# The role of remote sensing in invasive alien plant species detection and the assessment of removal programs in two selected reserves in the eThekwini Municipality, KwaZulu-Natal Province

**Yusuf Adam**

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

November 2016
Durban
South Africa

# ABSTRACT

One of the major current concerns by conservationists is alien invasive plants due to their rapid spread and threat to biodiversity. The detection of Invasive Alien Plant Species (IAPs) can aid in monitoring and managing their invasion on ecosystems. In South Africa approximately 10 million hectares of land have been invaded. To combat this invasion, the Working for Water program was initiated in 1995 aimed at manually removing them. Multispectral imagery can facilitate identification, assess removal initiatives and improve efficiency of IAP removal. The aim of this study is to determine the most appropriate sensor to detect three IAPs (*Acacia podalyriifolia*, *Chromolaena odorata* and *Litsea glutinosa*) and assess clearing programs of these species in two protected areas (Paradise Valley and Roosfontein Nature Reserves) within the eThekwini municipality, in KwaZulu-Natal province, South Africa using remote sensing. The three satellite sensors examined in this study included Landsat 7 ETM+, SPOT 5 and WorldView-2. The study also assessed four image classifiers (Parallelepiped, Maximum Likelihood, Spectral Angle Mapper and Iterative Self Organising Data Analysis Technique) in the detection of the selected IAPs. These sensors and techniques were compared based on their level of accuracy at detecting selected IAPs. The results of the study showed that WorldView-2 imagery and the Maximum Likelihood classifier had the highest overall accuracy (66.67%) , resulting in the successful classification of two (*Acacia podalyriifolia* and *Chromolaena odorata*) out of the three target species. This is due to the high spatial resolution of WorldView-2 imagery. This combination was then used to asses clearing of the selected IAPs by examining species distribution and density before and after clearing. Here the overall accuracies for the Paradise Valley and Roosfontein Nature Reserves were successful with accuracies above 85%. The density and distribution of all three IAPs decreased substantially in both sites except for the *L. glutinosa* species located in the Paradise Valley Nature Reserve which showed no significant decrease. These results show that geospatial data (especially remote sensing data) can be successfully used in both the detection of IAPs and the assessment of their removal.

# PREFACE

The work presented in this dissertation is the candidates own work and has not been submitted to another institute. This work has been supervised by Dr N.S. Ngetar and co-supervised by Dr S. Ramdhani. The study was conducted in the Paradise Valley and the Roosfontein nature reserves both located just West of Durban in the eThekwini Municipality, KwaZulu-Natal, South Africa.

This study was undertaken to examine the potential of remote sensing as a research and management tool in invasion biology within the South African context. The format of this study is a series of individual, inter-related papers submitted or to be submitted to various Journals. The dissertation comprises of five chapters, three of these represent independent research articles two of which are under revision for publication. These include chapter three, which is submitted to the journal, Landscape Ecology (an international journal) and chapter four which is submitted to the South African Journal of Geomatics (a local South African journal). This dissertation is in line with the University of KwaZulu-Natal style manual; however there has been a degree of repetition due to this dissertation being written as a series of journal papers. In addition, the in-text referencing and reference list for each aligns with the authors guide for the South African Geographical Journal. The chapters included in this dissertation are as follows.

- Chapter one is a general introduction to the study.
- Chapter two serves as literature review based on what has been achieved so far in the field of invasive alien plant spectroscopy, current challenges and the future of remote sensing in invasive plant detection and analysis.
- Chapter three examines various multispectral sensors and image classifiers in detecting three selected invasive species that occur in two reserves within the eThekwini municipality, KwaZulu-Natal Province.
- Chapter four is the application of remote sensing to asses clearing initiatives in the two reserves within the eThekwini Municipality.
- Chapter five is a general discussion of the results of chapter’s two to four.

# DECLARATION - ORIGINALITY

The research conducted towards this dissertation was carried out in the School of Agriculture, Earth and Environmental Science, University of KwaZulu-Natal, Howard College Campus, from March 2015 to November 2016, under the supervision of Dr. N.S. Ngetar and Dr. S. Ramdhani.

These studies represent original work by the author and have not otherwise been submitted in any form for any degree or diploma to any tertiary institution. Where use has been made of the work of others it is duly acknowledged in the text.

Yusuf Adam Signed: _________________________ Date: _________________

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

Dr N.S. Ngetar Signed: ____________________ Date: _________________

Dr S. Ramdhani Signed: ____________________ Date: _________________

# DECLARATION - PLAGIARISM

I, Yusuf Adam declare that:

1. The research reported in this dissertation, except where otherwise indicated, is my original research.

2. This dissertation has not been submitted for any degree or examination at any other university.

3. This dissertation does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

4. This dissertation does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:
   a. Their words have been re-written but the general information attributed to them has been referenced
   b. Where their exact words have been used, then their writing has been placed in italics and inside quotation marks, and referenced.

5. This dissertation does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the dissertation and in the References sections.

Signed: ………………………………………………………

# DECLARATION - MANUSCRIPTS

1. **Adam, Y,** Ngetar, N.S. and Ramdhani, S. "Invasive alien plant spectroscopy, successes and challenges'', *Southern African Geographical Journal*. Possible submission.

2. **Adam, Y,** Ngetar, N.S. and Ramdhani, S. "Detection of three invasive alien plant species by assessing three multispectral. A comparative analysis of four classifiers", *Landscape Ecology*. Submitted (In review).

3. **Adam, Y,** Ngetar, N.S. and Ramdhani, S. "The assessment of invasive alien plant species removal programs using remote sensing and GIS in two selected reserves in the eThekwini municipality", *South African Journal of Geomatics*. Submitted (In review).

Signed ________________________________________

# DEDICATION

*To my loving family, my mother, my father, my wife and darling daughter.*

ACKNOWLEDGEMENTS

This work would not have been possible without the grace of God, for this I thank him immensely. This work was also made possible by the support and resources of the following people and organisations.

Firstly, I would like to thank my supervisors Dr. N.S. Ngetar and Dr. S. Ramdhani whose support, continuous inspiration and advice has kept me motivated throughout the course of this dissertation.

Thanks to the University of KwaZulu-Natal for giving me the opportunity to do my Masters and for the provision of their research facilities and funding. In particular thanks to the staff of the Discipline of Geography in the School of Agriculture, Earth and Environmental Science for the provision of their GIS and remote sensing laboratory and support. Special thanks go to Mr J. Chana for his consistent technical support and advice. I would like to thank Mr M.A. Ally, Mr S. Gwala and Mr K. Phinzi for assisting with field work.

The Environmental Planning and Climate Protection Department (EPCPD) of the eThekwini Municipality, and the Wildlife and Environmental Society of South Africa (WESSA) are thanked for allowing access to study sites and data. In particular, thanks to Mr Bheka Cele, Mr Linda Mlotshwa and Mr Wayne Stead for their time and generous support. I would like to express my deep appreciation to the South African National Space Agency (SANSA) for providing partial funds for this study.

A special thanks to my mother and wife. Without their love and support this work would not have been possible.

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# CHAPTER ONE

# GENERAL INTRODUCTION

## 1.1 Invasive alien species monitoring

Alien plant species are those that have been moved out of their indigenous habitat into a new habitat (Kannan, Shackleton, & Uma Shaanker, 2013). Invasive alien plant species (IAPs) displace indigenous species and have detrimental environmental impacts (Bradley & Marvin, 2011). This has led to more importance placed by conservationists on IAPs because their rapid spread leads to ecosystem degradation and threatens biodiversity (Joshi, Leeuw, & Duren, 2004). After habitat destruction, IAP invasion is the second largest threat to global biodiversity (van Wilgen, Reyers, Le Maitre, Richardson, & Schonegevel, 2008). Currently land managers, ecologists and biologists involved in invasions by alien species usually do not have detailed knowledge of the spatial distribution of an IAP, therefore the detection of IAPs using remote sensing can aid in management efforts (He, Rocchini, Neteler, & Nagendra, 2011).

Monitoring and assessing the environment has become more reliant on remote sensing as it has the capacity to assess large spatial extents and examine historic distribution of IAPs (Mutanga, van Aardt, & Kumar, 2009). In order to successfully remove IAPs, they need to be mapped (Rowlinson, Summerton, & Ahmed, 1999). Manual field surveys as a method of mapping are time consuming and labour intensive, remote sensing is a more feasible alternative as it can reach inaccessible locations and assess large areas rapidly and comprehensively (Calviño-Cancela, Méndez-Rial, Reguera-Salgado, & Martín-Herrero, 2014).

## 1.2 Detection of IAPs using remote sensing

Remote sensing is successful at detecting IAPs as long as the target IAP exhibit distinctive characteristics when compared to surrounding indigenous species (Huang & Asner, 2009). The launch of a variety of new sensors coupled with Geographical Information Systems (GIS) and advanced modelling has resulted in many methods and tools in IAP detection (Evangelista et al., 2009). However remote sensing techniques differ due to spatial and spectral variations of sensors (Calviño-Cancela et al., 2014). Some of these include the use of hard classifiers such as the artificial neural network and maximum likelihood classifiers which provide definitive information on pixel classes, while others use soft classifiers such fuzzy, Bayesian and spectral mixture analysis which analyse the ratio of features within each pixel (Lu & Weng, 2007).

Various satellites provide multispectral imagery, however, the choice of satellite imagery is dependent on spectral resolution (number of bands), spatial resolution (pixel size), spatial coverage (area covered by image) and the cost of images (Cuneo et al., 2009). Spatial resolution is crucial as it determines the target feature's level of accuracy in terms of classification and the scale of the study. Finer spatial resolution increases classification accuracy but can make it difficult to separate spectral classes due to intra-pixel variability (He et al., 2011). Hyperspectral imagery is more useful at mapping species with a low density and a scattered distribution, and therefore more effective in a heterogeneous community (He et al., 2011).

Moderate spatial resolution satellites such as Landsat and SPOT are only effective at detecting a species if they form large stands (Huang & Asner, 2009). Other satellite imageries such as Quickbird and WorldView-2 are better suited at IAP detection as these are considered high spatial resolution multispectral data (Bradley, 2014). Worldview-2 is a very high spatial resolution sensor which collects data in the visible and infrared spectrum (Doody, Lewis, Benyon, & Byrne, 2014). However, high spatial resolution imagery may be inadequate when the spectral resolution is low, therefore hyperspectral imagery would be required (Huang & Asner, 2009).

Multispectral satellite imagery is a suitable data source in mapping IAPs (Cuneo, Jacobson, & Leishman, 2009). However, plant detection of a single species using remote sensing is a challenging task, where large scale infestations are generally easier to detect compared to small scale invasions (Evangelista, Stohlgren, Morisette, & Kumar, 2009). Therefore the use of remote sensing to detect IAPs using multispectral imagery would be feasible if the target IAP form dense stands and have distinct spectral signatures (Cuneo et al., 2009).

There are two categories of spectral image classifications: supervised and unsupervised. Supervised classification requires training sites which are used to classify features, whereas unsupervised classification creates classes first and then assigns them to feature classes (Adejoke & Badaru, 2014). Supervised classification methods to detect IAPs include the Maximum Likelihood classifier, which examines the probability of a pixel belonging to specific class and assigns the pixel to a class (Forsyth, Gibson, & Turner, 2014). Another supervised classifier is the Spectral Angle Mapper which examines the similarity between ground spectra and reference spectra by calculating their angles in an ‘n’ dimensional plain where smaller angles indicate a closer relationship between spectra (Narumalani, Mishra, Wilson, Reece, & Kohler, 2009). Another pixel based classification method which is not commonly used for IAP detection is the Iterative Self Organising Data Analysis Technique which is an unsupervised classifier (Rowlinson et al., 1999).

Time series analyses have been increasingly used to monitor the effect of IAP mitigation efforts (Evangelista et al., 2009) as it increases accuracy of the selected classification method, which helps distinguish between IAPs and indigenous species (He et al., 2011). A number of studies have been conducted in South Africa on IAP detection (Singh, Forbes, & Akombelwa, 2013; van den Berg, Kotze, & Beukes, 2014), however, many of these focused on large scale invasions that occur over large extents and few studies have examined detection at smaller spatial scales.

## 1.3 Invasive alien plant species in South Africa

It is estimated that 10% of South Africa is occupied by IAPs, spreading at an estimated rate of between 6 - 14% per an annum (Gillson, Midgley, & Wakeling, 2012). The total area covered by IAPs is approximately 10 million hectares, negatively impacting on biodiversity, land productivity and water resources in South Africa (Meijninger & Jarmain, 2014). It was predicted that woody IAPs would displace indigenous species and reduce stream flow, this led to the creation of the Working for Water program in 1995 (Meijninger & Jarmain, 2014), by the Department of Water and Environmental Affairs. This program is making continuous progress in removing invasive alien vegetation (Carbutt, 2012). Invasive alien plant species also impact the economy due to the cost of eradication and control (Calviño-Cancela et al., 2014). Between 1995 and 2007 approximately 3.2 billion ZAR spent on the removal of 1.6 million hectares of IAPs (van Wilgen et al., 2012).

Implementation of mitigation strategies to combat IAPs is slow due to the lack of data on the spatial distribution of IAPs (Shouse, Liang, & Fei, 2013). Frequent updates on the spatial extent of IAPs will aid in mitigation efforts, however, it is difficult to map rapidly spreading IAPs due to the continuous change of their spatial extent (Underwood, Ustin, & Ramirez, 2007). Remote sensing is able to map IAPs within a short time span and therefore provide frequent updates (Calviño-Cancela et al., 2014). Another issue related to IAP management is the uncertainty in the progress of current efforts to reduce IAP spread (van Wilgen et al., 2012). These control measures may not be keeping pace with the spread of IAPs (Gillson et al., 2012). In order to effectively manage invasion, a method is required to adequately assess the spatial distribution of IAPs in time and space (Calviño-Cancela et al., 2014).

## 1.4 Study area

In KwaZulu-Natal, the Working for Ecosystems Program which has stemmed from the Working for Water Program has been actively removing IAPs in small reserves in the eThekwini Municipality. Two of these reserves that have been targeted by the Working for Ecosystems Program are the Paradise Valley (29.83$^{o}$S, 30.89$^{o}$E) and the Roosfontein (29.86$^{o}$S, 30.92$^{o}$E) nature reserves (Figure 1).These reserves have had clearing programs initiated within them in 2011 and 2010 respectively. Both reserves are roughly 300ha in size and form part of the KwaZulu-Natal Coastal Belt vegetation type (Table 1). This region receives an average of 1010 mm of rainfall annually with majority of rainfall occurring between November and March, and an annual average temperature of 20.5 $^{o}$C (Preston-Whyte, 1980). The Environmental Planning and Climate Protection Department (EPCPD) in conjunction with Wildlife and Environmental Society of South Africa (WESSA) identified these reserves as highly invaded and removal initiatives were introduced into the Paradise Valley and Roosfontein reserves in 2011 and 2010 respectively.

**Table 1.1:** Details of study sites

| **Site** | **Location** | **Size** | **Altitude** | **Contractor** | **Protection** | **Vegetation** | **Invasion** |
|---|---|---|---|---|---|---|---|
| PVNR | Pinetown | 317 ha | 233m | WESSA[#] | Fenced | Coastal Belt* | High |
| RNR | Westville | 322 ha | 159m | WESSA[#] | Open | Coastal Belt* | High |

PVNR = Paradise Valley Nature Reserve, RNR = Roosfontein Nature Reserve.

[#] WESSA = Wildlife and Environmental Society of South Africa

* Muccina & Rutherford, 2006

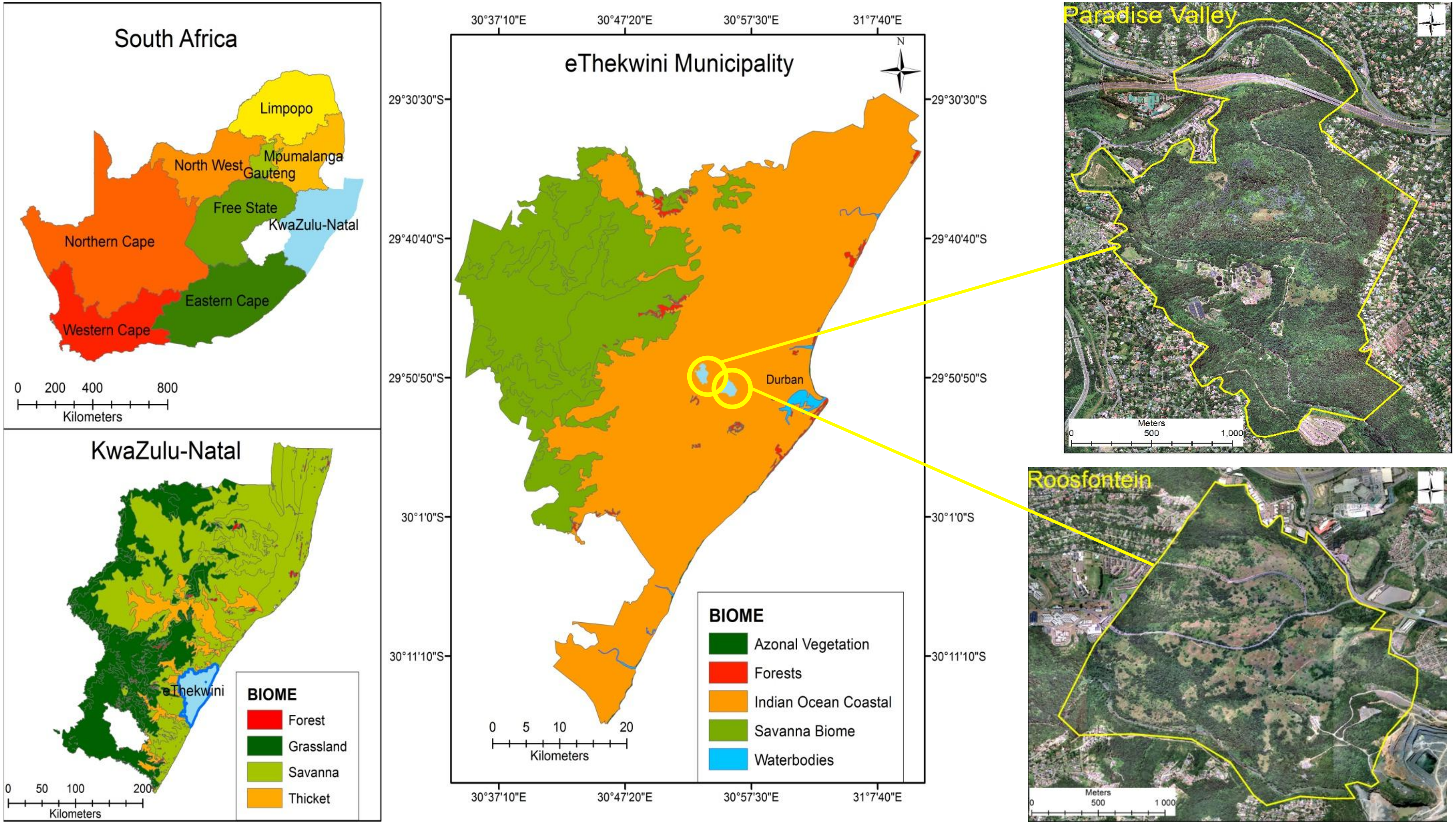



**Figure 1.1:** Location of the two study sites (Paradise Valley Nature Reserve and Roosfontein Nature Reserve) within the eThekwini Municipality, located in KwaZulu-Natal, South Africa.

Three IAPs that were targeted for removal within these reserves were *Acacia podalyriifolia* A.Cunn, *Chromolaena odorata* (L.) R.M. King & H. Rob. and *Litsea glutinosa* (Lour.) C.B.Rob. Three are present in the Paradise Valley Nature Reserve and only two are present in the Roosfontein Nature Reserve (*C. odorata* and *L. glutinosa*). There is no standard method of assessing or quantifying the efficiency of removal effects of the selected IAPs within these reserves. Consequently, this study will attempt to assess the success of removal initiatives 2010 to 2015 using remote sensing data.

### 1.5 Study aim, objectives and outcomes

The overall aim of this study is to examine the role of remote sensing in detecting selected invasive alien plants and assessing removal programs in two reserves in the eThekwini Municipality. Objectives of the study include:

1. Reviewing previous studies regarding the successes and challenges of utilising remote sensing in IAPs detection and management.
2. To assess three types of multispectral imagery (Landsat 7 ETM+, SPOT 5 and WorldView-2) and four classification methods (Parallel Piped, Maximum Likelihood, Spectral Angle Mapper and the Iterative Self-Organizing Data Analysis Technique Algorithm) in the detection of three IAPs (*Acacia podalyriifolia* (Pearl Acacia), *Chromolaena odorata* (Triffid Weed) and *Litsea glutinosa* (Indian laurel)) within the Paradise Valley Nature Reserve (eThekwini municipality, KwaZulu-Natal, South Africa).
3. To assess the effectiveness of clearing programs of three IAPs (*Acacia podalyriifolia*, *Chromolaena odorata* and *Litsea glutinosa)* in two protected areas within the eThekwini Municipality, KwaZulu-Natal, South Africa.

There are a number of issues to be clarified with regards to this study. In chapter three only the Paradise Valley Nature Reserve was examined as it contained all three of the selected species and therefore ideal to test the three sensors and four classifiers at IAP detection. Training site development in chapter four for the *L. glutinosa* species differed from chapter three as; training sites developed from field GPS points taken in 2015 (chapter three) produced low producer's accuracy. This could have resulted from the clearing of the species, as stands that were present were not homogenous.

Imaging spectroscopy in South Africa is not widely used and is relatively new field when dealing with vegetation (Mutanga et al., 2009). Remote sensing may provide an effective means for the future mapping of invasions which can provide insight for adequate mitigation strategies both at provincial and national levels (van den Berg et al., 2014). Results from this study will provides a method that could be standardised in detecting prominent IAPs which would be more time efficient than field studies (Carbutt, 2012) and further aid the assessment of IAP removal programs.

## References


Adejoke, A. O., & Badaru, Y. U. (2014). Accuracy Assessment of Pixel-Based Image Classification Of Kwali Council Area, Abuja, Nigeria. *Journal of Natural Science Research*, *4*(22), 133–140.

