COMMERCIAL FOREST SPECIES DISCRIMINATION AND MAPPING USING COST EFFECTIVE MULTISPECTRAL REMOTE SENSING IN MIDLANDS REGION OF KWAZULU-NATAL PROVINCE, SOUTH AFRICA

Mthembeni Mngadi

212518076

Thesis submitted to the College of Agriculture, Engineering and Science, at the University of KwaZulu-Natal, in fulfillment of the academic requirements of the degree of Masters of Science in Environmental Science

(Specialization: Remote Sensing)

Pietermaritzburg

South Africa

Abstract

Discriminating forest species is critical for generating accurate and reliable information necessary for sustainable management and monitoring of forests. Remote sensing has recently become a valuable source of information in commercial forest management. Specifically, high spatial resolution sensors have increasingly become popular in forests mapping and management. However, the utility of such sensors is costly and have limited spatial coverage, necessitating investigation of cost effective, timely and readily available new generation sensors characterized by larger swath width useful for regional mapping. Therefore, this study sought to discriminate and map commercial forest species (*i.e. E. dunii, E.grandis, E.mix, A.mearnsii, P.taedea* and *P.tecunumanii*, *P.elliotte*) using cost effective multispectral sensors. The first objective of this study was to evaluate the utility of freely available Landsat 8 Operational Land Imager (OLI) in mapping commercial forest species. Using Partial Least Square Discriminant Analysis algorithm, results showed that Landsat 8 OLI and pan-sharpened version of Landsat 8 OLI image achieved an overall classification accuracy of 79 and 77.8%, respectively, while WorldView-2 used as a benchmark image, obtained 86.5%. Despite low spatial of resolution 30 m, result show that Landsat 8 OLI was reliable in discriminating forest species with reasonable and acceptable accuracy. This freely available imagery provides cheaper and accessible alternative that covers larger swath-width, necessary for regional and local forests assessment and management. The second objective was to examine the effectiveness of Sentinel-1 and 2 for commercial forest species mapping. With the use of Linear Discriminant Analysis, results showed an overall accuracy of 84% when using Sentinel 2 raw image as a standalone data. However, when Sentinel 2 was fused with Sentinel's 1 Synthetic Aperture Radar (SAR) data, the overall accuracy increased to 88% using Vertical transmit/Horizontal receive (VH) polarization and 87% with Vertical transmit/Vertical receive (VV) polarization datasets. The utility of SAR data demonstrates capability for complementing Sentinel-2 multispectral imagery in forest species mapping and management. Overall, newly generated and readily available sensors demonstrated capability to accurately provide reliable information critical for mapping and monitoring of commercial forest species at local and regional scales.

Keywords: forest species discrimination, cross validation, linear discriminant analysis, synthetic aperture radar, polarization, spatial resolution

Preface

This study was conducted in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, from January 2017 to October 2018, under the supervision of Doctor John Odindi and Professor Onisimo Mutanga.

I declare that the work presented in this thesis has never been submitted in any form to any other institution. This work represents my original work except where due acknowledgements are made.

Mthembeni Mngadi Signed Mngadi . Date …. 20/11/2018….

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

Doctor John Odindi Signed……………….. Date………………………..

Professor Onisimo Mutanga Signed……………….. Date………………………..

Declaration

I Mthembeni Mngadi, declare that:

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

2. This thesis has not been submitted for any degree or examination at any other institution.

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

4. This thesis does not contain other persons writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted:

   a. Their words have been re-written and the general information attributed to them has been referenced.

   b. Where their exact words have been used, their writing has been placed in italics inside quotation marks and referenced

5. This thesis does not contain text, graphics or tables copied and pasted from the internet, unless specifically acknowledged, and the source being detailed in the thesis and in the references section.

Mngadi

Signed:……………………… Date…20/11/2018…………………..

Dedication

This dissertation is dedicated to my family, for trusting and granting me the opportunity to further my education. I hope to continue make them proud and happy for me.

Acknowledgements

I wish pass my gratitude to the University of KwaZulu-Natal, especially the School of Agricultural, Earth and Environmental Science for affording me the opportunity to pursue my Masters. To my supervisor Doctor John Odindi, for his constructive scientific criticism, patience and commitment in guiding this work, and most importantly for extending his professional expertise and knowledge towards the success of this research. Huge thanks to Professor Onisimo Mutanga (my co-supervisor), for his commitment and passion to see this work progresses, especially his advices and expertise towards the completion of this study.

A special appreciation to Sappi Forest Company for allowing this study to be conducted in one of their plantations (Clan forest) and for furnishing me with some of the dataset required to complete this study. I would also like to sincerely thank Dr Kabir Peerbhay (Institute of Commercial Forest Research, UKZN) for his valuable assistance and ideas he shared with me to ensure excellence of this research. To my dearest friends and colleagues for their very motivational and constructive words which kept me working very hard under stressful conditions, especially Sphamandla Njabulo Shezi, Silungile Dlamini, Omoshalewa Odebiri, Samantha Manqele, Samantha Chetty, Nonjabulo Shabalala, Ntombifuthi Nzimande, Phindile Ndlovu, Theolin Naidor and Nosipho Makaya. Selectively, I thank Dr Mbulisi Sibanda, Trylee Matongera and Sizwe Hlatshwayo for proof reading and strengthening this work. I really appreciate your time and comments which made huge impact to the final end of this research. To the staff members within the Discipline of Geography and Higher Degrees Office, I thank for friendly support.

Above all, to the most beneficent and omnipotent Nazareth Baptist church leader Shembe ("uNyazilweZulu") for his teachings and reviving conscious on me to be a better and most respecting person. Lastly, a special thanks to my family for giving me this chance to pursue masters, despite difficult times we are experiencing as a family, I strongly believe that the solution is near.

Table of Content

List of Figures

List of Tables

CHAPTER ONE

1. General introduction

1.1 The value of forest plantations in South Africa

Commercial forest plantations in South Africa cover approximately 1.3 million hectares (Roberts *et al.* 2007). These forest plantations play invaluable role in the country's economy, contributing approximately 2% towards the gross domestic product (GDP) through timber and non-timber products (Lottering and Mutanga 2012). In addition, forest plantations play a significant role in sequestrating atmospheric carbon, hence mitigating climate change and related greenhouse effects. Commercial forest plantations in the country are dominated by exotic plant species such as *Pinus*, *Acacia* and *Eucalyptus* (Lottering and Mutanga 2012, Peltzer *et al.* 2015, Peerbhay *et al.* 2013, 2016). Generally, plantations that are dominated by *Eucalyptus* and *Acacia* species are classified as hardwood forests, while *Pinus* dominated plantations are classified as softwood forests (Dube and Mutanga 2015, Peerbhay *et al.* 2016). The economic value and ecosystem services provided by these commercial forest plantations strongly depend on the tree species richness (Sheeren *et al.* 2015). Since different forest tree species are often affected by varying threats that include pests, diseases, vulnerability to wild fires, management regimes and harvest scheduling, information on forest tree species distribution, composition and productivity is critical for managing and monitoring commercial forests (Raczko and Zagajewski 2018). In this regard, the generation of accurate and up-to-date forest species discrimination maps, especially at regional scales is necessary for adopting informed management approaches and policies. In Southern Africa, forest species discrimination and mapping remains a major challenge due to limited standardised assessment and monitoring approaches and technical and scientific expertise. Thus, there is a need to establish viable and affordable spatial approaches and datasets for regional forest species mapping and monitoring.

Previously, traditional methods that include the use of field survey data and aerial photographs have been used for forest delineation and mapping. Although such methods are known to be highly accurate, they are costly, time consuming and difficult to implement in remote areas (Cho *et al.* 2012, Peerbhay *et al.* 2013). Furthermore, accessing regional forests and acquiring sufficient number of tree samples using traditional approach remains a huge challenge (Lu 2006). Recently, the combination of remote sensing techniques with field observation has proven valuable in providing reliable information necessary for forest species discrimination and mapping (Martin *et al.* 1998, Naidoo *et al.* 2012, Peerbhay *et al.* 2014, Waser *et al.* 2014). Remote sensing provides cheap and quick information necessary for up-to-date and reliable forest species discrimination and mapping. Remote sensing techniques capture unique spectral information of individual forest species based on species biochemical and biophysical characteristics at larger swath width, hence allowing for local and regional forest species assessment (Cho et al. 2012, Dube et al. 2018). Hence, there has been increasing interest in the adoption of remote sensing approaches in commercial forestry (Basuki *et al.* 2012, Carreiras *et al.* 2012, Govender *et al.* 2007, Peerbhay *et al.* 2016).

Although remote sensing provides detailed forest species spectral inventories, the utility of traditional multispectral sensors (e.g. Landsat TM, and MODIS) for mapping forest species is limited by broader bandwidth and larger pixel size, resulting in poor discrimination and mapping (Basuki *et al.* 2012, Brockhaus and Khorram 1992, Carreiras *et al.* 2012, Eklundh *et al.* 2009, Forkuor *et al.* 2018). For instance, Brockhaus and Khorram (1992), used Landsat TM spectral data to map various forest types in North Carolina forest, United State of America, with an overall accuracy of 70.8, while Eklundh *et al.* (2009) explored the potential of MODIS spectral information in mapping forest insect damage from various pine tree species in Norway, with an accuracy of 71%. According to Hossain (2016), the minimum accuracy threshold for effective decision making should be at least 75%. The lower classification accuracy mentioned above can be attributed to larger tracking footprints susceptible to the mixed pixel problem (Dube *et al.* 2014). According to Basuki *et al.* (2011), information contained in a broadband sensor's single pixel is a mixture of spectral reflectance recorded from various components that may include forest canopy, shadows and bare soils, a mixture that significantly compromises classification accuracy (Basuki *et al.* 2012, Carreiras *et al.* 2012). Furthermore, reliable landscape discrimination using traditional sensors is commonly impeded by a higher signal-to-noise ratio and the saturation problem, especially in a dense canopy cover (Le Maire *et al.* 2011, Mutanga and Skidmore 2004). Moreover, traditional sensors show a decreasing vegetation sensitivity, especially in increased forest canopy heterogeneity and age.

Several studies have demonstrated the capability and superiority of hyperspectral imagery in discriminating forest species when compared to broadband-multispectral sensors (Govender *et al.* 2007, Govender *et al.* 2008, Peerbhay *et al.* 2016). Hyperspectral imagery is characterized by narrow bandwidths that allow in-depth acquisition of spectral information, which could be lost with broadband-multispectral sensors. Nevertheless, hyperspectral data comes with a number of challenges such as cost, limited spatial coverage, data processing, redundancy and a high degree of data dimensionality (Dube *et al.* 2014, Govender *et al.* 2007). In this regard, the new generation high spatial resolution sensors such as WorldView-2 and RapidEye have increasingly become popular in vegetation mapping. This is attributed to their fewer but robust spectral bands, overcoming data redundancy associated with hyperspectral imagery (Adelabu *et al.* 2013, Dube *et al.* 2016, Peerbhay *et at.* 2014, Waser *et al.* 2014). For example, Waser *et al.* (2014) evaluated the potential of Worldview-2 data in discriminating forest tree species with an overall accuracy of 85.42%, while Adelabu *et al.* (2013) used RapidEye image dataset to discriminate various tree species with an overall accuracy of 85%. Although these sensors provide highly accurate forest species information, they have small spatial coverage and are costly, hence limiting their use to small spatial coverages. These limitations necessitate a shift towards new and freely available multispectral imagery characterized by large footprint and repeated coverage. The new generation freely available Landsat 8 Operational Land Imager (OLI) and Sentinel 2 multispectral sensors offer a larger swath width, which permit local and regional forest assessment. Furthermore, new generation medium spatial resolution sensors provide improved radiometric, spectral and spatial attributes which are assumed to be concise in wall-to-wall mapping and monitoring of forest species. Such improvements offer a cost-effective alternative for regional commercial forest species mapping and management.

A number of studies note that Sentinel 2's data offers better spatial and spectral resolution, with additional strategically positioned bands in the red-edge region (Korhonen *et al.* 2017, Forkuor *et al.* 2018, Sibanda *et al.* 2016). The red-edge region is critical for detecting numerous vegetation attributes such as chlorophyll, leaf area index, leaf angle distribution and biomass, necessary for improved forest species discrimination and mapping (Sibanda *et al.* 2016, Dube *et al.* 2018). Moreover, Sentinel's data provide access to Synthetic Aperture Radar (SAR) capabilities, which offer opportunities for complementarity between optical and SAR capabilities. SAR offers valuable surface characteristics like surface roughness, water content and structural geometry, which are valuable for landscape discrimination (Balzter *et al.* 2015). Furthermore, SAR imagery operate in all weather conditions, penetrating thin cloud and canopy cover, hence overcoming shadowing and clouding effects, a major shortcoming of multispectral sensors (Haack *et al.* 2000, Balzter *et al.* 2015). These capabilities provide a great opportunity for complementarity between optical and SAR data in discriminating and mapping forest species.

