters for texture analysis of panchromatic and other SPOT 6 spectral bands.

3.4.3. Classification Accuracy Assessment

For multispectral bands, the model produced an overall accuracy of 73% and a total disagreement of 27% using the first ten model components. The allocation and quantity disagreement was 20% and 7%, respectively. Parthenium achieved a user and producer accuracy of 56% and 77%, respectively (Table 3.4). The user accuracy ranged from 68-90% and the producer accuracy ranged from 58-90% for all classes. The highest (90%) and lowest (56%) user accuracy was commercial forest and parthenium, respectively. The highest and lowest producer accuracy was water (90%) and grass (58%), respectively.

Table 3.4: Confusion matrix of texture analysis using multispectral bands and the PLS-DA algorithm.

	A	BS/P	BU	CF	G	NF	P	R	W	Sum	User Accuracy (%)
A	982	57	44	204	218	106	47	2	39	1699	58
BS/P	17	1303	120	2	107	80	34	130	29	1822	72
B	4	120	1347	57	11	56	31	123	16	1765	76
CF	5	6	0	1588	54	108	0	1	2	1764	90
G	97	31	18	46	1495	58	48	75	2	1870	80
(NF)	69	7	11	105	22	1498	62	40	0	1814	83
(P)	84	23	18	113	176	183	902	86	17	1602	56
(R)	12	189	208	1	23	21	45	1304	32	1835	71
(W)	64	94	49	2	90	68	4	83	1175	1629	72
Sum	1334	1830	1815	2118	2196	2178	1173	1844	1312	15800	
Producer accuracy (%)	74	71	74	75	68	69	77	71	90		

Agriculture = A, Bare soil/pathways = BS/P, Buildings = B, Commercial forest = CF, Grass = G, Natural forests = NF, Parthenium = P, Roads = R, Water = W

Allocation disagreement = 20%, Quantity disagreement = 7%, Overall accuracy = 73%

The highlighted values indicate correctly classified features.

For the optimum number of components using the panchromatic band, the model produced an overall accuracy of 77% and a disagreement of 23%. The allocation and quantity disagreement was 18% and 5%, respectively. The user and producer accuracy of parthenium is 64% and 77%, respectively (Table 3.5). The user accuracy ranged from 61-93% and the producer accuracy ranged from 63-97% for all classes. The highest and lowest user accuracy was water (93%) and agriculture (61%), respectively. The highest and lowest producer accuracy was water (97%) and bare soil (63%), respectively.

Table 3.5: Confusion matrix of texture analysis using the panchromatic band and the PLS-DA algorithm.

	A	BS/P	B	CF	G	NF	P	R	W	Sum	User Accuracy (%)
A	1108	167	0	132	183	171	38	0	16	1815	61
BS/P	13	1192	172	2	0	67	26	108	12	1592	75
B	0	180	1457	9	19	13	26	158	0	1862	78
CF	1	1	0	1546	64	100	0	0	1	1713	90
G	112	111	8	44	1258	58	191	27	2	1811	69
NF	93	7	6	205	27	1386	30	22	0	1776	78
P	95	105	51	12	251	102	1140	0	18	1774	64
R	0	131	141	1	22	29	25	1472	0	1821	81
W	20	11	0	2	39	31	10	0	1523	1636	93
Sum	1442	1905	1835	1953	1863	1957	1486	1787	1572	15800	
Producer Accuracy (%)	77	63	79	79	68	71	77	82	97		

Allocation disagreement = 18%, Quantity disagreement = 5%, Overall accuracy = 77%

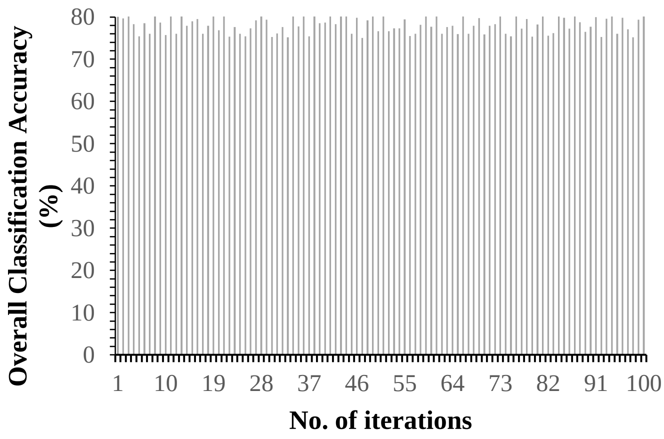

Figure 3.6: Change in overall classification accuracy produced by PLS-DA when running the model at 100 iterations for dividing the train and validation datasets.