Bradley, B. A. (2014). Remote detection of invasive plants: a review of spectral, textural and phenological approaches. *Biological Invasions*, *16*(7), 1411–1425. http://doi.org/10.1007/s10530-013-0578-9

Bradley, B. A., & Marvin, D. (2011). Using expert knowledge to satisfy data needs: mapping invasive plant distributions in the western United States. *Western North American Naturalist*, *71*(3), 302–315.http://www.bioone.org/doi/abs/10.3398/064.071.0314

Calviño-Cancela, M., Méndez-Rial, R., Reguera-Salgado, J., & Martín-Herrero, J. (2014). Alien plant monitoring with ultralight airborne imaging spectroscopy. *PloS One*, *9*(7), e102381. http://doi.org/10.1371/journal.pone.0102381

Carbutt, C. (2012). The emerging invasive alien plants of the Drakensberg Alpine Centre, southern Africa. *Bothalia*, *85*, 71–85. http://www.abcjournal.org/index.php/ABC/article/view/10

Cuneo, P., Jacobson, C. R., & Leishman, M. R. (2009). Landscape-scale detection and mapping of invasive African Olive (*Olea europaea L. ssp*. cuspidata Wall ex G. Don Ciferri) in SW Sydney, Australia using satellite remote sensing. *Applied Vegetation …*, *12*, 145–154. http://onlinelibrary.wiley.com/doi/10.1111/j.1654-109X.2009.01010.x/full

Doody, T. M., Lewis, M., Benyon, R. G., & Byrne, G. (2014). A method to map riparian exotic vegetation (*Salix spp*.) area to inform water resource management. *Hydrological Processes*, *28*(11), 3809–3823. http://doi.org/10.1002/hyp.9916

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. http://doi.org/10.3390/rs1030519

Forsyth, A. T., Gibson, L. A., & Turner, A. A. (2014). Assessment of SPOT 6 imagery for mapping the invasive alien plant species Pinus spp. in a mountainous area of the Western Cape. *Proceedings of the Second AfricaGEO Conference*, 1–12.

Gillson, L., Midgley, G., & Wakeling, J. (2012). Exploring the significance of land-cover change in South Africa. *South African Journal of Science*, *108*(1), 5–7. http://www.scielo.org.za/scielo.php?pid=S0038-23532012000300003&script=sci_arttext&tlng=es

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. http://doi.org/10.1111/j.1472-4642.2011.00761.x

Huang, C.-Y., & Asner, G. P. (2009). Applications of remote sensing to alien invasive plant studies. *Sensors (Basel, Switzerland)*, *9*(6), 4869–89. http://doi.org/10.3390/s90604869

Joshi, C., Leeuw, J. de, & Duren, I. van. (2004). Remote sensing and GIS applications for mapping and spatial modelling of invasive species. *Proceedings of ISPRS*. http://www.isprs.org/proceedings/xxxv/congress/comm7/papers/132.pdf

Kannan, R., Shackleton, C. M., & Uma Shaanker, R. (2013). Reconstructing the history of introduction and spread of the invasive species, Lantana, at three spatial scales in India. *Biological Invasions*, *15*(6), 1287–1302. http://doi.org/10.1007/s10530-012-0365-z

Meijninger, W., & Jarmain, C. (2014). Satellite-based annual evaporation estimates of invasive alien plant species and native vegetation in South Africa. *Water SA*, *40*(1), 95–108. http://www.scielo.org.za/scielo.php?pid=S1816-79502014000100020&script=sci_arttext

Muccina, L., & Rutherford, M. . (2006). *The vegetation of South Africa, Lesotho and Swaziland*. Pretoria: South African National Biodiversity Institute.

Mutanga, O., van Aardt, J. Van, & Kumar, L. (2009). Imaging spectroscopy ( hyperspectral remote sensing ) in southern Africa : an overview. *South African Journal of Science*, *105*(June), 193–198.

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. http://doi.org/10.1614/WT-08-007.1

Preston-Whyte. (1980). *Climate of Durban*. *Natal Town and Regional Planning Reports* (Vol. 44). Durban.

Rowlinson, L., Summerton, M., & Ahmed, F. (1999). Comparison of remote sensing data sources and techniques for identifying and classifying alien invasive vegetation in riparian zones. *Water SA*, *25*(4), 497–500. http://researchspace.csir.co.za/dspace/handle/10204/2076

Shouse, M., Liang, L., & Fei, S. (2013). Identification of understory invasive exotic plants with remote sensing in urban forests. *International Journal of Applied Earth Observation and Geoinformation*, *21*, 525–534. http://doi.org/10.1016/j.jag.2012.07.010

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), 296–308.

Underwood, E. C., Ustin, S. L., & Ramirez, C. M. (2007). A comparison of spatial and spectral image resolution for mapping invasive plants in coastal California. *Environmental Management*, *39*(1), 63–83. http://doi.org/10.1007/s00267-005-0228-9

van den Berg, E., Kotze, I., & Beukes, H. (2014). Detection, quantification and monitoring of Prosopis in the Northern Cape Province of South Africa using remote sensing and GIS. *South African Journal of Geomatics*, *2*(2), 68–81. http://www.ajol.info/index.php/sajg/article/view/106983

van Wilgen, B. W., Forsyth, G. G., Le Maitre, D. C., Wannenburgh, A., Kotzé, J. D. F., van den Berg, E., & Henderson, L. (2012). An assessment of the effectiveness of a large, national-scale invasive alien plant control strategy in South Africa. *Biological Conservation*, *148*(1), 28–38. http://doi.org/10.1016/j.biocon.2011.12.035

van Wilgen, B. W., Reyers, B., Le Maitre, D. C., Richardson, D. M., & Schonegevel, L. (2008). A biome-scale assessment of the impact of invasive alien plants on ecosystem services in South Africa. *Journal of Environmental Management*, *89*(4), 336–49. http://doi.org/10.1016/j.jenvman.2007.06.015

# CHAPTER TWO

# INVASIVE ALIEN PLANT SPECTROSCOPY, SUCCESSES AND CHALLENGES

This chapter is based on:

**Adam,** Y, Ngetar, N.S and Ramdhani, S. "Invasive alien plant spectroscopy, successes and challenges'', *Southern African Geographical Journal*. (In the process of submission)

## 2.1 Abstract

Invasive alien plants species (IAPs) pose a threat to agriculture, water resources, biodiversity and human welfare. Remote sensing is a powerful tool for detecting IAPs which could help decision makers manage alien plant invasion. Various types of sensors and techniques have been used in this field of research with various successes, however, challenges abound. There is paucity of literature discussing sensor types and their suitability for IAP detection. A review of the importance of IAP management, the role of remote sensing in IAP detection, different sensor capabilities, successes in IAP spectroscopy and challenges was conducted. The spatial and spectral resolutions of sensors are crucial factors to consider in the process of sensor selection. Multispectral sensors are suitable in detecting IAPs where stands are homogenous, facilitating change detection. On the contrary, hyperspectral sensors are better equipped to detect individual species within a heterogeneous landscape. Detection of sub-canopy invaders remains a major challenge in the field of IAP remote sensing. There is room for future research in increasing the spatial resolution of freely available imagery to reduce cost.

**Key words**: Invasive alien plants species, remote sensing, detection, multispectral, hyperspectral

## 2.2 Introduction

Globally invasive alien plants (IAPs) threaten biodiversity (Higgins, Richardson, Cowling, & Trinder-Smith, 1999), agriculture and human welfare (van den Berg, Kotze, & Beukes, 2014) and are the second largest threat to biodiversity (van Wilgen, Reyers, Le Maitre, Richardson, & Schonegevel, 2008). These IAPs accomplish this by altering soil nutrient content, habitat suitability for indigenous species and ecosystem function (Higgins et al., 1999). In South Africa approximately 10 % of the country is occupied by alien vegetation, and control measures are not keeping pace with their spread (Gillson, Midgley, & Wakeling, 2012). Therefore in order to employ adequate mitigation strategies frequent monitoring of IAPs are required (Hamada, Stow, Coulter, Jafolla, & Hendricks, 2007).

Spectroscopy (remote sensing) can be an effective tool for mapping, monitoring and managing IAPs (Cuneo, Jacobson, & Leishman, 2009). The aim of remote sensing is to extract information on IAPs without physical contact with the ground (Huang & Asner, 2009). There are various sensors used that differ in spatial resolution, spectral resolution, spatial extent and temporal resolution (Bradley, 2014). In terms of spectral resolution, two broad categories of sensors are utilised for IAPs detection which are multispectral and hyperspectral sensors. Each has its successes and challenges. Multispectral sensors exhibit a large bandwidth and a small number of spectral bands, however, offer a large range of spatial scales and are easily accessible. On the contrary, hyperspectral sensors have smaller bandwidths and a larger number of continuous spectral bands but are more difficult to access (He, Rocchini, Neteler, & Nagendra, 2011; Underwood, Ustin, & Ramirez, 2007). Research has also been directed at detecting IAPs that occur within other vegetation and sub-canopy invaders. This includes the use of sensors such as Light Detection and Ranging (LiDAR) in conjunction with other sensors to detect IAPs. LiDAR uses infrared wavelengths to measure distance between features and the sensor, allowing for the study of the three dimensional structure of IAPs (Huang & Asner, 2009).

The mitigation of IAPs impacts has become an important component in conservation. In order to adequately deal with IAP control and management, accurate spatial information on their distribution in time and space is required. Remote sensing provides a time and cost effective approach of mapping IAPs (Tsai & Chen, 2004). This article discusses IAP concerns, the role remote sensing in IAP detection, different sensor capabilities, successes in IAP spectroscopy and challenges.

## 2.3 Invasive alien plants, concerns and monitoring

One of the major current concerns of conservationists, natural resource managers and ecologists is the spread of IAPs (Joshi, de Leeuw, & van Duren, 2004). Alien species are those that have been moved intentionally or unintentionally out of their indigenous habitat into a new habitat (Kannan, Shackleton, & Uma Shaanker, 2013). However, to be considered an IAP the species must be able to propagate throughout the landscape with or without facilitation (Asner et al. 2008). Invasion occurs in three stages, the initial being the arrival of the species followed by its establishment and finally, its integration into the environment (Mack, Von Holle, & Meyerson, 2007).

### *2.3.1 Concerns*

Invasive alien plants are considered one of the primary contributors to biodiversity loss and a major contributor to species extinction, because of their rapid spread (Joshi et al., 2004). Factors which influence the spread of IAPs include life history, the environment and disturbances (Carbutt, 2012). Historically, IAPs have the ability to outcompete and displace indigenous vegetation due to their superior dispersal and reproductive traits (Joshi et al., 2006), leading to the degradation of pristine habitats (Higgins et al., 1999). Environmental factors include, changes in global climate and an increase in anthropogenic activities which contribute to disturbances, facilitating the spread of IAPs (van Wilgen et al., 2008). Humans act as a dispersal agent for IAPs as they move flora beyond their natural barriers. This has become more pronounced due to an increase in trade and travel (Carbutt, 2012). Disturbances such as anthropogenic induced vegetation removal and increased runoff facilitate invasion by altering ecosystem processes, freeing resources and reducing indigenous competitors (Carbutt, 2012).

An assessment of global ecosystems indicates that 60% of ecosystem services were declining due to IAPs and their impacts (van Wilgen et al., 2008). This has engendered the use of IAPs presence and distribution as indicators of ecosystem health (Miao, Patil, Heaton, & Tracy, 2011). The estimated global cost of managing and repairing damages caused by IAPs is approximately 137 billion dollars annually (Huang & Asner, 2009). This includes control methods employed which are either mechanical, chemical or biological (Higgins et al., 1999).

Predicting the likelihood of invasion would allow for managers to be more prepared and efficient at managing invasion (Bradley & Marvin, 2011). The adoption of preventive rather than reactive approaches (which are often too late) is favoured (Higgins et al., 1999). Alien species that are not currently invasive may be facilitated by current invasive species to become invasive, therefore ideal management strategies should target both existing and emerging invaders (Carbutt, 2012).

South Africa has a high climatic variability and topography which has resulted in high species diversity, richness and endemism (Stuckenberg, Münch, & van Niekerk, 2014). Invasive alien plants pose a risk to this biodiversity as they have an adverse effect on ecosystems (Carbutt, 2012). Approximately 10 million hectares of land has been invaded (Meijninger & Jarmain, 2014) and currently 379 alien species are declared invaders in South Africa (NEMBA, 2016). To combat this issue the Department of Water affairs and Forestry initiated the Working for Water program which aims at removing IAPs (Rowlinson, Summerton, & Ahmed, 1999). Removal methods are usually chemical or mechanical. This program was initiated in 1995 and aims to preserve water resources, safeguard biodiversity and create employment (Meijninger & Jarmain, 2014). The capital spent in mitigating IAPs in South Africa between 1998 and 2008 was estimated at approximately three billion rand (van Wilgen et al., 2008), which impacts the country's economy (Calviño-Cancela, Méndez-Rial, Reguera-Salgado, & Martín-Herrero, 2014).

### *2.3.2 Monitoring invasive alien plants*

Field surveys used to map IAPs provide limited information, and are labour intensive and time consuming (Calviño-Cancela et al., 2014). Other issues with field surveys include bias due to researcher misclassifying species, lack of temporal data and field workers are too few for comprehensive mapping to be achieved (He et al., 2011). Remote sensing provides a more feasible alternative as it can obtain information from inaccessible areas and is capable of assessing large areas rapidly and comprehensively (Calviño-Cancela et al., 2014), including the historic extent of IAPs (Mutanga, van Aardt, & Kumar, 2009). Field studies should not be replaced entirely with remote sensing, rather both methods complement each other in IAP mapping (He et al., 2011). For example, remote sensing can identify stands of homogenous species. However, some species composition are difficult to determine using remote sensing, and require field studies (Asner, Jones, Martin, Knapp, & Hughes, 2008).

There is a need for tools that can simultaneously determine species expansion and monitor invaded areas (Mack et al., 2007). Remote sensing techniques and GIS (Geographical Information Systems) are suitable tools which can accomplish this and furthermore map species distributions which will aid in removal and management efforts (Rowlinson et al., 1999). The advancements in remote sensing have allowed for the detection of subtle changes in the environment and vegetation at a species level (Mutanga et al., 2009). For adequate management strategies to be applied, historic records of invasion are needed (Mack et al., 2007). This can be achieved via remotely sensed high spatial and temporal resolution imagery.

## 2.4 Invasive alien plants and remote sensing

Remote sensing is the observation of features without any physical contact which includes digital image processing and mapping (Rowlinson et al., 1999). These techniques analyse variations in reflectance spectra of features and differ due to a specific sensors spatial and spectral resolution (Calviño-Cancela et al., 2014). Spatial resolution refers to pixel size (Stuckenberg et al., 2014), while spectral resolution refers to the  number, range, breath and contiguous nature of wavelengths of light. Thus a high spectral resolution would have many wavelengths bands and a contiguous coverage (Mutanga et al., 2009).

### *2.4.1 Remote sensing of vegetation*

Light absorption by vegetation produces a unique reflectance spectral signature which is influenced by leaf biochemistry (He et al., 2011) and canopy structure (Asner, Jones, et al., 2008; Cuneo et al., 2009). Leaf biochemistry refers to the chlorophyll content, lignin, cellulose and structural carbohydrate molecules, whereas canopy structure refers to leaf/branch size, orientation and density (Underwood et al., 2007). Solar radiation interacts with leaf properties in different ways which is dependent on wavelength. Absorption is high in the visible spectra due to pigments (eg, chlorophyll a and b) and in the mid infrared (MIR) due to water content, while reflectance is high in the near infrared (NIR) due to spongy mesophyll (Shouse, Liang, & Fei, 2013). These properties allow for the spectral differentiation between species and in some cases spectral signatures of IAPs may be unique to the signature of indigenous species (He et al., 2011). This differentiation is attributed to both physiological and biological variation (Asner, Knapp, et al., 2008).

Optical and imaging sensors employed in the detection of IAPs include multispectral and hyperspectral sensors (Calviño-Cancela et al., 2014). Multispectral sensors examine broad reflectance bands at various regions within the electromagnetic spectrum. These regions include visible and infrared wavelengths (near infrared to far infrared) used mainly to distinguish between broad land classes (Joshi et al., 2004). Due to the low spectral resolution (fewer bands) of multispectral sensors it is difficult to distinguish between species (Calviño-Cancela et al., 2014). Hyperspectral sensors have a large number of narrower spectral bands within the electromagnetic spectrum and are used more often to distinguish between species (Joshi et al., 2004). Due to its high spectral resolution, hyperspectral sensors are able to detect subtle differences in spectra between species and is an efficient tool for IAP mapping and monitoring (Calviño-Cancela et al., 2014; Mutanga et al., 2009; van der Meer, de Jong, & Bakker, 2002).

### *2.4.2 Mapping IAPs using GIS and remote sensing*

The integration of remote sensing and GIS has been used historically in mapping plant and vegetation distributions. This practice has increased recently with focus shifting to mapping IAPs (Joshi et al., 2004). This current shift toward IAP mapping using these geospatial technologies has been enhanced by advancement in sensor development, spatial statistics and modelling (Evangelista, Stohlgren, Morisette, & Kumar, 2009). There are a number of data sources offered which include multispectral data, synoptic view, multi-temporal coverage (Joshi et al., 2004) and hyperspectral data (He et al., 2011).

Land managers, ecologists and biologists involved in the study of plant invasions usually do not have detailed maps of the study area (He et al., 2011). Effective mapping of IAPs extent and determining the risk they pose for future invasions and impact requires an accurate study of species distributions (Joshi et al., 2004), and an insight into density and impacts of IAPs (van den Berg et al., 2014). These maps are required to aid in mitigating impacts, optimising control and predicting spread (Evangelista et al., 2009) at both a national and provincial level (van den Berg et al., 2014). However, plant species are not homogenously distributed in a particular environment, and more realistic maps should be created exhibiting the discontinuous patterns of their distributions (Joshi et al., 2004).

When undertaking remote sensing studies, spectral, spatial and temporal resolution needs to be considered (Stow et al., 2004). Spatial resolution is crucial as it determines the level of accuracy of feature detection, with a finer spatial resolution increasing classification accuracy (He et al., 2011). Spatial resolution of sensors can be improved by pan sharpening imagery. Pan sharpening involves fusing a high spatial, low spectral resolution greyscale panchromatic image with a low spatial, high spectral resolution image to produce a single image with an improved spectral and spatial resolution (Yuhendra, Alimuddin, Sumantyo, & Kuze, 2012). Various techniques have been proposed for pan sharpening images, which are usually user and sensor specific (Yuhendra et al., 2012; Zhang & Mishra, 2012). Pan sharpening an image would therefore increase spatial resolution which in turn will improve the reliability of classification results (Forsyth, Gibson, & Turner, 2014).

The classification of images has been improved by using time series analyses (He et al., 2011) and the use of indices such as the normalised difference vegetation index (NDVI) and the soils adjusted vegetation index (SAVI) (Haby, Tunn, & Cameron, 2010). The NDVI is a commonly used index that combines the visible and NIR bands to enhance the signal of photosynthetic vegetation (Huang & Asner, 2009). While the SAVI reduces the effect of soil reflection which in turn increases accuracy of classification results (Qi, Chehbouni, Huete, Kerr, & Sorooshian, 1994).

## 2.5 Multispectral

Several studies have used multispectral sensors for the detection and mapping of IAPs (Joshi et al., 2004). An important factor to consider when utilising multispectral data is spatial scale (Huang & Asner, 2009).

### *2.5.1 Successes with multispectral data*

Spatial resolution, among others, is an important determining factor in IAP classification accuracy. Higher spatial resolution imagery such as IKONOS, GeoEye-1 and Quickbird produce more accurate IAP classification results (He et al., 2011) as opposed to coarse spatial resolution sensors such as AVHRR (Advanced very high resolution radiometer) and MODIS (Moderate resolution imaging spectrometer). These coarse spatial resolution imagery are mainly used to monitor spread but have an increased chance of error if there are multiple IAPs present (Bradley, 2014; Huang & Asner, 2009). However, the MODIS sensor has enhanced spectral and spatial capabilities when compared to AVHRR, and is more suited for land cover change studies (Stow et al., 2004). Despite their poor spatial resolutions they have a high temporal resolution (ie. the return time of the satellite allows for frequent mapping of a region)(Huang & Asner, 2009; Mutanga et al., 2009).

Moderate spatial resolution sensors such as ASTER (Advanced space borne thermal emission and reflective radiometer), SPOT (Satellite Pour l'Observation de la Terre) and Landsat are not able to detect IAPs within a heterogeneous vegetation type and are only effective when targeting homogenous stands over a large area (Huang & Asner, 2009). The recent Landsat series of sensors (eg. Landsat 5 TM and Landsat 7 ETM+) are commonly used for IAP detection and mapping and have a 40 year record of data which is free, however, due to its moderate spatial resolution it is difficult to map individual species (Gavier-Pizarro et al., 2012). Landsat 5 TM used in a study to assess biodiversity was not able to differentiate between semi-natural, natural and alien vegetation due to its moderate spatial resolution (Stuckenberg et al., 2014). In another study, Landsat 7 (a moderate spatial resolution imagery) was successful used to detect a target IAP, however, this invader formed dense stands (Cuneo et al., 2009).

Spatial resolution of multispectral imagery has improved (He et al., 2011). Higher spatial resolution sensors such as IKONOS, Quickbird and WorldView (Bradley, 2014; Stow et al., 2004) are significantly more accurate than medium spatial imagery (Shouse et al., 2013). The use of high spatial resolution imagery results in accurate detection of IAPs. High spatial resolution multispectral data is only useful in detecting IAPs if the target species exhibit unique phenological attributes for example a unique inflorescence (Evangelista et al., 2009). These sensors are suitable for detecting IAPs when spectral resolution is low, however, this may not be feasible for large areas because of cost of imagery (Huang & Asner, 2009). It is possible that in smaller areas, high spatial resolution multispectral imagery like Quickbird multispectral imagery is more applicable than Hyperion hyperspectral imagery due to spectral mixing (He et al., 2011). Some high spatial resolution multispectral sensors such as IKONOS may not be suitable for mapping IAPs at a species level where there is a high degree of intra species variability (He et al., 2011). A study conducted in southern Australia using Quickbird experienced difficulty in separating *Pinuss radiata* (an invasive alien species) from other species in the same environment. The *P.radiata* species was better detected in the NIR than the visible spectrum but was only successful in certain areas (Haby et al., 2010).