Hence, this study sought to map commercial forest species using cost effective multispectral remote sensing. The conclusions of this study are restricted to the capabilities of Landsat 8 OLI and the ability of Sentinel 1 SAR data to complement Sentinel 2 MSI for improved forest species mapping and discrimination.

1.4 Aim and Objectives

The main aim of this study was to map commercial forest species using cost effective multispectral remote sensing in Midlands region of KwaZulu-Natal, South Africa. The objectives were:

- To evaluate freely available Landsat 8 Operational Land Imager (OLI) in mapping commercial forest species,
- To examine the effectiveness of Sentinel-1 and 2 imagery for commercial forest species mapping.

1.5 Research hypothesis

- The new and readily available Landsat 8 OLI multispectral imagery with improved sensor characteristics has the potential to provide accurate and reliable information for regional forest species monitoring and management.
- A Synthetic Aperture Radar capabilities has the ability to successfully improve classification potential of Sentinel-2 multispectral imagery for discriminating forest species.

1.6 Research structure

This dissertation consists of two research papers responding to research objectives and hypothesis. Each paper presents information which could be read independently, but contributing to the entire general introduction (chapter 1) and synthesis (chapters 4). The literature review and methodology are encompassed in both papers, hence duplication and overlap could be present. The entire dissertation is formed by four chapters:

1.6.1 Chapter one

This chapter provides general introduction and contextualization of the study, highlighting the importance and a need for discriminating and mapping commercial forest species. It also presents different methods and their related challenges in discriminating and mapping forest species. Furthermore, the research aim and objectives are provided in this chapter.

1.6.2 Chapter two

This chapter assesses cost effective and readily available remote sensing data for regional forest species discrimination and monitoring, particularly in resource limited areas. The chapter investigates new and freely available Landsat 8 OLI with wide spatial coverage, improved signal-to-noise ratio and 16-day temporal resolution for commercial forest species discrimination and mapping. The findings in this chapter are benchmarked on results obtained when using high spatial resolution WorldView-2 data. Benchmarking the results of Landsat 8 OLI with WorldView-2 is critical for determining the accuracy and precision of the Landsat 8 OLI data.

1.6.3 Chapter three

Although the utility of Landsat 8 OLI showed plausible performance in forest species discrimination, the newly launched Sentinel's data with improved temporal, spatial and spectral resolutions also requires further investigation for forest species discrimination. This freely available sensor comes with a red-edge region sensitive to vegetation characteristics. Furthermore, Sentinel's data comes with Synthetic Aperture Radar data which could be used to compliment multispectral image data, hence improving the classification potential of forest species. Therefore, this chapter evaluates the value of combining Sentinel 1 Synthetic Aperture Radar and Sentinel 2 multispectral image datasets for discriminating forest species.

1.6.4 Chapter four

This chapter provides a synthesis of all findings and conclusions made based on research objectives in chapter 2 and 3. Responses to research hypothesis (highlighted in chapter 1) are also provided in this chapter.

CHAPTER TWO

The utility of freely available Landsat 8 OLI in mapping commercial forest species in KwaZulu-Natal Province, South Africa

This chapter is based on:

Mthembeni Mngadi, John Odindi, Kabir Peerbhay and Onisimo Mutanga. 2018. The utility of freely available Landsat 8 Operational Land Imager in mapping commercial forest species in KwaZulu-Natal, South Africa. *Journal of Forest Research* (under review), manuscript number; JRES-D-18-00175.

Abstract

Species discrimination remains essential for the management of commercial forests. Recently, the adoption of remotely sensed data in forest applications has grown significantly. Whereas high spatial resolution sensors have proven successful in mapping and monitoring commercial forests, their cost, accessibility and spatial coverage remains a critical challenge. Hence, it is necessary to investigate the value of new and improved freely available sensors in forest species mapping. Using the Partial Least Square-Discriminant Analysis (PLSDA), this study sought to evaluate the performance new freely available and improved raw and pan-sharpened Landsat 8 Operational Land Imager (OLI) imagery in discriminating seven key plantation forest species in KwaZulu-Natal Province, South Africa. Accuracies achieved using the Landsat (OLI) imagery were benchmarked against the WorldView-2 imagery. Results show that both raw and pan-sharpened bands successfully delineated commercial forest species, with overall classification accuracies of 79% and 77.8%, respectively. Although these accuracies were lower than the 86.5% achieved from the higher resolution Worldview-2 image data, our findings demonstrate the lower spatial resolution (30 m) of freely available multispectral imagery generated a plausible performance in discriminating forest species. Hence, Landsat 8 could be useful in providing preliminary forestry assessment due to its value in terms of cost, rich archival data and wide swath coverage.

Keywords: Forest species discrimination, high spatial resolution, medium spatial resolution, partial least square discriminant analysis

2.1 Introduction

Plantation species are often characterised by varying impacts on local ecosystem services, biodiversity, management regimes and economic value (Mandle *et al.* 2011). Consolidation of species in commercial forest mapping may therefore oversimplify critical landscape differences (Fagan *et al.* 2015). Hence, information on spatial distribution of commercial forest species is critical for among others supporting forest inventory and estimating productivity, silvicultural practices and forest biodiversity (Honnay *et al.* 1999, Peerbhay *et al.* 2014, Shang and Chisholm 2014). Furthermore, the increasing awareness on climate change and need for optimal mitigation measures necessitate mapping forests at species level as different species within a commercial forest have varying implications on an ecosystem (Fagan *et al.* 2015). For instance, Mandle *et al.* (2011) and Siraj (2018) note that *Eucalyptus* and *Pinus* species are prone to wild fires, hence increased carbon emission while the Silk oak (*G. robusts*) is less prone to fires and known to effectively sequestrate carbon.

In South Africa, commercial forests cover approximately 1,257,341 ha (approximately 1%) of the country's surface area. These forests contribute about 2% to the Gross Domestic Product (GDP) and play a critical role in the carbon-oxygen budget (DWAF 2005, Lottering and Mutanga 2012). Therefore, information on commercial forest species is valuable in among others; managing forest and forest ecosystem, sustainable harvesting and harvest scheduling, managing landscape fragmentation and adopting integrated land use strategies (Geldenhuys 2000; Ismail and Mutanga 2010). Furthermore, understanding commercial forest species distribution is valuable in modelling forest pathogen and disease spread (Ismail and Mutanga 2010), species to environmental conditions matching to optimise growth and productivity (Morris and Pallet 2000), and sustainable allocation of water permits to other uses, as different species use varied amounts of water within a catchment (Peerbhay *et al.* 2013). Additionally, limited suitable sites for specific species require optimisation of available land to maintain profitability. Hence, determination of species using remotes sensing offer an efficient and cost effective means of generating information that can used to effectively manage plantation forests (Ghosh 2014; Peerbhay *et al.* 2013).

Whereas traditional approaches like use of aerial photographs, field observations and surveys are known to be highly accurate, they are often time consuming, expensive, labour intensive and logistically impractical, particularly at large spatial extents (Martin *et al.* 1998, Adam *et al.* 2010, Cho *et al.* 2012, Karlson et al. 2015). Hence, innovative approaches are required to generate spatially explicit information on species within a commercial forestry landscape

(Negandra 2001). Recently, new generation multispectral satellite sensors such as Worldview-2 (430 to 1050 nm) and RapidEye (400 to 800 nm) have demonstrated great capabilities in mapping and monitoring vegetation species. For instance, Worldview-2 captures information using 8-spetral bands with a finer spatial resolution of 2-m across the visible and Near-Infrared (NIR) regions. These bands are highly sensitive to the variability within forest attributes (Lottering *et al.* 2016, Peerbhay *et al.* 2014). Similarly, RapidEye acquires information with a finer spatial resolution of 5-m using 5-bands from visible and NIR portion of electromagnetic spectrum. The two sensors represent commercially available multispectral sensors that offer bands with unique imaging configurations, including the red-edge, valuable for vegetation mapping. Whereas several studies (Rapinel *et al.* 2014; Nouri *et al.* 2014; Peerbhay *et al.* 2014; Adelabu *et al.* 2013) have adopted these sensors with reliable accuracy in forestry, they are commercially operated, therefore costly and not readily accessible. Furthermore, theses sensors are characterised by a small swath width, limiting landscape analysis. These limitations create the need to explore the value of cost effective large swath imagery in commercial forestry mapping.

Several studies have demonstrated the potential of the new generation Landsat 8 sensor for mapping vegetation attributes such as aboveground biomass and leaf area index (Dube and Mutanga 2015, Hashemi 2016, Sothe *et al.* 2017). For instance, Hashemi (2016) successfully used Landsat 8 OLI in an Artificial Neural Network environment to predict changes in deciduous broadleaf forest in Siah Mazgi basin forest of North Iran, while Dube and Mutanga (2015) sucessfully tested the potential of Landsat 8 OLI imagery in predicting commercial forest aboveground biomass using a texture analysis approach in KwaZulu-Natal, South Africa. Despite these successes, several studies have noted that the Landsat 8 OLI's low spatial resolution (30m) impedes vegetation species discrimination (Goldblatt *et al.* 2017, Siddiqui and Zaidi 2016, Immitzer *et al.* 2012). However, Landsat data comes with a high spatial resolution panchromatic data (15 m) that can complement and enhance multispectral image data for landscape delineation. This complementarity offers great potential in commercial forest species discrimination. Pan-sharpening for instance, is an image enhancement process where a panchromatic high spatial resolution image data is merged with a medium spatial resolution multispectral image data to generate a higher spatial resolution image. This technique increases the spatial resolution of multispectral image, while maintaining spectral information (El-Mezouar *et al.* 2011). Whereas this approach holds great potential in generating higher spatial resolution imagery, the integration of the two forms of dataset, particularly in discriminating forest species remains largely unexplored. Investigating the performances of these image datasets for mapping and monitoring forest species could therefore be beneficial to resource poor Southern African countries, and indeed the rest of the developing world that find the cost of high spatial resolution imagery prohibitive.

Commonly, discriminating forest species has been a challenge due to high correlation (multi-collinearity) among variables when using multispectral datasets (Peerbhay *et al.* 2014). Furthermore, variability between forest species reduces the statistical ability to identify and discriminate stands of similar species or individual species. Hence, discriminating forest species using remotely sensed data requires a robust technique capable of dealing with multi-collinearity. Approaches like the Partial Least Squares-Discriminant Analysis (PLS-DA) technique has proven to effectively deal with multi-collinearity within the spectral data. Therefore, this study sought to evaluate the capability of freely available Landsat 8 multispectral data and its panchromatic band for discriminating commercial forest species composition, using the Partial Least Squares Discriminant Analysis (PLS-DA) algorithm. The results achieved from Landsat 8 and pan-sharpened Landsat 8 were benchmarked against accuracies achieved from higher spatial resolution Worldview-2 imagery. Whereas it is acknowledged that sensors like the recently launched Sentinel 2 possess similar or better data quality than Landsat 8, the latter's choice was motivated by the Landsat series rich archival data, valuable in both temporal and multi-temporal analysis.

2.2 Materials and methods

2.2.1 Study site description

This study was conducted at the Clan forest plantation in the midlands region of KwaZulu-Natal, South Africa. The commercial forest plantation occupies approximately 67 km^2 and situated between the latitudes: 29°24'47.14" S, 29°17'46.34" S and longitudes: 30°18'33.29" E, 30°28'28.21" E. The area experiences an average annual rainfall that varies from 730 to 1500mm during the summer, with annual mean temperature of 21.7°C (Dube *et al.* 2014, Dube and Mutanga 2015). The terrain in the area is characterized by gradual to moderately steep slopes at an altitude ranging from 644 to 1266m (Dube *et al.* 2014, Dube and Mutanga 2015). The plantation (Figure 2.1) is dominated by *Eucalyptus* and *Pine* tree species that are green throughout their growth (Dube *et al.* 2014).