Figure 3.6 illustrates the overall change in classification accuracy produced by PLS-DA when running the model at 100 iterations for dividing the entire data into train and validation datasets. The mean overall classification accuracy was over 73% with a standard deviation of 2.49%.

According to the results from the accuracy assessment, the panchromatic band performed better than the multispectral bands; therefore the panchromatic band was chosen to create the land cover map in Figure 3.6 using R statistical software package version 3.1.3 (R Development Core Team 2015).

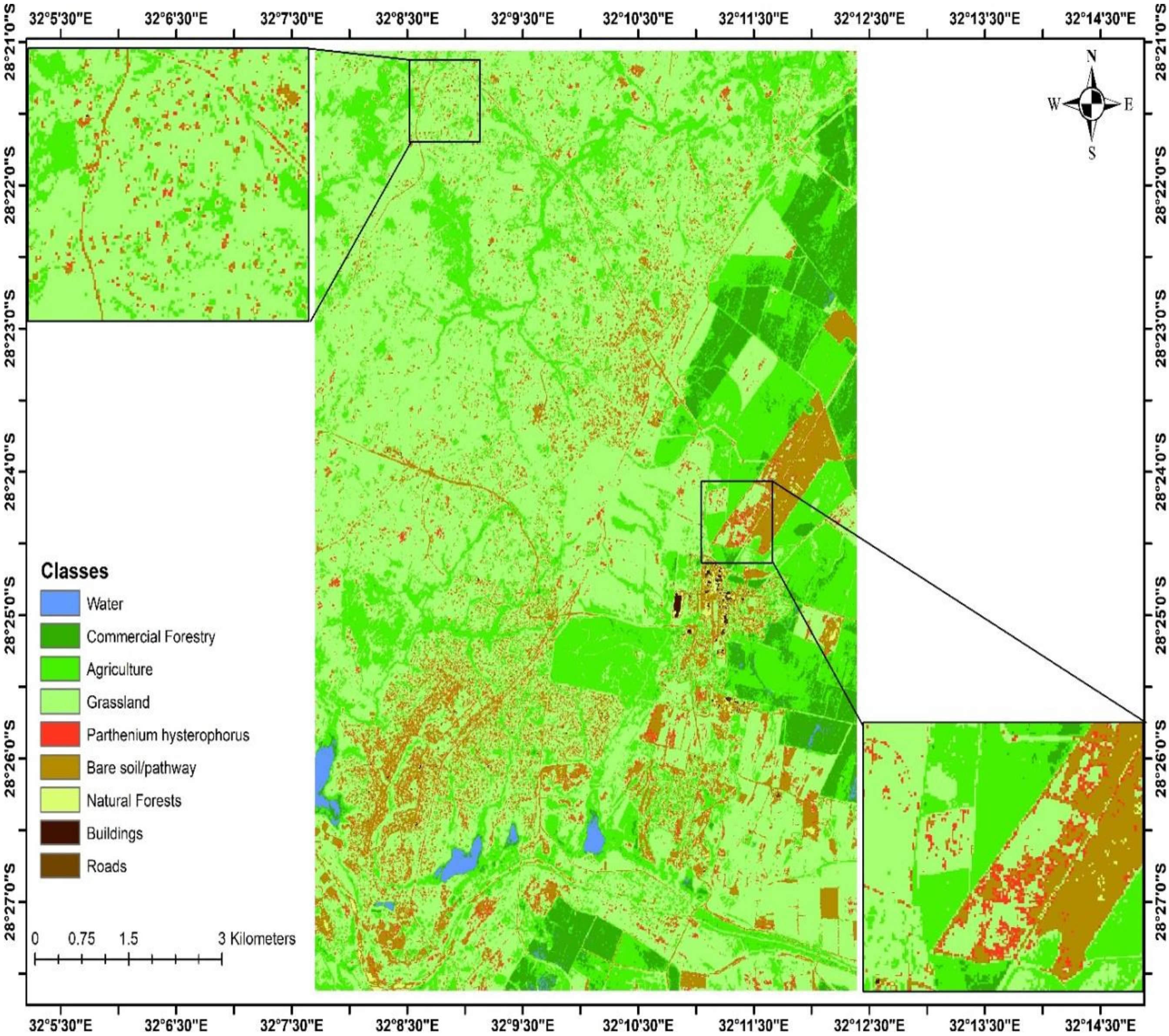

Figure 3.7: Land cover map produced using texture analysis of the panchromatic SPOT 6 band and classification using the PLS-DA algorithm.