### *2.5.2 Challenges of multispectral data*

High spatial resolution multispectral imagery increases classification accuracy but spectral classes are difficult to separate. If a pixel is smaller than the feature, this could lead to inaccuracies for example a tree may cover many pixels, therefore spectra may vary between the bark and leaves (He et al., 2011). Higher spatial resolution imagery allows for more robust mapping of the environment but freely available satellites cannot compete with the high spatial resolution of commercial high resolution satellites (Johansen, Phinn, & Witte, 2010). Technically, variations in brightness caused by terrain can also cause inaccuracies (Cuneo et al., 2009), as well as information is lost due to reflectance of vegetation being averaged across pixels (Mutanga et al., 2009).

Multispectral sensors are generally spectrally too coarse to identify plants at a species level (He et al., 2011) as multiple species may share the same spectral signature and therefore high spectral resolution imagery is more efficient (Miao et al., 2011). Multispectral imagery is applicable when there is a large study area and the species form dense stands and have distinct traits (He et al., 2011). Multispectral analyses has been used successfully to detect invasive species that are unique to their environment, however, when IAPs are spectrally similar to indigenous species, hyperspectral data and complex image analysis techniques should then be applied (Asner, Knapp, et al., 2008). A common issue in IAP detection is that taller species may obstruct invasive alien shrubs and thus induce biased classification  results, this is opposed to dense monotypic species stands which are easier to detect and result in a greater accuracy (Joshi et al., 2004).

## 2.6 Hyperspectral

Hyperspectral sensors gather information via narrow bands in the visible, NIR and MIR spectrum, (band widths are usually small (5-10nm) and 150-300 bands). Some sensors support sub-nano meter ranges (He et al., 2011). This high spectral resolution data is commonly used to assess and monitor environmental changes at specific wavelengths to allow for spectral characteristics of a feature to be determined which are aimed at solving specific issues (Mutanga et al., 2009). Hyperspectral remote sensing data has been around for the last 30 years and has been effective in examining the spatial extent of IAPs. There are a number of  studies which have used hyperspectral imagery to examine spatial extent and dispersal of IAPs from local to global scales (He et al., 2011).

### *2.6.1 Successes of hyperspectral data*

Hyperspectral data is either collected using a sensor or by the use of a spectrometer. Hyperspectral data is obtained from both airborne and spaceborne sensors (Mutanga et al., 2009). Commonly used hyperspectral sensors in IAP detection include AVIRIS (Airborne visible/infrared imaging spectrometer), CASI (Compact airborne spectrographic imager), HyMAP, Hyperion (Huang & Asner, 2009) and AISA (Airborne imaging spectrometer for application) because of their high spectral resolution (He et al., 2011). Hyperion is less commonly used for studying IAPs as it has a poor spatial resolution (Huang & Asner, 2009).

Hyperspectral data, in conjunction with high spatial resolution data can detect detailed spectral variations between species (Shouse et al., 2013). This allows for detection at a species level, for example invasive species have higher nitrogen and chlorophyll content (Asner, Jones, et al., 2008) and can be detected using hyperspectral sensors. Hyperspectral sensors capture information such as variations in leaf water, nitrogen, chlorophyll, lignin and carotenes content to provide a unique spectral signature for each species, however, these characteristics often can vary over environmental gradients (He et al., 2011). A typical example would be leaf water content which is in a constant state of flux due to variations in rainfall (Asner, Jones, et al., 2008).

Hyperspectral sensors also can asses canopy properties such as specific leaf area (SLA), leaf area index (LAI), branch/stem architecture and leaf angle (Asner, Jones, et al., 2008). These properties are used to discriminate between indigenous and alien invasive vegetation, for example the rapid growth rate that IAPs exhibit, result in higher LAI values (Asner, Jones, et al., 2008). These qualities may allow hyperspectral sensors to detect IAPs within a vegetation type, where lower spectral resolution sensors are only able to detect IAPs in homogenous landscapes (Shouse et al., 2013).

The advantage of hyperspectral data is that detailed species specific spectral profiles are developed, which can be used to examine species presence, species abundance, the relationship between indigenous and invasive alien species and ecosystem nutrient fluxes (Huang & Asner, 2009). Hyperspectral imagery results in a higher classification accuracy than multispectral imagery even when the spatial resolution of the hyperspectral image is degraded (Underwood et al., 2007). Higher spectral resolution imagery is able to detect IAPs with low density and a scattered distribution, which is a major challenge for multispectral imagery. Flowering and senescence can cause a larger variation in spectral signature of individuals of the same species (He et al., 2011) resulting in classification errors. A fusion of multispectral and hyperspectral imagery, resulted in the discrimination of guava (*Psidium guajava*) from other classes which include both green and dry vegetation (Walsh et al., 2008).

### *2.6.2 Challenges of hyperspectral data*

Taller indigenous species my obstruct IAPs found at lower vegetation strata. This is a common challenge for both multispectral and hyperspectral sensors. Most hyperspectral sensors are airborne sensors and therefore have a small coverage (He et al., 2011). Hyperspectral imagery of a fine spatial scale is acquired from air borne sensors, however these sensors are expensive to use as it requires the sensor to be flown over the intended study area (Calviño-Cancela et al., 2014). Additionally high spectral and spatial resolution imagery causes variation within a species when an individual of the species occupies an area larger than a pixel leading to inaccuracies (He et al., 2011). Plants at different development stages exhibit different spectral signatures, so there would be high intra-species variability which can create an underestimation (Joshi et al., 2004). Therefore the accurate detection of IAPs from hyperspectral data is uncertain due to inter- and intra- spectral variability (Huang & Asner, 2009). New techniques to solve this problem are being used such as spectral unmixing (Hestir et al., 2008).

Hyperspectral data comes in large volumes due to the large number of bands, which are time consuming to process (He et al., 2011). Patterns in the data of hyperspectral images are difficult to distinguish. To mitigate this issue, sophisticated algorithms are used (Huang & Asner, 2009) which can become taxing for non remote sensing specialists to perform (He et al., 2011). Hyperspectral remote sensing is an underused tool in the fields of conservation and invasion biology, as in certain circumstances it is not at the desired scale. In addition, there is a lack of interdisciplinary training between geographers (traditional practitioners of GIS and Remote sensing) on the one hand and biologists on the other hand (He et al., 2011).

## 2.7 Other detection approaches and challenges

### *2.7.1 Sub-canopy detection*

Management of IAPs is best done in the early stages of invasion, however, detection may be difficult due to invaders being sparse and occupying the sub-canopy (Ghulam, Porton, & Freeman, 2014). Conventional remote sensing currently has been restricted to mapping canopy dominant species, as these determine the spectral signature. This is a limitation as 67 of the worlds 100 worst invaders are sub-canopy invaders (Joshi et al., 2006). In the forest, sub-canopy invaders are difficult to detect. The use of multiple sensors such as multi-angle sensors can determine the forest vertical profile, and IAPs can be indirectly detected (Ghulam et al., 2014; Huang & Asner, 2009).

One of the proposed methods of detecting sub-canopy invaders is when there is a temporal variation in senescence between the invader and the canopy species. When canopy species are bare, the sub-canopy species can be detected. Another method employed for IAP detection within indigenous vegetation is to take into consideration the vegetation dynamics of an area. This can be tracked via time series analysis using high temporal resolution imagery (Huang & Asner, 2009) which will infer on the presence of an IAP. Time series analysis is extensively used for studying land cover change due to invasion and assessing mitigation efforts (Evangelista et al., 2009). The detection of herbaceous and understory species remains a challenge even with the use of the latest and highest quality sensors (Huang & Asner, 2009).

### *2.7.2 Indirect detection*

The invasion of an area by IAPs alters environmental conditions which can be detected using satellite imagery (He et al., 2011). This indirect method of IAP detection examines the relationship between the target species, its climatic envelope and its environment, then predicts the potential spread of the species by utilising a bioclimatic envelope model which follows the assumption that climatic variables determine species distribution (Joshi et al., 2006).

By detecting the variation in climatic variables, one can predict the presence of a sub-canopy invader, an example of this would be examining variations in light intensity to infer about the presence of *Chromolaena odorata* as light intensity is correlated to its reproductive and life history traits. Areas with insufficient light intensity are occupied with young or sterile individuals of *C. odorata* with low seed production. Predicting an IAPs potential distribution will be beneficial when planning mitigating strategies as invasion may increase in some regions and decrease in others. However, this study concentrated on a single vegetation type which was dominated by a single canopy species. Mapping canopy density can result in a number of classes instead of a continuous variable which would have an adverse effect on the accuracy of the model (Joshi et al., 2006).

#### *2.7.3 Light Detection and Ranging (LiDAR)*

Optical remote sensing can detect IAPs but does not deliver any information on vegetation structure. Light Detection and Ranging (LiDAR), which is an active remote sensing technique provides information on vegetation structure (Hantson, Kooistra, & Slim, 2012). Light detection and ranging utilises infrared wavelengths to measure distance between the feature and the sensor, to allow for information on the three dimensional structure of vegetation to be obtained, (for example height and biomass) (Huang & Asner, 2009). This sensor sends a pulse towards a feature and uses the time taken for the pulse to be reflected and returned to calculate height of the features, allowing for DEM's (digital elevation model) to be produced (Hantson et al., 2012). The LiDAR sensor alone is not efficient at detecting IAPs when there are little physical structural variations (height, leaf area index and biomass) between indigenous and invasive species. Rather these sensors can be used in conjunction with hyperspectral image to differentiate between vegetation canopies (Huang & Asner, 2009). This is achieved by using the hyperspectral data to compare spectral signatures and LiDAR data to compare species attributes, for example, variations in species height coupled with pixel based classification, will overcome intra species variability and increase classification accuracy (Naidoo, Cho, Mathieu, & Asner, 2012). In order to successfully combine LiDAR and hyperspectral data, data needs be collected at the same time period (Asner, et al. 2008).

A caveat of LiDAR sensors is that signal pulses cannot penetrate certain canopies, which compromises vertical accuracy. When vegetation senesces occurs in colder months, LiDAR signals are not accurately reflected, therefore creating a challenge in determining tree heights (Hantson et al., 2012).

## 2.8 Future Research and Challenges

Challenges for future research in remote sensing IAP detection should include methods to increase the accuracy of image classification, the development of simple models to determine impacts of IAPs and techniques to estimate spread (van Wilgen et al., 2008). Currently remote sensors and techniques are unable to determine species composition from spectral signatures (Asner, Jones, et al., 2008). Plant detection of a single species within a vegetation type is still a challenging task when IAPs do not form dense stands (Evangelista et al., 2009). The detection of an IAP on a regional scale is problematic because of cost and inadequate resources (Joshi et al., 2006).

The development of models to depict future spread is a crucial research area. Various models have been developed; which use climatic and topographic variables as inputs to infer on future extent of IAPs (He et al., 2011). An example of this is the Maximum Entropy model which proved the most accurate at predicting the spread of IAP *Lantana camara* (Neena & Joshi, 2013). Another study based in China, successfully predicted the distribution of *Eupatorium adenophorum* using the genetic algorithm for rule-set production. These models can serve as an early warning system to alert mangers to areas prone to invasion (Zhu, Ma, Sang, Li, & Ma, 2007). Spatial modelling of invasion risk will also allow for assessing areas where environmental variables are in a state of flux due to climate change (Stohlgren et al., 2010). However, the incorporation of hyperspectral data into model development is currently not well researched (He et al., 2011). The integrated use of sensors with various spectral and spatial capabilities to detect IAPs is not feasible in some countries due to limited resources (Huang & Asner, 2009).

South Africa's heterogeneous vegetation results in many challenges when applying remote sensing techniques to detect IAPs. The field of imaging spectroscopy of vegetation is still relatively new in South Africa (Mutanga et al., 2009). More research needs to be undertaken to study IAPs using these innovative approaches and technologies for the purpose of natural systems conservation (Shouse et al., 2013). It would be beneficial to develop regional scale protocols/techniques to detect IAPs as the dynamics of invasive vary from place to place. Sensors and techniques used would also vary from region to region and would be dependent on various factors such as resource availability, terrain, IAPs present and vegetation type (Joshi et al., 2004).

## 2.9 Conclusion

Remote sensing is a valuable tool as spatial information on IAP distribution allows policy makers to apply adequate mitigation strategies (Joshi et al., 2005). Both multispectral and hyperspectral sensors are useful at detecting IAPs (Bradley, 2014). Multispectral data is more generalised and involves broader categories and therefore is useful at mapping species that form distinguished homogenous stands (Huang & Asner, 2009) and species that have distinct characteristics (Cuneo et al., 2009). Hyperspectral data can isolate individual bands which can be used to answer specific questions which include mapping IAPs (Mutanga et al., 2009). High spectral and low spatial resolution imagery is effective for mapping IAPs that form monotypic stands. Whereas high spectral and high spatial resolution is useful for mapping IAPs in a heterogeneous community where species are scattered (He et al., 2011). Spatial resolution affects the accuracy and precision of IAP detection, and as spatial resolution decreases so does accuracy (Shouse et al., 2013).

Predicting the potential distribution will aid in determining invasion risk (Joshi et al., 2006), however this approach would have to be species specific and will be time consuming. Detection of an IAP using remote sensing is possible as long as the target IAP exhibits novel characteristics when compared to the indigenous species (Huang & Asner, 2009). One of the major challenges still faced is mapping a single IAP species in a heterogeneous landscape. Future research should include detection methods that are not resource demanding which still maintain a high level of accuracy.

## References


Africa, S. (2016). *National environmental managment: Biodiversity act (Act No, 10 of 2004)*. *Goverment Gazette* (Vol. 66).

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. http://doi.org/10.1016/j.rse.2007.02.043

Asner, G. P., Knapp, D. E., Kennedy-Bowdoin, T., Jones, M. O., Martin, R. E., Boardman, J., & Hughes, R. F. (2008). Invasive species detection in Hawaiian rainforests using airborne imaging spectroscopy and LiDAR. *Remote Sensing of Environment*, *112*(5), 1942–1955. http://doi.org/10.1016/j.rse.2007.11.016

Bradley, B. A. (2014). Remote detection of invasive plants: a review of spectral, textural and phenological approaches. *Biological Invasions*, *16*(7), 1411–1425. http://doi.org/10.1007/s10530-013-0578-9

Bradley, B. A., & Marvin, D. (2011). Using expert knowledge to satisfy data needs: mapping invasive plant distributions in the western United States. *Western North American Naturalist*, *71*(3), 302–315. http://www.bioone.org/doi/abs/10.3398/064.071.0314

Calviño-Cancela, M., Méndez-Rial, R., Reguera-Salgado, J., & Martín-Herrero, J. (2014). Alien plant monitoring with ultralight airborne imaging spectroscopy. *PloS One*, *9*(7), e102381. http://doi.org/10.1371/journal.pone.0102381

Carbutt, C. (2012). The emerging invasive alien plants of the Drakensberg Alpine Centre, southern Africa. *Bothalia*, *85*, 71–85. http://www.abcjournal.org/index.php/ABC/article/view/10

Cuneo, P., Jacobson, C. R., & Leishman, M. R. (2009). Landscape-scale detection and mapping of invasive African Olive (*Olea europapea L. ssp.* cuspidata Wall ex G. Don Ciferri) in SW Sydney, Australia using satellite remote sensing. *Applied Vegetation …*, *12*, 145–154. http://onlinelibrary.wiley.com/doi/10.1111/j.1654-109X.2009.01010.x/full

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. http://doi.org/10.3390/rs1030519

Forsyth, A. T., Gibson, L. A., & Turner, A. A. (2014). Assessment of SPOT 6 imagery for mapping the invasive alien plant species Pinus spp. in a mountainous area of the Western Cape. *Proceedings of the Second AfricaGEO Conference*, 1–12.

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. http://doi.org/10.1016/j.rse.2011.09.023

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. http://doi.org/10.1016/j.isprsjprs.2013.12.007

Gillson, L., Midgley, G., & Wakeling, J. (2012). Exploring the significance of land-cover change in South Africa. *South African Journal of Science*, *108*(1), 5–7. http://www.scielo.org.za/scielo.php?pid=S0038-23532012000300003&script=sci_arttext&tlng=es

Haby, N., Tunn, Y., & Cameron, J. (2010). Application of QuickBird and aerial imagery to detect Pinus radiata in remnant vegetation. *Austral Ecology*, *35*(6), 624–635. http://doi.org/10.1111/j.1442-9993.2009.02070.x

Hamada, Y., Stow, D. A., Coulter, L. L., Jafolla, J. C., & Hendricks, L. W. (2007). Detecting Tamarisk species (Tamarix spp.) in riparian habitats of Southern California using high spatial resolution hyperspectral imagery. *Remote Sensing of Environment*, *109*(2), 237–248. http://doi.org/10.1016/j.rse.2007.01.003

Hantson, W., Kooistra, L., & Slim, P. A. (2012). Mapping invasive woody species in coastal dunes in the Netherlands: a remote sensing approach using LIDAR and high-resolution aerial photographs. *Applied Vegetation Science*, *15*(4), 536–547. http://doi.org/10.1111/j.1654-109X.2012.01194.x

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. http://doi.org/10.1111/j.1472-4642.2011.00761.x

Hestir, E. L., Khanna, S., Andrew, M. E., Santos, M. J., Viers, J. H., Greenberg, J. a., … 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. http://doi.org/10.1016/j.rse.2008.01.022

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. http://doi.org/10.1046/j.1523-1739.1999.013002303.x

Huang, C.-Y., & Asner, G. P. (2009). Applications of remote sensing to alien invasive plant studies. *Sensors (Basel, Switzerland)*, *9*(6), 4869–4889. http://doi.org/10.3390/s90604869

Johansen, K., Phinn, S., & Witte, C. (2010). Mapping of riparian zone attributes using discrete return

LiDAR, QuickBird and SPOT-5 imagery: Assessing accuracy and costs. *Remote Sensing of Environment*, *114*(11), 2679–2691. http://doi.org/10.1016/j.rse.2010.06.004

Joshi, C., de Leeuw, J., Skidmore, A. K., van Andel, J., Lekhak, H. D., & van Duren, I. (2005). Remote sensing and GIS for mapping and management of invasive shrub *Chromolaena odorata* in Nepal. *International Institute for Geo-Information Science and Earth Observation (ITC)*. http://www.researchgate.net/profile/Jelte_Andel/publication/228976892_Remote_Sensing_And_GIS_For_Mapping_And_Management_Of_Invasive_Shrub_Chromolaena_odorata_In_Nepal/links/0fcfd50649c4e76495000000.pdf

Joshi, C., de Leeuw, J., van Andel, J., Skidmore, A. K., Lekhak, H. D., van Duren, I. C., & Norbu, N. (2006). Indirect remote sensing of a cryptic forest understorey invasive species. *Forest Ecology and Management*, *225*(1–3), 245–256. http://doi.org/10.1016/j.foreco.2006.01.013

Joshi, C., de Leeuw, J., & van Duren, I. (2004). Remote sensing and GIS applications for mapping and spatial modelling of invasive species. *Proceedings of ISPRS*, *35*, 669–677. http://www.isprs.org/proceedings/xxxv/congress/comm7/papers/132.pdf

Kannan, R., Shackleton, C. M., & Uma Shaanker, R. (2013). Reconstructing the history of introduction and spread of the invasive species, Lantana, at three spatial scales in India. *Biological Invasions*, *15*(6), 1287–1302. http://doi.org/10.1007/s10530-012-0365-z

Mack, R. N., Von Holle, B., & Meyerson, L. A. (2007). Assessing invasive alien species across multiple spatial scales: Working globally and locally. *Frontiers in Ecology and the Environment*, *5*(4), 217–220. http://doi.org/10.1890/1540-92955[217:AIASAM]2.0.CO;2

Meijninger, W., & Jarmain, C. (2014). Satellite-based annual evaporation estimates of invasive alien plant species and native vegetation in South Africa. *Water SA*, *40*(1), 95–108. http://www.scielo.org.za/scielo.php?pid=S1816-79502014000100020&script=sci_arttext

Miao, X., Patil, R., Heaton, J. S., & Tracy, R. C. (2011). Detection and classification of invasive saltcedar through high spatial resolution airborne hyperspectral imagery. *International Journal of Remote Sensing*, *32*(8), 2131–2150. http://doi.org/10.1080/01431161003674618

Mutanga, O., van Aardt, J. Van, & Kumar, L. (2009). Imaging spectroscopy ( hyperspectral remote sensing ) in southern Africa : an overview. *South African Journal of Science*, *105*(June), 193–198.

Naidoo, L., Cho, M. A., Mathieu, R., & Asner, G. P. (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. http://doi.org/10.1016/j.isprsjprs.2012.03.005

Neena, P., & Joshi, P. . (2013). Modeling spatial distribution of Lantana Camara - A comparative study. *Canadian Journal of Basic and Applied Science*, *1*(2), 100–117.

Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H., & Sorooshian, S. (1994). A modified soil adjusted vegetation index. *Remote Sensing of Environment*, *126*(48), 119–126.

Rowlinson, L., Summerton, M., & Ahmed, F. (1999). Comparison of remote sensing data sources and techniques for identifying and classifying alien invasive vegetation in riparian zones. *Water SA*, *25*(4), 497–500. http://researchspace.csir.co.za/dspace/handle/10204/2076

Shouse, M., Liang, L., & Fei, S. (2013). Identification of understory invasive exotic plants with remote sensing in urban forests. *International Journal of Applied Earth Observation and Geoinformation*, *21*, 525–534. http://doi.org/10.1016/j.jag.2012.07.010

Stohlgren, T. J., Ma, P., Kumar, S., Rocca, M., Morisette, J. T., Jarnevich, C. S., & Benson, N. (2010). Ensemble Habitat Mapping of Invasive Plant Species. *Risk Analysis*, *30*(2), 224–235. http://doi.org/10.1111/j.1539-6924.2009.01343.x

Stow, D. A., Hope, A., McGuire, D., Verbyla, D., Gamon, J., Huemmrich, F., … Myneni, R. (2004). Remote sensing of vegetation and land-cover change in Arctic Tundra Ecosystems. *Remote Sensing of Environment*, *89*(3), 281–308. http://doi.org/10.1016/j.rse.2003.10.018

Stuckenberg, T., Münch, Z., & van Niekerk, A. (2014). Multi-temporal remote sensing land-cover change detection for biodiversity assessment in the Berg River catchment. *South African Journal of Geomatics*, *2*(3), 189–205. http://www.ajol.info/index.php/sajg/article/view/106977

Tsai, F., & Chen, C.-F. (2004). Detecting invasive plants using hyperspectral and high resolution satellite images. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*.