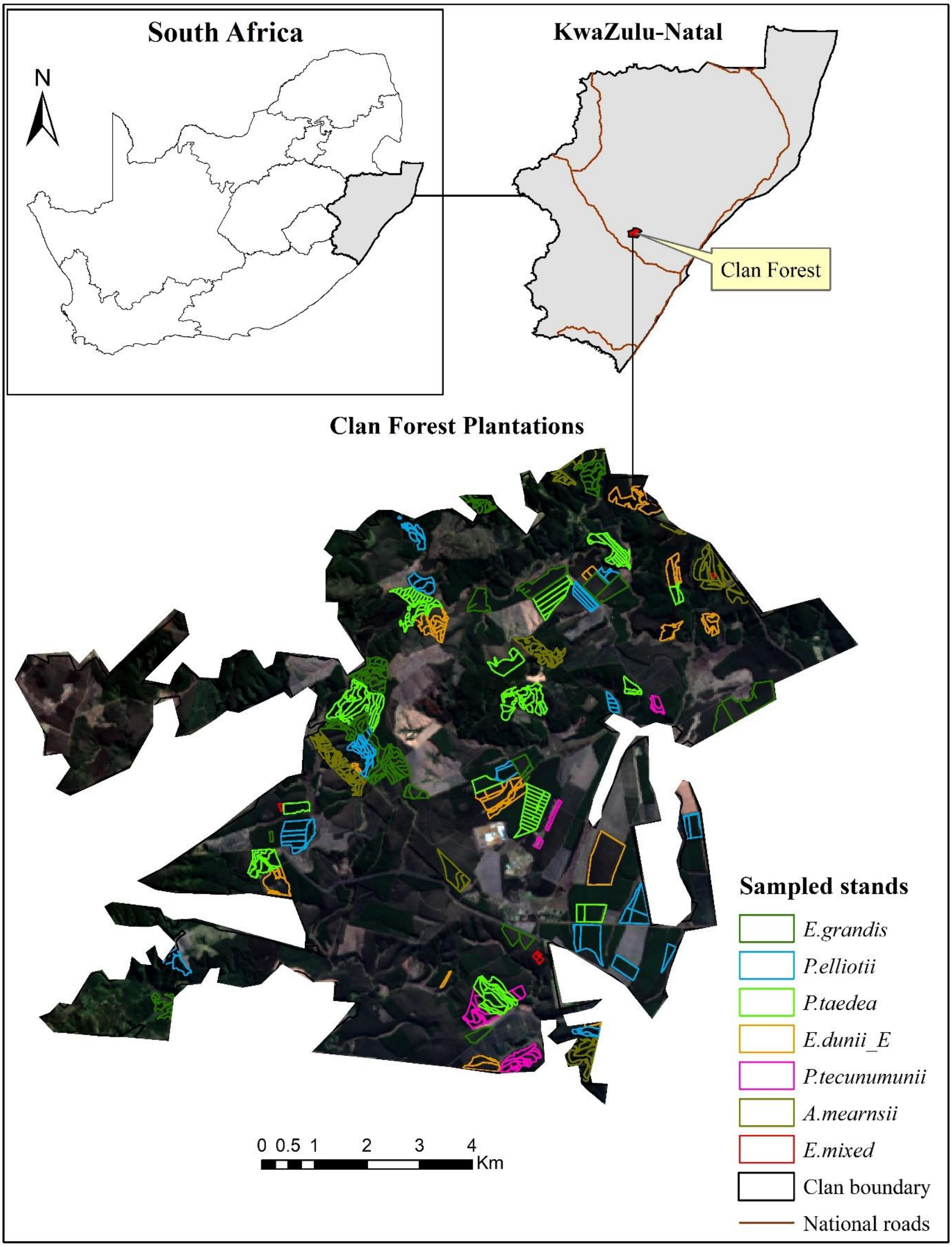

Figure 2.1. Location of the study area with sampled training forest stands.

2.2.2 Field data collection

Species stand data for *A.mearnsii*, *E.dunii*, *E.grandis,* and softwood species stands such as *P.tecunumanii*, *P.elloitii*, and *P.taedea* were collected from Sappi on 10th of May 2017. The number of forest species stands used in this study were selected randomly within the study area, and a field survey conducted to verify the status of the selected forest species. A number of mixed *Eucalyptus* stands was also observed in the study area and included in the sampling protocol to assess the effectiveness of a multispectral dataset for discriminating a stand consisting of a mixture of forest species. The total number of species stands (N) selected was 81, which comprised of *A.mearnsii* (n =12), *E.dunnii* (n =15), *E.grandis* (n = 15), *P.tecunumanii* (n = 5), *E.mix species* (n = 4), *P.elloitii* (n = 15) and *P.taedea* (n = 15) (Table 2.1). The spectral data for these randomly selected plantation stands was extracted at a compartment scale using Geographic Information System (GIS) tools.

Table 2.1. Forest species compartments used in this study.

Types of species	Total number of compartment per species	Sampled compartment	Training dataset	Test dataset
Acacia mearnsii	24	12	8	4
Eucalyptus dunnii	102	15	11	4
Eucalyptus grandis	222	15	11	4
Eucalyptus mixed	5	4	3	1
Pinus tecunumanii	11	5	3	2
Pinus elliotii	83	15	11	4
Pinus taedea	128	15	11	4

2.2.3 Image acquisition and pre-processing

2.2.3.1 Landsat 8 OLI

A multispectral Landsat 8 OLI satellite imagery was acquired from Earth Explorer commissioned by the United State Geological Survey (USGS). The Landsat-8 image covering the entire study site was acquired on 30 October 2013 during sunny and clear sky conditions. The image consists of eleven spectral bands with a 30-m spatial resolution. The bands obtained from visible section include coastal aerosol (435-451 nm), blue (452-512 nm), green (533-590 nm) and red (636-673 nm), with one band in the near-infrared (851-879 nm) and two short-wave infrared bands i.e. short-wave infrared 1 (1566-1651 nm) and short-wave infrared 2 (2107-2294 nm). Band 9, 10 and 11 which represent cirrus clouds (1363-1384 nm), thermal infrared-1 (10600-11190 nm) and thermal infrared-2 (11500-12510 nm) were excluded from the analysis. The multispectral Landsat-8 image with its eighth bands, including the panchromatic captured at 15-m resolution, were radiometrically corrected and transformed into reflectance using Fast Line of Sight Atmospheric Analysis of Spectral Hypercube (FLAASH) technique. The radiometrically corrected multispectral image and panchromatic bands were fused together using the Gram-Schmidt Pan-sharpening (GSP) tool in ENVI 5.2 software.

2.2.3.2 Worldview-2

The Worldview-2 image, covering the study area was acquired from Geo Data Design (Pty) Ltd on the 30 of October 2013. The Worldview-2 sensor is comprised of eight multispectral bands with a spatial resolution of 2m. The spectral configurations of these eight bands are coastal blue (400-450 nm), blue (450-510 nm), green (510-580 nm), yellow (585-625 nm), red (630-690 nm) and near-infrared-1 (770-895 nm). The imagery is also comprised of two new additional band settings positioned between red edge (705-745 nm) and near-infrared-2 (860-1040 nm) of the electromagnetic spectrum. The addition of these two new unique bands are known to improve the discrimination of forest species. Worldview-2 image was atmospherically corrected using the Quick Atmospheric Correction Model (QUAC). The radiometric calibration technique in ArcGIS environment was used to convert image into surface reflectance.

2.2.4 Partial Least Squares Discriminant Analysis

Partial Least Squares Discriminant Analysis (PLS-DA) is a statistical technique that finds a linear regression model by constructing predictive variables and response variables into a new space. The PLS technique provides the ability to minimize data dimensionality, where response variables are correlated to the predictor variables (Rajah *et al.* 2015). This technique produces few eigenvectors from spectral matrices, which serves as an explanatory for both the spectral data variance and correlation to the response variables (Peerbhay *et al.* 2013). As the variables in the PLS model are highly correlated, selecting relevant number of components from the input dataset is important in order to overcome the problem of overfitting (Peerbhay *et al.* 2013, Rajah *et al.* 2015). Therefore, the optimisation of training data in this study was critical for the selection of optimal number of components, which could improve the classification performance of the PLS-DA model. The most commonly used and accurate practical method for examining the optimal components in the model is cross validation (CV) (Peerbhay *et al.* 2013, Peerbhay *et al.* 2016). This study used tenfold cross validation technique to select the most optimal components from a training dataset. The CV process enables the selection of noise free components with reduced multicollinearity. Furthermore, a necessary process for the PLS model to yield a reasonable classification accuracy is by selecting relevant response variables using the variable importance in the projection (VIP) score (Palermo *et al.* 2009, Peerbhay *et al.* 2013). The VIP generate scores of importance from each spectral band that function as a representative measure of importance between the spectral bands (Peerbhay *et al.* 2013, Farrés *et al.* 2015). Therefore, in this study, the VIP was used to identify wavebands that were critical during the classification of individual forest species. VIP technique produces a hierarchical score for each spectral band within the input dataset through the following equation:

$$vip_E = \sqrt{\frac{p}{\sum_{m=1}^{M} Z(b_m \cdot tn)} \cdot \sum_{m=1}^{M} w^2 \cdot Z(b_m \cdot tn)}$$

Where vip_E stand for importance of the E^{th} spectral band which correspond to a model with *m* variables, *p* represents the total number of variables, M is the number of obtained predictive variables, W represent the weight of the E^{th} spectral band within the m^{th} predictive variables and $Z\ (b_m.t_n)$ is the explanatory percentage which is derived from m^{th} predictive variables. The important variables which are selected for the PLS-DA model should have a score greater than 1, as the mean of squared VIP scores is equivalent to 1.

2.2.5 Accuracy Assessment

A confusion matrix was calculated to compute an overall accuracy, user and producer accuracies for Landsat-8 OLI, Pan-sharpened Landsat 8 OLI and Worldview-2 imageries. From the total input sample, 70% was used as training dataset, while 30% as a test data. The producer's and user's accuracies were performed to test and compare the separability of individual forest species from each imagery dataset. The kappa statistic (or coefficient) was also computed to evaluate the significant differences between two error matrixes. The kappa coefficient (*K*) measures the agreement between the correctly classified and expected accuracies. Therefore, the *K* value, which is approximate to one or equivalent to one define a positive agreement, while the value of zero represent negative agreement.

2.3 Results

2.3.1 Selection of optimal latent component through cross validation (CV)

Figure 2.2, illustrates the CV error produced by each component from each satellite sensor dataset. The components that obtained a lowest error were used in the final model to discriminate forest species. For instance, the CV error for Landsat 8 OLI decreased from component 1 to 7 with the error rate ranging from 45.3 % to 15.08%. The PLS-DA model produced the lowest error at component 7 (15.08%). However, although the decrease in CV error between the components of original and pan-sharpened images was of a similar trend, the pan-sharpened Landsat 8 OLI imagery produced the lowest CV error at component 4, with the error rate of 11.41%.

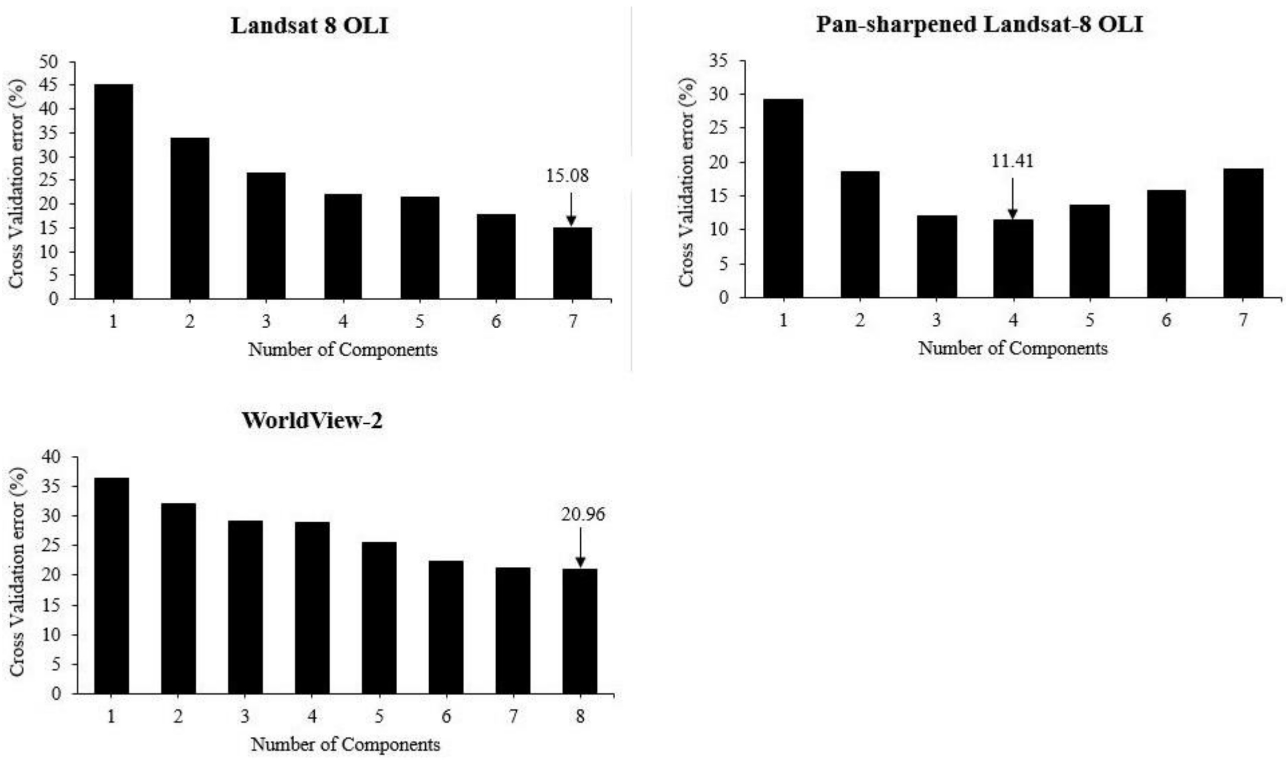

Figure 2. 2. Obtaining a descriptive power from the components of PLS-DA across the Landsat 8 OLI, Pan-sharpened Landsat 8 OLI and Worldview-2 dataset using tenfold cross validation error technique. The component that poses the least error rate is labelled with its error percentage.

