Spatial-temporal mapping of Parthenium (*P. HysterophoruL*) in the Mtubatuba municipality, KwaZulu-Natal, South Africa

Lwando Royimani

212559726

A thesis presented to the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, in fulfilment of the requirements for the degree of Master in Environmental Sciences.

Supervisor: Prof. Onisimo Mutanga

Co-Supervisor: Dr. John Odindi

Pietermaritzburg, South Africa

November 2017

Abstract

Detecting and mapping the occurrence, spread, and abundance of Alien Invasive Plants (AIPs) have recently gained substantial attention, globally. Therefore, the present study aims to assess remote sensing application for mapping the spatial and temporal spread of Parthenium (*P. HysterophoruL*) in the Mtubatuba municipality of KwaZulu-Natal, South Africa. Parthenium is an aggressive herbaceous plant from the South and Central America that has colonized many regions of the world including Asia, Australia, and Africa. The adverse social, economic and ecological impacts of the plant have emphasized the need for a robust control programme to combat its spread. However, data for the management of the weed has been gathered by means of manual methods such as field surveys which are time and labour intensive. Alternatively, remote sensing techniques provides cost effective approach to large-scale mapping of AIPs. The first objective of the study provides an overview of advancements in satellite remote sensing for mapping AIPs spread and the associated challenges and opportunities. Satellite remote sensing techniques have been successful in detecting and mapping of AIPs, exploring their spatial and temporal distribution in rangeland ecosystems. Although they provide fine spatial information, the excessive image acquisition costs associated with the use of high spatial and hyperspectral datasets are a limitation to continuous and large-scale mapping of AIPs. The signing of the license agreement between the South African Space Agency (SANSA) and Airbus Defense and Space (ADS) has ensured a continued provision of SPOT data with improved spatial properties for South Africa. Similarly, the signing of the single licence government multi-user agreement between the South African government and SANSA has ensured free provision of SPOT data for public use in South Africa to support land change monitoring. The second objective was to determine the spatial and temporal distribution of Parthenium from 2006 to 2016 using SPOT series data in concert with Random Forest and Land Change Modeler (LCM). Findings have shown a steady decrease in Parthenium distribution over the 10-year period of the study because of the low annual rainfall experienced in the area over the recent past. Furthermore, disturbances in the soil opens vacant spaces which are susceptible to Parthenium invasion. This study has demonstrated the value of readily available multispectral SPOT series data in concert with robust and advanced non-parametric Random Forest algorithm in detecting trends and patterns in the spatial and temporal spread of AIPs

Key words: Parthenium, remote sensing, satellite, multispectral, spatiotemporal, non-parametric.

Preface

The research work presented in this thesis was carried out in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, from February 2016 to November 2017, under the supervision of Prof. Onisimo Mutanga and Dr. John Odindi.

The author solemnly declares that the work presented in this research is his genuine work, except where otherwise acknowledged by means of referencing, and that the work has never been submitted to any institution of higher learning.

Lwando Royimani Signed …………………………. Date…………………….

As the candidate's supervisor, I certify the above-mentioned statement and therefore approve this thesis for submission.

Supervisor: Prof. Onisimo Mutanga Signed………………. Date…………………

Co-Supervisor: Dr. John Odindi Signed……………..... Date………………….

Declaration

I, Lwando Royimani, declare that:

1 The research presented in this thesis is my genuine work, except where otherwise indicated by means of referencing.

2 This research work has never been submitted to any institution of higher learning for the attainment of either a degree, diploma or certificate.

3 This thesis does not contain other peoples' data, pictures, graphs or other information, unless where specifically indicated by means of referencing.

Sign………………………………… Date…………………………………

Dedication

I dedicate this work to my beloved family, especially my uncle (Priest M.H. Gosa/Mantinsilili) for his unreserved moral support, prayers and encouragements throughout the course of this endeavor, I salute and respect you "*Lume*" and to my one and only lovely younger sister (Amahle Royimani) whom I inspire to purse the journey of academia.

Acknowledgements

I would like to express my sincere gratitude to the Almighty, the God who lives in flesh, for sustaining me throughout the rigorous academic and scholarly journey of my research life time.

Also, I am very grateful to my supervisor, Professor Onisimo Mutanga, for his unreserved constructive criticisms, comments and guidance that he provided to me throughout the course of this research. His Excellency, majesty, professional expertise, enthusiasm and commitment towards his work has indeed produced something (the current me) out of nothing (the previous me).

Furthermore, my special thanks are given to my co-supervisor (Dr. John Odindi) for his inestimable technical and narrative guidance and assistance during the production of the two manuscripts embedded in this thesis. I highly appreciate his willingness to share his knowledge and experience. I also Thank Dr. Timothy Dube for his contribution to my review paper (chapter two), encouragements and moral support. I further extend my words of appreciation to the entire University of KwaZulu-Natal Department of Geography, with special thanks to Dr. Mbulisi Sibanda for his motivation and contributions to the second paper (chapter three) of this thesis, Mr. Serge Kiala Zolo for his imperative assistance in the production of the second paper (chapter three), Mr. Trylee Nyasha Matongera for his continuous motivates and contributions to the review paper (chapter two), Mr. Charlse Otunga for his advises.

Also, special thanks are given to the National Research Fund (NRF) Chair for providing the financial support to carry out this research and the South African Space Agency (SANSA) program which covered my living expenses throughout the study period.

Table of contents

Abstract ii

Preface iii

Declaration iv

Dedication v

Acknowledgements vi

Chapter One: General Introduction 1

1.1 Introduction 1

1.2 Aims and objectives 3

13. Research questions 3

1.4 Hypothesis 3

1.5 Chapter outline 4

Chapter Two: Advancements in satellite remote sensing for mapping and monitoring of Alien Invasive Plant species (AIPs) spread 5

Abstract 5

2.1 Introduction 6

2.2 The ecology and spatial distribution of AIPs 8

2.3 Spectral properties of AIPs for remote sensing techniques 9

2.4 Multispectral remote sensing of alien invasion 11

2.5 Hyperspectral remote sensing of AIPs 14

2.6 The use of multisource data for detection of AIPs 14

2.7 Parametric and non-parametric image classifiers for invasive alien plants 15

2.8 The use of vegetation indices for detection of AIPs 17

2.9 Relationship between classification algorithms and remote sensing dataset 17

2.10 Challenges in remote sensing of alien invasion 18

2.11 Possible directions of future research 20

2.12 Conclusions 21

Chapter Three: Determining multi-temporal distribution of Parthenium (P. HysterophoruL) using SPOT series data and Random Forest 22

Abstract 22

3.1. Introduction 23

3.2 Methods and Material 25

3.2.1 Description of the study site 25

3.2.2 Field data collection 26
3.2.3 Image acquisition and preprocessing 26
3.2.4 Vegetation indices retrieval 27
3.2.5 Random Forest algorithm 28
3.2.6 Image classification and Random Forest optimization 29
3.2.6 Accuracy assessment 29
3.2.7 Post-classification and change detection 30
3.2.8 Annual rainfall distribution 30
3.3 Results 31
3.3.1 Assessment of classification accuracies 31
3.3.2 Land use/land cover transformation and Parthenium distribution 31
3.3.3 Spatial and temporal variability in Parthenium distribution 34
3.3.4 Comparing the spread of Parthenium between agricultural and non-agricultural dominated fields 36
3.4 Discussion 37
3.5 Conclusion 40
Chapter Four: Evaluation and conclusion 41
4.1 Introduction 41
4.2 Evaluation of research objectives 41
4.2.1 Objective one: 41
4.2.2 Objective two: 42
References: 44

List of Tables

Table 2. 1: A summary of satellite remote sensing sensors for mapping AIPs in relation to their resolutions, acquisition costs, scales of application and accuracies. 13

Table 3. 1: Image acquisition dates and sensor characteristics. 27

Table 3. 2: Selected vegetation indices for discerning green and non-green features 28

Table 3. 3: Accuracy assessment using error matrix for classifying the 2006, 2009, 2012 and 2016 SPOT scenes. 31

Table 3. 4: Assessing the 'from-to' class alterations and the degree of change. 32

List of Figures

Figure 2. 1: Spectral signatures for different Alien Invasive Plants (AIPs). Adapted from Strand (2007). 10
Figure 3. 1: Location of the study area in Mtubatuba municipality, KwaZulu-Natal, South Africa. 25
Figure 3. 2: Parthenium distribution and land use/land cover transformation............................ 32
Figure 3. 3: Parthenium distribution in relation to other land use/cover change for the study period. 33
Figure 3. 4: Trends in Parthenium distribution from 2006 to 2016. 34
Figure 3. 5: Spatial distribution of Parthenium for the period of the study. 35
Figure 3. 6: Change in Parthenium distribution in relation to agricultural and non-agricultural dominated fields. 36
Figure 3. 7: Rainfall and Parthenium distribution for the study period. 37
Figure 3. 8: Correlation between rainfall and Parthenium distribution. 38
Figure 3. 9: Relationship between bare soil and Parthenium distribution from (a) 2009 to 2012 and from (b) 2012 to 2016. 39

Chapter One

General Introduction

1.1 Introduction

The rapid proliferation of Alien Invasive Plants (AIPs) is increasingly becoming a global concern (Rocchini *et al.* 2015; Poona 2008; Weber *et al.* 2008), not only to biodiversity but also to food security, health and economic development. In general, AIPs are defined as plant species that are introduced, intentionally or accidentally, and spread outside their naturally occurring habitats (Karki 2009a; Poona 2008). Studies have shown that the rapid spread and proliferation of AIPs is one of the major non-climatic drivers to biodiversity loss and global change (Kganyago *et al.* 2017; Beck *et al.* 2009). Originating from the South and Central America, Parthenium (*P. hysterophorusL*), is one of the world's most invasive plant that has colonized many regions such as Australia, Asia and Africa (Zuberi *et al.* 2014; Ayele 2007; Karki 2009a). In Africa, the plant has favored the east and southern parts of the continent (McConnachie *et al.* 2011). Parthenium has been found to spread vigorously in the KwaZulu-Natal province of South Africa, following its first introduction in 1880 (Zuberi *et al.* 2014; Karki 2009a). Its unabated distribution to the invaded landscapes has been intensified by its tolerance to a wide range of environmental conditions (Ayele 2007). Studies have shown that, under favorable conditions, Parthenium can grow up to 2 meters in height and complete its life cycle in four weeks (Ayele 2007). The small seeds of Parthenium can easily be carried and dispersed by wind, vehicles and water movement (Ayele 2007).

Parthenium invasion presents major socioeconomic and ecological problems to the newly invaded landscapes (Ayele 2007). For instance, literature reveals that Parthenium invasion in grasslands can neutralize the acidic soil pH of the colonized habitats (Karki 2009a). Furthermore, Parthenium produces allelochemicals through its leaves, altering the physical and chemical properties of the soil in invaded landscapes, thereby inhibiting germination of native flora (Karki 2009a; Ayele 2007). In Ethiopia, Parthenium invasion has significantly affected the rangeland composition and diversity (Ayele 2007). Besides the aforementioned ecological impacts, several economic losses have been reported as a result of Parthenium invasion. For instance, farmers in Ethiopia were forced to abandon their productive grazing and cultivated lands because of Parthenium invasion (Zuberi *et al.* 2014). Studies (e.g. Ayele 2007) have shown that about 10-50% of Parthenium consumption by cattle or buffalos can kill the animals within 30 days. Similarly, significant reduction in meat and milk quality have been reported from animals feeding on Parthenium. On the other hand, numerous human health risks have been reported as a result of Parthenium invasion (McConnachie *et al.* 2011).

Despite the aforementioned factors, data for the monitoring of Parthenium spread has been gathered by means of manual methods such as field surveys (Karki 2009a). However, the limitations of using such methods in the monitoring of alien invasion are well documented in the literature (Ismail *et al.* 2016). As an alternative, remote sensing provides cost-effective, robust and repeatable approaches to the optimal identification, characterization and mapping of AIPs, both, at local and regional scales (Peerbhay *et al.* 2016b; Asner *et al.* 2010; Kimothi *et al.* 2010). Peerbhay *et al.* (2016a), successfully detected the invasive bugweed (*Solanum mauritianum*) in the midlands region of KwaZulu-Natal, South Africa using the hyperspectral AISA Eagle, Worldview-2 and Light Detection and Ranging (LiDAR) datasets. Their findings revealed that overall classification accuracies of 68.33%, 63.33% and 64% were obtainable when using the AISA Eagle, Worldview-2 and LiDAR data respectively. Similarly, Robinson *et al.* (2016), used the Worldview-2 data to detect the invasive Mesquite (*Prosopis spp*.) in the north-west of Pilbara in Australia with an overall classification accuracy varying from 80.7% to 84.7%. However, the excessive image acquisition costs coupled with small area coverage possible with the use of hyperspectral and high spatial resolution datasets are prohibitive to large-scale and continuous monitoring of AIPs spread.

The signing of the license agreement between the South African Space Agency (SANSA) and Airbus Defence and Space (ADS) coupled with the SANSA-AIRBUS single licence government multi-user agreement to distribute SPOT data for public use has ensured a steady supply of SPOT imagery for South Africa (Oumar 2016). From the SANSA-AIRBUS single licence government multi-user agreement, the SPOT mission provides large volumes of historical data free of charge for regions in South Africa to support the multi-temporal remote sensing of alien invasion by the public sector (i.e. government, universities and public entities). On the other hand, the developments in image classification algorithms such as the non-parametric Random Forest classifiers have been valuable for image classification processes. According to Cho *et al.* (2012), Random Forest does not assume normal data distribution and is free from the Hughes phenomenon of over-fitting. Therefore, it is hypothesized that the use of SPOT series data in concert with Random Forest can facilitate the precise delineation of trends and dynamics in AIPs spread, especially in financially constrained regions such as the southern Africa. Therefore, the present study aims to assess remote sensing application for mapping the spatial and temporal distribution of Parthenium in the Mtubatuba municipality of KwaZulu-Natal, South Africa.

1.2 Aims and objectives

The overall aim of the study was to assess remote sensing application for mapping the spatial and temporal distribution of the alien invasive Parthenium in the Mtubatuba municipality of KwaZulu-Natal, South Africa. To achieve this aim, the study set itself to the following objectives:

- To review the literature on the advancements of satellite remote sensing for optimal detection and mapping of AIPs spread and the associated challenges and opportunities.
- To detect and map the spatial and temporal distribution of Parthenium from 2006 to 2016 using the SPOT series data and Random Forest.

1.3 Research questions

- With recent advancements in satellite remote sensing sensor technology, what are the cost-effective ways of improving the detection and mapping of AIPs?
- Can the use of readily available SPOT series data in concert with robust non-parametric Random Forest help to detect trends and dynamics in Parthenium distribution?
- What are the major driving factors behind the expansion and distribution of Parthenium?

1.4 Hypothesis

- The provision of historical data with improved spatial resolution from the SPOT mission when used with the robust and advanced non-parametric Random Forest can enable the detection of dynamics in Parthenium distribution.
- The continued vegetation clearings and land use/cover transformations because of human activities are the major driving factors behind Parthenium spread.

1.5 Chapter outline

This thesis is organized into four chapters. As an introductory section, chapter one gives an overview of the thesis by highlighting the background of alien invasion, Parthenium distribution and its impact as well as the remote sensing techniques for monitoring of AIPs spread. Furthermore, this chapter set out the main aim and objectives of the research, research questions and the hypothesis.

Chapter two is a manuscript currently under review with the Geocarto International Journal. The paper reviews advancements in satellite remote sensing for mapping and monitoring of AIPs. The essence of such a review include the opportunity to explore the nexus between the use of cost-effective multispectral data, with improved spatial properties, in concert with non-parametric classification algorithms for accurate detection of current and historical trends in the spread of AIPs, especially in financially limited regions.

Chapter three is a manuscript currently under review with the International Journal Remote Sensing. This paper focuses on detecting and mapping the spatial and temporal distribution of Parthenium from 2006 to 2016 using SPOT series data and Random Forest. The temporal aspect of the study was necessary to understand the trends and dynamics in the spread of Parthenium as well as to test the hypothesis that Parthenium is the colonizer of vacant lands. Using the Land Change Modeller (LCM), the changes in the spread of Parthenium as well as the degree of change were determined.

Chapter four provides the evaluation of the objectives and major concluding remarks of the study. It further sets out recommendations for similar future research studies.

Chapter Two

Advancements in satellite remote sensing for mapping and monitoring of Alien Invasive Plant species (AIPs) spread

The following paper is based on a manuscript that is currently under review:

Royimani, L., Mutanga, O., Odindi, J., Dube, T. & Matongera, T. N. (**Under review**). Advancements in satellite remote sensing for mapping and monitoring of Alien Invasive Plant species (AIPs) spread. *Geocarto International*.

Abstract

Detection and mapping of the occurrence, spatial distribution, and abundance of AIPs have recently gained substantial attention, globally. This work, therefore, provides an overview of advancements in satellite remote sensing for mapping and monitoring of AIPs spread and associated challenges and opportunities. Although confounded by numerous factors, satellite remote sensing techniques have been successful in detecting and mapping AIPs, exploring their spatial and temporal distribution in rangeland ecosystems. However, the launch of high spatial resolution and hyperspectral remote sensing sensors has not been a complete solution to address the challenges experienced with the use of poor spatial and spectral resolution sensors. This is certainly due to associated acquisition costs as well as the limited swath-width and archival data in using such sensors. Therefore, the use of high spatial and hyperspectral dataset is prohibitive to long-term monitoring of AIPs which is a requirement for effective management of AIPs spread. The freely availability of multispectral data with improve spatial resolution can improve the large-scale and long-term mapping of AIPs spread. Furthermore, advancements in image classification algorithms such as the non-parametric Random Forest, Support Vector Machine, Artificial Neural Network, has been valuable to accurate detection of AIPs at the landscape scale. To promote the large-scale and long-term monitoring of AIPs spread, especially in resource limited regions such as South Africa, the present study recommends that future research should consider the use of SPOT series data with non-parametric image classifiers.