Underwood, E. C., Ustin, S. L., & Ramirez, C. M. (2007). A comparison of spatial and spectral image resolution for mapping invasive plants in coastal California. *Environmental Management*, *39*(1), 63–83. http://doi.org/10.1007/s00267-005-0228-9

van den Berg, E., Kotze, I., & Beukes, H. (2014). Detection, quantification and monitoring of Prosopis in the Northern Cape Province of South Africa using remote sensing and GIS. *South African Journal of Geomatics*, *2*(2), 68–81. http://www.ajol.info/index.php/sajg/article/view/106983

van der Meer, F., de Jong, S., & Bakker, W. (2002). Imaging spectrometry: Basic analytical techniques. In *maging Spectrometry: Basic Principles and Prospective Applications* (pp. 17–61).

van Wilgen, B. W., Reyers, B., Le Maitre, D. C., Richardson, D. M., & Schonegevel, L. (2008). A biome-scale assessment of the impact of invasive alien plants on ecosystem services in South Africa. *Journal of Environmental Management*, *89*(4), 336–49. http://doi.org/10.1016/j.jenvman.2007.06.015

Walsh, S. J., McCleary, A. L., Mena, C. F., Shao, Y., Tuttle, J. P., González, A., & Atkinson, R. (2008). QuickBird and Hyperion data analysis of an invasive plant species in the Galapagos Islands of Ecuador: Implications for control and land use management. *Remote Sensing of Environment*, *112*(5), 1927–1941. http://doi.org/10.1016/j.rse.2007.06.028

Yuhendra, Alimuddin, I., Sumantyo, J. T. S., & Kuze, H. (2012). Assessment of pan-sharpening methods applied to image fusion of remotely sensed multi-band data. *International Journal of Applied Earth Observation and Geoinformation*, *18*(1), 165–175. http://doi.org/10.1016/j.jag.2012.01.013

Zhang, Y., & Mishra, R. (2012). A review and comparison of commercially available pan-sharpening techniques for high resolution satellite image fusion. *Geoscience and Remote Sensing …*, 182–185. http://doi.org/10.1109/IGARSS.2012.6351607

Zhu, L., Ma, O., Sang, W., Li, Z., & Ma, K. (2007). Predicting the spatial distribution of an invasive plant species ( Eupatorium adenophorum ) in China. *Landscape Ecology*, *22*, 1143–1154. http://doi.org/10.1007/s10980-007-9096-4

# CHAPTER THREE

# DETECTING THREE INVASIVE ALIEN PLANT SPECIES USING MULTISPECTRAL IMAGES. A COMPARATIVE ANALYSIS OF FOUR CLASSIFIERS

This chapter is based on:

**Adam,** Y, Ngetar, N.S and Ramdhani, S. "Detecting three invasive alien plant species using multispectral images. A comparative analysis of four classifiers'', *Landscape Ecology* (In review).

## 3.1 Abstract

Invasive alien plants (IAPs) are a major concern because of their negative environmental impacts. Remote sensing can be used as a robust tool in the detection and mapping of IAPs. This study examined the use of three multispectral images and four classifiers in the detection of three IAPs (*Acacia podalyriifolia*, *Chromolaena odorata* and *Litsea glutinosa*). The four classifiers used were: Parallelepiped, Maximum Likelihood, Spectral Angle Mapper and the Iterative Self Organising Data Analysis Technique. Species identification and classification were performed on pan-sharpened images. Two of the three images were obtained from moderate spatial resolution sensors (Landsat 7 ETM+ and SPOT 5) and the third from a high spatial resolution sensor (WorldView-2). The most appropriate bands for spectral differentiation between species are the red and infrared bands. High spatial resolution imagery (WorldView-2) was the best for adequately detecting two of the selected species (*A. podalyriifolia* and *C. odorata*), using the Maximum Likelihood classifier. The study shows that there is a potential for detecting and mapping certain IAPs using high spatial resolution multispectral imagery and the Maximum Likelihood classifier.

**Keywords:** Invasive alien plants, remote sensing, spatial resolution, spectral resolution, classifiers.

## 3.2 Introduction

Analysing the spatial distribution of invasive alien plants (IAPs) is a field attracting increasing attention (Bradley, 2014). The rapid increase and spatial expansion of IAPs has caused irreversible damage across a number of habitat types because of their ability to alter ecosystem processes and the population dynamics of indigenous species present (Underwood, Ustin, & Ramirez, 2007). To accurately assess the impacts of IAPs with the view of applying effective control measures, comprehensive mapping of these species is a necessary requirement (Bradley, 2014). Mapping can aid in the management of invasions as it can provide the location of IAPs and further indicate their residence time (Trueman, Standish, Orellana, & Cabrera, 2014). Remote sensing is a tool, which has revolutionised mapping as advances in this geospatial technology can now provide information on species location, composition and structure (Asner, Hughes, et al., 2008; Trueman et al., 2014). However, the use of this technology is restricted due to the high cost of fine resolution imagery (Trueman et al., 2014).

Imaging spectroscopy using appropriate spatial and spectral resolutions has allowed for the identification and mapping IAPs (Schaepman et al., 2009). Early uses of multispectral imagery in the detection of IAPs were employed successfully, however, the requirement for accurate detection included that the target species was phenotypically distinct from other species and formed large dense stands (Cuneo, Jacobson, & Leishman, 2009; Underwood et al., 2007).

Spatial resolution and scale are other important factors in mapping the spatial distribution of IAP invasions, for example fine spatial resolution, large scale imagery is more useful at local level applications while coarse spatial resolution, small scale imagery is better suited at a regional level (Lu & Weng, 2007). Frequent re-evaluations of the spatial extent of IAPs is deemed essential for mitigation efforts (Underwood et al., 2007). Remote sensing can provide frequent re-evaluation as it is able to map accessible and inaccessible areas (Underwood et al., 2007) at a greater frequent sensor return time (high temporal resolution) (Huang & Asner, 2009).

Image classification is the technique used to assign pixels of a remotely sensed image into categories based on either their spectral signature or similarities in texture (Calviño-Cancela, Méndez-Rial, Reguera-Salgado, & Martín-Herrero, 2014). Spectral signature development for image classification is the most commonly used method for detecting IAPs (Bradley, 2014). Image classification for the detection of IAPs is still a challenge due to sensor types, different image resolutions, the large number of image pre-processing tasks and the selection of an appropriate classifier (Lu & Weng, 2007). When considering which image type is most applicable for a study, the spectral resolution (number of bands), spatial extent (image scale), spatial resolution (pixel size) and temporal resolution (data acquisition frequency) needs to be taken into account (Bradley, 2014). Images covering large spatial extent (small scale) usually have low spatial resolution (Bradley, 2014) which results in an impaired accuracy in terms of the location of features (Thenkabail et al., 2003). On the contrary, images covering small areas (large scale) have finer spatial resolution, enabling the detection of features at finer details including early infestations of IAPs. However, the temporal coverage may be limited. High spectral resolution imagery (many spectral bands) can allow for more accurate spectral separation of individual species as opposed to low spectral resolution imagery (few spectral bands) (Bradley, 2014).

There are two approaches when selecting image types for IAPs detection, one is high spatial and low spectral resolution, the other is high spectral but lower spatial resolution (Underwood, Ustin, & DiPietro, 2003). There is a trade-off between spectral and spatial resolution, for example SPOT 5 imagery has been used to map IAPs in the past and has a spatial resolution of 10m (Everitt, Yang, Fletcher, & Deloach, 2008), but has only 4 bands (low spectral resolution) (Trueman et al., 2014). Landsat 7 ETM+ imagery on the other hand has an improved spectral resolution due to the availability of more bands (Thenkabail et al., 2003), but possess a spatial resolution of 30m (Key, Warner, McGraw, & Fajvan, 2001). These moderate spatial resolution multispectral images may not be very effective for detecting IAPs (Huang & Asner, 2009). WorldView-2 (4 band imagery used in this study), though having a low spectral resolution has a higher spatial resolution (1.8m) and can be used to distinguish between indigenous vegetation and IAPs (Mazus & Chimboza, 2015). Pan-sharpening methods can be applied to both spatial and spectral properties of an image by merging a panchromatic high spatial resolution image with a moderate spatial resolution multispectral image (Chaves, Sides, & Anderson, 1991) to increase the accuracy of IAP detection in a previously moderate spatial resolution image.

The selection of an appropriate classifier is determined by the availability of classification algorithms, spatial resolution of imagery, time constraints and the user's needs (Lu & Weng, 2007). Two methods of spectral image classifications are: supervised and unsupervised. Supervised classification requires training sites which are used to classify features, whereas unsupervised classification creates classes first and then assigns them to feature classes (Adejoke & Badaru, 2014). Supervised image classification is commonly applied to remotely sensed data, with an adequate number of training sites (Stuckenberg, Münch, & van Niekerk, 2014). Two commonly used supervised classifiers in the detection of IAPs are the Maximum Likelihood classifier (ML) which utilises a statistical method that assigns pixels into classes by examining the probability of each pixel belonging to a class (Doody, Lewis, Benyon, & Byrne, 2014). The other classifier is the Spectral Angle Mapper (SAM) classifier which uses an algorithm that examines the relationship between reference spectra and the image's spectra and uses the angle of the result in this relationship to perform the classification, with smaller angles equating to a closer relationship (Doody et al., 2014). The Parallelepiped classifier is a non-parametric classifier that is not commonly used. It is based on Boolean logic and uses thresholds to subset pixels into classes (Hamada, Stow, Coulter, Jafolla, &

Hendricks, 2007). An unsupervised classifier that has been used for IAPs detection is the Iterative Self Organising Data Analysis Technique (ISODATA) which groups classes based on iterations (ie. which are divisions between clusters of pixel values that are plotted graphically) (Mazus & Chimboza, 2015).

This study attempts to determine the most accurate image type and classifier for the detection of three prominent IAPs namely, *Acacia podalyriifolia* A.Cunn (Pearl Acacia)., *Litsea glutinosa* (Lour.) C.B.Rob (Indian Laurel)., and *Chromolaena odorata* (L.) R.M. King & H. Rob (Triffid Weed), that occurs in the Paradise Valley Nature Reserve (eThekwini, KwaZulu-Natal, South Africa). All three IAPs chosen for this study are category 1b invasive (NEMBA, 2016). Category 1b species under the National Environmental Management: Biodiversity Act no. 10 of 2004 are prohibited from being imported, bred , translocated or sold in South Africa, furthermore permits are required to keep these plants (NEMBA, 2016). *Acacia podalyriifolia* is an Australian large shrub species, characterised by silver grey leaves and yellow flowers. *Chromolaena odorata* is an American species, which is characterised as a small shrub with white flowers, which forms dense thickets (Henderson, 1995). In KwaZulu-Natal *C. ordata* is considered as one of the most dominant IAPs (Stow et al., 2004). *Litsea glutinosa* species is a tropical Asian tree species, categorised by ever green leaves and yellow-orange flowers (Henderson, 1995).

This study compares and assesses the capabilities of three remotely sensed images in the detection of the above IAPs, namely two moderate range spatial resolution images (Landsat 7 ETM+ and SPOT 5) and one high spatial resolution image (WorldView-2). The classifiers used for each image type included the Parallelepiped (PP), Maximum Likelihood (ML), Spectral Angle Mapper (SAM) and the Iterative Self Organising Data Analysis Technique (ISODATA). The intended outcome of this study is to determine which method is best suited for change detection analysis where IAP eradication programs are implemented to asses clearing (chapter four).

## 3.3 Methods and materials

### *3.3.1 Study site*

The Paradise Valley Nature Reserve is located in the eThekwini Municipality (29.83$^{o}$S, 30.89$^{o}$E) just west of the city of Durban (KwaZulu-Natal, South Africa). The reserve is roughly 300ha in size, vegetation on site includes forest, thicket, and grassland. The average yearly temperature in this region is 20.5$^{o}$C with a variation of 8.3$^{o}$C.The maximum and minimum temperatures are in February and July respectively. The average rainfall is approximately 1010mm per an annum, with the majority of rainfall occurring between November and March (Preston-Whyte 1980). The Wildlife and Environmental Society of South Africa (WESSA) and the Environmental Planning and Climate Protection Department (EPCPD) initiated clearing programs of IAPs in the reserve since 2011.

### *3.3.2 Image processing*

Field data supplied by the Wildlife and Environmental Society of South Africa (WESSA) were created in spring (September to November), therefore images used in this study were obtained in September 2010 and 2015 for the purpose of consistency. Landsat 7 ETM+ images were acquired from the United States Geological Survey (USGS), while SPOT 5 and WorldView-2 were obtained from the South African National Space Agency (SANSA) (Table 3.1). All imagery was received geometrically corrected. Landsat 7 ETM+ images were supplied as single band images while SPOT 5 and WorldView-2 were supplied as image composites. The Landsat bands were stacked excluding band 6a, band 6b (thermal bands) and band 8 (panchromatic band) (Evangelista, Stohlgren, Morisette, & Kumar, 2009). Sensor fallout necessitated that, images were then de-striped by running the focal analysis tool multiple times using the mean function. The DN (digital number) values of images from all three sensors were then converted into surface reflectance (Naidoo, Cho, Mathieu, & Asner, 2012). This image pre-processing was performed in ERDAS Imagine (2013/2015) and ENVI (5.2). A single subset containing the study site was clipped from each of the three sensor images in ArcMap (ArcGIS 10.2).

**Table 3.1:** Characteristics of imagery used in this study.

| Imagery | Spatial resolution | Pan-sharpened | Spectral resolution | Spectral range | Temporal availability | Data source |
|---|---|---|---|---|---|---|
| Landsat 7 ETM+ | 30m | 15m | 7 bands | 450 -1250nm | 1999-present | *Earth Explorer |
| SPOT 5 | 10m | 5m | 4 bands | 480-1750nm | 2002-present | #SANSA |
| Worldview 2 | 1.8m | 0.5m | 4 bands | 450-895nm | 2009-present | #SANSA |

∗ Earth Explorer is the United States Geological Survey’s online sensor imagery database.

# SANSA is the South African National Space Agency, a South African government funded satellite imagery data source.

Image spatial resolution for the three set of images were improved through pan-sharpening using ERDAS Imagine (2013). Landsat 7 ETM+ images were pan-sharpened using a Hyperspherical Color Sharpening (HCS) algorithm with a smoothing filter of seven and the process area operator with intersection (Tu, Hsu, Tu, & Lee, 2012). The Brovey transform (BT) method (Kimothi & Dasari, 2010) was applied to SPOT 5 imagery. WorldView-2 imagery was pan-sharpened using a subtractive resolution merge with a centre value of 17 and a pan contribution weight of 1.00 as the imagery was 4-band, so both a high and low pass filter was applied (Zhang & Mishra, 2012).

### *3.3.3 Spectral signature development*

Training sites were identified using both the field data and spectral reflectance from high resolution imagery (WorldView-2) (Lu & Weng, 2007). Field data collection was species dependent as some species had been subjected to eradication in the field by clearing, therefore only certain species were present to serve as training sites. Polygons of the target IAPs digitised from field data by WESSA prior to clearing were used as guides to create 12 training sites each for both *A. podalyriifolia* and *C. odorata* using the WorldView-2 imagery. The training sites for *L. glutinosa* were created by digitising 10 polygons on the 2015 WorldView-2 imagery using GPS points collected in the field (Evangelista et al., 2009). All training sites on WorldView-2 for the three species were created in ArcMap (Pu & Landry, 2012) and then imported into ERDAS, where spectral signatures were produced for image classification. On the study site, *L. glutinosa* was the dominant species among others in the training sample.

The creation of spectral signatures for each image type was proceeded by the calculation of univariate statistics (mean and standard deviation) for each spectra. These data was then used to create spectral profiles using the mean pixel value of each band for each class (Forsyth, Gibson, & Turner, 2014). Furthermore, to determining spectral variability, the coefficient of variation (CV) was also calculated to determine the variability in the data sets (Kimothi & Dasari, 2010). Coefficient of variation (CV) is expressed as:

$$CV = \left(\frac{SD}{Mean}\right) * 100 \qquad [1]$$

The CV values were represented as percentages that indicate the variation within the spectral signature. An IAP class that exhibits a low CV value when compared to other classes, indicates that it is easier to discriminate that particular class from the other selected classes (Kimothi & Dasari, 2010).

### *3.3.4 Image classification*

Image classification was performed in ERDAS using four classifiers. This included three supervised classifiers namely one non-parametric classifier (PP), two parametric classifiers (ML and SAM) and, an unsupervised classifier (ISODATA). Only two species (*A. podalyriifolia* and *C. odorata*) were identified and classified using the ISODATA classifier, as the location of *L. glutinosa* on the 2010 imagery was not apparent.

The Landsat 7 ETM+ imagery was classified using a Maximum Likelihood classifier followed by a threshold of 0.05 to remove non-target features. Non-target features have the tendency to introduce error in classification requiring the application of an appropriate threshold. However, this resulted in only two (*A. podalyriifolia* and *C. odorata*) of the three IAPs classes being identified. The same threshold value was applied to the spectral angle mapper classifier and produced the same result. The PP classifier failed to identify *L. glutinosa* as well.

The same three supervised classification methods were performed on both SPOT 5 and WorldView-2 imagery, with different threshold values for the ML and SAM classifier because the 0.05 threshold did not correctly identify the three target IAPs. To overcome this predicament, the SPOT 5 ML classifier was performed at a threshold of 0.075 and the SAM classifier using a threshold of 0.035. Thresholds of 0.025 and 0.035 were applied to the WorldView-2 ML and SAM classifiers respectively.

The ISODATA unsupervised classifier was performed on the three types of imagery using a minimum of 30 classes and 60 maximum iterations to allow for an adequate number of classes to be created. Only *A. podalyriifolia* and *C. odorata* was detected in the unsupervised classification, as *L. glutinosa* did not form homogenous stands making pixel classes difficult to distinguish.

#### *3.3.5 Accuracy assessment*

Verification of classified results was conducted by overlaying sampled pre-clearing IAP locations provided by WESSA on WorldView-2 imagery. One hundred (100) such sampled points were imported into ERDAS and each assigned a reference value for accuracy assessment (Stuckenberg et al., 2014). An accuracy assessment was run, defining the producer's accuracy, user's accuracy, overall accuracy and the Kappa statistic (Everitt et al., 2008). Typically overall classifier accuracies should be over 85% whereas both producer's and user's classification accuracies of a single species should be above 70% to be considered a successful classification (Everitt et al., 2008). User's accuracy measures the percentage area which is correctly classified (Underwood et al., 2003). The producer's accuracy shows how accurately each individual class was classified (Doody et al., 2014). Furthermore, the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) were also calculated (Kumar & Sahoo, 2012). The MAE and RMSE are similar and are used to determine classifier performance with lower values closer to zero indicating a better performance (Kumar & Sahoo, 2012).

The Kappa statistic (Fleiss, Cohen, & Everitt, 1969), MAE and RMSE (Willmott & Matsuura, 2005) equations are expressed as follows:

$$\text{Kappa} = \frac{\alpha_{obs} - \alpha_{pred}}{1 - \alpha_{pred}} \qquad [2]$$

MAE = $\frac{1}{N}\sum_{i=1}^{N}[\alpha_{pred} - \alpha_{obs}]$ [3]

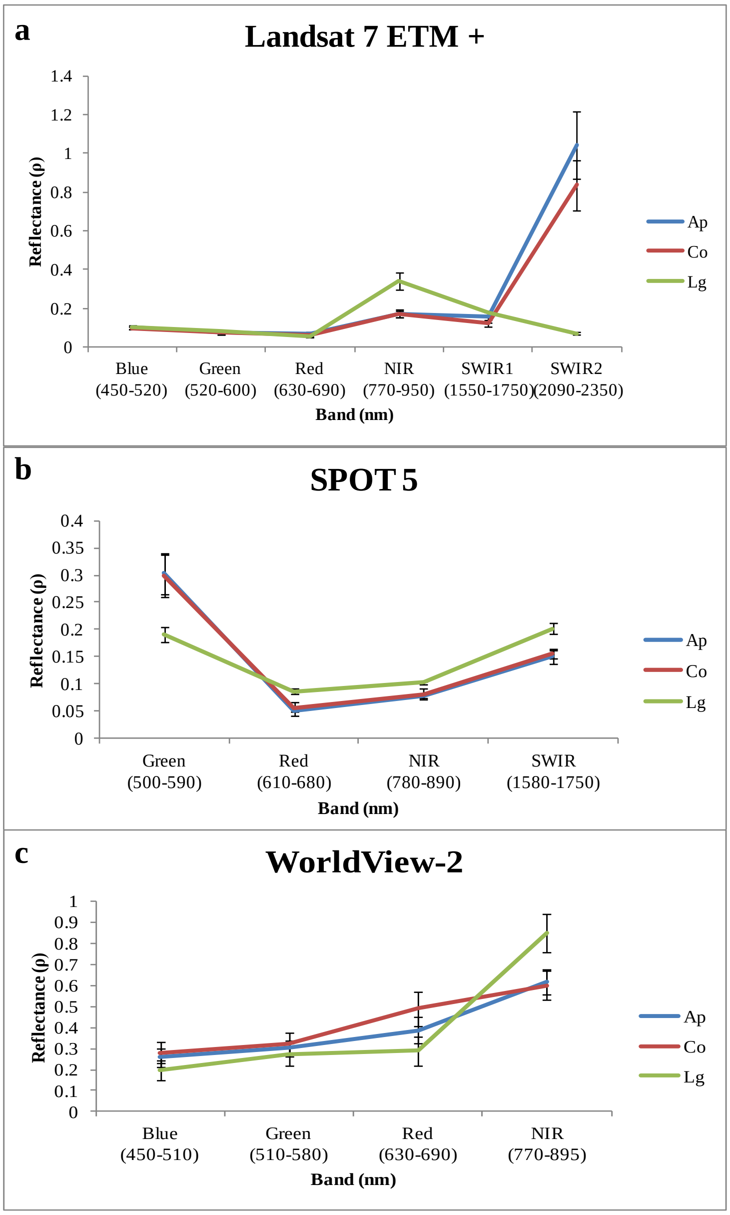
RMSE = $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\alpha_{pred} - \alpha_{obs})^2}$ [4]

The Kappa statistic uses multivariate techniques derived from an error matrix to indicate the accuracy of the classification (Doody et al., 2014). Values from 0 to 0.4 being a moderate agreement, 0.4 to 0.8 a substantial agreement and above 0.8 an excellent agreement (Kumar & Sahoo, 2012).