Similarly, the trend of partial decrease in the CV error from the first component to the last component was consistent with the high spatial resolution dataset. For example, the CV error of WorldView-2 imagery decreased from component 1 to component 8, with component 8 having produced the lowest error rate of 20.96. Selecting all these components with the lowest error rates was critical for eliminating components that contain unnecessary information, which could lower the performance of these sensors during discrimination of forest species.

2.3.2 The classification performance of individual forest species

Results in Table 2.2 show the ability of new generation moderate spatial resolution Landsat 8 OLI in discriminating commercial forestry at species level. Specifically, when the first seven spectral bands (excluding panchromatic band 9 and atmospheric conditions band 8, 10 and 11) were utilized, the overall accuracy obtained using the original image was 79% with the kappa coefficient of 0.76 (Table 2.2). These spectral wavebands were effective in the discrimination of individual species with individual class accuracies ranging from 50 to 92%. Spectra acquired from a pan-sharpened version of Landsat 8 OLI used to classify forest species produced a slightly lower overall accuracy of 77.8% and the kappa value of 0.74 (Table 2.2) when compared to the original image. However, the performances of individual species by the pan-sharpened image version were comparable to the original image with the accuracy between 69 and 92% (Table 2.2). These results demonstrate a great potential of Landsat 8 OLI spectral bands for discriminating individual species, albeit lower resolution.

Table 2.2. The performance of individual species and the overall classification accuracy produced using medium and high spatial resolution sensors.

Species type	**Landsat 8 OLI**		**Pan-sharpened Landsat 8 OLI**		**WorldView-2**	
	Producer	User	Producer	User	Producer	User
elliotii	81	87	81	87	88	100
grandis	85	73	87	87	71	80
mearnsii	85	92	85	92	100	100
mixed	40	50	0	0	100	50
taedea	79	73	79	73	94	100
tecunumanii	80	80	80	80	100	60
dunnii	80	80	69	73	79	73
Overall accuracy	79		76.8		86.5	
Kappa value	0.76		0.74		0.83	

The results of this study showed a great improvement in the performance of WorldView-2 sensor when compared to Landsat 8 OLI, producing an overall accuracy of 86.5% and kappa value of 0.83. The spectral information extracted from the raw bands of WorldView-2, including the red-edge band illustrated a superior ability to discriminate individual forest species based on producer and user accuracies ranging from 50 to 100% (Table 2.2).

2.3.3 Variable Importance in the Projection

The Variable Importance in the Projection (VIP) approach in this study identified important wavebands with the scores greater than one, hence effective for the discrimination of forest species. For the medium spatial resolution Landsat 8 OLI bands setting, band 3 (green 533-590 nm) and 5 (near infrared 851-879 nm) were the most important regions for discriminating species, with the VIP scores of between 1.13 to 1.19 (Figure 2.3). While pan-sharpened version of Landsat 8 OLI showed that band 4 (red 636-673 nm), 5 (near-infrared 851-879 nm) and 6 (short-wave infrared 1566-1651 nm) were effective for discriminating forest species, with VIP scores greater than 1 (Figure 2.3). From both datasets, the near infrared (band 5) region was predominant, hence boosting vegetation sensitivity and spectral response.

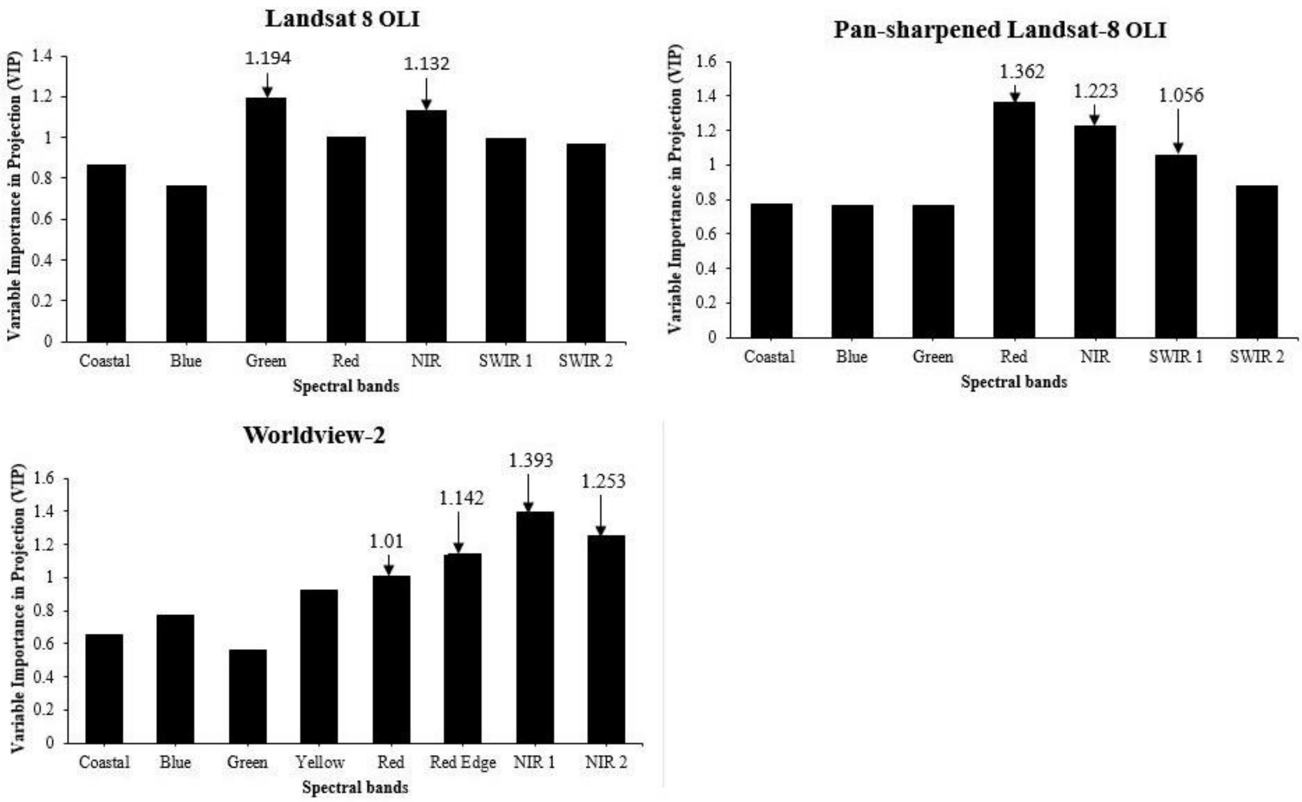

Figure 2. 3. Selection of the most important band(s) by the PLS algorithm effective for the discrimination of forest species using Landsat 8 OLI, Pan-sharpened Landsat 8 OLI and Worldview-2.

When using a high spatial resolution Worldview-2 imagery, the following bands were common in the classification of forest species: band 5 (red 630-690 nm), 6 (red edge 705-745 nm), 7 (near-infrared 770-895 nm) and 8 (near-infrared 860-1040 nm). In all the results, the visible and near infrared regions of electromagnetic spectrum were critical for discriminating commercial forest species. Figure 2.4, illustrates the individual forest species determined using WorldView-2 as a map to Landsat 8 OLI and Pan-sharpened Landsat 8 OLI classifications. Figure 2.4, shows the spatial distribution of individual forest stands generated using Python system.

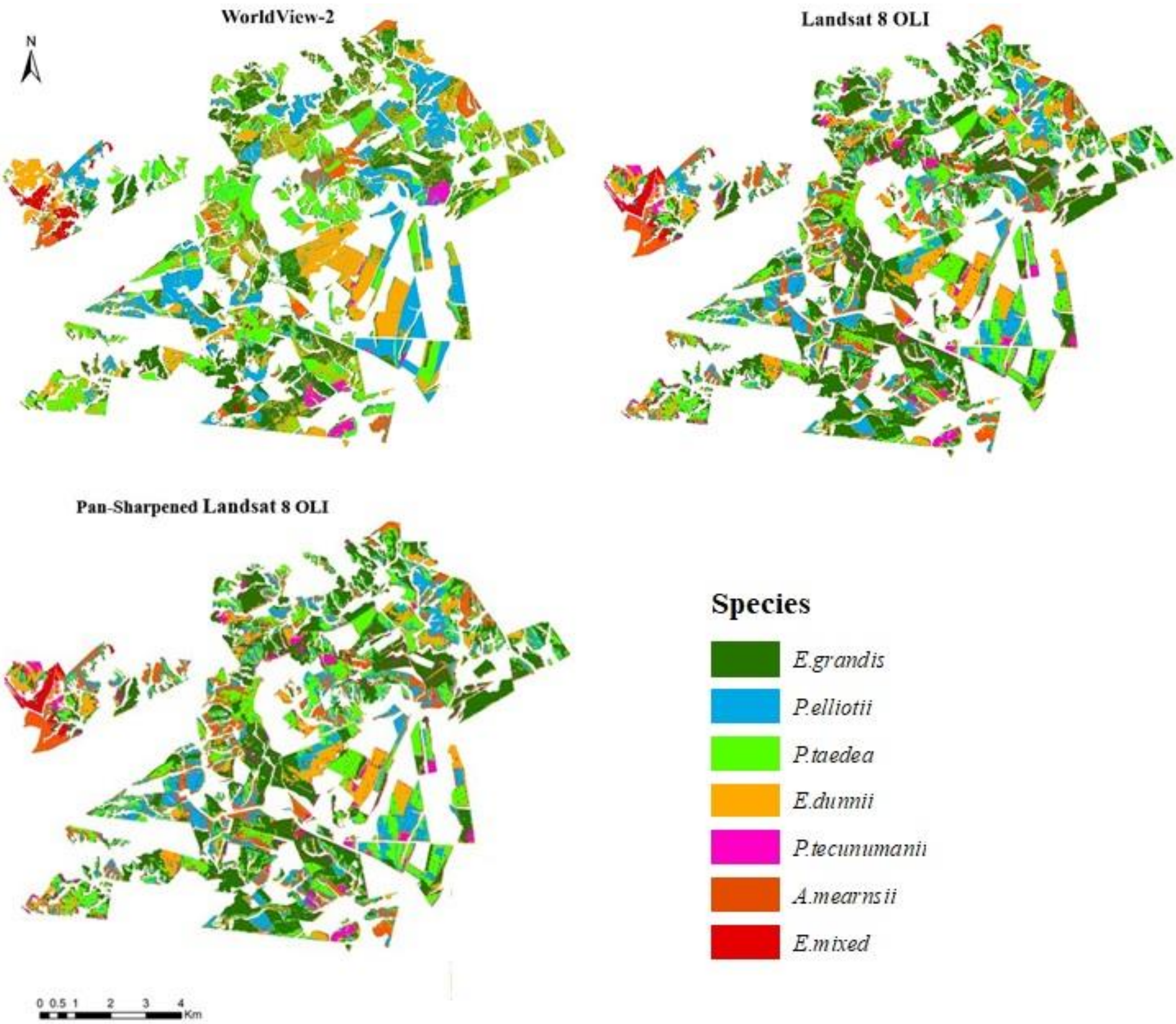

Figure 2. 4. The best performing image dataset between Landsat 8 OLI and Pan-Sharpened Landsat 8 OLI in the mapping of commercial forest species distribution when benchmarked to WorldView-2 imagery.