Keywords: Satellite remote sensing, spatial, spectral, temporal, AIPs, parametric, non-parametric.

2.1 Introduction

Globally, AIPs pose significant threats to, among others, natural ecosystems (Gurevitch and Padilla 2004), biodiversity (Gaertner *et al.* 2009; Higgins *et al.* 1999), forests (Peerbhay *et al.* 2016a), rangelands and agricultural productivity (Pimentel *et al.* 2005). Furthermore, AIPs are known to reduce species richness (Gaertner *et al.* 2009), alter fire regimes and soil properties (Pejchar and Mooney 2009) and homogenize biodiversity (Peerbhay *et al.* 2016c; Kimothi and Dasari 2010; Joshi *et al.* 2004) of invaded landscapes. Experimental studies have reported excessive economic losses as a result of alien invasion **(**Karki 2009b; Ayele 2007**)**. For instance, in the United States alone, the environmental impacts of alien invasion were estimated to be approximately 120 billion US dollars per annum (Pimentel *et al.* 2005). In Australia, parthenium invasion in prime grazing land costs the government about 16.8 million US dollars annually, while in India, forty percent crop production losses are attributed to AIPs (McConnachie *et al.* 2011). Lowe *et al.* (2000), presented a list of invasive species around the world. The list comprises of Tamarisk (*Tamarix ramosissima*), Siam weed (*Chromolaena odorata*), Caulerpa Seaweed (*Caulerpa taxifolia*), Strawberry guava (*Psidium cattleianum*) and the Yellow himalayan raspberry (*Rubus ellipticus*). Several other AIPs with global distribution like Parthenium (Nigatu *et al.* 2010), Bugweed (Peerbhay *et al.* 2015), *Tamarix* spp (Swayne *et al.* nd), Bracken fern (*Pteridium*) (Matongera *et al.* 2017; Singh *et al.* 2013) and *Pinus spp* (Forsyth *et al.* 2014) have also been reported.

To mitigate AIPs spread, timely and accurate information on spatial and temporal distribution, as well as abundance is required (Peerbhay *et al.* 2016a). This information is necessary to enhance the understanding of trends and patterns in AIPs spread for improved decision-making, optimal resource management and stewardship. Traditionally, field surveys and aerial photographs have been used to collect data on AIPs (Zuberi *et al.* 2014; Ayele 2007; Foxcroft *et al.* 2008; Crossman and Kochergen 2002; Everitt *et al.* 1996). However, many studies (e.g. Peerbhay *et al.* 2016c; Evangelista *et al.* 2009) note that such approaches are not sustainable due to excessive capital, time and labor required, especially for large-scale applications. Furthermore, the use of traditional approaches like surveys are hampered by accessibility to the regions of interest, particularly in remote areas (Matongera *et al.* 2016a; Curatola Fernández *et al.* 2013). Satellite remote sensing, on the other hand, has increasingly gained popularity as a plausible alternative in AIPs mapping (Dorigo *et al.* 2012; Aitkenhead and Aalders 2011; Gómez-Casero *et al.* 2010). Unlike traditional approaches, satellite remotely sensed data and techniques can be applied on large and remote geographical locations (Huang and Asner 2009). Similarly, the repeated coverage possible with satellite remote sensing approaches allows for detection of plant phenology which is necessary for the detection of AIPs spread (Flood 2013).

Several studies (e.g. Matongera *et al.* 2016a; Peerbhay *et al.* 2016c; Niphadkar and Nagendra 2016; Rocchini *et al.* 2015; Bradley 2014; Boyd and Foody 2011; Huang and Asner 2009; Lass *et al.* 2005; Joshi *et al.* 2004) have reviewed remote sensing techniques to optimize the detection and mapping of AIPs. For instance, Huang and Asner (2009) provided an overview of spatial, spectral and temporal sensor resolutions for detecting AIPs based on structural and functional traits at various canopy levels. Similarly, Peerbhay *et al.* (2016c) explored the value of multisource remotely sensed data for optimal detection of structural and functional properties of AIPs in commercial forests, while Bradley (2014) investigated the value of spectral, structural and phenological attributes in detecting AIPs. Lass *et al.* (2005), on the other hand, explored the use of hyperspectral dataset in detecting AIPs. To the best of our knowledge, there is no study that has tried to understand the relationship between the use of readily available multispectral data with improved spatial properties in concert with robust and advanced non-parametric image classifiers for detection of AIPs. In our opinion, it is necessary for future studies to establish this relationship to promote the continued and large-scale mapping of AIPs, currently constrained by existing acquisition cost of high spatial and hyperspectral data.

The present study explores the importance of using the advanced and robust non-parametric image classifiers on freely available and improved spatial resolution data provided by the new generation of multispectral sensors to promote mapping of AIPs at an operational scale. Firstly, this paper provides a background on the ecology, as well as the spatial distribution of AIPs around the world. Secondly, the paper discusses sensor vegetation spectral properties necessary for discriminating AIPs as well as other remote sensing techniques useful in the identification of AIPs from native vegetation. Thirdly, the review explores the applications of different satellite remote sensing techniques, such as multispectral, hyperspectral and multisource data in detecting and mapping AIPs as well as their financial implication in relation to scale of application and mapping accuracy. Fourthly, the paper outlines the importance of image classification with a detailed comparison of parametric and non-parametric or advanced robust machine learning algorithms in enhancing the detection of AIPs using remotely sensed data. Furthermore, the paper also draws a synergy between the type of remotely sensed data used and a chosen image classifier. Lastly, the paper highlights the challenges of using remote sensing in the detection and mapping of AIPs and suggest directions for future research.

2.2 The ecology and spatial distribution of AIPs

Broadly, the term AIPs is used to refer to plant species or sub-plant species growing outside their naturally occurring habitats, with a strong ability to survive, reproduce, disperse and subsequently displace native flora (Kimothi and Dasari 2010; Shezi and Poona 2010; Mack *et al.* 2000). Generally, AIPs have identical functional features, such as competitive aggression and increased encroachment on disturbed environments. In these areas, AIPs take advantage of reduced interspecies competition as soils are either left bare or the native flora are still at an early stage of rejuvenation (Le Maitre *et al.* 2002). Studies have noted for instance that Parthenium establishes and naturalize on empty niches along roadsides, railway tracks, fallow agricultural lands and around buildings (McConnachie *et al.* 2011). Similarly, Peerbhay *et al.* (2015) reported that the exotic Bugweed invades pasture lands, river-banks, forest margins and plantations. Other studies (e.g. Curatola Fernández *et al.* 2013) have also reported that areas disturbed by fire are often preferred by the Bracken fern while Dark (2004) found that areas close to roads have a high density of noxious species in California.

Furthermore, studies have shown that AIPs have the engineering ability to modify their newly invaded habitats (Peerbhay *et al.* 2016b; Bax *et al.* 2003), thereby making it more suitable for their exponential growth and distribution. For instance, the allelopathic chemicals produced by Parthenium do not only displace indigenous plants but also transform river banks, grasslands, floodplains and woodlands into monocultural shrublands (McConnachie *et al.* 2011). Nigatu *et al.* (2010), for instance, found that the allelopathic chemicals produced by AIPs can inhibit germination and growth of indigenous plant species, which can change the structure and type of vegetation, fauna and local climate. Also, the literature shows that invaded landscapes are more likely to remain dominated by one individual species for a very long time (Huang and Asner 2009). Although literature highlights some positive ecological and economic impact of AIPs, such as the provision of habitat to local fauna (Matongera *et al.* 2016a) and provision of fuelwood and carbon assimilation (Shackleton *et al*. 2007), the recorded ecological destruction as a result of the alien invasion is far-reaching. For instance, AIPs out-compete the indigenous plants for available natural resources (i.e. water, sunlight, nutrients, space), which are integral to growth and distribution (Dark 2004). Furthermore, the literature shows that AIPs are unpalatable to livestock and game grazing (Everitt *et al.* 1995; Pyšek 1998).

According to Kalusová *et al.* (2013) and Pyšek (1998), plant species that are highly invasive have their origin in Europe. Mack *et al.* (2000), attribute this to the early (1500s) European voyages that contributed significantly to the human-driven dispersion. Blossey and Notzold (1995), for instance, reported that the Purple loose strife (*Lythrum salicaria L.*), native to Eurasia, was introduced in North America during the 1800s. Despite the human-driven invasions i.e. migration and transportation of goods (Mack *et al.* 2000), studies have shown that AIPs can spread and invade new habitats through watercourses (Dorigo *et al.* 2012) and birds dispersal. However, Joshi (2006) and Mack *et al.* (2000) note that the human-driven invasion still remains the greatest contributing factor towards dispersion of exotic plant species globally. Dispersion of AIPs by humans can be either accidental or purposeful. Purposefully, people can introduce exotic plants in new regions for controlling of other problematic species, to improve agricultural productivity or for ornamental reasons (Goodwin *et al.* 1999). The South American miconia (*Miconia calvescens*) for instance was introduced intentionally to the island of Tahiti in 1937 for ornamental reasons (Lowe *et al.* 2000). Other studies have recognized the impact of changing climatic conditions, as well as physiographic factors to induce invasion processes (Dark 2004; Kriticos *et al.* 2003). Apart from the aforementioned forms of dispersion, the invasiveness and spreading of AIPs, generally, increases with time of habitation since their first introduction in a community (Howison 2016).

2.3 Spectral properties of AIPs for remote sensing techniques

The rapid spread of AIPs across the landscape renders the adoption of traditional field surveys to manage the encroachment of such species implausible, hence the need for alternative methods (Peerbhay *et al.* 2016c; Evangelista *et al.* 2009; Lass *et al.* 1996). Until recently, the viable alternative for detecting and mapping the spatial and temporal distribution of AIPs has relied on observing and detecting differences in their spectral reflectance using remote sensing techniques (Strand 2007; Joshi 2006). Several AIPs have been discriminated from their co-existing vegetation based on estimated spectral differences. These include the Bracken fern (Matongera *et al.* 2017; Singh *et al.* 2013), Bugweed (Peerbhay *et al.* 2016a; Peerbhay *et al.* 2016b; Peerbhay *et al.* 2015), Mesquite (Robinson *et al.* 2016), Broom snakeweed (*Gutierrezia sarothrae*) (Peters *et al.* 1992a) and the Tickberry (*Lantana camara*) (Oumar 2016). Studies have revealed that plants, either alien or native, have different spectral reflectance within different regions of the electromagnetic spectrum, attributable to dissimilar biophysical (e.g. texture, canopy, leaf structure and orientation) and biochemical (e.g. chlorophyll and water content) properties of the plant (Matongera *et al.* 2016a; Zhao *et al.* 2009). This can best be demonstrated in Figure 2.1 where the thickened and succulent leaves of the Iceplant (*Carpobrotus edulis*) increased the absorption of its spectra around 0.9 µm (see the up pointed arrow) while the dry foliage of Jubata grass (*Cortaderia jubata*) increased its spectral reflection around 0.55 µm (see the down pointed arrow) (Strand 2007). In these regions, the distinctiveness of spectral reflectance for the two AIPs has necessitated their spectral separation from native plants using remote sensing techniques.

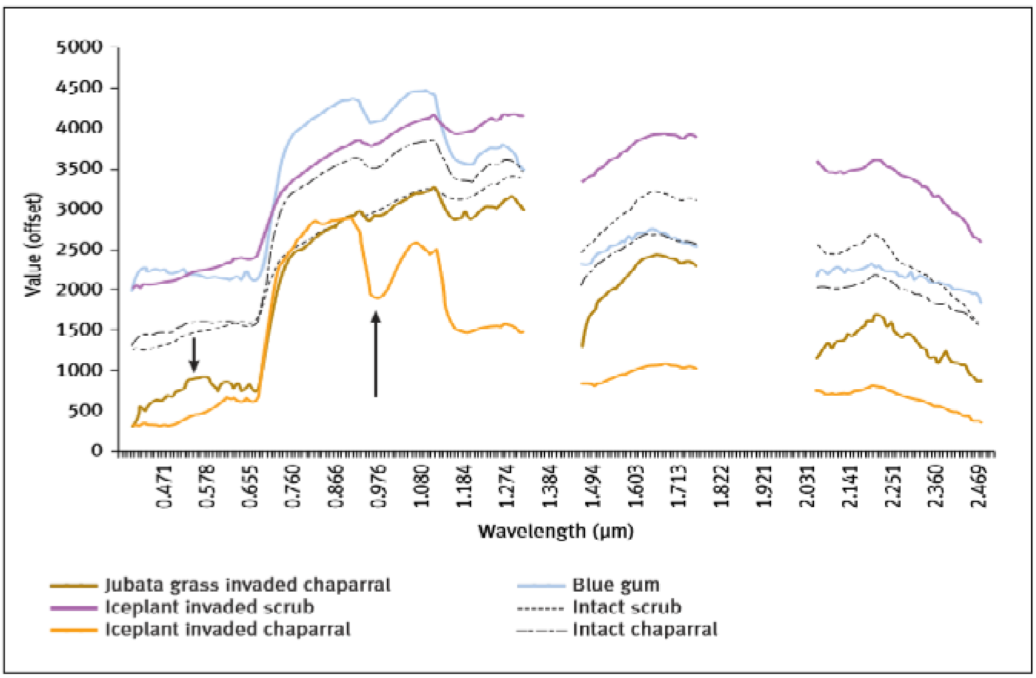

Figure 2. 1: Spectral signatures for different Alien Invasive Plants (AIPs). Adapted from Strand (2007).

According to Blossey and Notzold (1995), AIPs are often more vigorous and taller than co-existing vegetation due to disproportionate resource allocations. The improved physical development (i.e. vigor and height) of AIPs facilitates their discrimination from coexisting species, especially with active remote sensing sensors such as LiDAR, which can effectively detect the three-dimensional aspect of a feature on the ground. In an attempt to understand the invasiveness of exotic species with recognizable biological features to identify such plants, Goodwin *et al.* (1999) reported that differences in stem heights and flowering periods can be valuable in distinguishing AIPs from native plant species. Similarly, Everitt *et al.* (1995) reported that measuring plant species spectral reflectance at canopy level has been beneficial in delineating AIPs. Peerbhay *et al.* (2016c), further note that AIPs often form dense infestation stands in their new habitats, facilitating their discrimination using remote sensing techniques.

2.4 Multispectral remote sensing of alien invasion

The development of broadband remote sensing sensors such as Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), Satellite Pour l'Observation de la Terre (SPOT) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) marked the beginning of a new era in remote sensing of alien invasion (Lass *et al.* 2005). Generally, multispectral remote sensing sensors provide data collected between 10 – 100 m spatial resolution and in less than 20 bands (Huang and Asner 2009). Many studies (e.g. Evangelista *et al.* 2009; Savage and Lawrence 2010; Viana and Aranha 2010) have mapped and monitored AIPs spread using broadband coarse to medium spatial resolution data. As indicated in Table 2.1, the importance of these sensors includes not only the provision of large swath-width data but also repeated and free to cost-effective dataset (Mutanga *et al.* 2016; Matongera *et al.* 2016a) which can be archived to support multi-temporal remote sensing applications. Wilfong *et al.* (2009), for instance, used Landsat TM images captured in November 2005 and June 2007 together with a Landsat ETM+ image captured in January 2002 to detect the Amur honeysuckle (*Lonicera maackii* (Rupr.) Herder) in the Northeast of United States. Similarly, Evangelista *et al.* (2009) detected Tamarisk along Arkansas River in Colorado using Landsat ETM+ scenes acquired in April, May, June, August, September, and October.

The increased repeatability of earth observation using high temporal resolution sensors allows discerning vegetation types at different growth stages. Studies have shown that the use of images captured at different plant growing seasons is crucial for a precise detection and monitoring of changes in those plant species and in their coexisting vegetation (Hamilton *et al.* 2006; Joshi *et al.* 2004). Also, AIPs are characterized by distinctive contextual and structural features such flowering colour and canopy structures at various phenology, which can best be detected using images taken over time. For instance, the distinctive orange-brown colour of the Chinese tamarisk (*Tamarisk chinensis*), before leaf shading, aids its discrimination from neighboring vegetation (Everitt *et al.* 1995). Furthermore, the acquisition of images at different plant growing seasons offer a great opportunity to compare images taken at different sun's azimuth, reducing the impact of topography and cloud shadows (Matongera *et al.* 2016a). In some cases, AIPs obscure background of natural vegetation particularly at early stages of their growth (Peerbhay *et al.* 2015). Under such conditions, images acquired over time (e.g. during non-flowering and flowering seasons) facilitate reliable mapping (Huang and Asner 2009). On the other hand, the long-term and seasonal mapping of AIPs are vital to understand inter and intra annual distribution and abundance of such species. In addition, given that cloud cover is a challenge to satellite remote sensing, the use of multi-temporal remote sensing can optimize the acquisition of cloud-free images.

The launch of high spatial resolution multispectral sensors such as IKONOS, Quickbird and WorldView-2 are regarded a significant step towards the development of broadband sensor technology for improved detection and mapping of AIPs. For instance, Ngubane *et al.* (2014) reported an improved (91.67% overall accuracy) detection of Bracken fern in Durban, South Africa, using the high spatial resolution WordView-2 than the medium spatial resolution SPOT-5 (72.22% overall accuracy). Also, the *Pinus spp*. was successfully (84% overall accuracy) mapped by Forsyth *et al.* (2014) in mountainous regions of the Western Cape, using SPOT-6 imagery. Other studies that have reported an improved discrimination of vegetation types using high spatial resolution multispectral sensors include Oumar (2016), Peerbhay *et al.* (2016b), Li *et al.* (2016), Gómez-Casero *et al.* (2010), and Lawrence *et al.* (2006a). The strategically positioned bands in high spatial resolution multispectral sensors have significantly improved their performance in discrimination of vegetation types as compared to low spatial resolution multispectral sensors. Despite the improved spatial discrimination of features, literature shows that the utility of multispectral sensors in vegetation monitoring is still impeded by the poor spectral resolution (Ngubane *et al.* 2014).