## 3.4 Results

### *3.4.1 Spectral signature development*

The spectral signature profile graphs (Figure 3.1a) represent the spectral separation of the three selected IAPs. The mean of the spectral signatures for each species indicated that the Landsat 7 ETM+ imagery spectra for *L. glutinosa* differed from the other two species (*A. podalyriifolia* and *C. odorata*) in the NIR (near infrared) and SWIR2 (short wave infrared) bands. *Acacia podalyriifolia* and *Chromolaena odorata* discriminated against each other only in the SWIR2 band, however within this band these two spectra exhibited relatively high CV values indicating that there is a high intra spectra variation. Lower CV values are preferable (Kimothi & Dasari, 2010) as it indicates a better discrimination of a separate class from other classes. The development of spectral signatures from the SPOT 5 imagery (Figure 3.1b) also indicated that the *L. glutinosa* species differed from the other two species in the green, red and short wave infrared, with very little discrimination evident between *A. podalyriifolia* and *C. odorata*. The spectral signature of *C. odorata* had low CV values in the SWIR band indicating this band can be used as a means to determine separation. The WorldView-2 imagery indicated similar patterns to the other two image types, with *L. glutinosa* displaying a spectrally distinct signature (Figure 3.1c) from the other two species in the red and infrared bands. However, the higher *L. glutinosa* CV values in the visible bands resulted in a poor discrimination of this species from other species. The distinction between *A. podalyriifolia* and *C. odorata* is evident in the red band that is contrary to the spectral signatures of the other two images (Landsat 7 ETM+ and SPOT 5).




Coefficient of variation (%)

| | Ap | Co | Lg |
|---|---|---|---|
| Blue | 11 | 7.14 | 6.06 |
| Green | 12 | 9.59 | 3.85 |
| Red | 18.46 | 14.75 | 5.66 |
| NIR1 | 12.79 | 8.77 | 12.35 |
| SWIR1 | 17.31 | 13.11 | 4.52 |
| SWIR2 | 16.71 | 15.31 | 7.14 |

Coefficient of variation (%)

| | Ap | Co | Lg |
|---|---|---|---|
| Green | 12.54 | 13.38 | 7.37 |
| Red | 3.92 | 24.07 | 5.81 |
| NIR | 3.85 | 12.35 | 2.94 |
| SWIR | 8.61 | 5.16 | 4.98 |

Coefficient of variation (%)

| | Ap | Co | Lg |
|---|---|---|---|
| Blue | 17.44 | 17.02 | 24.87 |
| Green | 12.58 | 15.43 | 18.98 |
| Red | 16.28 | 16.73 | 23.71 |
| NIR | 10.02 | 11.13 | 10.46 |

**Figure 3.1:** Spectral signature differentiation in three different image types (a = Landsat 7 ETM+, b = SPOT 5 and c = WorldView-2) for three alien plant species (Ap = *Acacia podalyriifolia*, Co = *Chromolaena odorata*, Lg = *Litsea glutinosa*). Pixel values displayed on the graph represent means ± SD (NIR = near infrared, SWIR = shortwave infrared).

### *3.4.2 Image classification*

The thematic maps of detected IAPs (Figure 3.2) classified from three selected remotely sensed images are overlaid on an aerial photo of the study site. All four classifiers failed to identify *L. glutinosa* on the Landsat 7 ETM+. The three supervised classifiers (PP, ML and SAM) used on SPOT 5 and Worldview-2 imageries identified all three target species. The ISODATA classifier could not be used on the three images to identify *L. glutinosa* because the exact location of *L. glutinosa* could not be determined on the 2010 imagery.

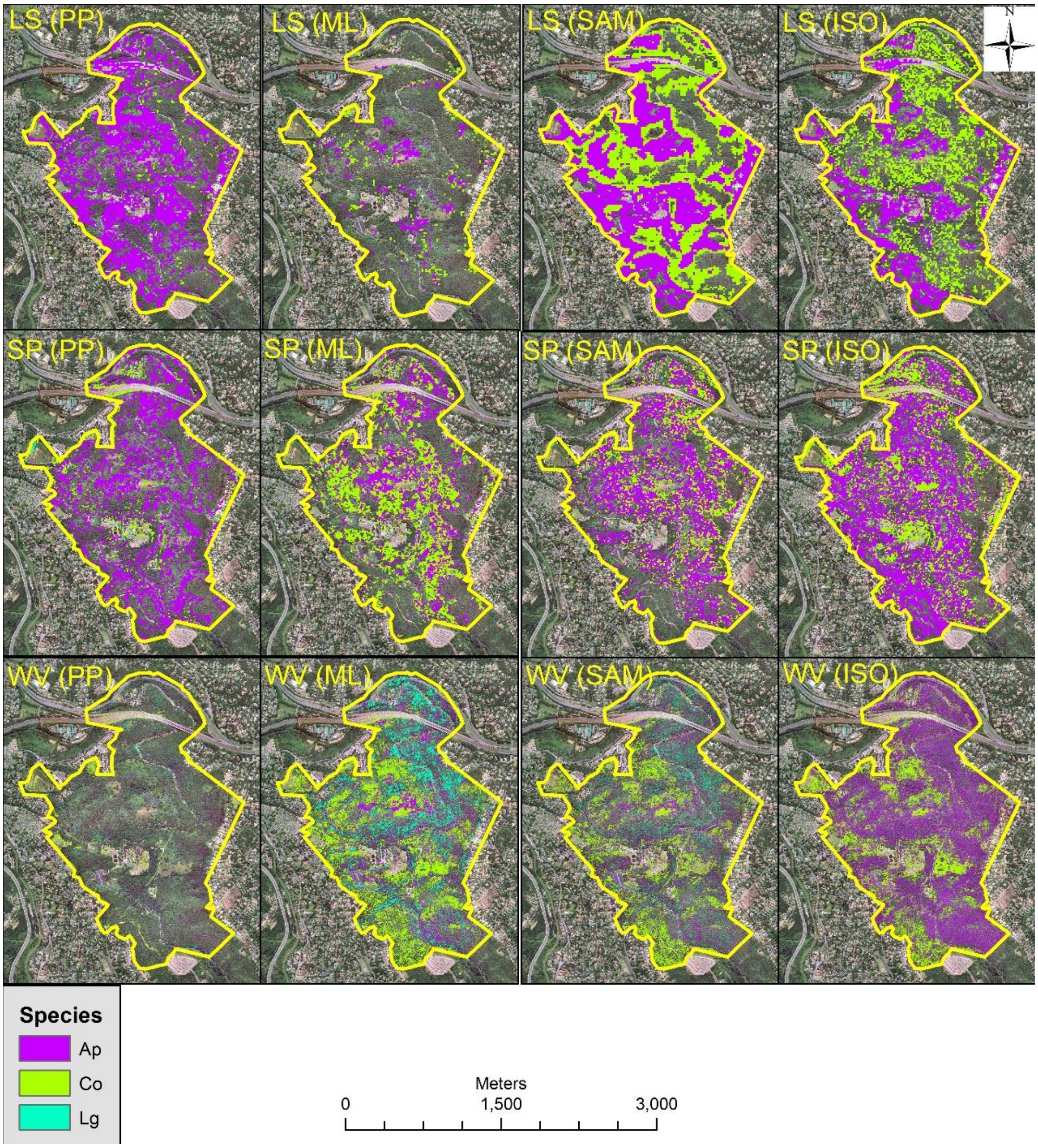



**Figure 3.2:** Classification results of three selected 2010 image types using four selected classifiers on three selected IAPs (Ap = *Acacia podalyriifolia*,, Co = *Chromolaena odorata*, Lg = *Litsea glutinosa*) in the Paradise Valley Nature Reserve. Classifiers: PP = Parallelepiped, ML = Maximum Likelihood, SAM = Spectral Angle Mapper, ISO = Iterative Self-Organising Data Analysis Technique. Imagery: LS = Landsat 7 ETM+, SP = SPOT 5 and WV = WorldView-2.

### *3.4.3 Accuracy assessment*

The accuracy assessment of the four classifiers (Table 3.2) indicate that overall classification accuracy is unsuitable (below 85%) (Everitt et al., 2008) for all image types and classifiers, therefore no method successfully detected all three target species. The ML classification performed on WorldView-2 imagery did produce a moderate accuracy (67%). This is further supported by the moderate agreement indicated by the Kappa statistic of the WorldView-2 ML classifier (0.57) and relatively low values for MAE (33) and RMSE (38).

**Table 3.2:** Overall accuracy of four classifiers for detecting three IAPs.

| | | **Overall accuracy (%)** | **Kappa** | **MAE** | **RMSE** |
|---|---|---|---|---|---|
| **Landsat 7 ETM+** | PP | 18.33 | 0.0392 | 81.67 | 85.68 |
| | ML | 16 | 0.1021 | 84 | 86.02 |
| | SAM | 32.33 | 0.0587 | 67.67 | 75.12 |
| | ISO | 19.5 | 0.0272 | 80.5 | 81.8 |
| **SPOT 5** | PP | 12.33 | 0.0283 | 87.67 | 89.12 |
| | ML | 31.67 | 0.1723 | 70 | 73.26 |
| | SAM | 13 | -0.0454 | 87 | 87.99 |
| | ISO | 35.50 | 0.0190 | 64.5 | 68.31 |
| **WorldView-2** | PP | 4 | 0.027 | 96 | 96.13 |
| | ML | 66.67 | 0.5702 | 33.33 | 38.22 |
| | SAM | 38.33 | 0.2912 | 61.67 | 65.53 |
| | ISO | 98 | 0.2177 | 62 | 64.85 |

Values represent overall accuracy, Kappa coefficient, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Classifier abbreviations are as follows, PP = Parallelepiped, ML = Maximum Likelihood, SAM = Spectral Angle Mapper, ISO = Iterative Self Organising Data Analysis Technique.

The Landsat 7 ETM+ imagery produced poor accuracy using all four classifiers for all the species (Table 3.3), except for the ML classifier, which had both good user's classification accuracy (100 %) and Kappa values (1.00) for *C. odorata*. The SAM also produced a moderate Kappa value (0.71) and a good producer's accuracy (77%) for *A. podalyriifolia*. In the SPOT 5 imagery, the ML classifier produced a substantial accuracy at detecting *A. podalyriifolia* with a Kappa value above 0.4 (indicating a substantial agreement or accuracy) and user's accuracies (above 70%). In WorldView-2 imagery classification, the ML classifier was successful in detecting *A. podalyriifolia* and *C. odorata* (producer's and user's accuracy above 70% and high Kappa values above 0.8), while *L. glutinosa* showed a substantial Kappa value (Kappa = 0.93) and a high user's accuracy (95%). The ISODATA classifier produced high user's accuracy (93%) and a high Kappa value (0.87) in the detection of *C. odorata*.

**Table 3.3:** Accuracy assessment of four classifiers and three imagery types at detecting the three IAPs individually.

| | | | **Producer's accuracy (%)** | **User's accuracy (%)** | **Kappa coefficient** |
|---|---|---|---|---|---|
| **Landsat 7 ETM+** | PP | Ap | 55 | 40.74 | 0.1111 |
| | | Co | 0 | 0 | 0 |
| | | Lg | 0 | 0 | 0 |
| | ML | Ap | 42 | 80.77 | 0.7115 |
| | | Co | 6 | 100 | 1 |
| | | Lg | 0 | 0 | 0 |
| | SAM | Ap | 77 | 40.53 | 0.7079 |
| | | Co | 20 | 31.75 | -0.0238 |
| | | Lg | 0 | 0 | 0 |
| | ISO | Ap | 34 | 61.82 | 0.2364 |
| | | Co | 5 | 35.71 | -0.2857 |
| | | Lg | n/a | n/a | n/a |
| **SPOT 5** | PP | Ap | 35 | 43.21 | 0.1481 |
| | | Co | 2 | 28.57 | -0.0714 |
| | | Lg | 0 | 0 | 0 |
| | ML | Ap | 55 | 73.33 | 0.6 |
| | | Co | 40 | 48.78 | 0.2317 |
| | | Lg | 0 | 0 | 0 |
| | SAM | Ap | 31 | 31 | -0.035 |
| | | Co | 8 | 15.69 | -0.2647 |
| | | Lg | 0 | 0 | 0 |
| | ISO | Ap | 58 | 51.79 | 0.0357 |
| | | Co | 13 | 52 | 0.04 |
| | | Lg | n/a | n/a | n/a |

**Table 3.3 ……Continued**

| | | | | | |
|---|---|---|---|---|---|
| **WorldView-2** | PP | Ap | 0 | 0 | 0 |
| | | Co | 1 | 100 | 1 |
| | | Lg | 11 | 100 | 1 |
| | ML | Ap | 85 | 100 | 1 |
| | | Co | 74 | 100 | 1 |
| | | Lg | 41 | 95.35 | 0.9302 |
| | SAM | Ap | 35 | 97.22 | 0.9583 |
| | | Co | 67 | 100 | 1 |
| | | Lg | 13 | 92.86 | 0.8929 |
| | ISO | Ap | 19 | 86.36 | 0.7273 |
| | | Co | 57 | 93.44 | 0.8689 |
| | | Lg | n/a | n/a | n/a |

Values were generated by using ERDAS Imagine 2013/2015 to perform an accuracy assessment. Values are representative of each species detected for each classifier. Classifier abbreviations are as follows, PP = Parallelepiped, ML = Maximum Likelihood, SAM = Spectral Angle Mapper, ISO = Iterative Self Organising Data Analysis Technique. Species abbreviations are as follows Ap = *Acacia podalyriifolia*, Co = *Chromolaena odorata*, Lg = *Litsea glutinosa*).

## 3.5 Discussion

In a landscape with heterogeneous vegetation cover in a largely urban matrix, a major challenge in remote sensing is distinguishing between IAPs and indigenous vegetation due to the similarity in their spectral signatures in the NIR and visible portions of the electromagnetic spectrum (Narumalani, Mishra, Wilson, Reece, & Kohler, 2009). In this study, *L. glutinosa* produced distinct spectra from *A. podalyriifolia* and *C. odorata* in the red and infrared bands of SPOT 5 and WorldView-2 imagery (Figure 3.1b and 3.1c). These two species have a unique leaf pigmentation when compared to other plant species, as leaf pigmentation is commonly used to identify IAPs (Bradley, 2014). Overall, the Landsat 7 ETM+ spectral signatures were poor as all three species were difficult to distinguish as the spatial resolution of the Landsat 7 ETM+ imagery is coarse. *Acacia podalyriifolia* and *Chromolaena odorata* showed little spectral separation in the SPOT 5 image (Figure 3.1b). These species have a different leaf pigmentation when compared to other species (Bradley, 2014), in the visible bands. Furthermore SPOT 5 does not acquire reflectance in the blue band. The blue band is sensitive to changes in chlorophyll and is considered the best band in tree species discrimination (Key et al., 2001), and therefore is useful in discriminating between *A. podalyriifolia* and *C. odorata*. Thus, the absence of the blue band in SPOT 5 imagery may explain the poor discrimination observed in *C.*

*odorata* and *A. podalyriifolia*. *Chromolaena odorata* species exhibited low CV values in the SWIR, which is determined by the biochemical content of the species (Underwood et al., 2007) indicating that this band may be ideal at separating this species from other species.

The spectral signatures developed from the WorldView-2 imagery indicate that the best band to discriminate IAPs from indigenous species is the red band. In addition to this, the red band was able to distinguish between *A. podalyriifolia* and *C. odorata*. This is the case because species identification is based on reflectance in the red and the NIR band (Haby, Tunn, & Cameron, 2010).In two of the three image types (Landsat 7 ETM+ and WorldView-2), the infrared bands were the most successful in differentiating between IAPs due to the IAPs tendency to exhibit an increased reflectance compared to indigenous species in the NIR band and the SWIR (Asner, Knapp, et al., 2008). This explains why in this study, spectral differentiation between *A. podalyriifolia* and *C. odorata* was evident in the SWIR regions of the Landsat 7 ETM+ imagery (Figure 3.1a).

The development of spectral signatures is site specific as a spectral signature developed for an IAP may not be suitable at detecting the same species in another location as the spectral similarity deteriorates with an increase in distance between sites due to location, season and environmental conditions (Laborte, Maunahan, & Hijmans, 2010; Ustin & Santos, 2000). For example dry and senesced vegetation may have a considerable spectral variation when compared to healthy vegetation (Bradley, 2014). Consequently, the development of a universal spectral signature for a species irrespective of season may be challenging and possibly not feasible.

Overall classification accuracies were unsuccessful across the three multispectral images and four classifiers. This was supported by the study done on the detection of the IAP Giant Reed (*Aurundo donax)* where overall accuracies were also below 85% (Everitt et al., 2008). The classification accuracy of individual species indicates a number of high user's accuracy and Kappa coefficient values but low producer's accuracy values. Producer's accuracy is important for the management of IAPs as it indicates the proportion of IAPs that are not detected (Müllerová, Pergl, & Pyšek, 2013). Producer's accuracies above 70 are considered as successful classifications when examining individual species accuracies (Everitt et al., 2008). Only WorldView-2 imagery was able to successfully detect *A. podalyriifolia* (78% producer's accuracy) and *C. odorata* (90% producer's accuracy) (Table 3.3) using the ML classifier. These results are supported by the study done on the detection of Giant Reed (*Aurundo donax)* which showed that imagery with higher spatial resolution increased detection accuracy (Everitt et al., 2008). The SAM produced poor classification results due to overlapping IAP spectral classes as it is a linear model (Rashmi, Addamani, & Ravikiran, 2014).

The poor IAP classification in Landsat 7 ETM+ is due to its coarse spatial resolution, compared to imagery from finer spatial resolution imagery like SPOT 5 and WorldView-2. However, Landsat 7 ETM+ has more spectral bands which has resulted in more refined vegetation mapping at a regional level (Narumalani et al., 2009; Thenkabail et al., 2003) when fused or pan-sharpened with higher spatial resolution imagery.

The poor detection of *L. glutinosa* in all three remotely sensed images could be attributed to the fact that, the spectral signature of *L. glutinosa* was developed from 2015 images composed of heterogeneous stands. Such stands of IAPs with similar reflectance would be difficult to detect unless they form dense monotypic stands (Bradley, 2014; Hestir et al., 2008). On the contrary, the stands of *A. podalyriifolia* and *C. odorata* were relatively homogenous, facilitating the creation of training sites, signature development and IAP classification. Overall, poor accuracies resulting from different classifications could also be due to presence of shadows in the images (Leckie, Jay, Gougeon, Sturrock, & Paradine, 2004). Object/texture based classification could potential improve the classification accuracy of this species (Müllerová et al., 2013).

### 3.6 Conclusion

The detection of prominent IAPs is an essential process to assist in their management (Trueman et al., 2014). This study in harmony with studies done elsewhere has revealed that the visible and infrared bands are appropriate in detecting IAPs. The main objective of this study was to determine the most accurate remotely sensed imagery and classification method for detecting three selected IAPs. The ML classifier applied on WorldView-2 imagery produced the best results with suitable identification and classification accuracies for both *A. podalyriifolia* and *C. odorata*. Thus based on producer's accuracy of above 70%, was found in only one spectral image (WorldView-2) that was successful at classifying two species (*A. podalyriifolia* and *C. odorata*). Species specific detection is usually rare, and dependent on dominant species and its spatial extent (Bradley, 2014). This method of classification will be used in change detection analyses to assess clearing initiatives of the three target species pre-and post-clearing in chapter four.

Invasive alien plant invasions in South Africa are increasing (van Wilgen et al., 2012) and land managers need to take into consideration all IAPs present in the landscape (Trueman et al., 2014). Therefore future studies using remote sensing in IAP detection should include all IAPs and time series analysis (Bradley, 2014). Periodic classification of a species can result in an indication of the rate of spread of a species, after which land managers can choose to target faster spreading species (Trueman et al., 2014).

Remote sensing is an underutilised tool in the detection and management of IAPs. There is a need for more collaborative efforts between remote sensing scientists and ecologists when dealing with IAPs. Selecting an appropriate image type will be dependent on the scale of the study (Bradley, 2014). Future research in this field should include hyperspectral spectral imagery in conjunction with high spatial resolution imagery to allow for increased accuracy in the classification of IAPs. Remotely sensed imagery with moderate spatial resolution such as the Landsat and SPOT sensors are not suitable for the detection of individual species at a local scale.

## References

Adejoke, A. O., & Badaru, Y. U. (2014). Accuracy assessment of pixel-based image classification of Kwali council area, Abuja, Nigeria. *Journal of Natural Science Research*, *4*(22), 133–140.

Africa, S. (2016). *National environmental managment: Biodiversity act (Act No, 10 of 2004)*. *Goverment Gazette* (Vol. 66).

Asner, G. P., Hughes, R. F., Vitousek, P. M., Knapp, D. E., Kennedy-Bowdoin, T., Boardman, J., … Green, R. O. (2008). Invasive plants transform the three-dimensional structure of rain forests. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(11), 4519–23. http://doi.org/10.1073/pnas.0710811105

Asner, G. P., Knapp, D. E., Kennedy-Bowdoin, T., Jones, M. O., Martin, R. E., Boardman, J., & Hughes, R. F. (2008). Invasive species detection in Hawaiian rainforests using airborne imaging spectroscopy and LiDAR. *Remote Sensing of Environment*, *112*(5), 1942–1955. http://doi.org/10.1016/j.rse.2007.11.016

Bradley, B. A. (2014). Remote detection of invasive plants: a review of spectral, textural and phenological approaches. *Biological Invasions*, *16*(7), 1411–1425. http://doi.org/10.1007/s10530-013-0578-9

Calviño-Cancela, M., Méndez-Rial, R., Reguera-Salgado, J., & Martín-Herrero, J. (2014). Alien plant monitoring with ultralight airborne imaging spectroscopy. *PloS One*, *9*(7), e102381. http://doi.org/10.1371/journal.pone.0102381

Chaves, P. s, Sides, S. c, & Anderson, J. A. (1991). Comparison of three different methods to merge multiresolution and multispectral data: Landsat TM and SPOT Panchromatic. *Photogrammetric Engineering and Remote Sensing*, *57*, 295–303.