2.4 Discussion

This study sought to investigate whether the high spatial resolution imagery could be compromised for the medium spatial resolution imagery in discriminating commercial forest species. The higher costs associated with acquisition of high spatial resolution imagery limits their adoption, especially in resource-constrained countries like South Africa. This necessitates the consideration and testing of the performance of freely available multispectral imagery. One of the key challenges on the utility of freely available imagery is the broad wavebands associated with medium spatial resolution, which could compromise accurate discrimination of forest species. Hence, this study sought to evaluate the performance of freely available imagery against expensive high-resolution imagery in discriminating seven plantation forest species (*i.e. elliotte, dunnii, grandis, mix, mearnsii, taedea* and *tecunumanii*) in Midlands region of KwaZulu-Natal Province, South Africa.

2.4.1 Classification performance of Landsat 8 OLI multispectral sensor for discriminating forest species.

The findings of this study demonstrate the capability of freely available multispectral Landsat 8 OLI wavebands for discriminating forest species of different genera (*e.g. Acacia mearnsii, Eucalyptus dunnii* and *Pinus taedea*) and the species within the same genus (*e.g. Pinus taedae* and *Pinus elliotii*). The results show that Landsat 8 OLI successfully discriminated forest species despite the coarser pixel size of 30 m to an accuracy of 79% and the kappa value of 0.76. This is above the required minimum overall accuracy threshold of 75% based on USGS classification standards (Hossain 2016). This study acknowledges that there is approximately 10% difference between results produced by this freely available imagery and those produced by the benchmark WorldView-2, which showed higher overall accuracy of 86.5%. These results are consistent with the previous study conducted by Motongera *et el.* (2017), which mapped Bracken fern weed distribution using Landsat 8 OLI in comparison with WorldView-2, with a 9% difference. The credible performance of this freely available imagery for discriminating forest species is attributed to the sensor's properties. For instance, the series of wavebands forming Landsat 8 OLI sensor are capable of accurately detecting and scanning various features on the earth′s surface based on their spectral signature differences. The sensor provides refined spectral range bands that are critically sensitive to vegetation's biophysical and biochemical properties. For instance, the sensor near infrared band is designed to track the spectral response of vegetation with a shortened wavelength of 850-880 nm (Matongera *et al.* 2017). Additionally, the sensor's high radiometric resolution (12bits) enhance the detection of various vegetation properties (Dube and Mutanga 2015, El-Askary *et al.* 2014).

The appropriate image processing method (*e.g.* extraction of spectra from band to band) and the utility of an advanced classification algorithm (PLS-DA) may have improved the performance of Landsat 8 OLI. According to Peerbhay *et al.* (2014), the robustness of PLS-DA is associated with its ability to successfully deal with multicollinearity, which is a major problem in remotely sensed information retrieval. This is achieved by selecting latent variables that have least error rate using cross validation technique. Generally, the improvements in the discrimination of forest species was associated with the utility of spectra acquired from 30-m resolution. Results have demonstrated that the use of spectral data derived from multispectral medium resolution sensor provides a robust strength for improving the separability of forest species from a complex forest canopy with tall trees. The reasonable performance shown by the use of spectral information extracted from Landsat 8 OLI could be attributed to the sensitivity of forest species biophysical properties such as tree structure, age, leaf area index and biomass (Champion *et al.* 2008, Dube and Mutanga 2015, Fuchs *et al.* 2009). A previous study by Dube and Mutanga (2015) noted a plausible performance of Landsat 8 OLI, primarily based on the ability of the sensor to provide distinctive spectra, reducing atmospheric effects and capability to match the angle of the sun. Although Landsat 8 OLI imagery showed a lower classification performance, when compared to the benchmark WorldView-2, the medium spatial resolution Landsat 8 OLI demonstrated a potential improvement in the discrimination of forest species compared to conventional multispectral data. This was shown by the high producers' and users' accuracies produced using the spectral data derived from freely available Landsat 8 OLI. Although Landsat 8 OLI showed a reasonable strength in mapping forest species, a broad misclassification was observed on the final map output. The misclassification between the species could be due to large scanning footprint of the Landsat 8 sensor, which is prone to the mixed-pixel phenomenon. Previous studies have also reported that discrimination of forest at a species level is a fundamental problem due to shadowing effect. This occurs as results of mixed pixels between the canopy, soils and shadow cast of the trees and commonly affect broadband sensors (Basuki *et al.* 2012, Dube *et al.* 2014 and Carreiras *et al.* 2012).

Based on the current findings, Landsat 8 OLI offer the opportunity to discriminate and manage forest species at a regional scale at a cheaper cost than the commercially available high spatial resolution WorldView-2 sensor. Whereas the capabilities of WorldView-2 for providing high discriminant spectral signature of vegetation and other covers cannot be ignored, the utility of high spatial resolution remote sensing is coupled with a number of challenges that include cost, accessibility, spectral processing and analysis (Dube and Mutanga 2015). Above all, WorldView-2 covers a small swath-width, which restricts their application to small spatial extents. Conversely, despite low spatial resolution, Landsat 8 OLI covers large swath-width of approximately 185km, making its application useful at both local and regional scales. The decision by the United States Geological Survey (USGS) to freely avail Landsat data offers an opportunity for temporal and multi-temporal mapping, monitoring and management of commercial forest species at minimal cost.

2.4.2 Classification of forest species using pan-sharpened Landsat 8 OLI multispectral data

The conversion of multispectral imagery by pan-sharpening process did not improve the overall classification accuracy. For example, a pan-sharpened version of Landsat 8 OLI produced an overall accuracy of 77.8%. This finding is consistent with Wicaksono and Adhimah (2017) in mapping benthic habitats using Quickbird dataset. Their results showed an accuracy of 64.28% for pan-sharpened data and 73.46% for the original imagery. McCarthy and Halls (2014) also found inconsistent performance when using pan-sharpened and original image data. Lin *et al.* (2015) notes that the pan-sharpening process can create noise as a results of heterogeneous variables within the multispectral image pixels, which can lower the estimation of biophysical properties. Therefore, in the environment where vegetation canopy is dense (*e.g.* commercial forest plantation), the impact of noise can be accentuated, due to the nonlinear measure of biophysical characteristics for different types of vegetation (*i.e.* forest species types). Additionally, pan-sharpening of Landsat 8 OLI could have increased incident of shadowing effect, where gaps and shadow casts between trees are picked up. Therefore, using broader spatial resolution sensor such original Landsat 8 OLI data (≥30 m) may be beneficial due to using fewer pixels that captures the average spectra of forest canopies rather than averaging many pixels of pan-sharpened data (15 m) that increase the incidence of shadows and noise, especially over broader regions of interest.

2.5 Conclusion

This study sought to investigate the performance of freely available medium spatial resolution Landsat 8 OLI multispectral data benchmarked on high spatial resolution WorldView-2 data for mapping commercial forest species. Based on the results, Landsat 8 OLI showed promising potential for discriminating forest species when benchmarked with WorlView-2. This medium spatial resolution imagery can provide a cheaper alternative that covers larger swath width, which enables mapping and monitoring of forestry on a regional scale. The utility of pan-sharpened Landsat 8 OLI data decreased the overall classification accuracy when compared to the original data. The inferiority of pan-sharpened image was associated with the distortion of spectral signature during the processing, as well as possible shadowing effect. However, despite failure to achieve expected results, pan-sharpening could still be considered for general land cover mapping. Moreover, the application of VIP approach successfully identified wavebands that were influential and important (*i.e.* band3, 4, 5 and 6) for the discrimination of commercial forest species in this study. The utility of partial least square discriminant analysis (PLS-DA) in this study, proved to be more appropriate for the classification of forest species and for the selection of most optimal wavebands using new generational multispectral remote sensing information.

CHAPTER THREE

Examining the effectiveness of Sentinel-1 and 2 imagery for commercial forest species mapping

This chapter is based on:

Mthembeni Mngadi, John Odindi, Kabir Peerbhay and Onisimo Mutanga. 2018. Examining the effectiveness of Sentinel-1 and 2 imagery for commercial forest species mapping. *Geocarto International Journal* (under review), manuscript number; TGEI-2018-0334.

Abstract
The successful launch and operation of the Sentinel satellite platform has provided access to freely available remotely sensed data useful for commercial forest species discrimination. Sentinel – 1 (S1) with a Synthetic Aperture Radar (SAR) sensor and Sentinel – 2 (S2) multi-spectral sensor with additional and strategically positioned bands offer great potential for providing reliable information for discriminating and mapping commercial forest species. In this study, we sought to determine the value of S1 and S2 data characteristics in discriminating and mapping commercial forest species. Using linear discriminant analysis (LDA) algorithm, S2 multi-spectral imagery showed an overall classification accuracy of 84% (kappa = 0.81), with bands such as the red-edge (703.9-740.2 nm), narrow near infrared (835.1-864.8 nm), and short wave infrared (1613.7-2202.4 nm) particularly influential in discriminating individual forest species stands. When Sentinel 2's spectral wavebands were fused with Sentinel 1's (SAR) Vertical transmit/Vertical receive (VV) and Vertical transmit/Horizontal receive (VH) polarimetric modes, overall classification accuracies improved to 87% (kappa = 0.83) and 88% (kappa = 0.85), respectively. These findings demonstrate the value of combining Sentinel's multispectral and SAR structural information characteristics in improving commercial forest species discrimination. These, in addition to the sensors free availability, higher spatial resolution and larger swath width, offer unprecedented opportunities for improved local and large-scale commercial forest species discrimination and mapping.

Keywords: Synthetic Aperture Radar, Linear Discriminant Analysis, forest species discrimination, Sentinel-2

3.1 Introduction

Knowledge on commercial forest species extents is critical for adopting informed forest plantation related decisions. Such decisions include site or species specific management practices, commercial output and viability, forest ecosystem health and harvest scheduling (Franklin *et al.* 2000, Wittwer *et al.* 2004, Peerbhay *et al.* 2013, Peerbhay *et al.* 2014). In South Africa, commercial forest plantations constitute approximately 2% of the country's gross domestic product (GDP), and complement the national environmental agreement requirements, which seeks to mitigate carbon emission and greenhouse effects (Dube *et al.* 2018, Peerbhay *et al.* 2014, 2016). Furthermore, commercial forests play a critical role in biodiversity and conservation planning and provision of ecosystem goods and its services (Peerbhay *et al.* 2014). Achieving these demands require accurate and precise information on a forest landscape. Traditionally, field surveys have been used to map forest species. Whereas surveys are known to be highly accurate, they are often time consuming, costly, and not ideal for large spatial extents (Henry *et al.* 2011, Adam *et al.* 2014, Dube *et al.* 2014). Over the past few decades, remote sensing has emerged as a viable cost effective approach for understanding forest plantations biophysical and biochemical attributes (Dube *et al.* 2014, Martin *et al.* 1998, Naidoo *et al.* 2012, Waser *et al.* 2014).

Recently, high spatial resolution commercial sensors such as WorldView-2 and RapidEye have gained popularity in discriminating forest species (Peerbhay *et al.* 2014). Such sensors are characterised by fewer, but strategically positioned wavebands and red-edge band, which is valuable for vegetation mapping (Eckert 2012, Dube *et al.* 2014, Cheng and Chaapel 2008). However, these datasets are costly and have limited spatial coverage, hence not ideal for the often large scale and sometimes regionally distributed commercial forest plantations. The emergence of the freely available Sentinel-2 sensor is viewed as a trade-off between advantages offered by lower spatial resolution freely available multispectral sensors and the new generation commercial sensors. Sentinel-2 is the first medium spatial resolution sensor with unique band setting that include the red-edge and improved spatial resolution. The sensor acquires information at spatial resolutions of 10, 20 and 60 m using thirteen wavebands positioned within the Visible (443.9-664.5 nm), NIR (835.1-864.8 nm) and SWIR (1613.7-2202 nm) regions of the electromagnetic spectrum. The sensor is freely available, has a larger swath width and a higher temporal resolution, which is useful for frequent monitoring and management of forestry. However, despite these benefits, the sensor has not been utilized for the discrimination of species in commercial forest plantations. It is therefore necessary to evaluate the capability and effectiveness of Sentinel-2 imagery for discriminating commercial forest species to support forest management decisions and monitoring interventions. Exploring the significance of the sensor's individual bands is also critical for understanding the value of new additional spectral bands on forest species discrimination and mapping.