3.5. Discussion

This study explored the capability of texture analysis to map *Parthenium hysterophorus L.* and the surrounding land cover. The ability of image texture computed from the 1.5 m panchromatic and 6 m multispectral SPOT 6 imagery to detect *Parthenium hysterophorus L.* and the surrounding land cover was compared. Generally, the panchromatic band achieved higher classification accuracies than the multispectral bands; therefore it was chosen to produce the land cover map. The land cover map produced by the SPOT 6 panchromatic band provided a good reflection of the land cover classes found within the study site. Notably, the parthenium was showcased in small and erratic patches, similar to what was observed in the study site (Figure 3.6). Furthermore, parthenium was found coinciding often with bare soil, which is a disturbed area. This finding supports current literature that states that parthenium is more likely to grow in areas where vegetation has been disturbed or removed (Singh, 2005; Belz *et al.*, 2009), providing a niche that enables parthenium to grow profusely without competition from naturally occurring vegetation.

The analysis was based on the PLS-DA classifier, which was chosen due its ability to reduce model-overfitting, data dimensionality and maximize prediction accuracy (Pérez-Enciso & Tenenhaus, 2003; Peerbhay *et al.*, 2013; Cavender-Bares *et al.*, 2016). The PLS-DA model was optimized using the ideal number of latent components with the lowest CV error. This was eight and ten latent components, and a CV error of 23.31% and 27.56% for panchromatic and multispectral bands, respectively. Subsequently, the VIP score was used and enabled the most important parameters to be chosen for the classification analysis (Peerbhay *et al.*, 2014). A study by Peerbhay *et al*. (2013) showed that using the VIP score produces the best PLS classification accuracy and effectively determines parameter (predictor) importance. They achieved an overall accuracy of 88.78% and a user and producer's accuracy between 70% and 100% using spectral information. Using texture analysis in our study achieved a good overall classification accuracy of 73% and 77% for multispectral and panchromatic bands, respectively. The allocation and quantity disagreement was 20% and 7%, respectively for multispectral and 18% and 5%, respectively for panchromatic bands. Franklin *et al*. (2000) stated that incorporating texture analysis into land cover mapping usually improves the classification accuracy by 10-15%. However, this includes both spectral and texture information, whereas our study focused purely on texture information.

Four out of nine designated land cover classes were vegetation classes, namely: commercial forest, natural forest, grass and parthenium. According to Li *et al*. (2019) spectral bands differ in their ability to capture differences between vegetation and their changes through time. The texture results from the multispectral bands showed that band 4 (near-infrared) contained majority of the information used for the classification analysis, while band 1 (blue) was the least important. Knipling (1970) states that reflectance of vegetation increases to a high in the infrared region, making it particularly useful to capture changes in reflectance for different vegetation types or species, thereby enabling discrimination. The red region was also frequently selected in this study and has been stated by Peerbhay *et al*. (2013) to be sensitive to pigmentation in leaf tissue, also helping with vegetation discrimination. Additionally, our study found that co-occurrence parameters, such as homogeneity and correlation, were a significant contributor to model development as compared to occurrence parameters. Homogeneity and second moment was also found by Salas *et al*. (2016) to play an important role in mapping vegetation in Tajikistan. These results were supported by various studies, such as Yuan *et al*. (1991) and Franklin *et al*. (2000). More recent studies by Lottering and Mutanga (2012) and Hlatshwayo *et al*. (2019) have also shown that co-occurrence measures contain majority of the vegetation information; thereby promoting accurate vegetation analysis. A recent study by Lottering *et al*. (2020) further iterated the importance of co-occurrence parameters, namely correlation, second moment and homogeneity to model development whilst detecting bugweed in a commercial forest with the use of the PLS-DA and SPLS-DA (Sparse Partial-Least-Squares Discriminant Analysis) algorithm.