Cuneo, P., Jacobson, C. R., & Leishman, M. R. (2009). Landscape-scale detection and mapping of invasive African Olive (*Olea europapaea L. ssp. cuspidata* Wall ex G. Don Ciferri) in SW Sydney, Australia using satellite remote sensing. *Applied Vegetation …*, *12*, 145–154. http://onlinelibrary.wiley.com/doi/10.1111/j.1654-109X.2009.01010.x/full

Doody, T. M., Lewis, M., Benyon, R. G., & Byrne, G. (2014). A method to map riparian exotic vegetation (Salix spp.) area to inform water resource management. *Hydrological Processes*, *28*(11), 3809–3823. http://doi.org/10.1002/hyp.9916

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. http://doi.org/10.3390/rs1030519

Everitt, J. H., Yang, C., Fletcher, R., & Deloach, C. J. (2008). Comparison of QuickBird and SPOT 5 satellite imagery for mapping giant reed. *Journal of Aquatic Plant Management*, *46*, 77–82.

Fleiss, J. L., Cohen, J., & Everitt, B. S. (1969). Large sample standard errors of kappa and weighted kappa. *Psychological Bulletin*, *72*(5), 323–327. http://doi.org/10.1037/h0028106

Forsyth, A. T., Gibson, L. A., & Turner, A. A. (2014). Assessment of SPOT 6 imagery for mapping the invasive alien plant species *Pinus spp.* in a mountainous area of the Western Cape. *Proceedings of the Second AfricaGEO Conference*, 1–12.

Haby, N., Tunn, Y., & Cameron, J. (2010). Application of QuickBird and aerial imagery to detect *Pinus radiata* in remnant vegetation. *Austral Ecology*, *35*(6), 624–635. http://doi.org/10.1111/j.1442-9993.2009.02070.x

Hamada, Y., Stow, D. A., Coulter, L. L., Jafolla, J. C., & Hendricks, L. W. (2007). Detecting Tamarisk species (*Tamarix spp.*) in riparian habitats of Southern California using high spatial resolution hyperspectral imagery. *Remote Sensing of Environment*, *109*(2), 237–248. http://doi.org/10.1016/j.rse.2007.01.003

Henderson, L. (1995). *Plant invaders of Southern Africa*. Agricultural Research Council.

Hestir, E. L., Khanna, S., Andrew, M. E., Santos, M. J., Viers, J. H., Greenberg, J. a., … 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. http://doi.org/10.1016/j.rse.2008.01.022

Huang, C.-Y., & Asner, G. P. (2009). Applications of remote sensing to alien invasive plant studies. *Sensors (Basel, Switzerland)*, *9*(6), 4869–4889. http://doi.org/10.3390/s90604869

Key, T., Warner, T. A., McGraw, J. B., & Fajvan, M. A. (2001). A comparison of multispectral and multitemporal information in high spatial resolution imagery for classification of individual tree species in a temperate hardwood forest. *Remote Sensing of Environment*, *75*(1), 100–112. http://doi.org/10.1016/S0034-4257(00)00159-0

Kimothi, M. 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. http://doi.org/10.1080/01431160903121126

Kumar, Y., & Sahoo, G. (2012). Analysis of Parametric & Non Parametric Classifiers for Classification Technique using WEKA. *I.J. Information Technology and Computer Science*, (July), 43–49. http://doi.org/10.5815/ijitcs.2012.07.06

Laborte, A. G., Maunahan, A. A., & Hijmans, R. J. (2010). Spectral signature generalization and expansion can improve the accuracy of satellite image classification. *PLoS ONE*, *5*(5). http://doi.org/10.1371/journal.pone.0010516

Leckie, D. G., Jay, C., Gougeon, F. A., Sturrock, R. N., & Paradine, D. (2004). Detection and assessment of trees with *Phellinus weirii* (laminated root rot) using high resolution multi-spectral imagery. *International Journal of Remote Sensing*, *25*(4), 793–818. http://doi.org/10.1080/0143116031000139926

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. http://doi.org/10.1080/01431160600746456

Mazus, H., & Chimboza, N. (2015). Spectral analysis of 8-band WorldView-2 data for monitoring regional vegetation condition : mapping of alien invasive plants species in the West Coast. *Geomatics Indaba Proceedings*, (2), 172–177.

Müllerová, J., Pergl, J., & Pyšek, P. (2013). Remote sensing as a tool for monitoring plant invasions: Testing the effects of data resolution and image classification approach on the detection of a model plant species *Heracleum mantegazzianum* (giant hogweed). *International Journal of Applied Earth Observation and Geoinformation*, *25*(1), 55–65. http://doi.org/10.1016/j.jag.2013.03.004

Naidoo, L., Cho, M. A., Mathieu, R., & Asner, G. P. (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. http://doi.org/10.1016/j.isprsjprs.2012.03.005

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. http://doi.org/10.1614/WT-08-007.1

Pu, R., & Landry, S. (2012). A comparative analysis of high spatial resolution IKONOS and WorldView-2 imagery for mapping urban tree species. *Remote Sensing of Environment*, *124*(2012), 516–533. http://doi.org/10.1016/j.rse.2012.06.011

Rashmi, S., Addamani, S., & Ravikiran, S. (2014). Spectral Angle Mapper Algorithm for Remote Sensing Image Classification. *International Journal of Innovative Science, Engineering & Technology*, *1*(4), 201–205.

Schaepman, M. E., Ustin, S. L., Plaza, A. J., Painter, T. H., Verrelst, J., & Liang, S. (2009). Earth system science related imaging spectroscopy-An assessment. *Remote Sensing of Environment*, *113*(SUPPL. 1), S123–S137. http://doi.org/10.1016/j.rse.2009.03.001

Stow, D. A., Hope, A., McGuire, D., Verbyla, D., Gamon, J., Huemmrich, F., … Myneni, R. (2004). Remote sensing of vegetation and land-cover change in Arctic Tundra Ecosystems. *Remote Sensing of Environment*, *89*(3), 281–308. http://doi.org/10.1016/j.rse.2003.10.018

Stuckenberg, T., Münch, Z., & van Niekerk, A. (2014). Multi-temporal remote sensing land-cover change detection for biodiversity assessment in the Berg River catchment. *South African Journal of …*, *2*(3), 189–205. http://www.ajol.info/index.php/sajg/article/view/106977

Thenkabail, P. S., Hall, J., Lin, T., Ashton, M. S., Harris, D., & Enclona, E. a. (2003). Detecting floristic structure and pattern across topographic and moisture gradients in a mixed species Central African forest using IKONOS and Landsat-7 ETM + images. *International Journal of Applied Earth Observation and Geoinformation*, *4*, 255–270. http://doi.org/10.1016/S0303-2434(03)00006-0

Trueman, M., Standish, R., Orellana, D., & Cabrera, W. (2014). Mapping the extent and spread of multiple plant invasions can help prioritise management in Galapagos National Park. *NeoBiota*, *23*(July 2015), 1–16. http://doi.org/10.3897/neobiota.23.7800

Tu, T.-M., Hsu, C.-L., Tu, P.-Y., & Lee, C.-H. (2012). An Adjustable Pan-Sharpening Approach for IKONOS/QuickBird/GeoEye-1/WorldView-2 Imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *5*(1), 125–134. http://doi.org/10.1109/JSTARS.2011.2181827

Underwood, E. C., Ustin, S. L., & DiPietro, D. (2003). Mapping nonnative plants using hyperspectral imagery. *Remote Sensing of Environment*, *86*(2), 150–161. http://doi.org/10.1016/S0034-4257(03)00096-8

Underwood, E. C., Ustin, S. L., & Ramirez, C. M. (2007). A comparison of spatial and spectral image resolution for mapping invasive plants in coastal California. *Environmental Management*, *39*(1), 63–83. http://doi.org/10.1007/s00267-005-0228-9

Ustin, S. L., & Santos, M. J. (2000). Spectral Identification of Native and Non-Native Plant Species. *Remote Sensing of Environment*, 1–17. http://doi.org/Art, Science and Applications of Reflectance Spectroscopy Symposium February 23-25, 2010 in Boulder, Colorado.

van Wilgen, B. W., Forsyth, G. G., Le Maitre, D. C., Wannenburgh, A., Kotzé, J. D. F., van den Berg, E., & Henderson, L. (2012). An assessment of the effectiveness of a large, national-scale invasive alien plant control strategy in South Africa. *Biological Conservation*, *148*(1), 28–38.

http://doi.org/10.1016/j.biocon.2011.12.035

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research*, *30*(1), 79–82. http://doi.org/10.3354/cr030079

Zhang, Y., & Mishra, R. (2012). A review and comparison of commercially available pan-sharpening techniques for high resolution satellite image fusion. *Geoscience and Remote Sensing …*, 182–185. http://doi.org/10.1109/IGARSS.2012.6351607

# CHAPTER FOUR

# THE ASSESSMENT OF INVASIVE ALIEN PLANT SPECIES REMOVAL PROGRAMS USING REMOTE SENSING AND GIS IN TWO SELECTED RESERVES IN THE ETHEKWINI MUNICIPALITY, KWAZULU-NATAL

This chapter is based on:

**Adam**, Y, Ngetar, N.S and Ramdhani, S. "The assessment of invasive alien plant species removal programs using remote sensing and GIS in two selected reserves in the eThekwini municipality, KwaZulu-Natal'', *South African Journal of Geomatics* (In review).

## 4.1 Abstract

The occupation of natural environments by invasive alien plant species (IAPs) are a growing threat to ecosystems. This has resulted in the creation of government-based initiatives to mitigate invasion, however there has been little progress towards assessing these initiatives. Remote sensing is a commonly used tool in the detection of IAPs; even so, there has also been little research towards its use as a tool to assess mitigation efforts. This study aims to assess the clearing initiatives of three IAPs which are *Acacia podalyriifolia* (Ap), *Chromolaena odorata* (Co) and *Litsea glutinosa* (Lg) in two nature reserves (Paradise Valley and Roosfontein) within the eThekwini municipality, KwaZulu-Natal, South Africa using remote sensing. To achieve this, image classification using the Maximum Likelihood was performed on both sites before and after clearing to compare density, distribution and area cover. All species were successful detected in both Reserves on both the 2010 and 2015 imagery except *L. glutinosa* in the Paradise Valley reserve in 2010. User's and producer's accuracy for *A. podalyriifolia* and *C. odorata* species (Paradise valley) and *C. odorata* and *L. glutinosa* (Roosfontein) was more than 70% in both 2010 and 2015, which is above agreed standards. The occurrence and area cover of all species in both reserves decreased substantially except *L. glutinosa* in Paradise Valley, which experienced only a slight decrease in area. Remote sensing is a suitable tool in the assessment of IAP removal strategies. Further research should consider early detection of IAPs in preventing spread.

**Key words:** Invasive alien plant species, remote sensing, species detection, removal assessment.

## 4.2 Introduction

Invasive alien plants affect human health, agriculture, forestry and biodiversity (Richardson & van Wilgen, 2004). They impact on ecosystems by displacing indigenous vegetation and changing ecosystem functions (Loh & Daehler, 2008). This leads to a reduction in the genetic variation of an environment due to localised extinction of endemic species. Invasion also has subtle socio-economic impacts such as interrupting the supply of ecosystem goods and resource availability for indigenous species by consuming large quantities of resources (Vilà et al., 2010).

Interest in the field of IAPs is growing with an increase in funds dedicated to dealing with invasion, however IAPs continue to expand (D'Antonio, Jackson, Horvitz, & Hedberg, 2004). The control of IAPs involve both reducing the introduction of new species and the management of current IAPs (van Wilgen et al., 2012). Therefore regular monitoring of IAPs is required to manage invasion effectively and efficiently, which in turn requires methods that can detect IAPs rapidly and precisely (Müllerová, Pergl, & Pyšek, 2013). Field surveys can be used to map IAPs, however these are inefficient over larger areas (Malahlela, Cho, & Mutanga, 2015). Aerial photographs have been successful to an extent as they are able to detect IAPs which are unique to other surrounding vegetation (Lass et al., 2005). Remote sensing is an ideal tool to be used in detecting IAPs as it can be employed in a variety of habitats (Lass et al., 2005), map species over large extents (Calviño-Cancela, Méndez-Rial, Reguera-Salgado, & Martín-Herrero, 2014) and detect vegetation at a species level (Mutanga, van Aardt, & Kumar, 2009).

Individual IAPs can be detected using remote sensing due to variations in their reflectance patterns in certain portions of the electromagnetic spectrum (Rocchini et al., 2015). Multispectral imagery can be applied successfully to map IAPs however these species would need to have unique reflectance patterns when compared to indigenous species (Cuneo, Jacobson, & Leishman, 2009). Remote sensing has been applied successfully in mapping invasive trees and shrubs. Herbaceous species can also be detected if they form dense stands and are spectrally distinct from other species within their environment (Müllerová et al., 2013).

In South Africa IAP intervention strategies have been employed nationally and have mitigated the impacts of invasion (van Wilgen et al., 2012). Despite the application of these removal strategies, the abundance and impact of IAPs is still increasing (Müllerová et al., 2013). The Working for Water program is a national program initiated by the South African government aimed at the control of IAPs (van Wilgen et al., 2012). This program was initiated in 1995 and between 1995 and in 2007 cleared 1.6 million ha of IAPs at the cost of ZAR 3.2 billion (van Wilgen et al., 2012). The program employs chemical, biological and physical removal strategies (van Wilgen et al., 2012) and is one of the largest IAP removal initiatives globally (Richardson & van Wilgen, 2004). Without these clearing initiatives, areas that experienced 22% invasion could become completely invaded within three decades (Le

Maitre et al., 2002). One of the major concerns with these clearing programs is the lack of an effective system for evaluating and monitoring the success of removal (van Wilgen et al., 2012).

Protected areas are a corner stone in terms of conservation and are designed to reduce biodiversity loss; however, these areas need to be maintained. The detection of changes in abundance of plant species within these areas will aid in maintenance (Nagendra et al., 2013). Also in smaller reserves density and abundance of IAPs are important factors to consider (Richardson & van Wilgen, 2004) to aid in mitigation. Change detection examines the differences between images of the same area at different time periods (Coppin & Bauer, 2009). Remote sensing is a powerful tool used for change detection (Kerr & Ostrovsky, 2003), due to the frequent return time of satellites (Singh, 1989), also referred as high temporal resolution (Bradley, 2014).

This study aims to investigate the use of remote sensing for mapping IAPs and assessing clearing programs of three IAPs namely, *Acacia podalyriifolia* A.Cunn (Pearl Acacia)., *Litsea glutinosa* (Lour.) C.B.Rob (Indian Laurel)., and *Chromolaena odorata* (L.) R.M. King & H. Rob (Triffid Weed) in two reserves (Paradise Valley and Roosfontein) within the eThekwini municipality. This was achieved by initially classifying WorldView-2 imagery before and after clearing using a Maximum Likelihood (ML) classifier and then producing distribution and abundance maps for each species. These maps were then compared to determine the success of clearing each species.

## 4.3 Methods

### *4.3.1 Study site*

The Paradise Valley (29.83$^{o}$S, 30.89$^{o}$E) and Roosfontein (29.86$^{o}$S, 30.92$^{o}$E) Nature reserves are located in the eThekwini municipality just west of the city of Durban (KwaZulu-Natal, South Africa), within close proximity to one another. Both reserves are roughly 300ha in size and include grasslands, thicket and forest vegetation. This region receives an average of 1010mm of rainfall annually with a majority of the rainfall occurring between November and March. The average annual temperature of 20.5 $^{o}$C (Preston-Whyte, 1980). The Environmental Planning and Climate Protection Department (EPCPD) in conjunction with Wildlife and Environmental Society of South Africa (WESSA) initiated clearing programs in the Paradise Valley and Roosfontein nature reserves in 2011 and 2010 respectively.

#### *4.3.2 Field data collection and image processing*

Field data for the classification IAPs were supplied by WESSA, these were created in spring therefore WorldView-2 (4 band) images of both 2010 and 2015 were purchased from SANSA (South African National Space Agency) for September of their respective years for the purpose of consistency. The time of image acquisition is crucial as species differ spectrally due to seasonal variations (Lass et al., 2005). Selecting images for the same time of year will reduce sun angle distortions and spectral distortions caused by phenotypic variation of species (Mas, 1999). These images were then pan sharpened using a subtractive resolution merge, with a sharpening centre value of 17, a pan contribution weight of 1 as these were 4 band images (Zhang & Mishra, 2012).

One of issues related to satellite image acquisition  is cloud cover (Kerr & Ostrovsky, 2003). The 2015 imagery had a significant amount of cloud cover (14.6%) over the Roosfontein site. Cloud correction was done using ATCOR 3 extension for ERDAS Imagine 2015. Initially solar zenith and solar azimuth was calculated then a DEM of the study area was created in ArcMap using 2m contours all of these were input into ATCOR 3 as part of the haze removal process. The correction module was run with a 35 cloud threshold and a 9 water threshold to remove haze. Thereafter a haze reduction tool from ERDAS was applied to further sharpen the image. The DN (digital numbers) of both the 2010 and 2015 images were then converted to top of atmosphere reflectance values by a conversion model created using  the spatial model editor in ERDAS Imagine (Miao, Patil, Heaton, & Tracy, 2011).

Three species (*A. podalyriifolia, C. odorata* and *L. glutinosa*) in the Paradise Valley Nature Reserve and two species (*C. odorata* and *L. glutinosa*) in the Roosfontein Nature Reserve were classified for the purpose of this study. Only two species were classified in the Roosfontein Nature Reserve as *A. podalyriifolia* occurred in negligible quantities. Training sites were created using 60 samples with 12 samples representing each IAP in each reserve. These were developed by digitizing polygons of each IAP on high resolution 2010 WorldView-2 imagery with the aid of field data provided by WESSA. These polygons were then imported into ERDAS imagine where spectra was extracted to be used for image classification.

#### *4.3.3 Image classification*

A Maximum Likelihood classifier was performed on imagery of both sites from 2010 and 2015 to detect the selected IAPs as in comparison to other classifiers (parallelepiped, unsupervised and the spectral angle mapper) resulted in the highest classification accuracy (Doody, Lewis, Benyon, & Byrne, 2014). The Maximum Likelihood classifier uses mean reflectance to determine the probability of a pixel belonging to a certain class (Lass et al., 2005). The threshold for the classification of the imagery was defined with 2 degrees of freedom and a 0.025 confidence level. Thereafter a post classification comparison approach was used where 2010 and 2015 individually classified images were compared (Singh, 1989).

Verification of the 2010 classified results was conducted by overlaying sampled pre-clearing IAP locations provided by WESSA on WorldView-2 imagery. One hundred (100) such sampled points were imported into ERDAS and each assigned a reference value for accuracy assessment (Stuckenberg, Münch, & van Niekerk, 2014). Furthermore, accuracy verification of the 2015 imagery was determined using points obtained in the field (Sarma et al., 2008). This was achieved by purposive random sampling; 10 locations were selected for each species at each study area and were given priority based on ease of site access (Underwood, Ustin, & DiPietro, 2003). In the Paradise Valley Nature Reserve the *L. glutinosa* species was not sampled as there was no change between the pre and post classification clearance.

An accuracy assessment was run on 2010 and 2015 imagery for both sites, defining the overall accuracy, user's accuracy, producer's accuracy and the Kappa statistic. For a classification to be regarded as successful an overall accuracy of 85% is required and for individual species, accuracies should be 70% and over (Everitt, Yang, Fletcher, & Deloach, 2008). Kappa values from 0 to 0.4 are regarded as a moderate agreement, with 0.4 to 0.8 as a substantial agreement and above 0.8 an excellent agreement. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were also calculated, these are similar indices which determine the performance of a classification, with values closer to zero indicating better performance (Y. Kumar & Sahoo, 2012). Multiple accuracy assessments indices were calculated as recommended due to each index having its own strengths and weaknesses (Foody, 2002).

#### *4.3.4 Spatial distribution and density of IAPs*

Distribution and density maps were created for both sites using the fishnet grid method (Vieira, Finn, & Bradley, 2014) in ArcMap 10.2. Initially grids representing quadrats measuring 5 by 5m (Johansen, Phinn, & Witte, 2010) were created and used to determine the spatial distribution and density of each IAP using a point grid density analysis method (van den Berg, Kotze, & Beukes, 2014). However this resulted in maps which did not adequately reveal the densities of the selected IAPs due to the small quadrat size. In order to reveal these densities, different fishnet sizes (grid sizes) were experimented and a quadrat size of 50 by 50m (a grid size of 100 by 100m is also recommended (ESRI, 2014)), proved adequate for revealing IAP densities pre-and post-clearance (Figures 4.1 and 4.2) that corroborated image classification accuracies (Tables 4.2 and 4.3). Density of species was categorised into low (4% - 33%), moderate (34% - 66%) and high density (67% - 100%) (van den Berg et al., 2014), density below 4% were considered errors of commission (Borak, 1999). This was represented by intensity of quadrat colour; quadrats with higher colour intensity indicate a higher species density. The area coverage of each IAP before and after clearing was calculated for both sites to aid change detection and determine the success of IAP removal program.

### 4.4 Results

Overall classification accuracy in the year 2010 for Paradise Valley (72%) and Roosfontein (82%) (Table 4.1) were unsuccessful considering the 85 % acceptable threshold for overall accuracy (Everitt et al., 2008). However, the RMSE and MAE values in 2010 for Roosfontein were lower than the Paradise valley values, indicating higher classification accuracy. Overall classification accuracy in the year 2015 was successful for both study sites with accuracies 85% and above, with very low RMSE and MAE values.