Additionally, Sentinel image data comes with Synthetic Aperture Radar (SAR) capabilities, which could be used to complement multispectral/optical sensors. Sentinel 1 sensor's interaction with features is based on the backscattering of physical properties such as roughness, water/moisture content and structural geometry (Balzter *et al.* 2015), which is different from the reflectance interactions of optical multispectral sensors. The sensor uses Interferometric Wide Swath (IW) mode to acquire radar information over the land surface, which provide a more advanced ability to retrieve canopy height and digital terrain, using dual polarization operations such as Vertical transmit/Vertical receive (VV) and Vertical transmit/Horizontal receive (VH) (Balzter *et al.* 2015). Due to the longer wavelength, SAR imagery can penetrate through canopy cover and thin cloud, and generate data in all weather conditions, hence is not affected by shadowing and clouding effects, which is a major limitation with optical sensors (Haack *et al.* 2000). In addition, despite the fact that optical sensors have a powerful ability to discriminate vegetation, data acquisition is often restricted to forest canopy, and unable to detect differences in vegetation structural geometry. In this regard, SAR data can be utilized to complement capabilities of optical sensors through fusion processes, which could facilitate robust discrimination of vegetation, and consequently improve the classification performances of optical data. To date, there has been a limited amount of literature that has fully exploited the capability of Sentinel's data through fusion of optical S2 and S1 SAR for discriminating commercial forest species.

Generally, information provided by remote sensing techniques is associated with high correlation and variability between the variables. This could pose a serious challenge in the performances of Sentinel 1 and 2 datasets in classification of individual forest species. According to Peerbhay *et al* (2015), a strong correlation between the spectra and noise in the image are the limiting factors for the techniques and methods used to analyse remotely sensed data. Therefore, discriminating forest species using remote sensing information requires a robust modelling technique to enhance better classification performance. Previous studies by Calviño-Cancela and Martín-Herrero (2016), Davidson *et al.* (2016) and German *et al.* (1999) demonstrated the value of the Linear Discriminant Analysis (LDA) algorithm in discriminating and mapping vegetation. LDA transforms input variables into a lower dimensional space, where data redundancy and noise between classes are reduced, hence guaranteeing maximum classification potential (Balakrishnama and Ganapathiraju 1998, Calviño-Cancela and Martín-Herrero 2016). This statistical model ensures maximum separability between classes by increasing the variance ratio of between-class relative to within-class variance. Where the non-linearity exists between classes, the LDA model uses kernel function to separate classes, proving its potential for discrimination purposes. Hence, the essence of this study was to investigate the capability and efficiency of combining Sentinel 1 and 2 data for discriminating commercial forest species using LDA.

3.2 Materials and methods

3.2.1 Description of study area

The research was done at Clan Sappi commercial forest plantation located in Midlands region of KwaZulu-Natal province, South Africa. The forest is situated between 29°25'46.14"S and 30°19'32.29"E and covers about 6700 ha (Figure 3.1). The study area experience sub-tropic climate with an average rainfall that range from 700 mm to 1500 mm per year (Dube *et al.* 2014). The plantation is dominated by hardwood such as *Eucalyptus* species (e.g. *Eucalyptus dunnii*, *Eucalyptus grandis*) and softwood such as *Pinus* species (e.g. *Pinus taedea*) (Dube *et al.* 2014).

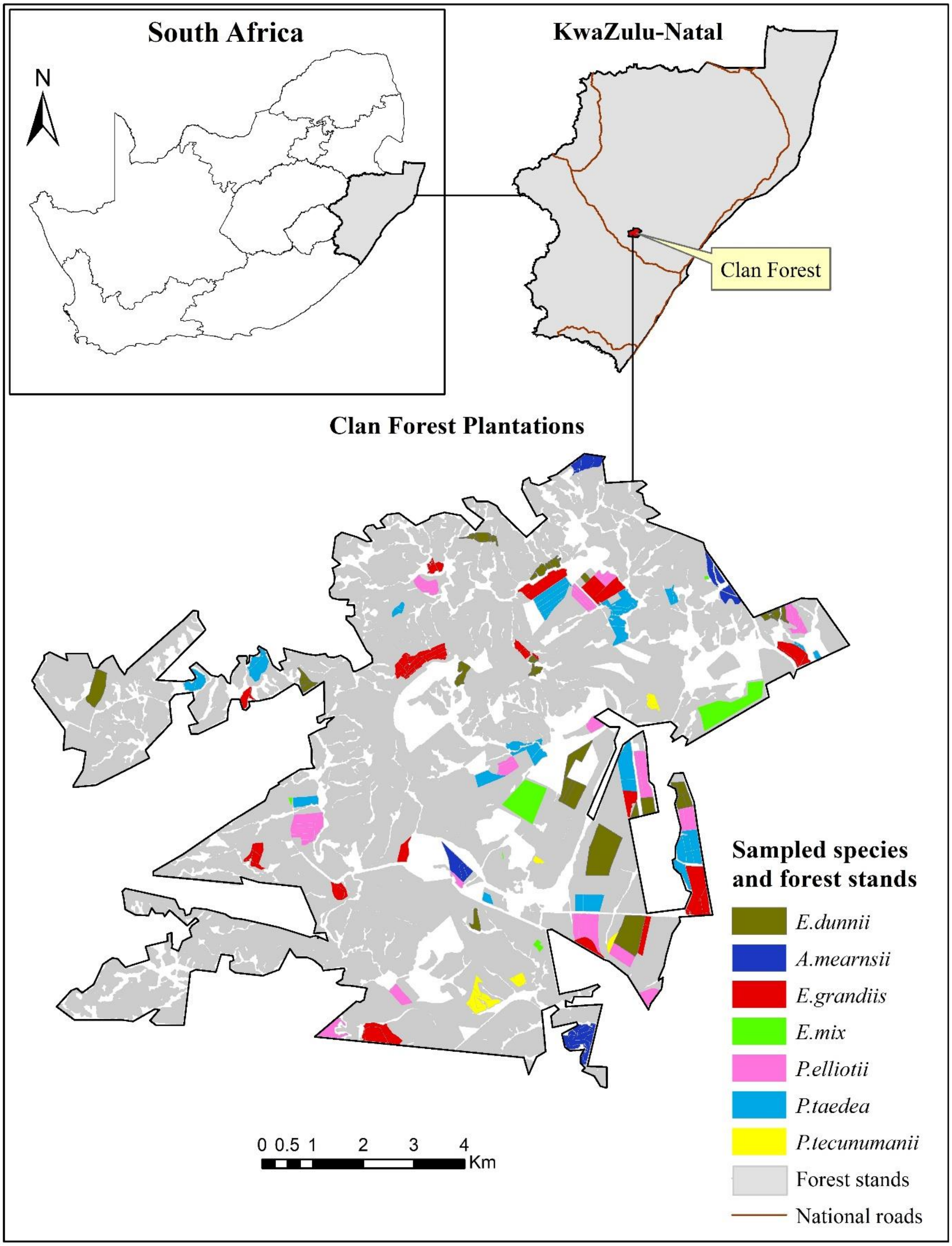

Figure 3. 1. Location of the study area with sampled training species in colours and forest stands in grey.

3.2.2 Image acquisition and pre-processing

3.2.2.1 Sentinel-2 and Sentinel-1 C-band Synthetic Aperture Radar (SAR)

Multispectral Sentinel-2 satellite imagery was acquired on the 24 October 2017 from European Space Agency (ESA) under sunny and cloudless conditions. The imagery comprises of thirteen wavebands with spectral wave range between 443 and 2190 nm. This medium spatial resolution satellite sensor captures information at various spatial resolutions (*e.g.* 10, 20 and 60 m) from the visible, near infrared and shortwave infrared regions of the electromagnetic spectrum. The image was atmospherically corrected using the Dark Object Subtraction 1 (DOS1) technique from which radiance values were converted into surface reflectance within a Quantum Geographic Information System (QGIS) platform. Sentinel-1 SAR data was captured from the European Space Agency (ESA) on the 30th October 2017, on a cloud free day. In this study, C-band SAR polarimetric data was converted to sigma0 (both Vertical transmit/Vertical receive and Vertical transmit/Horizontal receive polarizations), and radiometrically and geometrically (terrain) calibrated using Sentinel Application Platform tool (SNAP).

3.2.3 Image fusion

Many studies have used pixel level fusion techniques due to the approach's ability to maintain spectral information of the original image, hence reduce noise and data distortion (Luo *et al.* 2013). However, such technique requires highly accurate registration, a major challenge when using SAR and optical datasets. Conversely, feature level fusion technique does not require precise registration, hence suitable and efficient for fusing optical and SAR data. Feature level fusion avoids common problems associated with well-known pixel level effects which includes blurring, high level of noise and mis-registration (Kor and Tiwary 2004, Luo *et al.* 2013). Hence, this study used feature level approach to fuse the two datasets. This approach is particularly critical as it combines a feature set containing richer information about the input variables rather than matching score or output decisions from the classifier (Haghighat *et al.* 2016 and 2016). The input images are first segmented into regions and different region properties are calculated using Dual-Tree Complex Wavelet Transform (DT-CWT). Calculating region properties is necessary for determining features from the input images that are to be used in the fused image. Features are fused based on textural margins and DT-CWT technique is powerful in determining textural edges, hence combining relevant information required for better recognition and discrimination by the classifier (Kor and Tiwary 2004). Therefore, feature level fusion approach provides robust classification performance and reliable information for decision making (Majumdar and Bharadwaj 2014).

3.2.4 Field data collection

Field data for this study was collected on the 10th of May 2017 from Sappi after an extensive field survey. The data comprised of several forest species stands containing hardwood (*e.g. E.dunnii, E.grandis, E.mix, A.mearnsii*) and softwood (*e.g. P.elliotii, P.taedea, P. tecunumanii*) tree species. These forest stands were randomly sampled from stands covering the study area (Table 3.1). The study area was revisited to verify the status of resampled forest species. Furthermore, the sample forest stands were used as the input dataset to extract spectral data from a remotely sensed satellite imagery. However, a number of forest species stands had been harvested and some were very young, especially *A.mearnsii* and *P.tecunumanii*, resulting to an imbalance between sampled compartments.

Table 3.1. Selection of forest species compartments in the study area.

Species	Total number of compartments	Sampled compartment	Training dataset	Test dataset
A.mearnsii	24	5	3	2
E.dunnii	102	15	10	5
E.grandiis	222	15	10	5
E.mix	5	5	3	2
P.tecunumanii	11	5	3	2
P.elliotii	83	15	10	5
P.taedea	128	15	10	5

3.2.5 Statistical analysis

The study used Linear Discriminant Analysis (LDA) technique in the Tanagra data mining platform (Ye *et al.* 2005) to discriminate forest species. LDA is a statistical algorithm which guarantees maximum classification potential by projecting input variables into a new lower dimensional space, hence reducing redundancy and noise between the class variables (Tharwat *et al.* 2017). The LDA projects variables into new space using two approaches (*i.e.* class-dependent and class-independent approaches). Class-dependent projection approach maximizes the ratio between-class variance relative to the within-class variance (Balakrishnama and Ganapathiraju

1998). In this approach, input variables are independently transformed using two optimization criterion. Conversely, class-independent approach increases the overall variance ratio to within-class variance (Balakrishnama and Ganapathiraju 1998). This approach uses single criterion to transform a dataset and consequently, all the input training features irrespective of their class identity are transformed. LDA uses Fisher function to compute eigenvalues and eigenvectors, and transforms them into a new space (Carreira-Perpinan 1995, Tharwat *et al.* 2017). Eigenvectors are important for creating space between the classes, while eigenvalues represent the magnitude of the eigenvector (Li *et al.* 2006, Tharwat *et al.* 2017). Therefore, robustness of LDA depends on the maximum magnitude of eigenvectors between the classes, which increases the separability variance between classes. In this regard, if the distance between the means of different classes is greater, discrimination of classes by the LDA produces reasonable accuracy. In this study, where the classes were difficult to discriminate due to non-linearity existing between them, kernel function of the LDA was used to separate classes, hence increasing class separability potential. The *p*-values are also calculated for identifying spectral wavebands, which were valuable during the classification.

3.2.6 Accuracy assessment

A confusion matrix was used to compute the overall accuracy, kappa value and the performance of individual forest species based on producer and user accuracies (Congalton and Green 2008, Peerbhay *et al.* 2014). All were calculated from the spectral information and sigma0 values of Sentinel 2 and Sentinel 1 SAR imageries. Approximately 75 variables were acquired from Sentinel 1 and 2 imageries. Seventy percent of these variables were used as training set and 30% used as the accuracy validation dataset. The producer and user accuracies were computed by dividing the correctly classified samples with the total sample (Congalton and Green 2008). Calculating producer and user accuracies was necessary for evaluating the capability and efficiency of Sentinel 1 and 2 imageries in discriminating individual forest species. Furthermore, the kappa value was also calculated to measure the agreement between correctly classified and expected accuracies. Generally, the kappa value that equals or closer to one describes strong agreement, while the value that is approximate to zero define weak agreement (Congalton and Green 2008, Peerbhay *et al.* 2014).