Parthenium, which is the focus of our investigation, achieved a low user accuracy (58% for multispectral and 64% for panchromatic bands), which may have partially resulted from the way in which the field data was collected. Plots greater than 6 m^2 were chosen to ensure they were large enough to be captured by the SPOT 6 sensor. However, some patches were less than the SPOT 6 multispectral resolution (6 m^2), due to a lack of large parthenium stands. This may have caused textural confusion with surrounding vegetation, such as grass and natural forest, therefore reducing accuracy. The increase in user accuracy for the panchromatic band, with a higher spatial resolution than multispectral bands, may support this notion. However, parthenium achieved a good producer accuracy of 77% for both multispectral and panchromatic bands. According to Hay *et al*. (1996) and Wulder (1998), the relation of image texture to scene texture is highly dependent on scale, which influences accuracy; therefore it requires the use of optimally selected sensors that have a specific spatial resolution. SPOT-6 provides a very high spatial resolution panchromatic band that is extremely valuable for capturing the texture of small patches of parthenium in the field, which are more common than larger stands. Similar findings were made by Gebreslasie (2008) when comparing image texture from panchromatic and multispectral IKONOS-2. The panchromatic band achieved superior results compared to the multispectral bands. This is further supported by Lottering and Mutanga (2012) who compared the use of SPOT 5 2.5 metre panchromatic and 10 metre multispectral images to estimate road edge effects using texture analysis. Additionally, Dobrowski *et al*. (2008) state that image resolution which is finer than individual trees and vegetation patches is advantageous, because herein texture variables become increasingly correlated to vegetation physiognomy. Low-resolution imagery may result in textures that are unrelated to what is on the ground, while high-resolution imagery allows a strong geographical correlation between land features and image texture (Hay *et al*., 1996). Woodcock and Strahler (1987) also note that texture analysis should be performed on high resolution images, because numerous measurements are needed to characterize class texture.

Franklin *et al*. (2000) have also stated that, realistically, one should assume there are errors in both field and remote sensing data collection. There may be spatial error when comparing the GPS locations of the collected points to the corresponding location on the digital image. This may be further exacerbated when considering the spatial extent of an individual pixel, which may not correspond precisely with your plot on the ground and may cause overlap with a neighbouring pixel. Other sources of error that can influence accuracy are shadows created by the surrounding landscape, background soil and distortion in spectral signals received by the sensor (Lu, 2006). Franklin *et al*. (2000) further state that there are sources of error when applying texture analysis of digital images to forest inventory classification, which we may generalize for land cover classification. These sources of error could include the choice of window size, texture measure, class selection, type of sensor, accuracy of plot size in relation to sensor spatial resolution and the method in which field data is related to sensor data (for example regression or classification accuracy) (Franklin *et al*., 2000). These are potential sources of error that may have reduced the overall and individual class accuracy, especially of parthenium.

Vegetation produces variation in grey tones caused by, among others: different species, age, and crown closure (Franklin *et al*., 2001), which aid in texture analysis due to the specific growth patterns and physical characteristics of different types of vegetation. Ruiz-Gallardo *et al*. (2004) found that textural and spectral classifications were appropriate for different land cover types. Spectral classification is better suited to landscape covers that have a specific spectral response that can be easily differentiated from other land covers, for example fallow and pasture land (Ruiz-Gallardo *et al*., 2004). This is attributed to the homogeneity of the grey levels within those classes, which makes it difficult for texture analysis to discriminate between classes. Conversely, texture analysis is very efficient in classifying land cover that exhibit high spectral heterogeneity, for example scattered trees and dense shrub, which is challenging to classify using purely spectral information (Ruiz-Gallardo *et al*., 2004). Regarding the low accuracy of parthenium, this may provide some insight into the confusion with other classes, such as grass, agriculture and natural forest. The texture of these classes may be homogenous and quite similar to one another, making them difficult to discriminate. Ruiz-Gallardo *et al.* (2004), in agreement with Franklin *et al*. (2000) notes that combining spectral and texture information can improve classification accuracy; this could be a potential option to explore in future.

According to Xie *et al*. (2008), the separation of plant species is exceptionally difficult using multispectral images, therefore more studies rely on hyperspectral imagery, which provide contiguous spectral bands that capture the slight discrepancies in reflectance or absorption signatures given off by vegetation (Gairola *et al*., 2013). However, hyperspectral images are expensive and come with their own set of challenges; therefore it is important to investigate various methods that provide good results using multispectral imagery. The most significant finding of our study is that SPOT-6 imagery is capable of providing reasonably accurate results for detecting *Parthenium hysterophorus L.* and associated land cover using texture analysis. Furthermore, the panchromatic band attained better classification results than the multispectral bands, insinuating that texture analysis performs better with higher spatial resolution imagery. The very high spatial resolution provided by SPOT-6 imagery, notably the panchromatic band, is exceedingly beneficial as an increased availability of free imagery with adequate spatial resolution will allow us to gain insight into more accurate methodologies to detect and map alien invasion.