**Table 4.1:** Overall accuracy of the Maximum Likelihood classifier performed on both sites in 2010 and 2015.

| | **Year** | **Overall accuracy (%)** | **Overall Kappa** | **MAE** | **RMSE** |
|---|---|---|---|---|---|
| Paradise Valley | 2010 | 72.33 | 0.6272 | 27.67 | 28.63 |
| | 2015 | 100 | 1 | 0 | 0 |
| Roosfontein | 2010 | 81.5 | 0.6864 | 18.5 | 18.51 |
| | 2015 | 85 | 0.7 | 1.5 | 1,58 |

Individual user's and producer's accuracies above 70% have been recommended for successful image classification (Everitt et al., 2008). In the classification performed in 2010 Paradise Valley reserve *A. podalyriifolia* and *C. odorata* were both successfully detected with user's and producer's accuracies above 70% (Table 4.2), except for *L. glutinosa* (63%), representing the lowest classified species (Foody, 2002). Both *C. odorata* and *L. glutinosa* were successfully detected in the Roosfontein reserve with user's and producer's accuracies higher than 70%. Individual Kappa values for all species in both reserves were excellent (above 0.8) besides *L. glutinosa* in the Paradise Valley reserve (0.73).

**Table 4.2:** Individual accuracy assessment of classified IAPs in 2010

| | | **Producer's accuracy (%)** | **User's accuracy (%)** | **Kappa coefficient** |
|---|---|---|---|---|
| Paradise Valley | Ap | 81 | 98.78 | 0.9817 |
| | Co | 73 | 100 | 1 |
| | Lg | 63 | 81.82 | 0.7273 |
| Roosfontein | Co | 81 | 100 | 1 |
| | Lg | 82 | 98.8 | 0.9759 |

Abbreviations are as follows Ap = *Acacia podalyriifolia*, Co = *Chromolaena odorata* and Lg = *Litsea glutinosa.*

Individual user's and producer's accuracies of the 2015 imagery produced similar results to the 2010 imagery in both reserves. The two IAPs, *A. podalyriifolia* and *C. odorata* in the Paradise valley reserve and *C. odorata* and *L. glutinosa* in the Roosfontein reserve (Table 4.3) produced accuracies above 70% (Everitt et al., 2008). Individual Kappa values were excellent (0.8 and above) for all species in both reserves besides *C. odorata* in the Roosfontein reserve (0.6).

**Table 4.3:** Individual accuracy assessment of classified IAPs in 2015

| | | **Producer's accuracy (%)** | **User's accuracy (%)** | **Kappa coefficient** |
|---|---|---|---|---|
| Paradise Valley | Ap | 100 | 100 | 1 |
| | Co | 100 | 100 | 1 |
| Roosfontein | Co | 80 | 80 | 0.6 |
| | Lg | 90 | 90 | 0.8 |

Abbreviations are as follows Ap = *Acacia podalyriifolia*, Co = *Chromolaena odorata* and Lg = *Litsea glutinosa.*

Figure 4.1 represents a comparative distribution and density of three selected IAPs between 2010 and 2015. Density of species is represented by intensity of quadrat colour; quadrats exhibiting higher colour intensity indicate a higher species density. The figure shows that in 2010 *A. podalyriifolia* was concentrated towards the centre of the reserve, whereas 2015 shows a decrease in extent and density of the species. In 2010, *C. odorata* was found throughout the map, whereas in 2015 *C. odorata* density decreased across the map and exhibits a definite decrease in occurrence and density. The 2010 and 2015 imagery showed *L. glutinosa* abundantly distributed across both maps with very little to no indication of a decrease in occurrence or density between 2010 and 2015.

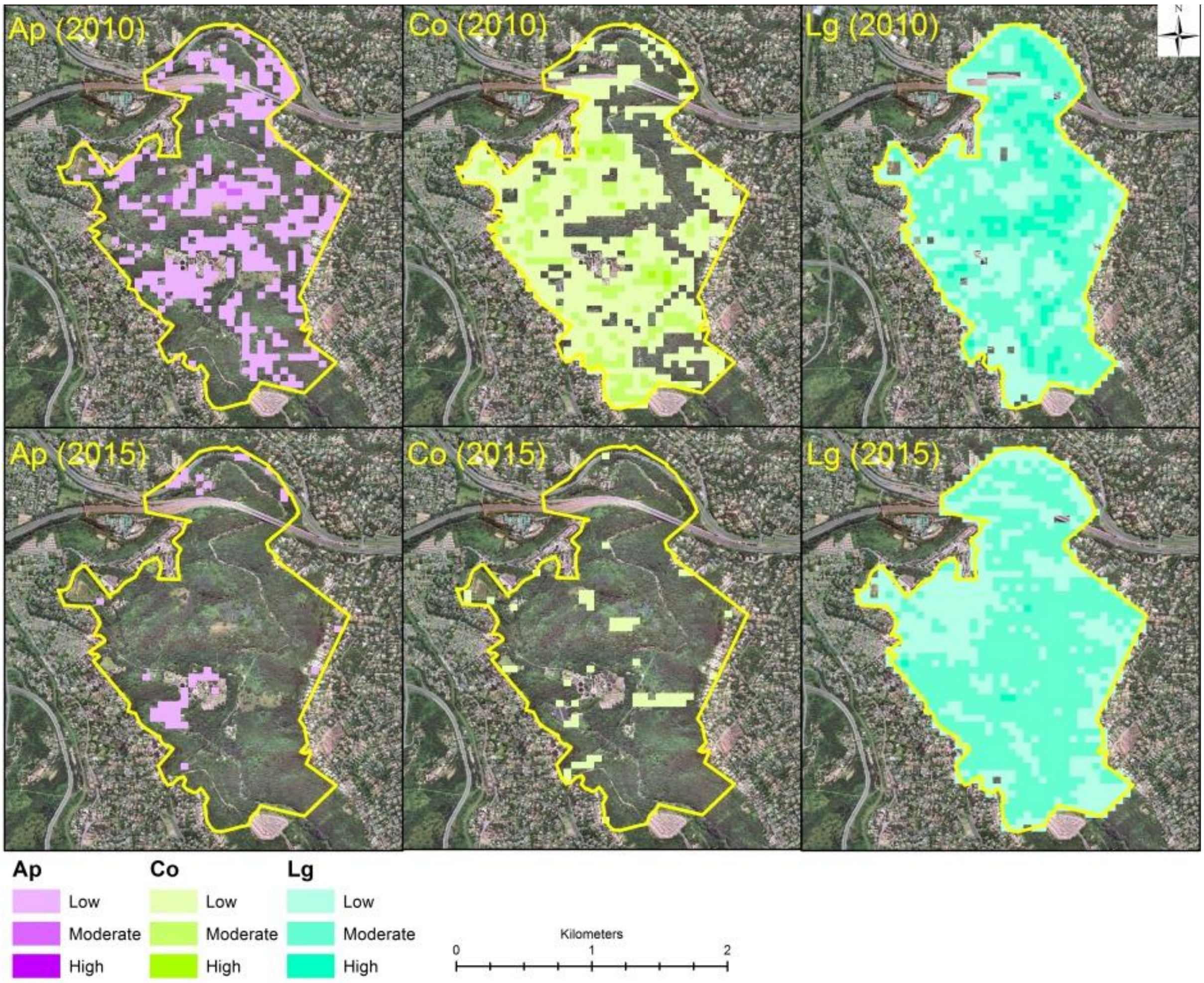



**Figure 4.1:** Comparative IAP distribution maps for 2010 and 2015 in the Paradise Valley nature reserve. IAPs (Ap = *A. podalyriifolia*, Co = *C. odorata* and Lg = *L. glutinosa*). Density of species is represented by intensity of quadrat colour, (low = 4-33%, moderate = 34-66% and high = 67-100%).

Figure 4.2 represents the density and distribution of the two selected species in the Roosfontein Nature Reserve between the years of 2010 and 2015. The *C. odorata* species in 2010 was spread throughout the reserve, whereas in 2015 there was a significant decrease in its occurrence, with only small isolated patches located in the centre of the reserve. The occurrence of *L. glutinosa* in 2010 is mainly towards the West and South of the reserve, whereas in 2015 there is a decrease in occurrence and density of the species in the East but a persistent occurrence in the North West of the reserve.

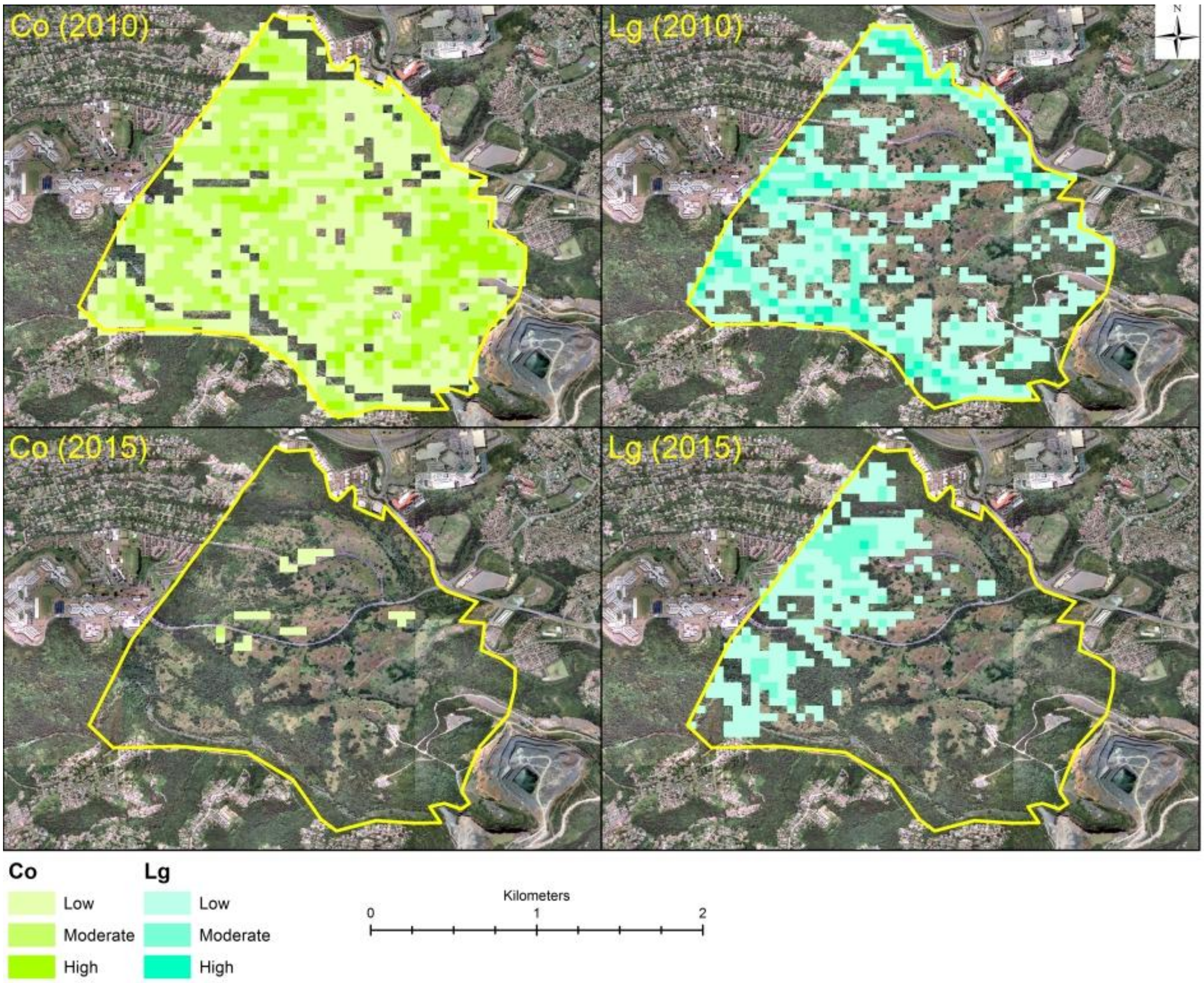



**Figure 4.2:** Comparative IAP distribution maps for 2010 and 2015 in the Roosfontein nature reserve IAPs (Co = *C. odorata* and Lg = *L. glutinosa*). Density of species is represented by intensity of quadrat colour, (low = 4-33%, moderate = 34-66% and high = 67-100%).

Table 4.3 presents the percentage change in hectares (ha) of each species in both reserves. Positive values (+) indicate an increase in area cover of IAP, while negative values (-) indicate a decrease in area cover. In the Paradise Valley reserve, *A. podalyriifolia* and *C. odorata* both showed a high percentage decrease in area cover (81.6 % and 94.7% respectively). The *L. glutinosa* species also decreased in cover but with a much lower percentage (8.42%). In the Roosfontein nature reserve, *C. odorata* cover decreased significantly by 98.9%, while *L. glutinosa* decreased by 66.4%.

**Table 4.3:** Invasive alien plant percentage change in area cover between IAPs 2010 and 2015 in the Paradise Valley and the Roosfontein nature reserves.

| | | **Area 2010 (ha)** | **Area 2015 (ha)** | **Percent change** |
|---|---|---|---|---|
| Paradise Valley | Ap | 12.23 | 2.25 | -81.63 |
| | Co | 47.11 | 2.49 | -94.72 |
| | Lg | 129.76 | 118.83 | -8.42 |
| | | | | |
| Roosfontein | Co | 107.17 | 1.16 | -98.92 |
| | Lg | 39.58 | 13.29 | -66.42 |

Abbreviations: Ap = *Acacia podalyriifolia,* Co = *Chromolaena odorata* and Lg = *Litsea glutinosa.*

## 4.5 Discussion

Overall accuracies of the classification (Table 4.1) of the 2010 imagery indicate unsuccessful classification results as all were below 85%; however, the 2015 resulted in successful classification for both reserves. The 2010 result was supported by the study done on the detection of the IAP Giant Reed (*Aurundo donax)* where overall accuracies were also below 85% (Everitt et al., 2008). The accuracy assessment results of individual species in both 2010 (Table 4.2) and 2015 (Table 4.3) for both reserves were successful (above 70%) (Everitt et al., 2008) for all species except *L. glutinosa* (63%) in the 2010 imagery for the Paradise Valley Reserve which was the lowest classified species. Classification of multispectral imagery can result in high accuracies; however large commission errors may exist due to poor spectral resolution (Rocchini et al., 2015). The successful classification of *A. podalyriifolia* is due to its leaves exhibiting dense velvety hairs (Henderson, 1995), this surface texture affects the reflection of radiation resulting a unique spectral signature compared to other vegetation present (Kumar, Schmidt, Dury, & Skidmore, 2002). The *C. odorata* species has been successfully detected in other studies using WorldView-2 imagery (Malahlela et al., 2015). The *L. glutinosa* species is noted to occur in heterogeneous stands when compared to the other two selected species (*A. podalyriifolia,* and *C. odorata*) which form dense monotypic stands and is therefore more difficult to detect (Bradley, 2014). Therefore, Hyperspectral imagery could be more suitable at detecting *L. glutinosa* (Rocchini et al., 2015).

The majority of errors produced when conducting field surveys resulted from seedlings of the species. The distribution and density maps allow us to analyse the change in occurrence and density of the selected IAPs between 2010 and 2015 (van den Berg et al., 2014) which is useful at assessing risk (Joshi et al., 2006). Invasive alien plant density and cover patterns are important factors to consider when applying clearing initiatives (Forsyth, Gibson, & Turner, 2014; van Wilgen et al., 2012) to prioritise for clearing and help asses clearing.

The *A. podalyriifolia* species, a woody invasive species, experienced a large decrease in percentage cover within the Paradise Valley Nature Reserve. This implies the ongoing clearing programs were successful in this reserve. Furthermore, those pixels that were detected as *A.*

*podalyriifolia* in the 2015 imagery appear to be errors of commission (false positives) (Calviño-Cancela et al., 2014). Even though the clearing of this woody IAP species has been successful in this reserve, their removal IAPs could facilitate the recruitment of other IAPs (Loh & Daehler, 2008).

The shrub species *C. odorata* is indigenous to Central and North America, it has an allelopathic effect which inhibits seedling recruitment of indigenous species (Malahlela et al., 2015). In both the Paradise Valley and the Roosfontein nature reserves it has experienced a large decrease in percent cover (more than 90%) also indicating successful clearing as with *A. podalyriifolia* in the Paradise Valley Nature Reserve. The clearing of *L. glutinosa,* which is a tree species, in the Paradise Valley reserve, has made very little progress, whereas clearing of this species in the Roosfontein reserve reduced the percentage cover by almost two thirds (66.5%), and eradicated the species towards the East of the reserve.

In the Paradise Valley reserve, the failure in clearing *L. glutinosa* could have resulted from clearing of other IAPs. Manual clearing can disturb soil and therefore facilitate invasion by other IAPs (Flory & Clay, 2009). Chemical removal may inhibit the growth of entire functional groups including indigenous species (Flory & Clay, 2009), therefore promoting growth of IAPs belonging to other functional groups.

Further research should consider early detection of IAPs as prevention of spread is more cost effective than combating invasion, therefore remote sensing can be applied as an early detection tool to effectively combat invasion (D'Antonio et al., 2004). Once a species become established, it is difficult to reduce their spread and almost impossible to halt invasion. It is easier to deal with areas that are in the initial stages of invasion as there is no seed bank present (Müllerová et al., 2013). The means to detect IAPs in South Africa maybe available, however in addition to the high cost of imagery remote sensing is not a well-established field. Furthermore, government has limited resources and battles with a host of issues such as crime, poverty and service delivery, therefore IAP eradication may not be regarded as a priority. To reduce cost of detection a predictive modelling approach is suggested at aiding in the removal of IAPs (Richardson & van Wilgen, 2004), as patterns of past invasions can be used to predict future invasion (Bradley & Mustard, 2006).

## 4.6 Conclusion

This paper aimed to examine the role of remote sensing in assessing clearing programs within two nature reserves (Paradise Valley and Roosfontein), with the goal to asses previous removal programs and facilitate planning towards future removal programs. This study found that when considering the user's and producer's accuracy of both 2010 and 2015 imagery in these reserves only *L. glutinosa* in the Paradise Valley Nature Reserve was the lowest classified species. The assessment of the removal program showed mostly positive results as two IAPs (*A. podalyriifolia,* and *C.*

*odorata*) in the Paradise Valley Nature Reserve and two IAPs (*C. odorata* and *L. glutinosa*) in the Roosfontein Nature Reserve showed a large decrease in spatial extent.

While the majority of the results are positive it is not known what species have replaced those that have been removed. This study did show that remote sensing is able to assess removal programs, thereby highlighting its use a tool to aid in mitigation efforts. Worldview-2 imagery proved successful in detecting target IAPs; however, a higher spectral resolution sensor will result in higher accuracies. There is a need to establish methods to assess removal programs of IAPs in South Africa. There has been a significant amount of research within South Africa in IAP detection using remote sensing; however, the application of this tool is not very wide spread.

## References


Bradley, B. A. (2014). Remote detection of invasive plants: a review of spectral, textural and phenological approaches. *Biological Invasions*, *16*(7), 1411–1425. http://doi.org/10.1007/s10530-013-0578-9

Bradley, B. A., & Mustard, J. F. (2006). Characterizing the Landscape Dynamics of an Invasive Plant and Risk of Invasion Using Remote Sensing. *Ecological Applications*, *6*(1), 1132–1147.

Borak, J. S. (1999). Feature selection and land cover classification of a MODIS-like data set for a semiarid environment. *International Journal of Remote Sensing*, *20*(5), 919–938. http://doi.org/10.1080/014311699212993

Calviño-Cancela, M., Méndez-Rial, R., Reguera-Salgado, J., & Martín-Herrero, J. (2014). Alien plant monitoring with ultralight airborne imaging spectroscopy. *PloS One*, *9*(7), e102381. http://doi.org/10.1371/journal.pone.0102381

Coppin, P. R., & Bauer, M. E. (2009). Digital change detection in forest ecosystems with remote sensing imagery. *Remote Sensing Reviews*, *13*(3–4), 207–234. http://doi.org/10.1080/02757259609532305

Cuneo, P., Jacobson, C. R., & Leishman, M. R. (2009). Landscape-scale detection and mapping of invasive African Olive (*Olea europaea L. ssp. cuspidata* Wall ex G. Don Ciferri) in SW Sydney, Australia using satellite remote sensing. *Applied Vegetation …*, *12*, 145–154. http://onlinelibrary.wiley.com/doi/10.1111/j.1654-109X.2009.01010.x/full

D’Antonio, C. M., Jackson, N. E., Horvitz, C. C., & Hedberg, R. (2004). Invasive plants in wildland ecosystems: Merging the study of invasion processes with management needs. *Frontiers in Ecology and the Environment*, *2*(10), 513–521. http://doi.org/10.1890/1540-9295(2004)002[0513:IPIWEM]2.0.CO;2

Doody, T. M., Lewis, M., Benyon, R. G., & Byrne, G. (2014). A method to map riparian exotic vegetation (*Salix spp.*) area to inform water resource management. *Hydrological Processes*, *28*(11), 3809–3823. http://doi.org/10.1002/hyp.9916

ESRI. (2014). How point density works. *ArcGis Descktop Help 10.2*. Redlands, California.

Everitt, J. H., Yang, C., Fletcher, R., & Deloach, C. J. (2008). Comparison of QuickBird and SPOT 5 satellite imagery for mapping giant reed. *Journal of Aquatic Plant Management*, *46*, 77–82.

Flory, S. L., & Clay, K. (2009). Invasive plant removal method determines native plant community responses. *Journal of Applied Ecology*, *46*(2), 434–442. http://doi.org/10.1111/j.1365-2664.2009.01610.x

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of*

*Environment*, *80*(1), 185–201. http://doi.org/10.1016/S0034-4257(01)00295-4

Forsyth, A. T., Gibson, L. A., & Turner, A. A. (2014). Assessment of SPOT 6 imagery for mapping the invasive alien plant species Pinus spp. in a mountainous area of the Western Cape. *Proceedings of the Second AfricaGEO Conference*, 1–12.

Henderson, L. (1995). *Plant invaders of Southern Africa*. Agricultural Research Council.