Table 2. 1: A summary of satellite remote sensing sensors for mapping AIPs in relation to their resolutions, acquisition costs, scales of application and accuracies.

Sensor	Resolutions			Accessibility	Application scale	Accuracy	Authors
	Spatial	**Spectral**	**Temporal**				
ASTER	15 to 90 m	14 bands	16 days	Free	Local to regional	Very low to low	Viana and Aranha (2010)
AVHRR	1 to 4 km	5 bands	Daily	Free	Regional to global	Very low	Peters *et al*. (1992a)
Landsat 5 TM	30 to 120 m	7 bands	16 days	Free	Regional	Low to moderate	Gavier-Pizarro *et al*. (2012)
Landsat 7 ETM+	15 to 60 m	8 bands	16 days	Free	Local to regional	Moderate	Gavier-Pizarro *et al.* (2012), Viana and Aranha (2010)
Landsat 8 OLI/TIRS	15 to 100 m	11 bands	16 days	Free	Local to regional	Moderate	Matongera *et al*. (2017)
SPOT - 5	2.5 to 20 m	4 bands	2-3 days	Free in southern Africa	Local to regional	Moderate	Ngubane *et al.* (2014)
SPOT - 6	1.5 to 6 m	4 bands	Daily	Free in southern Africa	Local to regional	High	Oumar (2016), Forsyth *et al.* (2014)
WorldView-2	0.46 to 2.4m	8 bands	1 to 3 days	Expensive	Local	Very high	Robinson *et al.* (2016), Peerbhay *et al.* (2016b), Matongera *et al.* (2017), Ngubane *et al.* (2014)
IKONOS	0.82 to 4 m	5 bands	3 days	Expensive	Local	Very high	Li *et al.* (2016), Gil *et al.* (2013), Fuller (2005), Casady *et al.* (2005)
QuickBird	65 cm to 2.90 m	5 bands	1 to 3 days	Expensive	Local	Very high	Curatola Fernández *et al*. (2013)
Hyperspectral	< 1	>100	-	Very expensive	Local	Very high	Peerbhay *et al.* (2016a), Goel *et al.* (2002), Hunt (2010), Williams and Hunt (2002), Pu *et al*. (2008)

2.5 Hyperspectral remote sensing of AIPs

To compensate for the poor spectral resolution that characterizes multispectral sensors, hyperspectral sensors emerged with hundreds of narrow contiguous spectral bands to distinguish subtle inter and intra-species spectral variations (Atkinson *et al.* 2014; Cho *et al.* 2012). Generally, the hyperspectral dataset is collected at 2 to 16 nm spectral bandwidth across hundreds of spectral bands (Lass *et al.* 2002) and has been used to overcome the saturation problem commonly experienced with the adoption of multispectral sensors (Mutanga and Skidmore 2004). This has been demonstrated by Hunt *et al.* (2007), who tested the potential of Airborne Visible / Infrared Imaging Spectrometer (AVIRIS) with two broadband sensors (Landsat ETM+ and SPOT-4) to discriminate the Leafy spurge (*Euphorbia esula*L.) near Devils Tower National Monument in Crook County, Wyoming, USA. Their findings showed a superior classification accuracy of 74% when using the hyperspectral AVIRIS in comparison to Landsat ETM+ and SPOT-4, which yielded 49% and 48% overall accuracy, respectively.

Furthermore, the improved spectral resolution possible with hyperspectral dataset allows a superior classification of AIPs based on their biochemical and structural properties (Atkinson *et al.* 2014). With the improved spectral resolution that characterizes hyperspectral sensors, it has been possible to discern AIPs with superior accuracy, even on heterogeneous landscapes (Lawrence *et al.* 2006b). Other studies that have explored the utility of hyperspectral remote sensing in detection and mapping of AIPs include Peerbhay *et al.* (2015), He *et al.* (2011), Andrew and Ustin (2009), Hestir *et al.* (2008), Asner *et al.* (2008), Underwood *et al.* (2003) and Lass *et al.* (2002). Although the use of hyperspectral remote sensing has been essential in vegetation monitoring, the issue of small swath-width and high acquisition cost, as shown in Table 2.1, remains a challenge. Also, the huge amount of spectral information provided by hyperspectral sensors can increase data dimensionality and redundancy, thereby reducing classification accuracy when mapping AIPs (Peerbhay *et al.* 2016b).

2.6 The use of multisource data for detection of AIPs

Data fusion or multisource dataset is increasingly being adopted for detection and mapping of AIPs using remote sensing approaches (e.g. Skowronek *et al*. 2017; Ghulam *et al*. 2014; Asner *et al*. 2010). Data fusion involves the integration of datasets from two or more remote sensing sensors, with various strengths and limitations (Huang and Asner 2009). The fusion of multiple spectral, spatial and temporal properties in the same classification process push the limits of current remote sensing techniques. Peerbhay *et al.* (2016a), for instance, fused an AISA Eagle airborne hyperspectral dataset and a high spatial resolution WorldView-2, with LiDAR data to detect Bugweed in commercial plantation forests of KwaZulu-Natal, South Africa. Superior classification accuracies (78% for AISA with LiDAR) and (74% for WorldView-2 with LiDAR) were obtained with the integration of these datasets compared to 68%, 63% and 64% produced by AISA, WorldView-2 and LiDAR datasets alone. Similarly, Kimothi *et al.* (2010) optimized the detection and mapping of the *Lantana camara* in the Rajaji National Park of India using three Indian remote sensing sensors (IRS LISS-IV, LISS-IV and Cartosat-1) fused or in isolation. Whereas Cartosat-1 produced a poor classification accuracy of 65% when used alone, its accuracy was significantly improved to 96.4% and 92.9% when fused with IRS LISS-IV and LISS-IV, respectively.

However, the full potential of data fusion for optimal detection and mapping of AIPs has not been adequately explored. Whereas studies have shown the success of this method in detection of tree species from rangelands environment (Ghosh *et al.* 2014; Naidoo *et al.* 2012; Cho *et al.* 2012), the high-performance computing power required to process fused remotely sensed data makes the approach costly, especially for large-scale mapping purposes (Huang and Asner 2009). Furthermore, data fusion for detection of AIPs has mainly been dominated by the integration of either hyperspectral or multispectral dataset with LiDAR, which is costly, hence not a viable alternative for large-scale and continuous monitoring of AIPs. On the other hand, Peerbhay *et al.* (2016a) suggest that the impact of Bidirectional Reflectance Distribution Function (BRDF) still needs to be addressed to minimize false classifications that can, potentially, arise because of differences in solar and sensor geometry when using multisource data.

2.7 Parametric and non-parametric image classifiers for invasive alien plants

Despite the above-mentioned factors that may influence mapping accuracy, classification algorithms remain a major factor in landscape mapping and output reliability (Lu and Weng 2007). Broadly, image classification processes are performed using either supervised or unsupervised classification approaches (Strand 2007; Lass *et al*. 2005; Kelly *et al*. 2004). Image classifying algorithms could also be categorized based, among others, on either the obtainable information from the sensor, nature of the training dataset or on the basis of various parameters (Nath *et al.*

2014). The later could be subdivided to parametric and non-parametric image classifiers. The parametric image classifiers such as the Spectral angle mapper (SAM), Minimum Distance to Mean (MDM) and Maximum Likelihood (MLH) have been popular to enhance the discrimination of AIPs on the landscape and to reduce redundancy in remotely sensed data (Lu and Weng 2007). The advantage of these algorithms includes not only their easily accessibility with almost every image classifying software but also the unsophisticated nature in the application. Although the application of these image classifiers has been successful (e.g. Ngubane *et al.* 2014; Curatola Fernández *et al.* 2013; Peters *et al.* 1992b), numerous challenges are reported to impair their performance. For instance, parametric image classifiers provide classification output at a pixel level (Curatola Fernández *et al.* 2015) and that significantly compromise the classification accuracy, especially with poor spatial resolution multispectral dataset (Kumar and Min 2008). Also, parametric image classifiers assume that the chosen dataset for training the classification process represents an ideal (100%) cover of the feature or surface (Mather and Tso 2009; Campbell and Wynne 2011; Carson *et al.* 1995). Furthermore, parametric classifiers suffer from mixed pixel problem which is increased on heterogeneous landscapes (Matongera *et al.* 2016a; Lass *et al.* 2005), Hughes curse of dimensionality, Gaussian distribution of data (Abdel-Rahman *et al.* 2014) as well as the use of statistics to calculate class separation (Lu and Weng 2007).

On the other hand, the non-parametric classifiers such as the Artificial Neural Networks, Random Forest and Support Vector Machine have emerged with improved capabilities to retrieve biophysical features in vegetation. Odindi *et al.* (2014), tested the performance of the Random Forest on two multispectral datasets (WorldView-2 and SPOT-5) with an overall classification accuracy of 84.72 and 72.22% for WorldView-2 and SPOT images respectively. Gavier-Pizarro *et al.* (2012), successfully employed the Support Vector Machine to analyze the expansion of glossy privet (*Ligustrum lucidum*) using Landsat series data in Córdoba, Argentina. Similarly, Jay *et al.* (2009), classified patches of the Leafy spurge in a heterogeneous rangeland of Montana in the United States, using Random Forest on a single date and time-series, with a classification accuracy varying between 72% and 95%. The main advantage of non-parametric image classifiers is the ability to treat individual pixels as mixtures of pure materials and end-members in the classification process (Curatola Fernández *et al.* 2013). In this process, the classifiers sub-divide each individual pixel data to increase the spectral variance of different features within the pixels for superior and meaningful land cover composition as well as improved classification accuracy

(Kumar and Min 2008). As opposed to parametric classifiers that use statistics, non-parametric image classifiers such as the Artificial Neural Networks are not driven by statistical properties of the data and they are effective in extracting vegetation-type information even in heterogeneous landscapes (Gil *et al.* 2011). Generally, the non-parametric classifiers are suitable for classifying change than the parametric (Gavier-Pizarro *et al.* 2012).

2.8 The Importance of vegetation indices for detection of AIPs

Besides, vegetation indices, which are a ratio or linear band combinations, have been very instrumental in the mapping of AIPs (Lass *et al.* 2005; Gómez-Casero *et al.* 2010). Commonly used vegetation indices with AIPs mapping include the Normalized Difference Vegetation Index (NDVI) (Savage and Lawrence 2010; Underwood *et al.* 2003), Principal Component Analysis (PCA) (Carson *et al.* 1995), Enhanced Vegetation Index (EVI) (Wilfong *et al.* 2009), Tasseled Cap (TCAP) (Savage and Lawrence 2010), Simple Ratio (Wilfong *et al.* 2009), Soil Adjusted Vegetation Index (Waser *et al.* 2008), Visible Atmospherically Resistant Index (VARI) and Normalized Difference Moisture Index (NDMI) (Wilfong *et al.* 2009). Wilfong *et al.* (2009), tested the capabilities of six vegetation indices (EVI, TCAP, SR, SAVI, VARI and NDMI) against Landsat TM and Landsat ETM+'s traditional bands in predicting the Asian Amur honeysuckle invasion in the south-west of Ohio and eastern Indiana, United States. In the study, a superior classification model (coefficient (R^2) of 0.75 for quadratic regression and 0.65 for linear regression) were achieved using NDVI. Similarly, the incorporation of the NDVI in the classification of Bracken fern on Landsat 8 and Worldview-2 images significantly improved the mapping accuracy from 76.02% and 82.93% to 80.08% and 87.8% for Landsat 8 and WorldView-2 respectively (Matongera *et al*. 2017). Although vegetation indices are valuable for minimizing the spectral variability caused by differences in sun viewing angles, atmospheric conditions and soil background, Mutanga and Skidmore (2004), noted that some indices such as the NDVI are affected by saturation problem, especially in high canopy densities.

2.9 Relationship between classification algorithms and remote sensing dataset

Based on research, there is a limited literature to clearly show the synergies between a type of remotely sensed data used in conjunction with a chosen image classification algorithm. However, Nath *et al.* (2014), highlight that many image classification algorithms perform well on medium resolution multispectral data. Robinson *et al*. (2016), for instance, detected the invasive Mesquite in the north-western Pilbara, Australia using the multispectral WorldView-2 image with 80.7% overall classification accuracy. Although sensor resolutions, especially spectral and spatial, are significant factors for discriminating vegetation types (Oumar 2016), image classification algorithms also allow the appreciation of precise separation among different plants even when using the averaged spectral and poor spatial resolution data. For instance, Matongera *et al.* (2017), compared the performance of two different sensors with various spatial and spectral properties (i.e. high spatial WorldView-2 and medium spatial Landsat 8 OLI) in detecting Bracken fern using Discriminant Analysis. Despite the difference in resolutions of these two datasets, obtainable results reveal an insignificant or negligible (9%) magnitude of difference in overall classification accuracies. Evidently, the choice of an image classifier chosen for a particular image classification process is vital to improve the capabilities of a remote sensing sensor data used.

Therefore, the launch of the new generation of multispectral sensors such as SPOT-6 can improve the detection of AIPs even by resource-limited region. The improvement in detection of AIPs will not only be due to improved sensor resolutions but rather the large swath-width and cost-effectiveness that allows repeated and operational scale monitoring of AIPs. Also, the application of robust and advanced non-parametric image classification algorithms can significantly improve the performance of these recently launched multispectral sensors. To demonstrate the role of non-parametric image classifiers over parametric classifiers Gil *et al.* (2011), tested the performance of two parametric (Maximum Likelihood and Mahalanobis Distance) and non-parametric (Artificial Neural Network and Support Vector Machine) algorithms in assessing the potential of high-resolution satellite imagery in vegetation mapping. Although the Maximum Likelihood performed well (76.93%) the Mahalanobis Distance performed badly with an overall accuracy of 66.04%. On the other hand, both the non-parametric classifiers were successful (76.95% and 76.25% for Support Vector Machine and Artificial Neural Network, respectively) in spectral separation between different vegetation classes. Furthermore, the Spectral Angle Mapper performed poorly when classifying the Leafy spurge using SPOT-4, Landsat ETM+ and AVIRIS data with overall accuracies of 48%, 49% and 74% respectively.

2.10 Challenges in remote sensing of alien invasion

As aforementioned, the success of remote sensing of alien invasion relies on the identification of unique spectral signatures for such plants as facilitated by differences in their biophysical and biochemical characteristics (Matongera *et al.* 2016a). However, when differences in these properties are not sufficiently pronounced to increase spectral variance, erroneous spectral resemblance will be recorded by the sensor for dissimilar plant species, reducing mapping accuracy of target AIPs. This is common when using broadband coarse to medium spatial resolution sensors (Huang and Asner 2009). Also, because AIPs often grow in a mix of co-existing vegetation, their detectability can be considerably compromised, especially with averaged spectral and lower spatial resolution datasets (Matongera *et al.* 2016a; Huang and Asner 2009). The large pixel sizes coupled with averaged spectral data offered by multispectral sensor highlights that their adoption for AIPs mapping is limited to homogenous landscapes (Hamilton *et al.* 2006; Carson *et al.* 1995; Cardina *et al.* 1997). Carson *et al.* (1995), for instance, recommends that infestation stands should be large enough or dominate the canopy to compensate for the poor spatial and spectral resolution of these sensors. Hamilton *et al.* (2006), indicated that a precise detection of Russian olive (*Elaeagnus angustifolia L.*) in central Utah was influenced by patch sizes, with small patches being underestimated or even entirely missed. According to Peerbhay *et al.* (2016c), the uniformity and extensiveness required when detecting the distribution of AIPs, especially with poor spatial and averaged spectral resolution datasets, is not always attainable in the newly invaded landscapes. Although these sensors provide data for multi-temporal mapping of AIPs, the success of discerning AIPs use images taken during different plant phenology depends on the availability of clear or cloud-free skies (Huang and Asner 2009) and a precise core-geo-registration (Singh 1989).

Moreover, studies show that the development of satellite sensor technology is caught between balancing improvements in sensors resolutions and reducing acquisition cost while simultaneously achieving large-scale mapping of vegetation (Mutanga *et al.* 2016). Besides the improved mapping accuracy possible with fine resolution sensors, their value for precise mapping at an operational scale has not been fully explored (Lu and Weng 2007). More so, the excessive acquisition costs for high spatial and hyperspectral resolution imagery is prohibitive for long-term and continuous monitoring of AIPs spread in countries and institutions with limited resources. The swath-width or area coverage and the application scale of fine spatial resolution multispectral and hyperspectral sensors are given in Table 2.1. Studies have shown that hyperspectral sensors suffer from effects of multicollinearity and multidimensionality (Gómez-Casero *et al.* 2010) and hence not the ultimate solution to the current problem of poor AIPs mapping accuracy. Therefore, it can be concluded that the current research focus of vegetation monitoring on exploration and utility of high spatial resolution and hyperspectral dataset prevent great opportunity to appreciate the continued and operational scale monitoring of AIPs spread. This is likely due to the associated cost of acquiring these datasets and their small area coverage. The insignificance of this is increasingly being a problem, particularly for rangelands monitoring programmes which are broad and extensive in extent. More so, the integration of data from different sensors does not address the small swath-width dataset provided by high spatial resolution and hyperspectral image data.

2.11 Possible directions of future research

Whereas there is considerable progress in the detection and mapping of AIPs using remote sensing techniques, the full potential of this technology in estimating and mapping the distribution of AIPs has not been adequately explored. This has been demonstrated by the current tradeoffs in sensor developments (i.e. resolution and acquisition costs) and application scale (Mutanga *et al.* 2016). Also, numerous attempts in detection and mapping of AIPs are increasingly dominated by the utility of high spatial and hyperspectral dataset (e.g. Peerbhay *et al*. 2016b; Peerbhay *et al*. 2015; Curatola Fernández *et al*. 2013; Narumalani *et al*. 2009; Casady *et al*. 2005). The acquisition costs of such dataset are prohibitive to repeated and large-scale mapping of AIPs spread, particularly in countries and institutions with limited capital. Also, recent developments in remote sensing sensors technology (i.e. unmanned aerial vehicle) do not address the aforementioned challenges of image acquisition costs in relation to scale of application.