3.6. Conclusion

This study focused on comparing the ability of 1.5 m panchromatic and 6 m multispectral SPOT-6 imagery in mapping *Parthenium hysterophorus L.* and the surrounding land cover using texture analysis and the PLS-DA algorithm. We found that:

- The panchromatic band produced a higher overall classification accuracy than the multispectral bands (77% and 73%, respectively) and higher user accuracy for parthenium (64% and 56%, respectively).

- The higher spatial resolution of the panchromatic band most likely played a large role in producing superior texture results, due to its ability to capture small stands of parthenium and texture analysis being dependent on spatial resolution.
- Grey-level-co-occurrence measures (GLCM) were a more significant contributor to model development than grey-level-occurrence measures (GLOM), as studies have shown that GLCM contain more vegetation information than GLOM, improving classification accuracy.
- Due to SPOT 6 imagery containing very high spatial resolution in the panchromatic band, it is highly beneficial for mapping and tracking of *Parthenium hysterophorus L.* using texture analysis.
- Future research could combine spectral and textural information that have contrasting strengths and weaknesses, thereby overcoming their weaknesses and enhancing their strengths, resulting in improved classification accuracy.

4. CONCLUSION

4.1. Introduction

Parthenium hysterophorus L. (parthenium) is alien invasive plant species that has severe environmental, biological and human impacts. Remote sensing and GIS provide a very useful form of tracking alien plant distribution, due its cost effectiveness, the ability to capture large geographic areas and its multi-temporal coverage. Different remote sensors offer a range of spectral and spatial resolution. There are two spectral types, namely: multispectral and hyperspectral sensors, with varying spatial resolutions. Hyperspectral resolution provides in-depth detail of changes throughout the electromagnetic spectrum of designated investigated classes, attaining high classification accuracy. However, there are several shortcomings to the usage of hyperspectral imagery, for example its high expense, high data-dimensionality and difficulty to analyse. Hence it is practical to find suitable multispectral alternatives that can achieve good results. There are several new generation sensors that may be valuable to parthenium detection, i.e. Sentinel-2, RapidEye and SPOT 6, which were investigated in this study. Sentinel-2 is an innovative sensor that provides freely available imagery, with a spatial resolution of 10, 20 and 60 m and a spectral resolution of 13 bands. RapidEye is a commercial sensor with a higher spatial resolution of 5 m, but a lower spectral resolution of 5 bands. These contrasting strengths and weaknesses in spectral and spatial resolution make these two sensors somewhat comparable and requiring further investigation into parthenium detection performance. SPOT-6 features high spatial resolution in its multispectral bands (6 m) and very high spatial resolution in its panchromatic band (1.5 m). The panchromatic band can be used to investigate other imagery analysis, beyond spectral analysis, such as texture analysis. Texture analysis makes use of patterns and colour in grey tones and takes into consideration spatial arrangement of land cover features, thereby allowing their detection. It has also proven to be quite useful for detecting different species of vegetation, therefore offers an interesting prospect for invasion monitoring.

With this understanding, this dissertation has the following objectives:

I. Comparing the ability of new generation multispectral sensors Sentinel-2 and RapidEye to detect parthenium and the surrounding land cover using spectral information and SGB algorithm

II. Evaluate the ability of texture analysis to map parthenium and the surrounding land cover using the PLS-DA algorithm

4.2. Comparing the ability of new generation multispectral sensors Sentinel-2 and RapidEye to detect Parthenium Hysterophorus L. and the surrounding land cover using spectral information and the SGB algorithm

This study compared two multispectral sensors, namely Sentinel-2 and RapidEye, in their ability to detect *Parthenium hysterophorus L.* and the surrounding land cover using spectral bands and vegetation indices. According to literature, the red-edge band plays a significant role in classification analysis, due to its sensitivity to vegetation characteristics. However, our study did not place emphasis on the red-edge band as it ranked 23rd out of 43 vegetation indices and raw bands for RapidEye. Furthermore, according to spectral curves there seems to be high visual overlap of land cover classes in the red-edge region, indicating that there is difficulty in differentiating between different classes. Sentinel-2 showed a similar trend of spectral overlap within the first red edge band. However, the other red edge and near-infrared bands showed an increased separability on the spectral curve, meaning that they were more useful in the classification analysis. RapidEye near-infrared band also showed an increased separability of land cover classes. The wavelength between 704 and 881 specifically from Sentinel-2 (band 5-8A) was important for class discrimination.