Johansen, K., Phinn, S., & Witte, C. (2010). Mapping of riparian zone attributes using discrete return LiDAR, QuickBird and SPOT-5 imagery: Assessing accuracy and costs. *Remote Sensing of Environment*, *114*(11), 2679–2691. http://doi.org/10.1016/j.rse.2010.06.004

Joshi, C., de Leeuw, J., van Andel, J., Skidmore, A. K., Lekhak, H. D., van Duren, I. C., & Norbu, N. (2006). Indirect remote sensing of a cryptic forest understorey invasive species. *Forest Ecology and Management*, *225*(1–3), 245–256. http://doi.org/10.1016/j.foreco.2006.01.013

Kerr, J. T., & Ostrovsky, M. (2003). From space to species: Ecological applications for remote sensing. *Trends in Ecology and Evolution*. http://doi.org/10.1016/S0169-5347(03)00071-5

Kumar, L., Schmidt, K., Dury, S., & Skidmore, A. . (2002). Imaging Spectrometry and Vegetation Science. In *Imaging spectrometry* (pp. 111–156). http://doi.org/10.1007/s13398-014-0173-7.2

Kumar, Y., & Sahoo, G. (2012). Analysis of parametric & non parametric classifiers for classification technique using WEKA. *I.J. Information Technology and Computer Science*, (July), 43–49. http://doi.org/10.5815/ijitcs.2012.07.06

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. http://doi.org/10.1614/WS-04-044R2

Le Maitre, D. C., van Wilgen, B. W., Gelderblom, C. ., Bailey, C., Chapman, R. ., & 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*(1–3), 143–159. http://doi.org/10.1016/S0378-1127(01)00474-1

Loh, R. K., & Daehler, C. C. (2008). Influence of woody invader control methods and seed availability on native and invasive species establishment in a Hawaiian forest. *Biological Invasions*, *10*(6), 805–819. http://doi.org/10.1007/s10530-008-9237-y

Malahlela, O. E., Cho, M. a., & Mutanga, O. (2015). Mapping the occurrence of *Chromolaena odorata* (L.) in subtropical forest gaps using environmental and remote sensing data. *Biological Invasions*, *17*(7), 2027–2042. http://doi.org/10.1007/s10530-015-0858-7

Mas, J.-F. (1999). Monitoring land-cover changes: a com parison of change detection techniques.

*International Journal of Remote Sensing*, *20*(1), 139–152. http://doi.org/10.1080/014311699213659

Miao, X., Patil, R., Heaton, J. S., & Tracy, R. C. (2011). Detection and classification of invasive saltcedar through high spatial resolution airborne hyperspectral imagery. *International Journal of Remote Sensing*, *32*(8), 2131–2150. http://doi.org/10.1080/01431161003674618

Müllerová, J., Pergl, J., & Pyšek, P. (2013). Remote sensing as a tool for monitoring plant invasions: Testing the effects of data resolution and image classification approach on the detection of a model plant species *Heracleum mantegazzianum* (giant hogweed). *International Journal of Applied Earth Observation and Geoinformation*, *25*(1), 55–65. http://doi.org/10.1016/j.jag.2013.03.004

Mutanga, O., van Aardt, J. Van, & Kumar, L. (2009). Imaging spectroscopy ( hyperspectral remote sensing ) in southern Africa : an overview. *South African Journal of Science*, *105*(June), 193–198.

Nagendra, H., Lucas, R., Honrado, J. P., Jongman, H. . R., Tarantino, C., Adamo, M., & Mairota, P. (2013). Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats. *Ecological Indicators*, *33*, 45–59. http://doi.org/10.1017/CBO9781107415324.004

Preston-Whyte. (1980). *Climate of Durban*. *Natal Town and Regional Planning Reports* (Vol. 44). Durban.

Richardson, D. M., & van Wilgen, B. W. (2004). Working for Water: Invasive alien plants in South Africa: how well do we understand the ecological impacts? *South African Journal of Science*, *100*(February 2004), 45–52.

Rocchini, D., Andreo, V., Forster, M., Garzon-Lopez, C. X., Gutierrez, a. P., Gillespie, T. W., … Neteler, M. (2015). Potential of remote sensing to predict species invasions: A modelling perspective. *Progress in Physical Geography*, *n.a.*, 1–27. http://doi.org/10.1177/0309133315574659

Sarma, P. K., Lahkar, B. P., Ghosh, S., Rabha, A., Das, J. P., Nath, N. K., … Brahma, N. (2008). Land-use and land-cover change and future implication analysis in Manas National Park, India using multi-temporal satellite data. *Current Science*, *95*(2), 223–227.

Singh, A. (1989). Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, *10*(6), 989–1003. http://doi.org/10.1080/01431168908903939

Stuckenberg, T., Münch, Z., & van Niekerk, A. (2014). Multi-temporal remote sensing land-cover change detection for biodiversity assessment in the Berg River catchment. *South African Journal* *of Geomatics*, *2*(3), 189–205. http://www.ajol.info/index.php/sajg/article/view/106977

Underwood, E. C., Ustin, S. L., & DiPietro, D. (2003). Mapping nonnative plants using hyperspectral imagery. *Remote Sensing of Environment*, *86*(2), 150–161. http://doi.org/10.1016/S0034-4257(03)00096-8

van den Berg, E., Kotze, I., & Beukes, H. (2014). Detection, quantification and monitoring of Prosopis in the Northern Cape Province of South Africa using remote sensing and GIS. *South African Journal of Geomatics*, *2*(2), 68–81. http://www.ajol.info/index.php/sajg/article/view/106983

van Wilgen, B. W., Forsyth, G. G., Le Maitre, D. C., Wannenburgh, A., Kotzé, J. D. F., van den Berg, E., & Henderson, L. (2012). An assessment of the effectiveness of a large, national-scale invasive alien plant control strategy in South Africa. *Biological Conservation*, *148*(1), 28–38. http://doi.org/10.1016/j.biocon.2011.12.035

Vieira, R., Finn, J. T., & Bradley, B. A. (2014). How does the landscape context of occurrence data influence models of invasion risk? A comparison of independent datasets in Massachusetts, USA. *Landscape Ecology*, (2014), 1601–1612. http://doi.org/10.1007/s10980-014-0080-5

Vilà, M., Basnou, C., Pyšek, P., Josefsson, M., Genovesi, P., Gollasch, S., … Hulme, P. E. (2010). How well do we understand the impacts of alien species on ecosystem services? A pan-European, cross-taxa assessment. *Frontiers in Ecology and the Environment*. http://doi.org/10.1890/080083

Zhang, Y., & Mishra, R. (2012). A review and comparison of commercially available pan-sharpening techniques for high resolution satellite image fusion. *Geoscience and Remote Sensing …*, 182–185. http://doi.org/10.1109/IGARSS.2012.6351607

# CHAPTER FIVE

# THE ROLE OF REMOTE SENSING IN INVASIVE ALIEN PLANT DETECTION AND ASSESSMENT OF REMOVAL INITIATIVES: A SYNTHESIS

## 5.1 Introduction

Though considered as the second greatest threat to global biodiversity (van Wilgen, Reyers, Le Maitre, Richardson, & Schonegevel, 2008), IAP detection and mapping, is still considered a challenge to an extent, this can be tackled through geospatial technology like remote sensing (Cuneo, Jacobson, & Leishman, 2009). There have been a number of studies focused on mapping IAPs both globally and nationally (Hantson, Kooistra, & Slim, 2012; Joshi, Leeuw, & Duren, 2004; Trueman, Standish, Orellana, & Cabrera, 2014). However, few of these studies have focused on smaller protected areas (nature reserves) (Götmark & Thorell, 2003). The spread of IAPs in protected reserves (if not monitored) can lead to serious negative conservational impacts such as a loss of biodiversity. In South Africa, there have been government initiatives to remove IAPs, however; the success of such removal efforts has not been thoroughly investigated. Moreover, remote sensing technology has not been well explored as a tool to asses such removal programs.

The objectives of this study were:

- To examine the relevant literature, and gain an understanding of the successes and challenges relative to invasive alien plant spectroscopy.
- To assess three types of multispectral imagery (Landsat 7 ETM+, SPOT 5 and WorldView-2) and four classification methods (Parallel piped, Maximum Likelihood, Spectral Angle Mapper and the Iterative Self-Organizing Data Analysis Technique Algorithm) at the detection of three IAPs (*Acacia podalyriifolia* (Pearl Acacia), *Chromolaena odorata* (Triffid Weed) and *Litsea glutinosa* (Indian Laurel)*)* within the Paradise Valley Nature Reserve of the eThekwini Municipality in KwaZulu-Natal of South Africa).
- To asses clearing programs of three IAPs (*Acacia podalyriifolia*, *Chromolaena odorata* and *Litsea glutinosa)* within two protected areas (Paradise Valley and Roosfontein) within the eThekwini Municipality in KwaZulu-Natal of South Africa.

## 5.2 Invasive alien plant spectroscopy

Remote sensing is a valuable tool as spatial information on IAP distribution allows policy makers to apply adequate mitigation strategies (Joshi & Leeuw, 2005). Chapter two discussed the concerns of IAPs, the role remote sensing plays in IAP detection and the successes and challenges of various sensors used in this field of research.

This chapter indicates that multispectral and hyperspectral sensors are useful at detecting IAPs (Bradley, 2014). Multispectral data involves broader categories and is useful at mapping species that form distinguished homogenous stands (Huang & Asner, 2009) and species that have distinct characteristics (Cuneo et al., 2009). Hyperspectral data consists of individual bands that can be isolated (Mutanga, van Aardt, & Kumar, 2009) that would increase classification accuracy of IAPs in a heterogeneous community where the respective IAPs are scattered (He, Rocchini, Neteler, & Nagendra, 2011). Spatial resolution needs be considered as it affects the accuracy of IAP detection, because as spatial resolution decreases, so too does accuracy (Shouse, Liang, & Fei, 2013).

Remote sensing is an effective tool to assess the effects of IAPs on the ecosystem (Miao, Patil, Heaton, & Tracy, 2011). Detection of IAPs, using remote sensing is possible as long as the target IAP exhibits novel characteristics when compared to the indigenous species (Huang & Asner, 2009). The mapping of a single IAP species in a heterogeneous landscape still remains a challenge (Evangelista, Stohlgren, Morisette, & Kumar, 2009). In addition, there is a lack of interdisciplinary training between geographers (traditional practitioners of GIS and Remote sensing) on the one hand and biologists on the other hand (He et al., 2011).

## 5.3 IAPs detection methods, sensors and classifiers

The detection of prominent IAPs is an essential process to assist in their management (Trueman et al., 2014). Chapter three assessed the use of three sensors and four classifiers at detecting three prominent IAPs. The main objective in this chapter (paper) was to determine the most accurate remotely sensed imagery and classification method for detecting three selected IAPs. The outcome from this chapter would be used in chapter four as to assess removal programs of the three selected species.

Results from this chapter, reveal that the visible and infrared bands are appropriate in detection of IAPs. The Maximum Likelihood Classifier applied on WorldView-2 imagery produced the most accurate results with suitable identification and classification for both *A. podalyriifolia* and *C. odorata*, based on the producer's accuracy above 70% (Table 5.1). The results are significant as specific species detection is usually rare, dependent on dominant species and its spatial extent (Bradley, 2014). This method of classification was used in change detection analysis, to assess the effectiveness of clearing initiatives of the three target species before and after clearing in chapter four.

**Table 5.1:** Accuracy assessment of the Maximum likelihood classifier performed on WorldView-2 imagery for detecting three IAPs in the Paradise Valley Nature Reserve (2010).

| | **User's accuracy (%)** | **Producer's accuracy (%)** | **Kappa coefficient** |
|---|---|---|---|
| **Ap** | 100 | 85 | 1 |
| **Co** | 100 | 74 | 1 |
| **Lg** | 95.35 | 41 | 0.9302 |

Species abbreviations: Ap = *Acacia podalyriifolia*, Co = *Chromolaena odorata*, Lg = *Litsea glutinosa*).

The selection of an appropriate image type is dependent on the respective scale of the study area (Bradley, 2014). Future research in this field should include hyperspectral imagery in conjunction with high spatial resolution imagery to allow for increased accuracy in the classification of IAPs. This study also concluded that remotely sensed imagery with moderate spatial resolution, such as the Landsat and SPOT sensors, are not suitable for the detection of individual species at a local scale.

## 5.4 Assessment of removal strategies within two protected areas

In South Africa, there has been a significant proportion of resources and capital invested in the removal of IAPs. Chapter four examined the role of remote sensing, in assessing clearing programs within two nature reserves (Paradise Valley and Roosfontein), with the objective of comparing images pre- and post- IAP removal, to inform planning and management of future removal programs.

In the results, all selected IAPs were successfully detected in the 2010 and 2015 imageries based on user's and producer's accuracy above 70%, except *L. glutinosa* in the Paradise Valley reserve, which was the lowest classified species. Further assessment showed that two IAPs (*A. podalyriifolia,* and *C. odorata*) in the Paradise Valley Nature Reserve and two IAPs (C. *odorata* and *L. glutinosa*) in the Roosfontein Nature Reserve have been successfully removed to a large extent (substantially decreasing in area cover, for example Ap (82%), Co ( 95% and 99%) (Table 5.2).

**Table 5.2:** IAP percentage change in area cover between IAPs 2010 and 2015 in the Paradise Valley and the Roosfontein nature reserves.

| | | Area 2010 (ha) | Area 2015 (ha) | Percent change |
|---|---|---|---|---|
| Paradise Valley | Ap | 12.23 | 2.25 | -81.63 |
| | Co | 47.11 | 2.49 | -94.72 |
| | Lg | 129.76 | 118.83 | -8.42 |
| | | | | |
| Roosfontein | Co | 107.17 | 1.16 | -98.92 |
| | Lg | 39.58 | 13.29 | -66.42 |

Abbreviations are as follows Ap = *A. podalyriifolia,* Co = *C. odorata* and Lg = *L. glutinosa*. Positive (+) values represent an increase in percent change a negative (-) represents a decrease in percent change.

While the majority of the results are positive it is unknown which species have replaced those that have been removed. Chapter four highlights the potential of remote sensing as a tool to assess removal programs. Worldview-2 imagery (high spatial resolution) proved successful in detecting target IAPs. There is a need for those who deal with invasion for future research to allow for the establishment of methods to assess removal programs of IAPs in South Africa.

## 5.5 Conclusion

The purpose of this study was to determine suitable methodologies to detect three IAPs occurring within two reserves in the eThekwini Municipality and then apply the method to assess removal of the target species. The conclusions here are based on both the detection of the IAPs and the assessment of removal programs for these species.

The results validate the inability of freely available multispectral imagery to detect IAPs and confirm high spatial resolution imagery (WorldView-2) as a better alternative though only two of the three selected species were detected successfully. Furthermore, the results support the use of the Maximum Likelihood classifier at detecting IAPs. It has been proven that appropriate remotely sensed imagery can assist not only in the detection of IAPs but also in assessing the removal in time and space.

This study has brought to light the success and challenges of clearing initiatives in the two selected reserves, with success dependent on species and location. The method used in this study can allow for the detection and assess clearing of these IAPs in other areas. This will allow land mangers to rethink clearing methods of persisting IAPs to allow for successful clearing. Furthermore, clearing methods applied to successfully removed IAPs can be applied to other areas that contain these species.

### 5.6 Recommendations for future research

Invasion by IAPs is increasing in South Africa (van Wilgen et al., 2012) and land managers need to take account of all IAPs present in the landscape (Trueman et al., 2014) when considering mitigation efforts. Therefore future studies using remote sensing to detect IAPs to aid in control should include all IAPs present in the targeted study site and time series analysis (Bradley, 2014). Periodic classification of a species can result in an indication of the rate of spread of a species, after which land managers can choose to target faster spreading species first (Trueman et al., 2014).

Remote sensing is an effective tool to assess the effects of IAPs on ecosystems (Miao et al., 2011). The next step would be to identify areas that are in their initial stages of invasion and target these areas to reduce spread (Walsh et al., 2008). Thereafter research is needed to determine the vulnerability of areas to invasion, by examining spatial configuration of IAPs and landscape conditions, areas can then be identified that can be potentially invaded and therefore protected (Huang & Asner, 2009).

More specific to South Africa, research needs to be undertaken to study IAPs using remote sensing for the purpose of natural systems conservation (Shouse et al., 2013). It would be beneficial to develop local scale protocols/techniques to detect IAPs as the dynamics of invasion vary from place to place. Sensors and techniques used would also vary from region to region and would be dependent on various factors such as resource availability, terrain, IAPs present and vegetation type (Joshi et al., 2004).

Other future research recommendations

- The use of image fusion techniques to improve spatial resolution of sensors as there are many freely available sensors that are sufficient in spectral resolution but have a poor spatial resolution.
- Sub-pixel analysis and spectral unmixing for more detail IAP detection and classification.
- Conduct research to allow for the general discrimination between invaded and non invaded region so as to identify areas at risk of IAP invasion.
- Research on the effects of IAP clearing on biodiversity.
- Assessment of cooperation between stakeholders involved in the management programs within the reserves.

## References

Bradley, B. A. (2014). Remote detection of invasive plants: a review of spectral, textural and phenological approaches. *Biological Invasions*, *16*(7), 1411–1425. http://doi.org/10.1007/s10530-013-0578-9

Bradley, B. A., & Marvin, D. (2011). Using expert knowledge to satisfy data needs: mapping invasive plant distributions in the western United States. *Western North American Naturalist*, *71*(3), 302–315. http://www.bioone.org/doi/abs/10.3398/064.071.0314

Calviño-Cancela, M., Méndez-Rial, R., Reguera-Salgado, J., & Martín-Herrero, J. (2014). Alien plant monitoring with ultralight airborne imaging spectroscopy. *PloS One*, *9*(7), e102381. http://doi.org/10.1371/journal.pone.0102381

Cuneo, P., Jacobson, C. R., & Leishman, M. R. (2009). Landscape-scale detection and mapping of invasive African Olive (*Olea europaea L. ssp. cuspidata* Wall ex G. Don Ciferri) in SW Sydney, Australia using satellite remote sensing. *Applied Vegetation …*, *12*, 145–154. http://onlinelibrary.wiley.com/doi/10.1111/j.1654-109X.2009.01010.x/full

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. http://doi.org/10.3390/rs1030519

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. http://doi.org/10.1016/j.rse.2011.09.023

Götmark, F., & Thorell, M. (2003). Size of nature reserves: Densities of large trees and dead wood indicate high value of small conservation forests in southern Sweden. *Biodiversity and Conservation*, *12*(6), 1271–1285. http://doi.org/10.1023/A:1023000224642

Hantson, W., Kooistra, L., & Slim, P. a. (2012). Mapping invasive woody species in coastal dunes in the Netherlands: a remote sensing approach using LIDAR and high-resolution aerial photographs. *Applied Vegetation Science*, *15*(4), 536–547. http://doi.org/10.1111/j.1654-109X.2012.01194.x

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. http://doi.org/10.1111/j.1472-4642.2011.00761.x

Huang, C.-Y., & Asner, G. P. (2009). Applications of remote sensing to alien invasive plant studies. *Sensors (Basel, Switzerland)*, *9*(6), 4869–89. http://doi.org/10.3390/s90604869

Joshi, C., De Leeuw, J., van Andel, J., Skidmore, A. K., Lekhak, H. D., van Duren, I. C., & Norbu, N. (2006). Indirect remote sensing of a cryptic forest understorey invasive species. *Forest Ecology and Management*, *225*(1–3), 245–256. http://doi.org/10.1016/j.foreco.2006.01.013

Joshi, C., & Leeuw, J. De. (2005). Remote sensing and GIS for mapping and management of invasive shrub *Chromolaena odorata* in Nepal. *Proceedings of Eighth …*. http://www.researchgate.net/profile/Jelte_Andel/publication/228976892_Remote_Sensing_And_GIS_For_Mapping_And_Management_Of_Invasive_Shrub_Chromolaena_odorata_In_Nepal/links/0fcfd50649c4e76495000000.pdf

Joshi, C., Leeuw, J. de, & Duren, I. van. (2004). Remote sensing and GIS applications for mapping and spatial modelling of invasive species. *Proceedings of ISPRS*. http://www.isprs.org/proceedings/xxxv/congress/comm7/papers/132.pdf

Miao, X., Patil, R., Heaton, J. S., & Tracy, R. C. (2011). Detection and classification of invasive saltcedar through high spatial resolution airborne hyperspectral imagery. *International Journal of Remote Sensing*, *32*(8), 2131–2150. http://doi.org/10.1080/01431161003674618

Mutanga, O., Aardt, J. Van, & Kumar, L. (2009). Imaging spectroscopy ( hyperspectral remote sensing ) in southern Africa : an overview. *South African Journal of Science*, *105*(June), 193–198.

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. http://doi.org/10.1614/WT-08-007.1

Richardson, D. M., & van Wilgen, B. W. (2004). Working for Water: Invasive alien plants in South Africa: how well do we understand the ecological impacts? *South African Journal of Science*, *100*(February 2004), 45–52.

Shouse, M., Liang, L., & Fei, S. (2013). Identification of understory invasive exotic plants with remote sensing in urban forests. *International Journal of Applied Earth Observation and Geoinformation*, *21*, 525–534. http://doi.org/10.1016/j.jag.2012.07.010

Trueman, M., Standish, R., Orellana, D., & Cabrera, W. (2014). Mapping the extent and spread of multiple plant invasions can help prioritise management in Galapagos National Park. *NeoBiota*, *23*(July 2015), 1–16. http://doi.org/10.3897/neobiota.23.7800 van Wilgen, B. W., Forsyth, G. G., Le Maitre, D. C., Wannenburgh, A., Kotzé, J. D. F., van den Berg, E., & Henderson, L. (2012). An assessment of the effectiveness of a large, national-scale invasive alien plant control strategy in South Africa. *Biological Conservation*, *148*(1), 28–38. http://doi.org/10.1016/j.biocon.2011.12.035

van Wilgen, B. W., Reyers, B., Le Maitre, D. C., Richardson, D. M., & Schonegevel, L. (2008). A biome-scale assessment of the impact of invasive alien plants on ecosystem services in South Africa. *Journal of Environmental Management*, *89*(4), 336–49. http://doi.org/10.1016/j.jenvman.2007.06.015

Walsh, S. J., McCleary, A. L., Mena, C. F., Shao, Y., Tuttle, J. P., González, A., & Atkinson, R. (2008). QuickBird and Hyperion data analysis of an invasive plant species in the Galapagos Islands of Ecuador: Implications for control and land use management. *Remote Sensing of Environment*, *112*(5), 1927–1941. http://doi.org/10.1016/j.rse.2007.06.028