To optimize detection and mapping of AIPs in these regions, it is necessary to explore the capabilities of the freely available and improved spatial and spectral resolution multispectral datasets such as SPOT 6 and 7 as well as Sentinel-2 in concert with robust and advanced machine learning algorithms. The newly launched SPOT 6 and 7 provide daily coverages with improved spatial resolution (i.e. 6m, see Table 2.1), valuable for multi-temporal vegetation monitoring. On the other hand, the Sentinel-2 offers large area coverages captured at 10 m by 10 m spatial resolution, necessary for an improved operational approach in vegetation monitoring. Equally important, the advanced machine learning image classifiers have been valuable for vegetation monitoring as well as detection of AIPs. For instance, using the multispectral WorldView-2 and SPOT-5 data in concert with Random Forest Odindi *et al.* (2014), mapped Bracken ferm distribution with overall classification accuracies of 84.72% and 72.22%, respectively. Oumar

(2016), also detected the Lantana camara in rangelands of KwaZulu-Natal, South Africa using SPOT-6 data and Random Forest with an overall accuracy of 75%. Furthermore, The Support Vector Machine and Random Forest yielded good classification accuracies (91.80% and 93.07%, respectively) when mapping patterns and spatial distribution of land-use/cover types in a heterogeneous landscape of KwaZulu-Natal, South Africa, using RapidEye data (Adam *et al.* 2014). However, studies of alien invasion using the improved resolution data and non-parametric classification algorithms are mainly based on single-date image scene. With increased free provision of multispectral data with improved resolution combined with the value of non-parametric algorithms to facilitate classification accuracies, timely and large-scale updates pertaining the spatial and temporal distribution of AIPs are achievable.

2.12 Conclusions

The current study reviewed existing literature on the adoption of remote sensing data and techniques for detection and mapping of AIPs spread. Empirical evidence has revealed that the use of traditional methods, such as field surveys and aerial photographs are not appropriate for mapping and monitoring of invasive species encroachment at a regional scale. The early multispectral datasets with poor spatial resolution, e.g. ASTAR, AVHRR and Landsat series, has been imperative for the detection and mapping of AIPs. On the other hand, the literature shows that limited spatial resolution and poor radiometric resolution of these data sets compromise AIPs detection and mapping accuracy. Furthermore, high spatial resolution multispectral sensors such as WorldView-2, Quickbird and IKONOS have emerged with improved capabilities to discriminate AIPs from other co-existing vegetation species. The major challenges in detection and mapping of AIPs established in this review include heterogeneity in infested landscapes, causing spectral confusion during classification. Also, the review found out that the increasing use of high spatial resolution and hyperspectral datasets for monitoring AIPs is not sustainable due to its excessive acquisition costs, especially for resource-limited institutions. Recent advancements in the multispectral remote sensing, e.g. SPOT 6 and Sentinel-2, have balance these challenges by providing repeated coverages with improved spatial and spectral properties at relatively cost-effective or free of charge for some regions (e.g. SPOT 6 in southern Africa). To improve the large-scale and continuous mapping of AIPs spread, the current study recommends that future studies should focus on integrating the freely available and improved resolution multispectral data with robust machine learning algorithms.

Chapter Three

Determining multi-temporal distribution of Parthenium (*P. HysterophoruL)* using SPOT series data and Random Forest

The following paper is based on a manuscript currently under review:

Royimani, L., Mutanga, O., Odindi, J., Kiala, Z.S. & Sibanda M. (**Under review**). Determining multi-temporal distribution of Parthenium (*P. HysterophoruL*) using SPOT series data and Random Forest. *International Journal of Remote Sensing*.

Abstract

Detecting the spatial and temporal distribution of AIPs such as Parthenium is crucial for facilitating management and mitigation of spread. The availability of historical remotely sensed data with a fine spatial resolution from the SPOT 5, 6 and 7 mission offers greater prospects to cost-effective management of AIPs spread. This study sought to determine the spatial and temporal distribution of Parthenium using multi-temporal SPOT series data, Random Forest and Land Change Modeler (LCM). Findings shown that, Parthenium has been, generally, decreasing over the 10-year period of the study. The general decline in Parthenium distribution is attributed to the low annual rainfall in the recent past. However, the sharp incline in Parthenium spread in the year 2016 is attributed to the high rainfall, leading to increased invasion on vacant or bare areas. Generally, low rainfall has not only affected Parthenium distribution but also other vegetation classes such as grassland, thereby increasing the area of bare soils. Moreover, increased Parthenium spread has been recorded from areas with frequently altered soils, as opposed to areas of infrequent manipulated soils. This study has demonstrated the value of cost-effective multispectral SPOT series data in concert with robust and advanced non-parametric Random Forest classifier in detecting and mapping the spatial and temporal spread of AIPs.

Key words: SPOT series, Random Forest, Parthenium, distribution, spatial, temporal

3.1. Introduction

Parthenium is an aggressive herbaceous plant from the south and central America that has colonized and naturalized in many regions of the world, such as Australia, Asia and Africa (McConnachie 2015; Zuberi *et al.* 2014; Goodall *et al.* 2010). In Africa, the plant has become prevalent in the eastern and southern parts of the continent (Zuberi *et al.* 2014). In South Africa, Parthenium was first recorded at the Inanda area of KwaZulu-Natal in 1880 and later spread to other regions following the Tropical Cyclone Domoina in 1984 (McConnachie 2015; Goodall *et al.* 2010). Its tolerance and adaptability to a wide range of environmental conditions as well as soil types has intensified its exponential growth and expansion to the newly invaded landscapes (Ayele 2007). Parthenium is characterized by longitudinal grooved stem and leaves that are covered by short hairs and a general growth of up to 2 meters height under favorable conditions (McConnachie *et al.* 2011). At optimum conditions, Parthenium can complete its life cycle in four weeks, with approximately 15 000 to 25 000 seeds produced per plant (Goodall *et al.* 2010; Adkins *et al.* 2010). At dense infestations, the plant forms a large seed bank, estimated to 200 000 seeds per m^{-2}, that remain in the soil for a long time (Goodall *et al.* 2010). Seed dispersal is by wind, water and vehicles (Wabuyele *et al.* 2014). Literature shows that the annual germination and growth of Parthenium is limited by soil moisture (Goodall *et al.* 2010).

Studies have shown that Parthenium establishes and develops well in disturbed areas, such as roadsides, overgrazed areas and fallow agricultural lands (Karki 2009a) where native plants are still in the early stages of rejuvenation. The ecological impact of Parthenium includes displacement of native flora and fauna as well as the significant decline in local biodiversity (Karki 2009a). Its capabilities to displace native plants are strengthened by its allelopathic qualities (McConnachie 2015; Ayele 2007; Karki 2009a). In allelopathy, poisonous allelochemicals such as phenolics and lactones are produced by Parthenium leaves, thereby inhibiting germination and growth of native species (McConnachie *et al.* 2011). Also, the weed is unpalatable to grazers (Karki 2009a), thereby allowing its long-lasting growth and spread. Parthenium is also known to affect rangeland quality and quantity (Shrestha *et al.* 2015; Brunel *et al.* 2014). Its uncontrollable and fast-growing rate has the ability to reduce forage productivity by up to 90% (Ayele 2007). It is also known to affect animal health, milk and meat production (Evans 1997). In croplands, Parthenium can act as a host to crop pests and disease (Evans 1997). Similarly, there are numerous human health risks reported from Parthenium and these include, asthma, dermatitis and rhinitis (Evans 1997).

Traditionally, data for the monitoring and control of Parthenium has been acquired by means of manual methods such as field surveys (McConnachie 2015; McConnachie *et al.* 2011). However, the success of such methods in the monitoring of alien invasion has been mainly limited to small-scale applications (Peerbhay *et al.* 2016b). Alternatively, remote sensing has emerged as a reliable approach for mapping the spread of AIPs spread at the landscape scale (Matongera *et al.* 2017; Odindi *et al.* 2016; Oumar 2016). Studies have demonstrated the successes of remote sensing in the detection and mapping of the AIPs spread (Robinson *et al.* 2016; Ngubane *et al.* 2014; Casady *et al.* 2005). Gil *et al.* (2013), for instance, mapped the invasive *Pittosporum undulatum* in a Protected Area of Sao Miguel Island, Portugal, using IKONOS dataset, while Fuller (2005) mapped the distribution of the Melaleuca (*Melaleuca quinquenervia* (Cav.) S.T. Blake) with 85.66% overall classification accuracy using IKONOS data in the south of Florida, United States. Despite the fine spatial resolution in these sensors, the excessive acquisition costs coupled with small area coverage are prohibitive to the continuous and large-scale mapping of AIPs, especially for financially constrained regions such as southern Africa.

The signing of the license agreement by the South African National Space Agency (SANSA) and Airbus Defence and Space (ADS) has ensured a steady supply of SPOT imagery for South Africa (Oumar 2016). Furthermore, the South African government has signed a single licence government multi-user agreement with SANSA to ensure that SPOT images are freely available for public use, making it an alternative to the high spatial and hyperspectral dataset. The SPOT mission, also, offers large volumes of archival data with improved spatial properties (Oumar 2016) to detect trends and patterns, both, in the current and historical distribution of AIPs. More so, the robust and advanced non-parametric image classifiers such as Random Forest have been valuable for detecting AIPs spread (Kganyago *et al.* 2017; Abdel-Rahman *et al.* 2014; Pal 2005). Therefore, the current study aims to determine the spatial and temporal distribution of Parthenium using SPOT series data and Random Forest. Several studies (e.g. Matongera *et al.* 2017; Oumar 2016) have shown that the incorporation of vegetation indices is instrumental for improving classification accuracy, hence the computation of the eight vegetation indices. The Land Change Modeler (LCM) was used to determine the temporal changes in Parthenium distribution as well as the degree of change. Determining the dynamics in Parthenium distribution was necessary to examine the hypothesis that its spread is intensified by the creation of bare or vacant lands.

3.2 Methods and Material

3.2.1 Description of the study site

The study was conducted within the Mtubatuba local municipality on the north-east coast of KwaZulu-Natal, South Africa (Figure 3.1). The extent of the study area is approximately 4750 ha. The area falls within the Maputaland-Pondoland-Albany biodiversity hotspot and is characterized by subtropical climates with hot to warm summers and mild winters (Grundling *et al.* 2013). The mean annual rainfall is approximately 980 mm with most of it occurring during the summer months (i.e. September to March) (Wigley *et al.* 2009). Dominant vegetation includes tropical bush and savannas as well as coastal tropical forests (Wigley *et al.* 2009). The underlying geological formation includes granitoids and gneisses of the Mzumbe Terrane of the Natal Metamorphis Province (Thomas, 1989). Also, these rocks are overlaid by arkosic and quartz arenites of the Natal Province (Marshall, 2002).

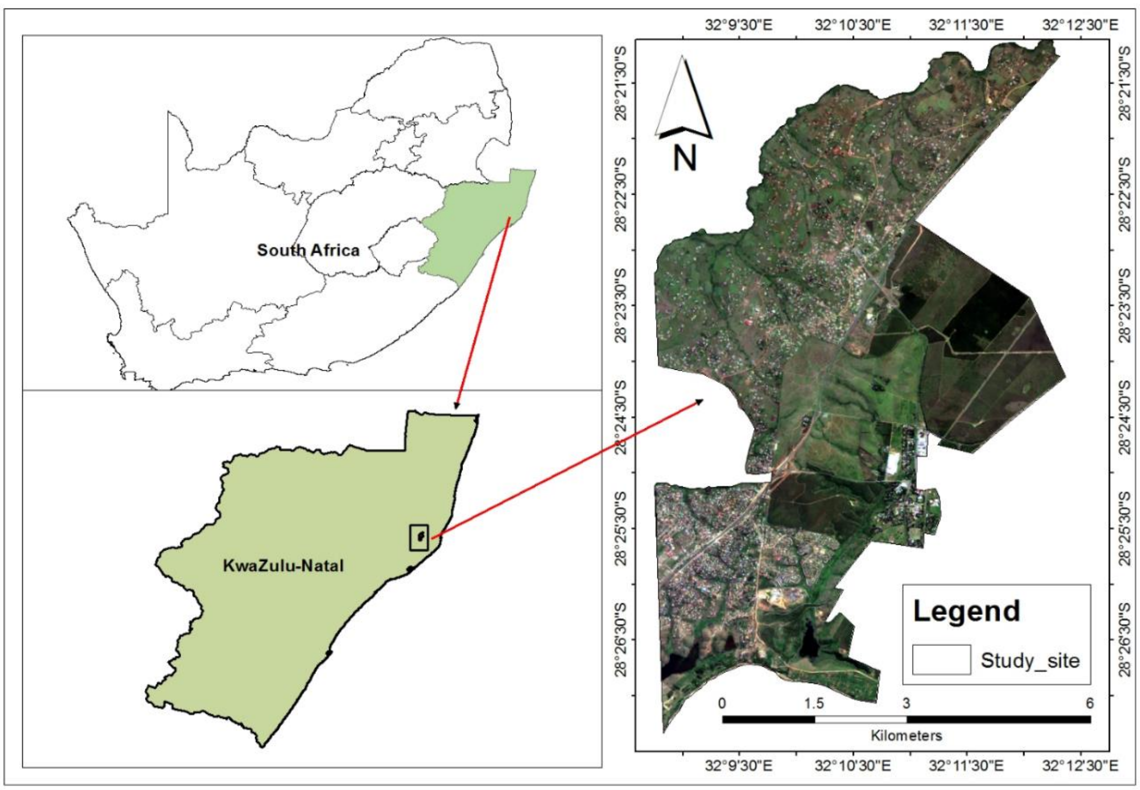

Figure 3. 1: Location of the study area in Mtubatuba municipality, KwaZulu-Natal, South Africa.

The area is known for its long history of Parthenium infestation. According to the National Implementation Plan for the management of Parthenium in South Africa, this region falls within the “asset protection” zone in the province of KwaZulu-Natal.

3.2.2 Field data collection

Field data were collected from the 30th of January to the 5th of February 2017 using a differentially corrected Trimble GeoXT handheld Global Positioning System (GPS) receiver with a sub-meter accuracy. The ground truth data were collected for Parthenium infestations and other classes such as forests, grassland as well as bare soils in the study area. However, training points for built-up areas were digitized on-screen using aerial photographs. According to Ismail *et al.* (2016), AIPs are generally not distributed uniformly in their invaded habitats, therefore, purposive sampling approach was used to identify Parthenium patches that are larger than 10 m2. The 10 m2 patch size of Parthenium infestation was necessary to complement the spatial resolution of the SPOT-5 sensor. Parthenium locational information and percentage cover were recorded while only the locational information was recorded for the other classes. An average of 100 GPS points was recorded for Parthenium infestations while 60 GPS points were recorded for each of the other classes. A total of 340 GPS points were collected for all the five classes across the study area. The data was then divided into 70% training and 30% validation.

3.2.3 Image acquisition and preprocessing

Three SPOT-5 and one SPOT-6 scene were acquired from the SANSA online catalog. The images used were chosen based on either the availability from the supplier’s archive or the amount of cloud cover. Besides the improved spatial resolution (Oumar 2016), SPOT mission provides large volumes of historical datasets to promote multi-temporal remote sensing of alien invasion. Table 3.1 provides the acquisition dates and characteristics of all the four SPOT data used in this study. All the images were acquired in summer (i.e. December to March) when vegetation was full of vigor due to high precipitation in the area (Wigley *et al.* 2009). For consistency in the dataset, the SPOT-6 image was sampled to 10 m2, which is comparable to SPOT-5’s spatial resolution. Additionally, Otunga *et al.* (2014), emphasized the importance of image co-rectification when using multi-temporal remote sensing to allow conformity in the dataset and meaningful spatial comparison. The 2006, 2009 and 2012 image scenes were co-registered to the 2016 SPOT-6 image to less than half a pixel Root Mean Square Error (RMSE). In this study, image normalization was done as described by El Hajj *et al*. (2008), using dark object subtraction (DOS) approach available on ENVI 5.2. The DOS approach is data dependent (Gilmore *et al*. 2015).

Table 3. 1: Image acquisition dates and sensor characteristics.

Sensor	Acquisition date	Resolutions		Center coordinates
		Spatial	Spectral	
SPOT-6	2016 – 02 – 11	6m	4 bands	S28° 28' 02": E32° 29' 03"
SPOT-5	2012 – 12 – 09	10m	4 bands	S28° 28' 22": E31° 53' 29"
SPOT-5	2009 – 12 – 22	10m	4 bands	S28° 28' 26": E31° 53' 20"
SPOT-5	2006 – 12 – 15	10m	4 bands	S28° 28' 24": E32° 27' 15"

3.2.4 Vegetation indices retrieval

Eight vegetation indices (Table 3.2) were computed in this study to improve classification accuracy. These indices were chosen based on their importance for minimizing the effect of soil background or to enhance greenness in vegetation. For instance, the NDVI has been successful in estimating biomass and crop yields (Oumar 2016; Matongera *et al.* 2017). Also, the use of NDVI as opposed to the classification of raw bands is recommended for change detection techniques (Blaschke 2005). According to Evangelista *et al.* (2009), the Simple Ratio (SR) works relatively similar to the NDVI by measuring the spectral responses between the red and NIR bands respectively. The Soil Adjusted Vegetation Index (SAVI) has been imperative in minimizing the effect of soil background as well as sparsely distributed vegetation (Amiri and Tabatabaie 2009). The Difference Vegetation Index (DVI), which subtracts the red band from the near infrared bad, has been instrumental for vegetation monitoring (Mulla 2013). The Green Ratio Vegetation Index (GRVI), Green Normalized Difference Vegetation Index (GNDVI), Green Difference Vegetation Index (GDVI) and the Infrared Percentage Vegetation Index (IPVI) have also been recommended for use in remote sensing of vegetation monitoring (Wu 2014; Amiri and Tabatabaie 2009).