Sentinel-2 achieved a higher overall classification accuracy of 82% compared to 71% for RapidEye. For most land cover classes, Sentinel-2 outperformed RapidEye, despite the coarser spatial resolution of Sentinel-2 (10 and 20 m^2 used in this study) to RapidEye (5 m^2). However, Sentinel-2 has a superior spectral resolution of 13 bands compared to RapidEye 5 bands. This proved very beneficial for the analysis, because it captured areas of the electromagnetic spectrum that were very important for class discrimination that were not available in the RapidEye bands. The bands available in Sentinel-2 are more sensitive to detecting spectral discrepancies between different land cover classes. Additionally, the use of vegetation indices may have assisted class discrimination by enhancing electromagnetic signals given off by land cover, while reducing spectral noise.

Hsieh *et al*. (2001) states that even though high spatial resolution imagery generally provides an increased level of detail it may not always improve classification accuracy. Small pixel sizes may actually increase in-class spectral variability, reducing separability of classes and thus reducing classification accuracy. Parthenium attained the lowest classification accuracy compared to other land cover classes, for both RapidEye and Sentinel-2. This may be a result of how the data was collected, i.e. small parthenium stands which may not have been captured efficiently with coarse spatial resolution. It may also be a result of the mixed pixel problem, whereby different land cover classes are captured in one pixel, which distorts the reflectance, resulting in misclassification. Parthenium also tends to grow in disturbed areas and amongst other vegetation, thereby contributing to the mixed pixel effect. This may be supported by the low accuracy of grass for both sensors, which parthenium frequently grew amongst at the site and where the GPS points were taken.

It has to be further highlighted that mapping with pixels removes information and creates generalization within each pixel, hence it must be understood that there will always be some level of inaccuracy, especially with coarser resolution imagery. Despite this, Sentinel-2 achieved very promising results, considering its poor spatial resolution in comparison to RapidEye. The high spectral resolution of Sentinel-2 makes it quite capable of distinguishing classes and will be useful for alien invasive plant mapping, including parthenium, provided that the stands focused on were large enough for detection.

4.3. Comparing the ability of panchromatic and multispectral spot-6 bands to detect and map Parthenium Hysterophorus L. using image texture analysis

This study focused on the detection and mapping of parthenium and the surrounding land cover with the use of SPOT 6 imagery. This imagery was chosen due its very high spatial resolution of its panchromatic band (1.5 m), which is very beneficial to the chosen analysis, i.e. texture analysis. This is a spatial analysis that involves pattern detection of grey tones to discriminate and classify different land cover types. Our aim was to determine whether the panchromatic or multispectral bands performed better in detecting and classifying parthenium and other land cover classes with the use of texture analysis and the PLS-DA algorithm. The panchromatic band was found to achieve superior classification results (77% compared to 73% for multispectral). This may be primarily attributed to the higher spatial resolution of the panchromatic band, which is imperative for texture analysis. Hay *et al.* (1996) and Wulder (1998) state that image texture is highly dependent on scale; therefore influencing accuracy.

This can also be supported by Gebreslasie (2008) and Lottering and Mutanga (2012) who achieved similar results when comparing panchromatic and multispectral bands.

Specifically, the panchromatic band enables the capturing of small patches of parthenium, which the coarser multispectral bands may sometimes not accurately detect. This may be the reason why parthenium achieved low user accuracy (58%) for multispectral bands and an improved user accuracy using the panchromatic band (64%). This may be caused by a potential spatial discrepancy between the GPS points taken during field data collection and the precise overlay of the image in reference to that point. It may also be due to the fact that some of the parthenium patches were smaller than the pixel size of the multispectral band, due to unavailability of many large patches of parthenium in the field. This may have resulted in confusion with other land cover classes, especially since parthenium grows in conjunction with other vegetation types, such as grass. Dobrowski *et al.* (2008) further state that a very high spatial resolution with pixels smaller than the size of individual trees or patches of vegetation is valuable, because texture variables become more related to the physiognomy of vegetation. Furthermore high resolution imagery allows a stronger geographical correlation between texture images and on-the-ground features, contrary to low spatial resolution imagery.