3.4 Results

3.4.1 Forest species discrimination using Sentinel 2 MSI

Using Linear Discriminant Analysis, results in Table 3.2 shows the capability of Sentinel-2 raw bands in discriminating individual forest species, with producer and user accuracies ranging from 74 to 100%. The overall accuracy obtained using this imagery was 84%, with the kappa value of 0.81. From Table 3.2, it is clear that the total number of correctly classified samples per species is higher than incorrectly classified samples, hence a higher overall performance of all forest species.

Table 3.2. Classification of individual forest species by the Linear Discriminant Analysis algorithm and all Sentinel-2 spectral wavebands. Diagonal values (highlighted bold) in the table represent the samples that were correctly classified.

Species Type	*dunnii*	*elliotii*	*grandis*	*mearnsii*	*mix*	*taedea*	*tecunumanii*	**Sum**	**User**
dunnii	**14**	0	1	0	0	0	0	**15**	**93**
elliotii	0	**14**	0	1	0	0	0	**15**	**93**
grandis	1	0	**14**	0	0	0	0	**15**	**93**
mearnsii	1	0	0	**4**	0	0	0	**5**	**80**
mix	0	0	2	0	**3**	0	0	**5**	**60**
taedea	0	1	0	0	0	**14**	0	**15**	**93**
tecunumanii	0	4	0	0	0	1	**0**	**5**	**0**
Sum	**16**	**19**	**17**	**5**	**3**	**15**	**0**	**75**	
Producer	**88**	**74**	**82**	**80**	**100**	**93**	**0**		

Overall classification accuracy: 84%,

Kappa coefficient value: 0.81

The results in Figure 3.2 illustrate the spectral bands of Sentinel-2 which were significantly critical in the classification of forest species. Based on the statistical analysis, the spectral bands that obtained *p*-values equals or less than 0.05 are significant. Therefore, the red-edge band 7 (703.9-740.2 nm), Narrow NIR band 8A (835.1-864.8 nm), SWIR band11 (1373.5-1613.7 nm) and SWIR band12 (1613.7-2202.4 nm) achieved *p*-values ranging between 0.001 and 0.0039, and were considered influential in the discrimination of forest species.

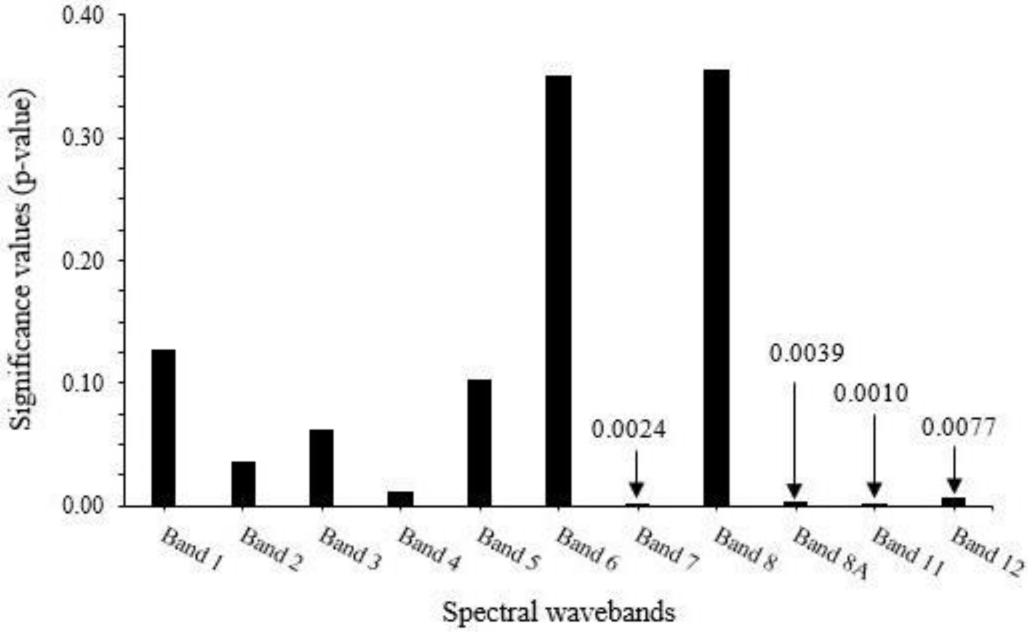

Figure 3. 2. Significance of Sentinel-2 raw bands in the discrimination of forest species. The bands highlighted with arrows were more sensitive and essential during the classification.

3.4.2 Classification potential of fused Sentinel-2 and Sentinel-1

The fusion of individual polarimetric data (*i.e.* VV and VH) with Sentinel-2 wavebands significantly increased the classification performance of forest species. Results in Table 3.3 show that the fusion of VH polarimetry with Sentinel-2 produced an overall accuracy of 88% and kappa value of 0.85, while VV produced 87% with a kappa value of 0.83. Although both polarizations showed higher producer and user accuracies ranging between 74 and 100%, best results were achieved using VH polarization.

Table 3.3. Discrimination of forest species using Synthetic Aperture Radar (VH and VV polarizations) data fused with the spectral wavebands of Sentinel-2.

Interferometric Data	**VH Polarization**		**VV Polarization**	
Species type	Producer	User	Producer	User
dunnii	94	100	88	100
elliotii	74	93	74	93
grandis	94	100	94	100
mearnsii	83	100	80	80
mix	100	60	100	60
taedea	93	93	93	93
tecunumanii	0	0	0	0
Overall accuracy	88%		87%	
Kappa value	0.85		0.83	

Results in Figure 3.3 show the capability of Sentinel-2 multispectral image data in mapping individual forest plantation stands. Although Sentinel-2 showed a smooth outline of individual forest compartment, the inclusion of SAR data visually increased the mapping potential of Sentinel-2 data. For instance, Figure 3.3 illustrate the effectiveness of SAR VH and VV polarimetric data for improving the mapping potential of Sentinel-2 through image fusion process.

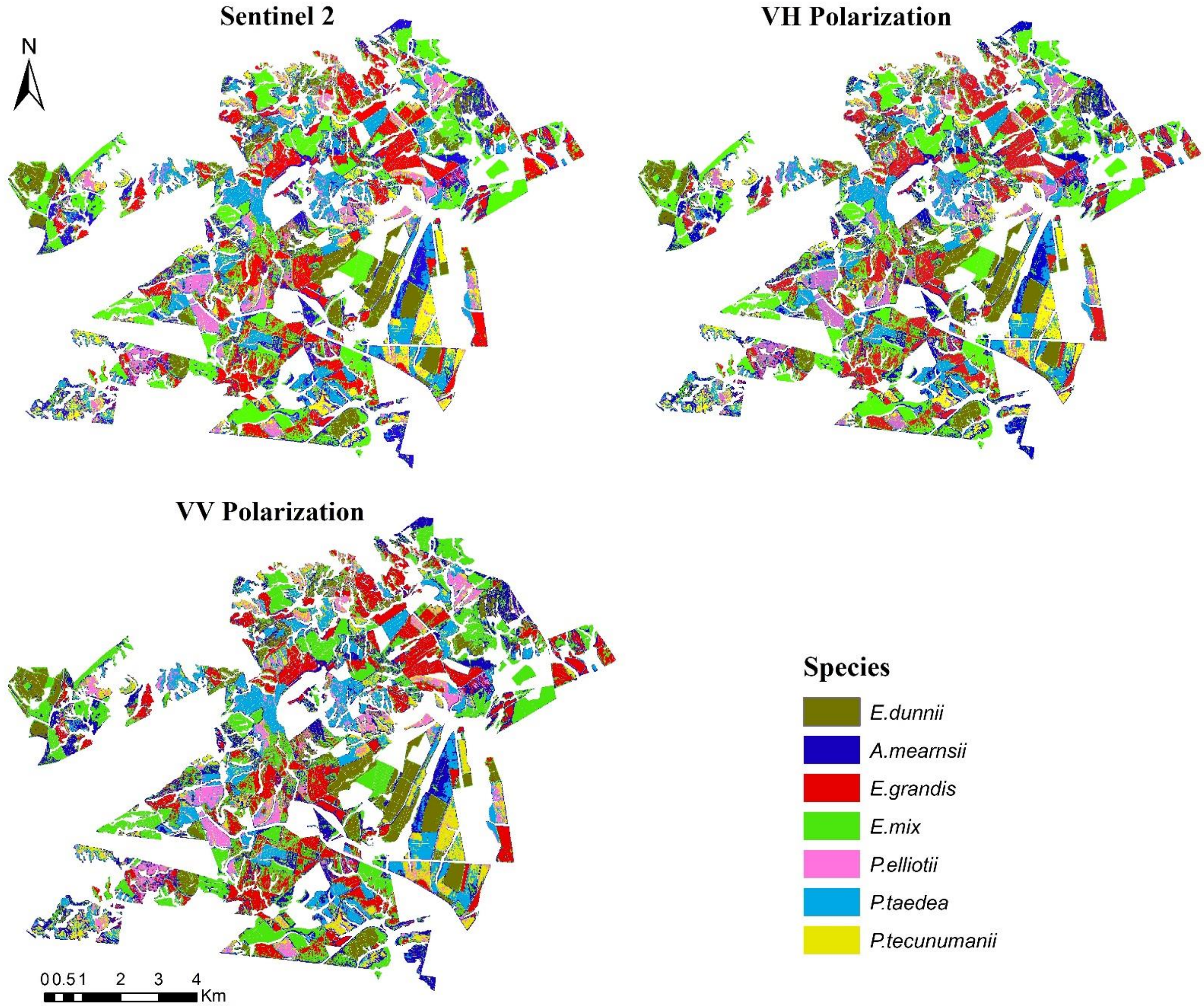

Figure 3. 3. Species classification maps using Synthetic Aperture Radar data (*i.e.* VH and VV polarizations) fused with Sentinel-2 multispectral image data.

3.5 Discussion

Accurate and reliable mapping of commercial forest species is critical for effective management and monitoring of forestry. However, mapping forest species using broadband optical images has been a critical challenge due to larger scanning window size which is susceptible to mixed-pixels, hence poor discrimination and mapping. This study demonstrates that combining Sentinel 2 MSI with SAR data can be used to improve the mapping accuracy of commercial forest species.

3.5.1 Classification performance of Sentinel-2 MSI in discriminating forest species

Results in this study show that Sentinel-2 spectral bands achieved an overall accuracy of 84% and kappa value of 0.81. The image data was successfully used to discriminate individual forest species of same genus (*i.e*. *E.grandis, E.dunnii,* and *E.mix*) and different genera (*e.g. E.dunnii*, *P.elliotii* and *A.mearnsii*) with producer and user accuracies ranging from 74 to 100%. The plausible performance of this sensor could be attributed to the fact that it covers strategic portions of the electromagnetic spectrum such as red-edge, providing three bands (*i.e.* band 5, 6 and 7). Previous studies by Dube *et al.* (2014), Sibanda *et al.* (2016) and Peerbhay *et al.* (2014) revealed the importance of red-edge bands for increasing vegetation sensitivity and its spectral response. The significance of red-edge bands is associated with the ability to measure numerous vegetation leaf properties such as chlorophyll content, biomass and canopy structure, necessary for discriminating forest species (Dube *et al.* 2014, Thenkabail *et al.* 2013;Ramoelo *et al.* 2015). According to Sibanda *et al.* (2016) and Lee *et al.* (2004), sensors with red-edge configurations produce reasonable overall accuracy in vegetation mapping. Furthermore, in addition to the red-edge bands, the *p*-value results show that NIR and SWIR wavebands were also significant for the classification of forest species. These findings are consistent with Immitzer *et al.* (2016) and Ramoelo *et al.* (2015), which found that red-edge and SWIR bands are the most useful regions in vegetation mapping using Sentinel-2 data. Short wave infrared bands are associated with crucial vegetation properties such as lignin, starch and nitrogen (Ramoelo *et al.* 2015, Wang *et al.* 2004). These important absorbers of light reflect very high on the short wave infrared region, hence necessary for vegetation mapping (Ramoelo *et al.* 2013, Skidmore *et al.* 2010). Although several studies that used Sentinel-2 MSI found near infrared region not optimal, our study present the significance of this region, especially for its ability to provide refined spectral bands that are highly sensitive to the biophysical and biochemical properties of vegetation (Dube and Mutanga 2015, El-Askary *et al.* 2014). Near infrared bands are designed to scan the spectral response of vegetation with very narrow wavelengths of between 850-880 nm (Matongera *et al.* 2017). Overall, the utility of Sentinel-2 in this study showed potential to effectively map commercial forest species. This, in addition to free availability and large swath width offer a cost-effective option for large scale assessment.