Table 3. 2: Selected vegetation indices for discerning green and non-green features.

Vegetation indices	Formula	Reference
Normalized Difference Vegetation Index (NDVI)	NIR-red/NIR+red	Matongera *et al.* (2017)
Difference Vegetation Index (DVI)	NIR-red	Dube *et al.* (2015)
Green Difference Vegetation Index (GDVI)	NIR-green	Mulla (2013)
Green Normalized Difference Vegetation Index (GNDVI)	NIR-green/NIR+green	Mulla (2013)
Green Ratio Vegetation Index (GRVI)	NIR/green	Wu (2014)
Infrared Percentage Vegetation Index (IPVI)	NIR/NIR+red	Amiri and Tabatabaie (2009)
Simple Ratio (SR)	NIR/red	Evangelista *et al.* (2009)
Soil Adjusted Vegetation Index (SAVI)	NIR-red/NIR+red * (1+L)	Amiri and Tabatabaie (2009)

3.2.5 Random Forest algorithm

The Random Forest is a machine learning approach developed by Breiman (2001) to facilitate the classification process by combining a large set of decision trees. The benefits of Random Forest is that it is non-parametric (distribution-free) and does not suffer from the Hughes phenomenon of over-fitting (Abdel-Rahman *et al.* 2014). Furthermore, the Random Forest is stable and faster (Chan and Paelinckx 2008), and can be easily implemented and interpreted (Odindi *et al.* 2014). The approach uses a bagging (bootstrap) operation to randomly fit numerous decision trees on various subset of samples of the data and employs the averaging technique to improve the predictive accuracy and control over-fitting (Abdel-Rahman *et al.* 2014). In the process, multiple classification trees are created based on a random subset of samples. The multiple classification trees then vote by plurality on the correct classification (Oumar 2016). The one-third samples not used in the bootstrap samples (out-of-bag (OOB)) are used to estimate the misclassification error and the variable importance (Chan and Paelinckx 2008).

3.2.6 Image classification and Model optimization

Spectral reflectance values were extracted using the 340 sampling points collected from the field to train the classification of the 2016 SPOT scene. The non-parametric Random Forest (Adelabu *et al.* 2014; Abdel-Rahman *et al.* 2014; Odindi *et al.* 2014) was then used to classify all the image pixels based on the trained parameters. The older images were classified by the use of combined data sources such as the very high spatial resolution ($0.5m^{-2}$) aerial photograph, Google Earth Imagery and thematic maps from the preceding image classification outputs. The Google Earth Imagery and aerial photographs were acquired on the 20^{th}, 10^{th} and 12^{th} of December 2012, 2009 and 2006 respectively. In the process, the initial (2016) thematic map was overlaid with the aerial photograph and Google Earth Imagery to obtain training dataset for the 2012 image scene. The process was iterated with the 2012 SPOT scene to train classification of the 2009 image scene and the 2009 image used to classify the 2006 image scene. However, optimal discrimination between Parthenium and grassland, and built-up and bare soils was not achieved. To compensate for this error, areas of clearly recognizable land use/cover types were identified on-screen from each thematic map and aerial photographs to gather training datasets to repeat the image classification process until satisfactory results were obtained.

Random Forest model optimization was achieved by using feature selection and hyperparameter tuning. This process was necessary to determine the best performing parameters for the highest obtainable classification output (Abdel-Rahman *et al.* 2014; Adelabu *et al.* 2014 Breiman 2001). To facilitate the process, spectral band importance rankings were generated using the tree-based feature selection process. Subsequently, multiple thresholds were calculated for selecting bands based on their importance. Starting with all the bands and ending with the most important band, the model was trained and evaluated on the test dataset using the overall classification accuracy metric to find the optimal subset of bands. The use of feature selection in the model criterion was beneficial because it decreases data training time while improving classification accuracy concurrently. Hyperparameter tuning was performed on the model created from relevant bands using the Grid-search approach.

3.2.7 Accuracy assessment

The contingency table also known as the confusion matrix is one of the most popular methods used to test the performance of the classification process and a chosen classifier thereafter (Oumar

2016). Subsequently, the confusion matrix was used in this study to validate the performance of the Random Forest algorithm. The user's, producer's and the overall classification accuracies were used as criteria to assess the performance of the classifier. The user's accuracy indicates the probability that a pixel belongs to a certain class as assigned by the classifier, while the producer's accuracy expresses the likelihood of a particular feature being correctly classified (Abdel-Rahman *et al.* 2014). The overall accuracy is a ratio in percentage between the number of correctly classified classes and the number of test data (Abdel-Rahman *et al.* 2014).

3.2.8 Post-classification and change detection

To quantify changes in earth surface land cover features using remote sensing data, Waser *et al.* (2008), suggest that dissimilarities between different images (i.e. *imag1 – imag2*) of the same area be computed after image co-registration. Therefore, in this study, to detect changes and determine the degree of change in areas of land occupied by different land use/cover types, a 'from-to' post-classification procedure was applied using LCM available in IDRIS software. Studies reveal that this procedure is valuable for separating multi-temporal image classification and for image comparisons (Otunga *et al.* 2014). Also, the LCM was essential to detail the spatial increases and decreases as well as the degree of change from one class to the other. To identify land use activities that are more influential to Parthenium expansion, the study area was divided into agricultural and non-agricultural dominated fields. The agricultural dominated fields were made up of forest plantation and pastoral or grazing lands whereas non-agricultural dominated fields formed by residential areas.

3.2.9 Annual rainfall distribution

According to literature, growth and distribution of Parthenium is determined by the available soil moisture (Goodall *et al.* 2010). Therefore, historical rainfall data were acquired for the Mtubatuba local municipality from the South African Sugarcane Research Institute (SASRI) to understand the influence of rainfall on Parthenium distribution. Rainfall data from SASRI is presented in three respective categories; daily, weekly and monthly reports. To fulfill the objective of this study, the monthly rainfall data were downloaded from the year 2006 to 2016. Then, all the monthly datasets were averaged for each year to get the annual rainfall for each year. However, only annual rainfalls for the years that were complementary to the chosen years of image analysis (i.e. 2006, 2009, 2012 and 2016) were used.

3.3 Results

3.3.1 Assessment of classification accuracies

Table 3.3, shows the user, producer and overall classification accuracies obtained based on the Random Forest algorithm. The bands from the visible region (i.e. green, red and the Near Infrared) yielded the highest overall classification accuracies when using the SPOT-5 scenes whereas all the four bands (blue, green, red and Near Infrared) of SPOT-6 were significant in discriminating among the chosen land use/cover types. Although the chosen vegetation indices were valuable for discrimination between vegetation classes (i.e. forest, grassland and Parthenium) and non-vegetated area, their performance was inferior in separating vegetation classes and between bare soils and built-up areas.

Table 3. 3: Accuracy assessment using error matrix for classifying the 2006, 2009, 2012 and 2016 SPOT scenes.

Sensor	Acquisition year	PA (%)	UA (%)	OA (%)
SPOT-6	2016	68	64	71
SPOT-5	2012	75	71	75
SPOT-5	2009	78	78	78
SPOT-5	2006	64	65	70

Notes: PA= Producer Accuracy, UA= User Accuracy, OA= Overall Accuracy.

3.3.2 Land use/land cover transformation and Parthenium distribution

Figure 3.2 and 3.3 illustrate the dynamics in Parthenium distribution in relation to other land cover/use transformations in year 2006, 2009, 2012 and 2016. According to these figures (Figure 3.2 and 3.3) Parthenium has remained a dominant class covering most (29% and 28%) of the study area in the year 2006 and 2009, respectively. During the same period, the class of bare soil was significantly reduced to 12% and 14% in 2006 and 2009, respectively.

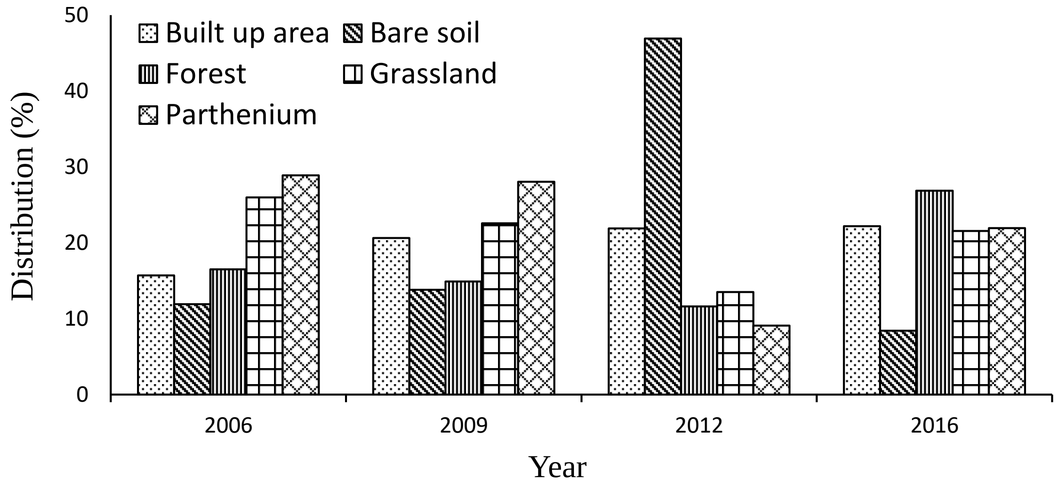

Figure 3. 2: Parthenium distribution and land use/land cover transformation.

However, in the year 2012, the area of bare soil increased substantially (47%), taking over most of what previously used to be covered by Parthenium and grassland (Figure 3.9(a)). A detailed class succession among these different classes is given in Table 3.4. It is evident that the spreading of Parthenium is influenced by changes in other land cover/use types in the study area. For instance, the slight decrease in the area of land occupied by Parthenium in year 2009 has intensified the creation of open and bare soils in the same year (Figure 3.2 and 3.3). Similarly, the drastic decline in all vegetation classes (i.e. forest, grassland and Parthenium) in year 2012 led to the sharp incline in land area of bare soils.

Table 3. 4: Assessing the 'from-to' class alterations and the degree of change.

Year	Succeeded class	Succeeding class	Succeeding value (%)
2009	Forest	Bare soil	1.6
	Parthenium	Bare soil	1
	Grassland	Built-up area	3.4
2012	Forest	Bare soil	3.3
	Grassland	Bare soil	7.8
	Grassland	Built-up area	1.3
	Parthenium	Bare soil	19
2016	Bare soil	Built-up area	0.3
	Bare soil	Forest	15.3
	Bare soil	Grassland	8
	Bare soil	Parthenium	12.9

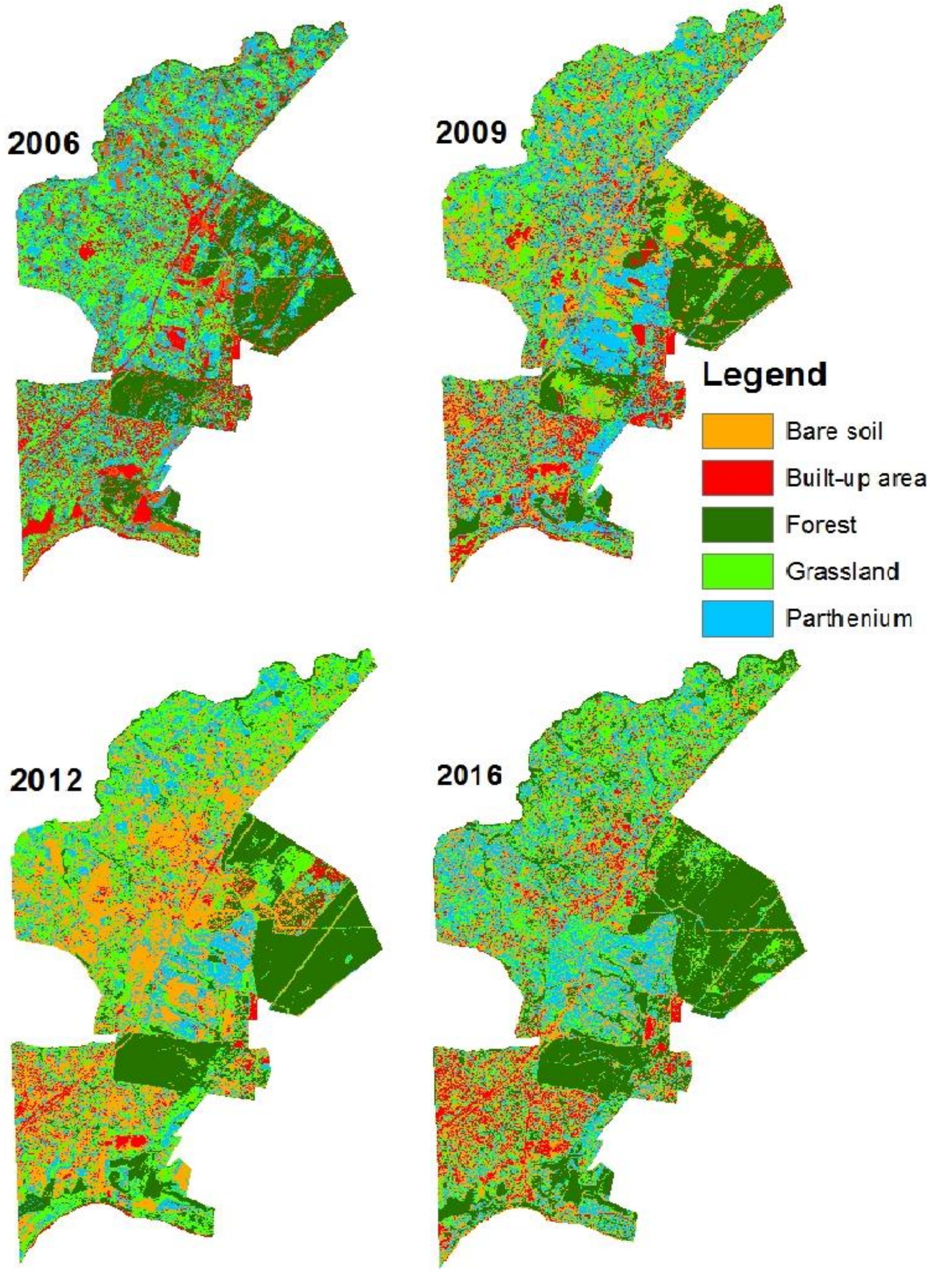

Figure 3. 3: Parthenium distribution in relation to other land use/cover change for the study period.

In the year 2016, there was a recovery in all the vegetation classes invading most of the previously vacant or bare soil area. Meanwhile, the built-up area class maintained its consistency for most of the study period.

3.3.3 Spatial and temporal variability in Parthenium distribution

In general, Parthenium has shown an uneven trend of either increase or decrease over the 10-year period from 2006 to 2016 (Figure 3.4 and 3.5). Besides, the highest infestations of Parthenium, covering 29% and 28% of the study site, were recorded in the year 2006 and 2009 respectively. In the year 2012, the area occupied by Parthenium dropped significantly to 12% of the total land area within the study site. However, in the year 2016, Parthenium spread increased to almost 22% of the total land mass. The low or poor R-squared (R^2 = 0.5024) value in Figure 3.4 also confirms this uneven distribution in Parthenium spreading across the study area.

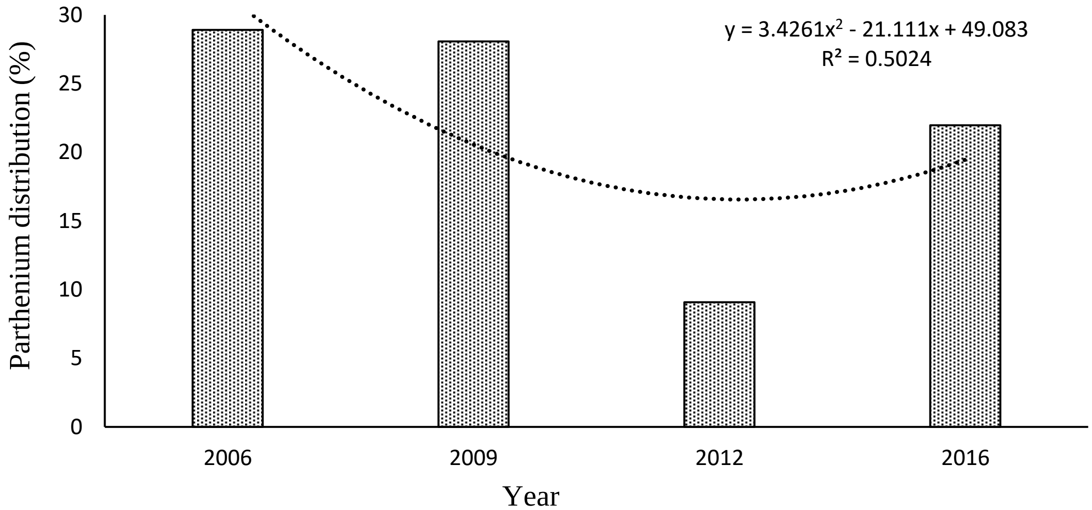

Figure 3. 4: Trends in Parthenium distribution from 2006 to 2016.