The map produced using texture analysis showcased that parthenium grows in erratic patches, generally coinciding with disturbed areas, such as bare soil. Literature states that parthenium is more likely to grow where disturbance of vegetation has occurred, allowing parthenium a niche to establish and grow rapidly due to its ecology and allelopathic effects.

4.4. Recommendations

Several recommendations for future research are highlighted below:

- Multispectral sensors possess a limited ability to distinguish land cover types with subtle spectral differences due to their low spectral and spatial resolution. Hence it may be difficult to detect herbaceous species, such as parthenium, especially since it may grow in between spectrally similar vegetation. Alien invasive species also tend to grow in small, erratic patches in their early stages of invasion, which cannot be detected using sensors with coarser spatial resolution, such as Sentinel-2. Consequently, future studies should either focus only on large stands of parthenium, or sensors with high spatial resolution, such as RapidEye or SPOT 6, to capture these smaller parthenium stands.

- Alien invasive species need to be sufficiently distinct from to co-existing vegetation to allow detection using imagery. Spectral curves in Chapter 2 have insinuated that there are certain regions of the electromagnetic spectrum that are more important for class discrimination, namely the two red-edge and near-infrared bands of Sentinel-2 which span 704-881 nm and the near-infrared band of RapidEye (760-850 nm). This indicates that sensors that have strategically placed bands are important for classification analysis as these bands are more sensitive to subtle changes in reflectance of land cover than conventional multispectral bands. Future research should explore new generation multispectral sensors to test their class discrimination ability, especially those classes that are spectrally similar, such as parthenium and grass in this study.
- Due to the tendency of alien plant species, such as parthenium, to grow in between natural vegetation, a method has to be developed that aids in differentiating between the species that it grows amongst. A potential solution would be to capture images throughout the seasons, as different species may exhibit varying spectral characteristics that can be captured easily.
- Despite less than satisfactory classification results for parthenium using Sentinel-2, the superior classification results for most of the other land cover types indicate that Sentinel-2 is a good alternative to commercial imagery. This is further supported by spectral curves which insinuate that Sentinel-2 is more efficient in class discrimination than RapidEye. This free imagery could prove extremely beneficial for plant alien invasion monitoring and many other applications, especially in resource-constrained countries.
- Texture analysis proved to be quite a successful form of spatial analysis, for both the multispectral and panchromatic bands. However the panchromatic band achieved superior results due to the fact that texture is influenced greatly by scale, thereby influencing accuracy. Consequently, texture analysis should be performed on imagery that is of finer spatial resolution. With increasingly finer spatial resolution of remote sensors, texture analysis is a viable option that is capable of providing very good results for plant invasion monitoring.

- Texture analysis has proven to achieve superior results in comparison to spectral analysis; thereby indicating that texture analysis should be explored in future. It helped us achieve our objective of mapping parthenium distribution, which was otherwise difficult using spectral information, due to the low parthenium accuracy and lower spatial resolution. SPOT 6 is a visionary sensor that boasts very high spatial resolution, implying a need for more research that focuses on investigating its capabilities.
- It must be noted that texture and spectral analysis tend to be suited to different types of land cover. Spectral analysis is more suited to classes that have a more homogenous reflectance per class, such as grass and bare soil. On the other hand, texture analysis is more valuable for classes that exhibit high spectral heterogeneity, such as dense shrub, which is more challenging to classify using spectral information. For this reason, texture and spectral information should be combined to achieve superior results, by offsetting their limitations and enhancing their strengths.
- Remote sensing, while still flawed, remains a viable method to map alien invasion, especially considering numerous technological advancements and innovations, such as improved sensors and better performing classification algorithms. It is a fast and efficient method that allows us to track areas that are becoming invaded and areas that are heavily invaded to make informed decisions as to where to allocate limited resources for rehabilitation.
- Potential future studies can examine the utility of spectral unmixing techniques to recover signatures of pure materials from the scene, hence improving accuracy.
- A final recommendation would be for decision/policy makers to give deep consideration to the meaningful research that has been done at universities and to work closely and collaborate with universities, research institutes and others.

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