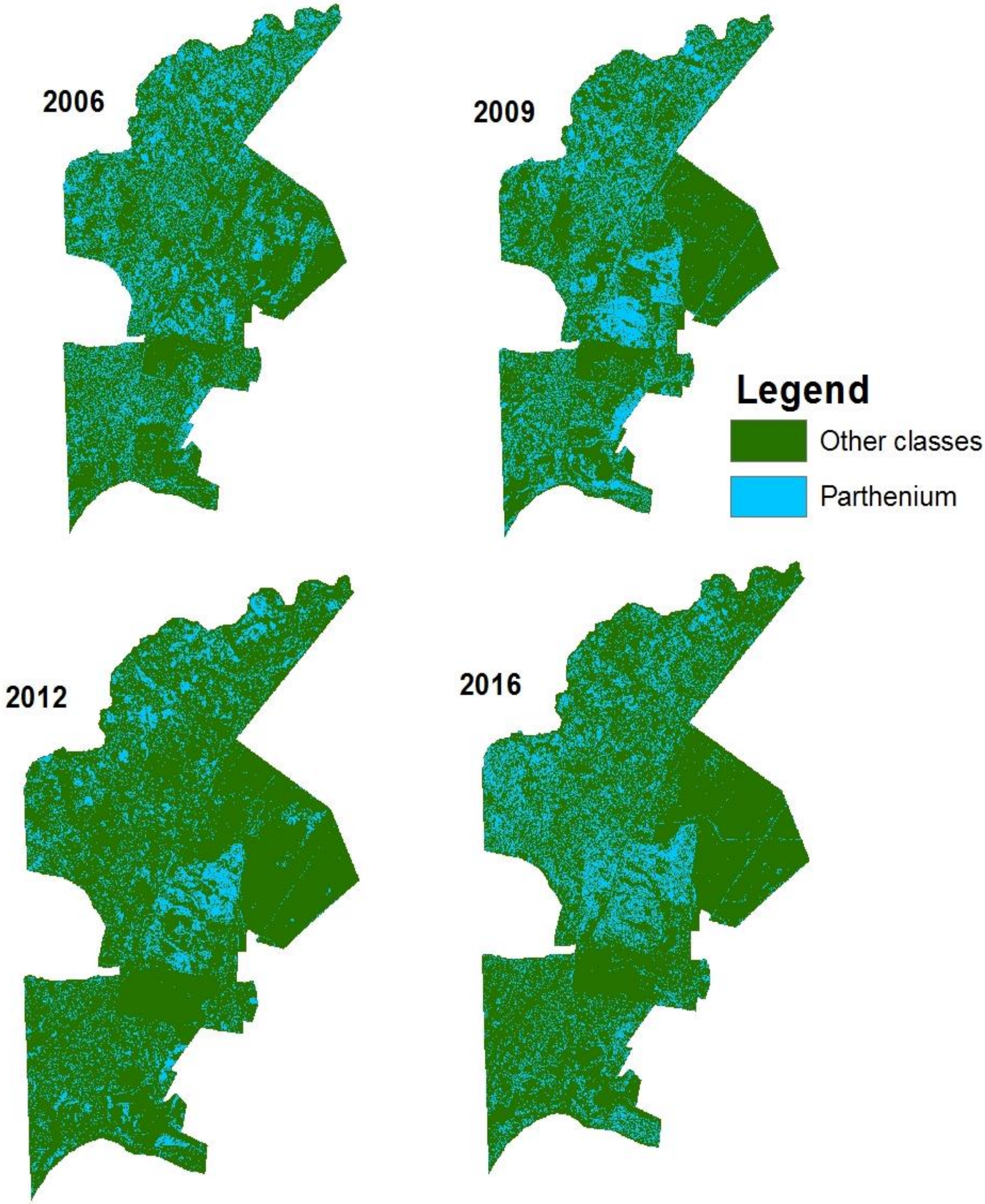

Figure 3. 5: Spatial distribution of Parthenium for the period of the study.

3.3.4 Comparing the spread of Parthenium between agricultural and non-agricultural dominated fields

Figure 3.6 depicts changes in the area of land occupied by Parthenium from agricultural and non-agricultural dominated fields. The figure shows that Parthenium infestation is prevalent in the non-agricultural dominated than in agricultural dominated fields. Although the amount of land occupied by Parthenium has remained consistently high in non-agricultural dominated fields, there has been a sharp incline in the area of this class after 2013 in both land uses.

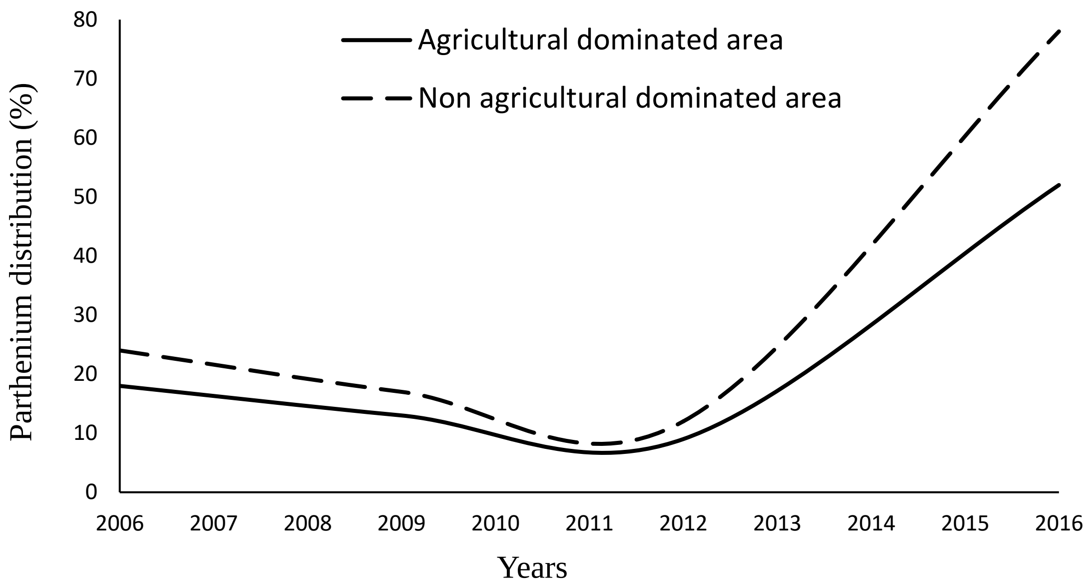

Figure 3. 6: Change in Parthenium distribution in relation to agricultural and non-agricultural dominated fields.

Figure 3.7 shows the correlation between annual rainfall and Parthenium distribution for the study site from the year 2006 to 2016. Generally, the annual rainfall remained very low for most of the study period. According to figure 3.7, the spread of Parthenium is directly influenced by rainfall. For instance, the highest infestation of Parthenium in the study site was recorded in the year 2006 when the rainfall was above 70 millimeters per year and the lowest was in 2012 when rainfall was 47 millimeters. Since 2006, Parthenium has been consistently decreasing with declining rainfall until the year 2016 where it boomed following the increased annual rainfall of 65 millimeters per year (Figure 3.7).

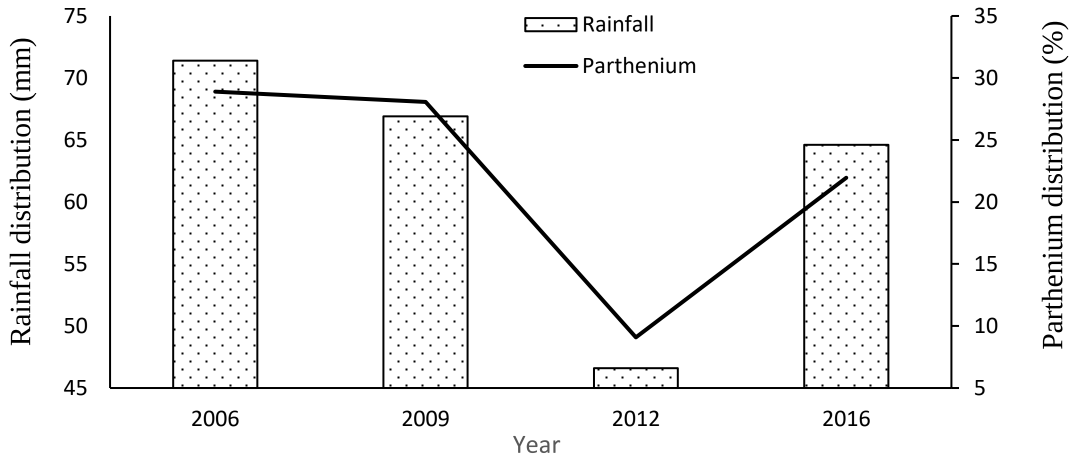

Figure 3. 7: Rainfall and Parthenium distribution for the study period.

3.4 Discussion

Based on the results of this study, there was a steady decline in Parthenium spread over the 10-year period. The noticeable trend of reduction in Parthenium (i.e. from 2006 to 2012) in the present study could be attributed to the low rainfall (Figure 3.7) experienced in the area over the recent past (Grundling *et al.* 2013). These results are consistent with Goodall *et al.* (2010), who observed a decrease in Parthenium distribution in a 5 km buffer outside the Hluhluwe game reserve. Generally, low rainfall means a reduction in soil water (Jaleel *et al.* 2009), leading to reduced soil moisture. Given that soil moisture is the major limiting factor to growth and distribution of Parthenium (Goodall *et al.* 2010), low rainfall could have had a significant impact on the spread of the weed during this period. The rapid increase in the land area occupied by Parthenium in the year 2016 could be attributed to increased rainfall experienced in the area by the end of the year 2016 (Figure 3.7). This is in conformity with results of other studies (e.g. Goodall *et al.* 2010), who reported a high growth and spread in Parthenium following rainy seasons within the Hluhluwe game reserve. Furthermore, the strong correlation between Parthenium distribution and rainfall has been confirmed by the good R-squared (R^2 = 0.9631) indicated in Figure 3.8. Therefore, it is evident that, among others, the spread of Parthenium is highly influenced by the distribution of rainfall.

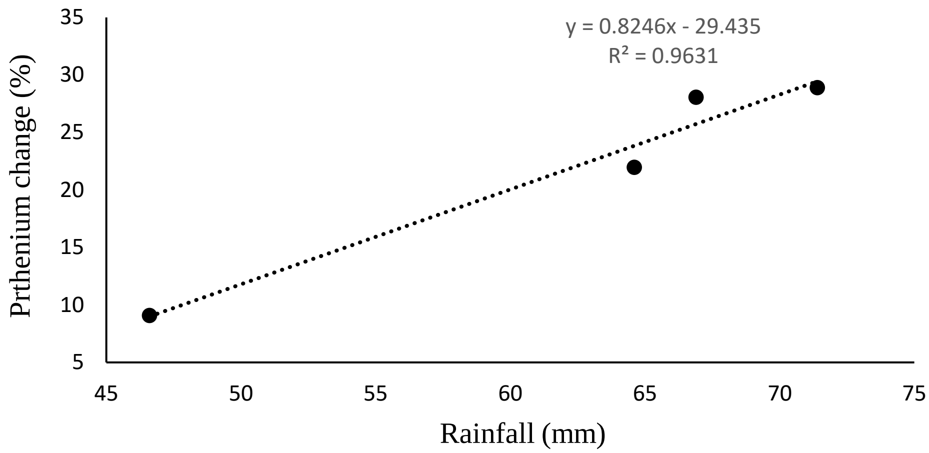

Figure 3. 8: Correlation between rainfall and Parthenium distribution.

Despite the effect of low rainfall, Parthenium distribution has shown a direct relation with land use/cover transformations in the study area. For instance, the sharp reduction in the area of land occupied by Parthenium and grassland in the year 2012 (Figure 3.2 and 3.3), can be attributed to the increase in the area of bare soils (Figure 3.9(a)). During this period, grasses and Parthenium are believed to have decreased because of low rainfall (Figure 3.7) while leaving out most of the study area's landscape uncovered by vegetation. With its rapid and aggressive behaviour (Kganyago *et al.* 2017; Adkins *et al.* 2010; Ayele 2007) Parthenium is assumed to have capitalized on the availability of these bare soils to spread following the increased rainfall in 2016 (Figure 3.9 (b)). Furthermore, landscape disturbances and vegetation clearing are known to destroy natural vegetation (Otunga *et al.* 2014), thereby creating vacant niches that are susceptible to Parthenium invasion. Subsequently, the reported spread of Parthenium in 2016 was more pronounced on frequently disturbed landscapes of residential areas, fallow agricultural and grazing lands. This unabated trend of increased Parthenium spread in disturbed landscapes is further shown in Figure 3.6. As confirmed by Kganyago *et al.* (2017), it is evident that Parthenium is a major invader of residential peripheries which capitalizes on the creation of vacant niches.

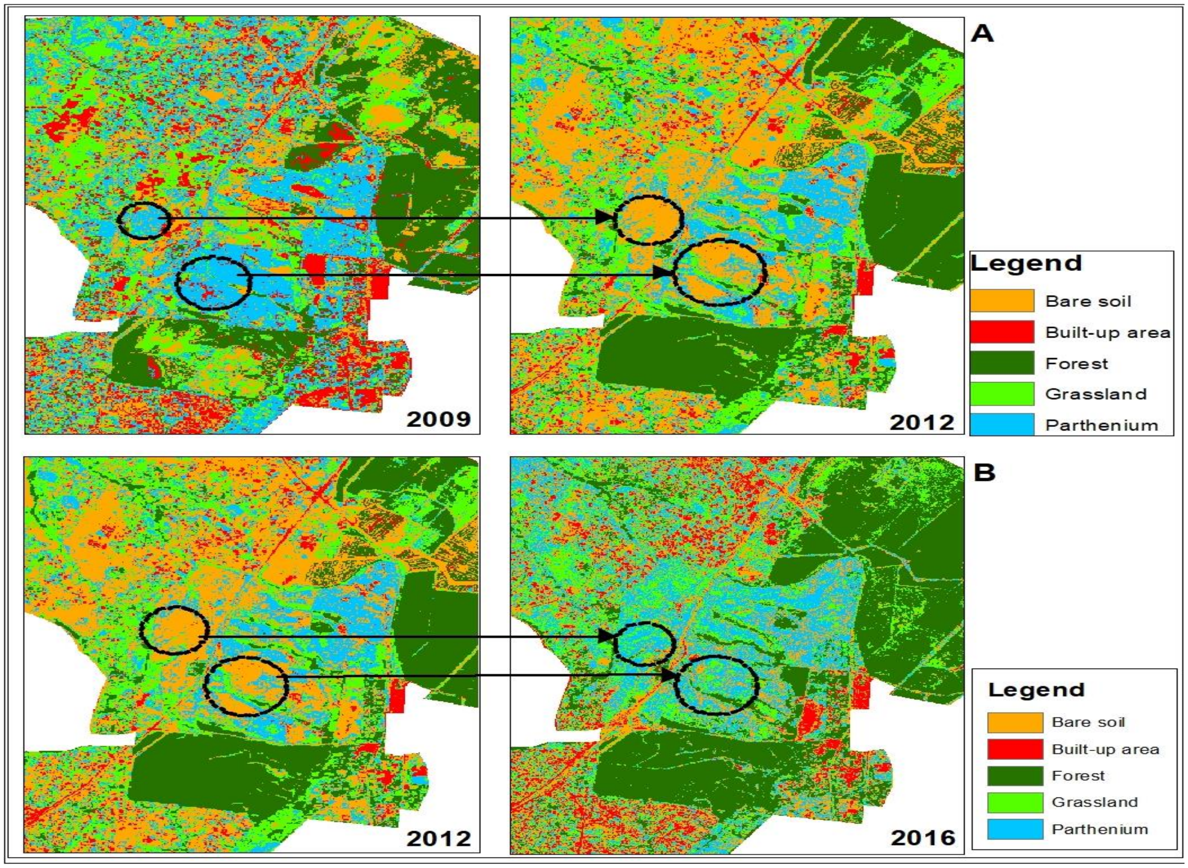

Figure 3. 9: Relationship between bare soil and Parthenium distribution from (a) 2009 to 2012 and from (b) 2012 to 2016.

However, on the other hand, the closed canopy covers of forests are believed to have prohibited the germination and spread of Parthenium within the forest environments (Figure 3.3). Besides, up-to-date information pertaining the distribution of AIPs is a requirement for monitoring and combating the spread (Kganyago *et al.* 2017; Oumar 2016). The provision of historical data from the SPOT mission offers an opportunity to map the spatial and temporal spread of AIPs such as Parthenium. More so, the use of improved resolution SPOT series data in concert with robust non-parametric image classification algorithm proved to be valuable in discriminating Parthenium from other classes such as grasses, forests and built-up area. However, although advocated in literature to improve classification accuracy, the chosen vegetation indices performed poorly in discerning Parthenium from forest and grasslands, hence were not reported in the study.

3.5 Conclusion

The objective of the study was to map the spatial and temporal spread of Parthenium using the multi-temporal SPOT series data. The results show that there has been a persistent decline in Parthenium distribution during the study period. Such a decrease has been attributed to the dry conditions associated with low rainfall activities. However, in the year 2016, there has been a boom in Parthenium spread following increased rainfall in the area. Furthermore, Parthenium has shown a strong relationship with land use/cover transformation across the study area, with frequently transformed soils being prone to Parthenium spread than infrequently changed landscapes. Moreover, this study demonstrated the value of using the robust and advanced non-parametric Random Forest in concert with improved resolution SPOT series data to facilitate the precise delineation of trends in AIPs such as Parthenium. The incorporation of these tools (i.e. non-parametric classifiers and freely available multispectral data with improved resolution) in southern Africa offers an affordable opportunity to the continued and operational scale monitoring of AIPs, a task previously confounded by excessive image acquisition costs. Due to the insignificant role of the management efforts currently in place to mitigate the spread of the weed, coupled with the imminent impact of Parthenium on subsistence agriculture, it is recommended that future research focus on national or provincial scale mapping of this weed to allow a comprehensive viewing of its distribution.

Chapter Four

Evaluation and conclusion

4.1 Introduction

The present study aimed to assess remote sensing application for mapping the spatial and temporal distribution of Parthenium in the Mtubatuba municipality of KwaZulu-Natal, South Africa. This chapter provides an evaluation of the objectives established in the introductory section (chapter one) of this research. More so, the chapter highlights the major concluding remarks of the research as well as prescribing a possible way forward for future research studies.

4.2 Evaluation of research objectives

4.2.1 Objective one:

The first objective of the study was to review literature on the advancements of satellite remote sensing for optimal detection and mapping of AIPs spread and the associated challenges and opportunities. The rapid spread of AIPs presents a number of socioeconomic and ecological problems to the invaded landscapes. Although providing cost-effective techniques for monitoring of AIPs spread, remote sensing of alien invasion is still confounded by a number of challenges such as balancing improvements in sensors technology (resolutions), image acquisition costs as well as the scale of application. For instance, although often provides large volumes of cost-effective dataset for continuous and large-scale mapping of AIPs, averaged spectral and poor spatial resolution data are inadequate for optimal detection of AIPs spread. With its small swath-width and excessive acquisition, the high spatial and hyperspectral dataset is also not an alternative. The increased free provision of multispectral data with improved spatial and spectral properties seem to be the alternative to achieve precise large-scale and long-term monitoring of AIPs. Also, developments in classification algorithms such as the Support Vector Machine and Random Forest with their robustness, are more valuable for accurate detection of earth features using remote singing data. Therefore, with the fusion of these two approaches mentioned above it is possible to achieve, both, the large-scale and long-term mapping of AIPs even by resource limited countries.

4.2.2 Objective two:

The second objective was to detect and map the spatial and temporal distribution of Parthenium from 2006 to 2016 using the SPOT series data and Random Forest. The signing of the license agreement between SANSA and ADS coupled with SANSA-single licence government multi-user agreement have ensured a steady supply of SPOT series data, free of charge in South Africa, to promote large-scale landscape analysis and long-term monitoring of AIPs spread. Findings have shown a consistent decrease in Parthenium spread for the study period. However, such decrease in Parthenium spread is assumed to be due to a low rainfall distribution. Also, Parthenium spread is influenced by land use/cover transformations with areas of frequent soils manipulation being more prone to expansion than infrequent altered soils. As a result, Parthenium spreading is high in residential peripheries, fallow agricultural lands and grazing lands than competitive places of forest environments. The increased availability of improved spatial resolution data from the SPOT mission provides the most appropriate approach to large-scale and long-term mapping of AIPs in South Africa. Furthermore, the use of non-parametric image classifiers when classifying SPOT images yield some promising results for optimal detection of AIPs spread and continuous vegetation monitoring.

4.3 Conclusion

The main aim of the study was to assess remote sensing application for mapping the spatial and temporal spread of Parthenium in the Mtubatuba municipality of KwaZulu-Natal, South Africa. Evidently, the use of the improved spatial resolution multispectral data in concert with non-parametric classification algorithms provides a cost-effective approach to long-term and operation scale mapping of AIPs. On the other hand, the spread of Parthenium in the invaded landscapes is intensified by the availability of rainfall. Moreover, Parthenium spread is encouraged by vegetation clearings and land use/cover transformations. Therefore, this study concludes that, Parthenium does capitalize on available vacant spaces and spread throughout the landscape. This has been revealed by its strong relationship with bare soils established from the study. This study is beneficial to both crop and animal farmers to identify and avoid Parthenium invaded landscapes in their farming activities. This will then help avoid the potential economic loss that can arise when livestock fed on and crops ploughed on Parthenium invaded areas. The major limitation of the study was the increased time interval in between the chosen years of analysis and the time length was governed by image availability. Given that Parthenium growth mostly depends on moisture availability, this could have prevented a great opportunity to understand the annual and seasonal distribution of the weed. However, to improve the understanding of the spatial and temporal distribution of the weed, interested parties such as the Department of Agriculture and Rural Development as well as the Department of Economic Development, Tourism and Environmental Affairs can increase the available images by using techniques such as drones or Unmanned Aerial Vehicle (UAV). Furthermore, soil characteristics, soil moisture and topography can be incorporated in analysis of future studies to fully understand the spread of the weed.

References:

Abdel-Rahman, E. M., Mutanga, O., Adam, E. & Ismail, R. 2014. Detecting Sirex noctilio grey-attacked and lightning-struck pine trees using airborne hyperspectral data, random forest and support vector machines classifiers. *ISPRS Journal of Photogrammetry and Remote Sensing,* 88**,** 48-59.

Adam, E., Mutanga, O., Odindi, J. & Abdel-Rahman, E. M. 2014. Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. *International Journal of Remote Sensing,* 35(10)**,** 3440-3458.

Adelabu, S., Mutanga, O. & Adam, E. 2014. Evaluating the impact of red-edge band from Rapideye image for classifying insect defoliation levels. *ISPRS Journal of Photogrammetry and Remote Sensing,* 95**,** 34-41.

Adkins, S. W., O'Donnell, C., Khan, N., Nguyen, T., Shabbir, A., Dhileepan, K., George, D. & Navie, S. Year: Published. Parthenium weed (Parthenium hysterophorus L.) research in Australia: new management possibilities. *Proceedings 17th Australasian Weeds Conference'.(Ed. SM Zydenbos.) pp*. 120-123.

Aitkenhead, M. & Aalders, I. 2011. Automating land cover mapping of Scotland using expert system and knowledge integration methods. *Remote Sensing of Environment,* 115(5)**,** 1285-1295.

Amiri, F. & Tabatabaie, T. 2009. Operational Monitoring of Vegetative Cover by Remote Sensing in Semi-arid Lands of Iran.

Andrew, M. E. & Ustin, S. L. 2009. Habitat suitability modelling of an invasive plant with advanced remote sensing data. *Diversity and Distributions,* 15(4)**,** 627-640.

Asner, G. P., Jones, M. O., Martin, R. E., Knapp, D. E. & Hughes, R. F. 2008. Remote sensing of native and invasive species in Hawaiian forests. *Remote Sensing of Environment,* 112(5)**,** 1912-1926.

Asner, G. P., Martin, R. E., Knapp, D. E. & Kennedy-Bowdoin, T. 2010. Effects of Morella faya tree invasion on aboveground carbon storage in Hawaii. *Biological Invasions,* 12(3)**,** 477-494.

Atkinson, J. T., Ismail, R. & Robertson, M. 2014. Mapping bugweed (solanum mauritianum) infestations in pinus patula plantations using hyperspectral imagery and support vector machines. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* 7(1)**,** 17-28.

Ayele, S. 2007. The impact of Parthenium (Parthenium hysterophorus L.) on the range ecosystem dynamics of the Jijiga rangeland, Ethiopia. *Department of Animal Sciences, School of Graduate Studies, Haramaya University***,** 134.

Bax, N., Williamson, A., Aguero, M., Gonzalez, E. & Geeves, W. 2003. Marine invasive alien species: a threat to global biodiversity. *Marine policy,* 27(4)**,** 313-323.

Beck, K. G., Zimmerman, K., Schardt, J. D., Stone, J., Lukens, R. R., Reichard, S., Randall, J., Cangelosi, A. A., Cooper, D. & Thompson, J. P. 2009. Invasive species defined in a policy context: Recommendations from the Federal Invasive Species Advisory Committee.

Blaschke, T. 2005. Towards a framework for change detection based on image objects. *Göttinger Geographische Abhandlungen,* 113**,** 1-9.

Blossey, B. & Notzold, R. 1995. Evolution of increased competitive ability in invasive nonindigenous plants: a hypothesis. *Journal of Ecology,* 83(5)**,** 887-889.

Boyd, D. S. & Foody, G. M. 2011. An overview of recent remote sensing and GIS based research in ecological informatics. *Ecological Informatics,* 6(1)**,** 25-36.

Bradley, B. A. 2014. Remote detection of invasive plants: a review of spectral, textural and phenological approaches. *Biological invasions,* 16(7)**,** 1411-1425.

Breiman, L. 2001. Random forests. *Machine learning,* 45(1)**,** 5-32.

Brunel, S., Panetta, D., Fried, G., Kriticos, D., Prasad, R., Lansink, A. O., Shabbir, A. & Yaacoby, T. 2014. Preventing a new invasive alien plant from entering and spreading in the Euro-Mediterranean region: the case study of Parthenium hysterophorus. *EPPO Bulletin,* 44(3)**,** 479-489.

Campbell, J. B. & Wynne, R. H. 2011. *Introduction to remote sensing*, Guilford Press.

Cardina, J., Johnson, G. A. & Sparrow, D. H. 1997. The nature and consequence of weed spatial distribution. *Weed Science***,** 364-373.

Carson, H. W., Lass, L. W. & Callihan, R. H. 1995. Detection of yellow hawkweed (Hieracium pratense) with high resolution multispectral digital imagery. *Weed technology***,** 477-483.

Casady, G. M., Hanley, R. S. & Seelan, S. K. 2005. Detection of leafy spurge (Euphorbia esula) using multidate high-resolution satellite imagery. *Weed Technology,* 19(2)**,** 462-467.

Chan, J. C.-W. & Paelinckx, D. 2008. Evaluation of Random Forest and Adaboost tree-based ensemble classification and spectral band selection for ecotope mapping using airborne hyperspectral imagery. *Remote Sensing of Environment,* 112(6)**,** 2999-3011.

Cho, M. A., Mathieu, R., Asner, G. P., Naidoo, L., van Aardt, J., Ramoelo, A., Debba, P., Wessels, K., Main, R. & Smit, I. P. 2012. Mapping tree species composition in South African savannas using an integrated airborne spectral and LiDAR system. *Remote Sensing of Environment,* 125**,** 214-226.

Crossman, N. D. & Kochergen, J. 2002. *Mapping environmental weeds in the Mount Lofty Ranges, South Australia, using high resolution infrared aerial photography*, Plant Protection Society of WA Incorporated.

Curatola Fernández, G., Silva, B., Gawlik, J., Thies, B. & Bendix, J. 2013. Bracken fern frond status classification in the Andes of southern Ecuador: combining multispectral satellite data and field spectroscopy. *International journal of remote sensing,* 34(20)**,** 7020-7037.

Curatola Fernández, G. F., Obermeier, W. A., Gerique, A., López Sandoval, M. F., Lehnert, L. W., Thies, B. & Bendix, J. 2015. Land cover change in the Andes of Southern Ecuador—Patterns and drivers. *Remote Sensing,* 7(3)**,** 2509-2542.

Dark, S. J. 2004. The biogeography of invasive alien plants in California: an application of GIS and spatial regression analysis. *Diversity and Distributions,* 10(1)**,** 1-9.

Dorigo, W., Lucieer, A., Podobnikar, T. & Čarni, A. 2012. Mapping invasive Fallopia japonica by combined spectral, spatial, and temporal analysis of digital orthophotos. *International Journal of Applied Earth Observation and Geoinformation,* 19**,** 185-195.

Dube, T., Mutanga, O., Abdel-Rahman, E. M., Ismail, R. & Slotow, R. 2015. Predicting Eucalyptus spp. stand volume in Zululand, South Africa: an analysis using a stochastic gradient boosting regression ensemble with multi-source data sets. *International Journal of Remote Sensing,* 36(14)**,** 3751-3772.

El Hajj, M., Bégué, A., Lafrance, B., Hagolle, O., Dedieu, G. & Rumeau, M. 2008. Relative radiometric normalization and atmospheric correction of a SPOT 5 time series. *Sensors,* 8(4)**,** 2774-2791.

Evangelista, P. H., Stohlgren, T. J., Morisette, J. T. & Kumar, S. 2009. Mapping invasive tamarisk (Tamarix): a comparison of single-scene and time-series analyses of remotely sensed data. *Remote Sensing,* 1(3)**,** 519-533.

Evans, H. C. 1997. Parthenium hysterophorus. a review of its weed status and the possibilities for biological control. *Biocontrol News and Information*, 18**,** 89N-98N.

Everitt, J. H., Escobar, D. E., Alaniz, M. A., Davis, M. R. & Richerson, J. V. 1996. Using spatial information technologies to map Chinese tamarisk (Tamarix chinensis) infestations. *Weed Science***,** 194-201.

Everitt, J. H., Escobar, D. E. & Davis, M. R. Year: Published. Using remote sensing for detecting and mapping noxious plants. *Weed Abstracts*. 639-649.

Flood, N. 2013. Seasonal composite Landsat TM/ETM+ images using the Medoid (a multi-dimensional median). *Remote Sensing,* 5(12)**,** 6481-6500.

Forsyth, A. T., Gibson, L. A. & Turner, A. A. Assessment of SPOT 6 imagery for mapping the invasive alien plant species Pinus spp. in a mountainous area of the Western Cape.

Foxcroft, L. C., Richardson, D. M. & Wilson, J. R. 2008. Ornamental plants as invasive aliens: problems and solutions in Kruger National Park, South Africa. *Environmental management,* 41(1)**,** 32-51.

Fuller, D. 2005. Remote detection of invasive Melaleuca trees (Melaleuca quinquenervia) in South Florida with multispectral IKONOS imagery. *International Journal of Remote Sensing,* 26(5)**,** 1057-1063.

Gaertner, M., Den Breeyen, A., Hui, C. & Richardson, D. M. 2009. Impacts of alien plant invasions on species richness in Mediterranean-type ecosystems: a meta-analysis. *Progress in Physical Geography,* 33(3)**,** 319-338.

Gavier-Pizarro, G. I., Kuemmerle, T., Hoyos, L. E., Stewart, S. I., Huebner, C. D., Keuler, N. S. & Radeloff, V. C. 2012. Monitoring the invasion of an exotic tree (Ligustrum lucidum) from 1983 to 2006 with Landsat TM/ETM+ satellite data and Support Vector Machines in Córdoba, Argentina. *Remote Sensing of Environment,* 122**,** 134-145.

Ghosh, A., Fassnacht, F. E., Joshi, P. & Koch, B. 2014. A framework for mapping tree species combining hyperspectral and LiDAR data: Role of selected classifiers and sensor across three spatial scales. *International Journal of Applied Earth Observation and Geoinformation,* 26**,** 49-63.

Ghulam, A., Porton, I. & Freeman, K. 2014. Detecting subcanopy invasive plant species in tropical rainforest by integrating optical and microwave (InSAR/PolInSAR) remote sensing data, and a decision tree algorithm. *ISPRS Journal of Photogrammetry and Remote Sensing,* 88**,** 174-192.

Gil, A., Lobo, A., Abadi, M., Silva, L. & Calado, H. 2013. Mapping invasive woody plants in Azores Protected Areas by using very high-resolution multispectral imagery. *European Journal of Remote Sensing,* 46(1)**,** 289-304.

Gil, A., Yu, Q., Lobo, A., Lourenço, P., Silva, L. & Calado, H. 2011. Assessing the effectiveness of high resolution satellite imagery for vegetation mapping in small islands protected areas. *Journal of Coastal Research,* 64**,** 1663-1667.

Gilmore, S. Saleem, A. and Dewan, A. 2015. Effectiveness of DOS (Dark-Object Subtraction) method and water index techniques to map wetlands in a rapidly urbanizing megacity with Landsat 8 data.

Goel, P., Prasher, S., Patel, R., Smith, D. & DiTommaso, A. 2002. Use of airborne multi–spectral imagery for weed detection in field crops. *Transactions of the ASAE,* 45(2)**,** 443.

Gómez-Casero, M. T., Castillejo-González, I., García-Ferrer, A., Peña-Barragán, J. M., Jurado-Expósito, M., García-Torres, L. & López-Granados, F. 2010. Spectral discrimination of wild oat and canary grass in wheat fields for less herbicide application. *Agronomy for Sustainable Development,* 30(3)**,** 689-699.

Goodall, J., Braack, M., De Klerk, J. & Keen, C. 2010. Study on the early effects of several weed-control methods on Parthenium hysterophorus L. *African Journal of Range & Forage Science,* 27(2)**,** 95-99.

Goodwin, B. J., McAllister, A. J. & Fahrig, L. 1999. Predicting invasiveness of plant species based on biological information. *Conservation Biology,* 13(2)**,** 422-426.

Grundling, A. T., Van den Berg, E. C. & Price, J. S. 2013. Assessing the distribution of wetlands over wet and dry periods and land-use change on the Maputaland Coastal Plain, north-eastern KwaZulu-Natal, South Africa. *South African Journal of Geomatics,* 2(2)**,** 120-138.

Gurevitch, J. & Padilla, D. K. 2004. Are invasive species a major cause of extinctions? *Trends in Ecology & Evolution,* 19(9)**,** 470-474.

Hamilton, R., Megown, K., Lachowski, H. & Campbell, R. 2006. Mapping Russian olive: using remote sensing to map an invasive tree. *US Department of Agriculture Forest Service, Remote Sensing Application Center RSAC-0087-RPT1.* http://www*. fs. fed. us/eng/rsac/invasivespecies/documents/0087-RPT1. pdf. Accessed: September,* 15**,** 2011.

He, K. S., Rocchini, D., Neteler, M. & Nagendra, H. 2011. Benefits of hyperspectral remote sensing for tracking plant invasions. *Diversity and Distributions,* 17(3)**,** 381-392.

Hestir, E. L., Khanna, S., Andrew, M. E., Santos, M. J., Viers, J. H., Greenberg, J. A., Rajapakse, S. S. & Ustin, S. L. 2008. Identification of invasive vegetation using hyperspectral remote sensing in the California Delta ecosystem. *Remote Sensing of Environment,* 112(11)**,** 4034-4047.

Higgins, S. I., Richardson, D. M., Cowling, R. M. & Trinder-Smith, T. H. 1999. Predicting the landscape-scale distribution of alien plants and their threat to plant diversity. *Conservation Biology,* 13(2)**,** 303-313.

Howison, O. E. 2016. How do alien plants invade: an analysis of the historical spread and potential distribution of the invasive alien plant Chromolaena odorata in and around Hluhluwe game reserve.

Huang, C.-y. & Asner, G. P. 2009. Applications of remote sensing to alien invasive plant studies. *Sensors,* 9(6)**,** 4869-4889.

Hunt, E. R., Daughtry, C. S., Kim, M. S. & Williams, A. E. P. 2007. Using canopy reflectance models and spectral angles to assess potential of remote sensing to detect invasive weeds. *Journal of Applied Remote Sensing,* 1(1)**,** 013506-013506-19.

Ismail, R., Mutanga, O. & Peerbhay, K. 2016. The identification and remote detection of alien invasive plants in commercial forests: An Overview. *South African Journal of Geomatics,* 5(1)**,** 49-67.

Jaleel, C. A., Manivannan, P., Wahid, A., Farooq, M., Al-Juburi, H. J., Somasundaram, R. & Panneerselvam, R. 2009. Drought stress in plants: a review on morphological characteristics and pigments composition. *Int J Agric Biol,* 11(1)**,** 100-105.

Jay, S., Lawrence, R., Repasky, K. & Keith, C. Year: Published. Invasive species mapping using low cost hyper spectral imagery. *ASPRS 2009 Annual Conference, March*. 9-13.

Joshi, C. 2006. *Mapping cryptic invaders and invisability of tropical forest ecosystems: Chromolaena odorata in Nepal*.

Joshi, C., de Leeuw, J. & van Duren, I. C. Year: Published. Remote sensing and GIS applications for mapping and spatial modelling of invasive species. *Proceedings of ISPRS*. B7.

Kalusová, V., Chytrý, M., Kartesz, J. T., Nishino, M. & Pyšek, P. 2013. Where do they come from and where do they go? European natural habitats as donors of invasive alien plants globally. *Diversity and Distributions,* 19(2)**,** 199-214.

Karki, D. 2009a. Ecological and socio-economic impacts of Parthenium hysterophorus L invasion in two urban areas in Nepal. *Ecological and Socio-Economic impacts of Parthenium hysterophorus L. invasion in two urban areas in Nepal*.

Karki, D. 2009b. *Ecological and Socio-Economic impacts of Parthenium hysterophorus L. invasion in two urban areas in Nepal.* Department of Botany, Tribhuvan University.

Kelly, M., Shaari, D., Guo, Q. & Liu, D. 2004. A comparison of standard and hybrid classifier methods for mapping hardwood mortality in areas affected by "sudden oak death". *Photogrammetric Engineering & Remote Sensing,* 70(11)**,** 1229-1239.

Kganyago, M., Odindi, J., Adjorlolo, C. & Mhangara, P. 2017. Selecting a subset of spectral bands for mapping invasive alien plants: a case of discriminating Parthenium hysterophorus using field spectroscopy data. *International Journal of Remote Sensing,* 38(20)**,** 5608-5625.

Kimothi, M., Anitha, D., Vasistha, H., Soni, P. & Chandola, S. 2010. Remote sensing to map the invasive weed, Lantana camara in forests. *Trop Ecol,* 51(1)**,** 67-74.

Kimothi, M. & Dasari, A. 2010. Methodology to map the spread of an invasive plant (Lantana camara L.) in forest ecosystems using Indian remote sensing satellite data. *International Journal of Remote Sensing,* 31(12)**,** 3273-3289.

Kriticos, D., Sutherst, R., Brown, J., Adkins, S. & Maywald, G. 2003. Climate change and the potential distribution of an invasive alien plant: Acacia nilotica ssp. indica in Australia. *Journal of Applied Ecology,* 40(1)**,** 111-124.

Kumar, A. & Min, H. 2008. Some issues related with sub-pixel classification using Hyperion data. *Proc. Int. Archives of the Photogrammetry, Remote Sensing, and Spatial Information Sciences,* 37**,** 249-254.

Lass, L. W., Carson, H. W. & Callihan, R. H. 1996. Detection of yellow starthistle (Centaurea solstitialis) and common St. Johnswort (Hypericum perforatum) with multispectral digital imagery. *Weed technology***,** 466-474.

Lass, L. W., Prather, T. S., Glenn, N. F., Weber, K. T., Mundt, J. T. & Pettingill, J. 2005. A review of remote sensing of invasive weeds and example of the early detection of spotted knapweed (Centaurea maculosa) and babysbreath (Gypsophila paniculata) with a hyperspectral sensor. *Weed Science*, 53(2)**,** 242-251.

Lass, L. W., Thill, D. C., Shafii, B. & Prather, T. S. 2002. Detecting spotted knapweed (centaurea maculosa) with hyperspectral remote sensing technology 1. *Weed Technology,* 16(2)**,** 426-432.

Lawrence, R., Hurst, R., Weaver, T. & Aspinall, R. 2006a. Mapping prairie pothole communities with multitemporal IKONOS satellite imagery. *Photogrammetric Engineering & Remote Sensing,* 72(2)**,** 169-174.

Lawrence, R. L., Wood, S. D. & Sheley, R. L. 2006b. Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). *Remote Sensing of Environment,* 100(3)**,** 356-362.

Le Maitre, D. C., van Wilgen, B. W., Gelderblom, C., Bailey, C., Chapman, R. A. & Nel, J. 2002. Invasive alien trees and water resources in South Africa: case studies of the costs and benefits of management. *Forest Ecology and management,* 160(1)**,** 143-159.

Li, J., Liu, Y., Mo, C., Wang, L., Pang, G. & Cao, M. 2016. IKONOS Image-Based Extraction of the Distribution Area of Stellera chamaejasme L. in Qilian County of Qinghai Province, China. *Remote Sensing,* 8(2)**,** 148.

Lowe, S., Browne, M., Boudjelas, S. & De Poorter, M. 2000. 100 of the world's worst invasive alien species: a selection from the global invasive species database.

Lu, D. & Weng, Q. 2007. A survey of image classification methods and techniques for improving classification performance. *International journal of Remote sensing,* 28(5)**,** 823-870.

Mack, R. N., Simberloff, D., Mark Lonsdale, W., Evans, H., Clout, M. & Bazzaz, F. A. 2000. Biotic invasions: causes, epidemiology, global consequences, and control. *Ecological applications,* 10(3)**,** 689-710.

Marshall, C.G.A. 2002. The stratigraphy, sedimentology and basin evolution of the Natal Group. *Council for Geoscience,* Memoir 91. Pretoria, 179 pp.

Mather, P. & Tso, B. 2009. *Classification methods for remotely sensed data*, CRC press Boca Raton.

Matongera, T. N., Mutanga, O., Dube, T. & Lottering, R. T. 2016a. Detection and mapping of bracken fern weeds using multispectral remotely sensed data: a review of progress and challenges. *Geocarto International***,** 1-16.

Matongera, T. N., Mutanga, O., Dube, T. & Sibanda, M. 2017. Detection and mapping the spatial distribution of bracken fern weeds using the Landsat 8 OLI new generation sensor. *International Journal of Applied Earth Observation and Geoinformation,* 57**,** 93-103.

McConnachie, A., Strathie, L., Mersie, W., Gebrehiwot, L., Zewdie, K., Abdurehim, A., Abrha, B., Araya, T., Asaregew, F. & Assefa, F. 2011. Current and potential geographical distribution of the invasive plant Parthenium hysterophorus (Asteraceae) in eastern and southern Africa. *Weed Research,* 51(1)**,** 71-84.

McConnachie, A. J. 2015. Host range and risk assessment of Zygogramma bicolorata, a defoliating agent released in South Africa for the biological control of Parthenium hysterophorus. *Biocontrol science and technology,* 25(9)**,** 975-991.

Mulla, D. J. 2013. Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems engineering,* 114(4)**,** 358-371.

Mutanga, O., Dube, T. & Ahmed, F. 2016. Progress in remote sensing: vegetation monitoring in South Africa. *South AfricAn GeoGrAphicAl JournAl,* 98(3)**,** 461-471.

Mutanga, O. & Skidmore, A. K. 2004. Narrow band vegetation indices overcome the saturation problem in biomass estimation. *International Journal of Remote Sensing,* 25(19)**,** 3999-4014.

Naidoo, L., Cho, M., Mathieu, R. & Asner, G. 2012. Classification of savanna tree species, in the Greater Kruger National Park region, by integrating hyperspectral and LiDAR data in a Random Forest data mining environment. *ISPRS Journal of Photogrammetry and Remote Sensing,* 69**,** 167-179.

Narumalani, S., Mishra, D. R., Wilson, R., Reece, P. & Kohler, A. 2009. Detecting and mapping four invasive species along the floodplain of North Platte River, Nebraska. *Weed Technology,* 23(1)**,** 99-107.

Nath, S. S., Mishra, G., Kar, J., Chakraborty, S. & Dey, N. Year: Published. A survey of image classification methods and techniques. *Control, Instrumentation, Communication and Computational Technologies (ICCICCT), 2014 International Conference on*. IEEE, 554-557.

Ngubane, Z., Odindi, J., Mutanga, O. & Slotow, R. 2014. Assessment of the contribution of WorldView-2 strategically positioned bands in Bracken fern (Pteridium aquilinum (L.) Kuhn) mapping. *South African Journal of Geomatics,* 3(2)**,** 210-223.

Nigatu, L., Hassen, A., Sharma, J. & Adkins, S. W. 2010. Impact of Parthenium hysterophorus on grazing land communities in north-eastern Ethiopia. *Weed Biology and Management,* 10(3)**,** 143-152.

Niphadkar, M. & Nagendra, H. 2016. Remote sensing of invasive plants: incorporating functional traits into the picture. *International Journal of Remote Sensing,* 37(13)**,** 3074-3085.

Odindi, J., Adam, E., Ngubane, Z., Mutanga, O. & Slotow, R. 2014. Comparison between WorldView-2 and SPOT-5 images in mapping the bracken fern using the random forest algorithm. *Journal of Applied Remote Sensing,* 8(1)**,** 083527-083527.

Odindi, J., Mutanga, O., Rouget, M. & Hlanguza, N. 2016. Mapping alien and indigenous vegetation in the KwaZulu-Natal Sandstone Sourveld using remotely sensed data. *Bothalia-African Biodiversity & Conservation,* 46(2)**,** 1-9.

Otunga, C., Odindi, J. & Mutanga, O. 2014. Land Use Land Cover Change in the fringe of eThekwini Municipality: Implications for urban green spaces using remote sensing. *South African Journal of Geomatics,* 3(2)**,** 145-162.

Oumar, Z. 2016. Assessing the utility of the spot 6 sensor in detecting and mapping Lantana camara for a community clearing project in KwaZulu-Natal, South Africa. *South African Journal of Geomatics,* 5(2)**,** 214-226.

Pal, M. 2005. Random forest classifier for remote sensing classification. *International Journal of Remote Sensing,* 26(1)**,** 217-222.

Peerbhay, K., Mutanga, O., Lottering, R., Bangamwabo, V. & Ismail, R. 2016a. Detecting bugweed (Solanum mauritianum) abundance in plantation forestry using multisource remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing,* 121**,** 167-176.

Peerbhay, K., Mutanga, O., Lottering, R. & Ismail, R. 2016b. Mapping Solanum mauritianum plant invasions using WorldView-2 imagery and unsupervised random forests. *Remote Sensing of Environment,* 182**,** 39-48.

Peerbhay, K. Y., Mutanga, O. & Ismail, R. 2015. Random forests unsupervised classification: The detection and mapping of solanum mauritianum infestations in plantation forestry using hyperspectral data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* 8(6)**,** 3107-3122.

Peerbhay, K. Y., Mutanga, O. & Ismail, R. 2016c. The identification and remote detection of alien invasive plants in commercial forests: An Overview. *South African Journal of Geomatics,* 5(1)**,** 49-67.

Pejchar, L. & Mooney, H. A. 2009. Invasive species, ecosystem services and human well-being. *Trends in ecology & evolution,* 24(9)**,** 497-504.

Peters, A. J., Reed, B. C., Eve, M. D. & McDaniel, K. C. 1992a. Remote sensing of broom snakeweed (Gutierrezia sarothrae) with NOAA-10 spectral image processing. *Weed Technology***,** 1015-1020.

Peters, A. J., Reed, B. C., Eve, M. D. & McDaniel, K. C. 1992b. Remote sensing of broom snakeweed (Gutierrezia sarothrae) with NOAA-10 spectral image processing. *Weed Technology,* 6**,** 1015-1015.

Pimentel, D., Zuniga, R. & Morrison, D. 2005. Update on the environmental and economic costs associated with alien-invasive species in the United States. *Ecological economics,* 52(3)**,** 273-288.

Poona, N. 2008. Invasive alien plant species in South Africa: Impacts and management options. *Alternation,* 15(1)**,** 160-179.

Pu, R., Gong, P., Tian, Y., Miao, X., Carruthers, R. I. & Anderson, G. L. 2008. Invasive species change detection using artificial neural networks and CASI hyperspectral imagery. *Environmental monitoring and assessment,* 140(1-3)**,** 15-32.

Pyšek, P. 1998. Is there a taxonomic pattern to plant invasions? *Oikos***,** 282-294.

Robinson, T., Wardell-Johnson, G., Pracilio, G., Brown, C., Corner, R. & Van Klinken, R. 2016. Testing the discrimination and detection limits of WorldView-2 imagery on a challenging invasive plant target. *International Journal of Applied Earth Observation and Geoinformation,* 44**,** 23-30.

Rocchini, D., Andreo, V., Förster, M., Garzon-Lopez, C. X., Gutierrez, A. P., Gillespie, T. W., Hauffe, H. C., He, K. S., Kleinschmit, B. & Mairota, P. 2015. Potential of remote sensing to predict species invasions: A modelling perspective. *Progress in Physical Geography,* 39(3)**,** 283-309.

Savage, S. L. & Lawrence, R. L. 2010. Vegetation Dynamics in Yellowstone's Northern Range: 1985 to 1999. *Photogrammetric Engineering & Remote Sensing,* 76(5)**,** 547-556.

Shackleton, C. M., McGarry, D., Fourie, S., Gambiza, J., Shackleton, S. E. & Fabricius, C. 2007. Assessing the effects of invasive alien species on rural livelihoods: case examples and a framework from South Africa. *Human Ecology,* 35(1)**,** 113-127.

Shezi, M. I. Z. & Poona, M. N. K. UKZN/DAEA.

Shrestha, B., Shabbir, A. & Adkins, S. 2015. Parthenium hysterophorus in Nepal: a review of its weed status and possibilities for management. *Weed research,* 55(2)**,** 132-144.

Singh, A. 1989. Review article digital change detection techniques using remotely-sensed data. *International journal of remote sensing,* 10(6)**,** 989-1003.

Singh, K., Forbes, A. & Akombelwa, M. 2013. The Evaluation of High Resolution Aerial Imagery for Monitoring of Bracken Fern. *South African Journal of Geomatics,* 2(4)**,** 296-208.

Skowronek, S., Asner, G. P. & Feilhauer, H. 2017. Performance of one-class classifiers for invasive species mapping using airborne imaging spectroscopy. *Ecological Informatics,* 37**,** 66-76.

Strand, H. Year: Published. Sourcebook on remote sensing and biodiversity indicators. Secretariat of the Convention on Biological Diversity.

Swayne, D. A., Yang, W., Voinov, A., Rizzoli, A. & Filatova, T. Remote Sensing Time Series for Modeling Invasive Species Distribution: A Case Study of Tamarix spp. in the US and Mexico.

Thomas, R.J. 1989. The tale of two tectonic terranes. *South Africa Journal of Geology*, 92, 306-321.

Underwood, E., Ustin, S. & DiPietro, D. 2003. Mapping nonnative plants using hyperspectral imagery. *Remote Sensing of Environment,* 86(2)**,** 150-161.

Viana, H. & Aranha, J. Year: Published. Mapping invasive species (Acacia dealbata Link) using ASTER/TERRA and LANDSAT 7 ETM+ imagery. *Forest Landscapes and Global Change-New Frontiers in Management, Conservation and Restoration. Proceedings of the IUFRO Landscape Ecology Working Group International Conference*.

Wabuyele, E., Lusweti, A., Bisikwa, J., Kyenune, G., Clark, K., Lotter, W. D., McConnachie, A. J. & Wondi, M. 2014. A Roadside Survey of the Invasive Weed Parthenium hysterophorus (Asteraceae) in East Africa. *Journal of East African Natural History,* 103(1)**,** 49-57.

Waser, L., Baltsavias, E., Ecker, K., Eisenbeiss, H., Feldmeyer-Christe, E., Ginzler, C., Küchler, M. & Zhang, L. 2008. Assessing changes of forest area and shrub encroachment in a mire ecosystem using digital surface models and CIR aerial images. *Remote Sensing of Environment,* 112(5)**,** 1956-1968.

Weber, E., Sun, S.-G. & Li, B. 2008. Invasive alien plants in China: diversity and ecological insights. *Biological Invasions,* 10(8)**,** 1411-1429.

Wigley, B., Bond, W. & Hoffman, M. 2009. Bush encroachment under three contrasting land-use practices in a mesic South African savanna. *African Journal of Ecology,* 47(s1)**,** 62-70.

Wilfong, B. N., Gorchov, D. L. & Henry, M. C. 2009. Detecting an invasive shrub in deciduous forest understories using remote sensing. *Weed Science,* 57(5)**,** 512-520.

Williams, A. P. & Hunt, E. R. 2002. Estimation of leafy spurge cover from hyperspectral imagery using mixture tuned matched filtering. *Remote Sensing of Environment,* 82(2)**,** 446-456.

Wu, W. 2014. The generalized difference vegetation index (GDVI) for dryland characterization. *Remote Sensing,* 6(2)**,** 1211-1233.

Zhao, B., Yan, Y., Guo, H., He, M., Gu, Y. & Li, B. 2009. Monitoring rapid vegetation succession in estuarine wetland using time series MODIS-based indicators: An application in the Yangtze River Delta area. *Ecological Indicators,* 9(2)**,** 346-356.

Zuberi, M. I., Gosaye, T. & Hossain, S. 2014. Potential threat of alien invasive species: Parthenium hysterophorus L. to subsistence agriculture in Ethiopia. *Sarhad Journal of Agriculture,* 30(1)**,** 117-125.