3.5.2 Classification performance of Sentinel-2 MSI and S1

Results in this study demonstrate successful improvement in the performance of Sentinel-2 spectral information when fused with Synthetic Aperture Radar data (Sentinel-1). These results produced an overall accuracy of 88% using interferometric data of VH receive-cross polarization and 87% using VV receive polarizations. In consistency with this study, Dabrowska-Zielinska *et al.* (2016) noted that the best results are determined using VH polarization. In this study, forest species reflected very high on the value of sigma-zero calculated from VH polarization data when compared to VV polarization data. According to Dabrowska-Zielinska *et al.* (2016), polarizations that have higher penetration ratios and higher incidence angles, such as VH, produce better results due to higher backscattering acquisition. Additionally, an appropriate image processing technique such as the conversion of C-band SAR data to noise equivalent sigma zero (NESZ) was necessary to improve classification performance of Sentinel-2 spectral data. Moreover, SAR data provides access to information related to the physical properties of each commercial forest species, in addition to its sensitivity to surface roughness, moisture content and geometric structures (Balzter *et al.* 2015). In contrast, optical sensors like Sentinel-2 are more sensitive to chemical properties of ground features, therefore, fusion of SAR and optical sensor (*i.e.* Sentinel-2) allows detection of both physical and chemical attributes of forest canopies, hence providing robust spectral signatures for discrimination. Overall, the findings of this study implies that Sentinel-1 SAR data can be effectively used to complement capabilities of optical sensors such as Sentinel-2 in vegetation mapping, providing significant advantage for commercial forest species discrimination and management.

3.6 Conclusion

The essence of this study was to investigate the capability of combined freely available Sentinel 1 and 2 data for discriminating commercial forest species. Based on the results, Sentinel-2 spectral data can be used to effectively discriminate forest species with reasonable accuracy. Regions such as red-edge (703.9-740.2 nm), near infrared (835.1-864.8 nm) and shortwave infrared (1613.7-2202.4 nm) were critical in boosting the sensitivity and spectral response of vegetation, which increased the classification potential of Sentinel-2 imagery. However, maximum classification performance was achieved when Sentinel-2 spectral bands were fused with SAR data. This clearly showed the advantage of image enhancement, especially when using SAR data, which is sensitive to the backscattering of physical attributes of vegetation, while multispectral sensors like Sentinel-2 are more sensitive to chemical properties. In this study, we conclude that Sentinel-1 SAR data can be effectively used to improve the classification potential of multispectral optical sensors such as Sentinel-2 for forest species discrimination.

CHAPTER FOUR: SYNTHESIS

4.1 Introduction

Precise discrimination and mapping of commercial forest plantations is critical for optimal forestry management. In addition to economic contribution, commercial forests play an important role in regional and local carbon cycle, hence complementing requirement of Kyoto Protocol, which seek to reduce climate change and associated greenhouse effects (Dube *et al.* 2018). Such provision of economic and ecosystem services depends on species stand diversity, hence information on species spatial patterns, composition and productivity is crucial for understanding forest ecosystem dynamics (Peerbhay *et al.* 2014, 2015, Raczko and Zagajewski 2018). Moreover, forest species discrimination and mapping is required for conservation planning strategies and maintaining species diversity, demands necessitate accurate and reliable information for effective decision making. The utility of conventional methods for forest species discrimination and mapping has been a serious challenge as they are costly, time consuming and impractical over larger areas (Henry *et al.* 2011, Adam *et al.* 2014, Dube *et al.* 2014). However, the emergence of remote sensing approaches offers quick and cost effective means of generating information necessary for accurate forest species discrimination and mapping. Nevertheless, the costs associated with high spatial resolution satellite sensors and the mixed pixel problem associated with broadband sensors has been a major limitation in remote sensing of forestry, particularly in resource scarce regions. Recently, the emergence of new and readily available multispectral sensors, with larger spatial coverage and improved radiometric, spatial and spectral resolutions offer unprecedented opportunities for local and regional forest species discrimination and mapping. Therefore, the current study sought to map forest species using cost effective multispectral remote sensing in Midlands region of KwaZulu-Natal Province, South Africa. This chapter provide analysis of the objectives highlighted in the introduction (Chapter 1). Conclusions and responses to research hypothesis are also articulated in this chapter.

4.2 Objectives review

4.2.1 The utility of freely available Landsat 8 Operational Land Imager (OLI)for forest species mapping

Discriminating forest species using broadband multispectral data has been a challenge, particularly when mapping highly dense canopies, because of saturation and mixed pixels′ problems (Dube *et el.* 2015). Despite the fact that high spatial resolution sensors such as WorldView-2 and RapidEye can overcome these challenges, acquisition of such datasets is costly and have limited spatial coverage, hence limiting regional assessment, especially in resource scarce regions. Therefore, the use of new and readily available multispectral data, with improved radiometric, spatial and spectral attributes offers a viable alternative for forest species discrimination and mapping. In this study, evidence on the capability of new generation freely available dataset such as Landsat 8 OLI to accurately discriminate and map forest species is presented (Chapter 2). To achieve the objective of this study, forest species predictor variables were acquired from Landsat 8 OLI and Pan-sharpened Landsat 8 OLI image sets and analysed using partial least square discriminant analysis (PLS-DA) algorithm. These results were benchmarked on the outcome of the WorldView-2 image dataset. Despite the low spatial resolution (30 m), results demonstrated competence of new and readily available multispectral Landsat 8 OLI in discriminating and mapping species within the same genus (*i.e. P.taedea and P.elliotii*) and species of different genera (*e.g. A.mearnsii, E.grandis and P.taedea*). Contrary to expectation, the pan-sharpened Landsat 8 OLI did not improve forest species discrimination accuracies. This could be attributed to noise and distortion during pan-sharpening process, which compromised the strength of measuring biophysical attributes, especially in dense canopies. This study acknowledges the approximate 10% difference between the performances of freely available image and commercial WorldView-2 image benchmark, which is within the acceptable range. Furthermore, the results achieved in this study were above the minimum accuracy threshold of 75% (Hossain 2016), hence the information presented by this study is reliable for effective decision making. Overall, Landsat 8 OLI offers a cheaper alternative which characterized by larger spatial coverage, that allows for regional forest species mapping and monitoring. However, pan-sharpening could still be used for general land cover classification.

4.2.2 Examining the effectiveness of Sentinel 1 and 2 for commercial forest species mapping

This study investigated the capability of newly launched freely available Sentinel 2 multispectral imagery with improved spatial and spectral resolutions, characterized by new unique band setting such as red-edge, for forest species discrimination and mapping. Moreover, additional benefits of Sentinel data such as Sentinel's 1 Synthetic Aperture Radar (SAR) capabilities useful for complementing multispectral imagery was examined. Sentinel's 1 SAR data characterized by high penetration ratio provides advance forest physical attributes such as height, texture and structural geometry, required for complementing multispectral imageries (i.e. Sentinel 2). Multispectral sensors are often restricted to only the top biochemical canopy characteristics due to low penetration ratio. Therefore, combining Sentinel 1 and 2 properties using feature level fusion technique was critical for enhancing classification accuracy of forest species. With the application of linear discriminant analysis (LDA) algorithm, results in this chapter demonstrated the value of exploiting full capabilities of Sentinel data (*e.g.* Sentinel 2 and SAR) for improved forest species discrimination and mapping. Furthermore, larger swath width of these sensors offer a great opportunity for local and regional forest species discrimination and mapping.

4.3 Conclusions

The main aim of this study was to discriminate and map commercial forest species using cost effective multispectral remote sensing imagery. Based on the findings of this study, new generation multispectral satellite images demonstrated capabilities to accurately provide invaluable information for mapping and monitoring of commercial forest species at local and regional scales. Conclusions answering research hypothesis highlighted in chapter 1 were:

- **New and readily available Landsat 8 OLI multispectral image with improved sensor characteristics has the potential to provide accurate and reliable information for regional forest species monitoring and management**

The new and readily available Landsat 8 OLI multispectral imagery offer cost effective discrimination and mapping of commercial forest species at regional scale. The improved sensor characteristics such as signal-to-noise radiometric resolution of 12-bit dynamic range, larger swath width of 185 km and a 16-day temporal resolution makes Landsat 8 OLI imagery one of the most valuable sources of remotely sensed data for regional and local forest species management and monitoring. Furthermore, Landsat 8’s products are freely accessible, hence providing remarkable information for comprehensive decision making based on commercial forest management.

- **Sentinel’s 1 Synthetic Aperture Radar capabilities has the ability to successfully improve the classification potential of Sentinel 2 multispectral imagery in discriminating forest species**

The emergence of Sentinel 2 multispectral imagery, with better spatial and spectral properties, provides access to a new red-edge region useful for vegetation mapping and forest species discrimination. In this study, Sentinel’s Synthetic Aperture Radar (SAR) data was useful in complementing capabilities of Sentinel 2 multispectral image for forest species discrimination and mapping. In addition to the sensors larger spatial coverage, combining S1 and S2 offers improved and invaluable information at no cost.

4.4 The future

Newly launched and readily available multispectral imageries offer new data sources critical for commercial forest species discrimination and mapping. The findings of this study present an insight on the utility of freely available multispectral sensors in forest species discrimination and mapping. However, for future research;

- Freely available sensors need to be further tested, in conjunction with forest ancillary data (*e.g.* canopy volume, tree crown, height and age) and texture analysis for the improved regional forest species discrimination and mapping.
- The capability of forthcoming sensors such as Sentinel-3 requires investigation for forest species mapping and monitoring.

References

Adam, E., et al. (2010). "Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: a review." Wetlands Ecology and Management **18**(3): 281-296.

Adelabu, S., et al. (2013). "Exploiting machine learning algorithms for tree species classification in a semiarid woodland using RapidEye image." Journal of Applied Remote Sensing **7**(1): 073480-073480.

Aggarwal, S. (2004). "Principles of remote sensing." Satellite remote sensing and GIS applications in agricultural meteorology: 23-38.

Alonzo, M., et al. (2014). "Urban tree species mapping using hyperspectral and lidar data fusion." Remote Sensing of Environment 148: 70-83.

Amuzu-Sefordzi, B., et al. (2016). "Biomass-derived hydrogen energy potential in A frica." Environmental Progress & Sustainable Energy **35**(1): 289-297.

Anderson, J. E., et al. (2008). "Integrating waveform lidar with hyperspectral imagery for inventory of a northern temperate forest." Remote sensing of environment **112**(4): 1856-1870.

Arenas-García, J. and G. Camps-Valls (2008). "Efficient kernel orthonormalized PLS for remote sensing applications." IEEE Transactions on Geoscience and Remote Sensing **46**(10): 2872-2881.

Ashraf, M. A., et al. (2011). Introduction to remote sensing of biomass. Biomass and Remote Sensing of Biomass, InTech.

Balakrishnama, S. and A. Ganapathiraju (1998). "Linear discriminant analysis-a brief tutorial." Institute for Signal and information Processing **18**: 1-8.

Balzter, H., et al. (2015). "Mapping CORINE land cover from Sentinel-1A SAR and SRTM digital elevation model data using random forests." Remote Sensing **7**(11): 14876-14898.

Basuki, T. M., et al. (2012). "The potential of spectral mixture analysis to improve the estimation accuracy of tropical forest biomass." Geocarto international **27**(4): 329-345.

Boahene, K. (1998). "The challenge of deforestation in tropical Africa: reflections on its principal causes, consequences and solutions." Land Degradation & Development **9**(3): 247-258.

Brockhaus, J. and S. Khorram (1992). "A comparison of SPOT and Landsat-TM data for use in conducting inventories of forest resources." International Journal of Remote Sensing **13**(16): 3035-3043.

Bunting, P. and R. Lucas (2006). "The delineation of tree crowns in Australian mixed species forests using hyperspectral Compact Airborne Spectrographic Imager (CASI) data." Remote sensing of environment **101**(2): 230-248.

Carreiras, J. M., et al. (2012). "Understanding the relationship between aboveground biomass and ALOS PALSAR data in the forests of Guinea-Bissau (West Africa)." Remote Sensing of Environment **121**: 426-442.

Carreira-Perpinan, M. (1995). "Compression neural networks for feature extraction: Application to human recognition from ear images." MSc thesis, Faculty of Informatics, Technical University of Madrid.

Calviño-Cancela, M. and J. Martín-Herrero (2016). "Spectral Discrimination of Vegetation Classes in Ice-Free Areas of Antarctica." Remote Sensing **8**(10): 856.

Champion, I., et al. (2008). "Radar image texture as a function of forest stand age." International journal of remote sensing **29**(6): 1795-1800

Cheng, P. and C. Chaapel (2008). "Increased image collection opportunities, Digital Globe's worldview-1 satellite." Geoform. Online Mag.

Cho, M. A., et al. (2012). "Mapping tree species composition in South African savannas using an integrated airborne spectral and LiDAR system." Remote sensing of environment **125**: 214-226.

Clark, M. L., et al. (2005). "Hyperspectral discrimination of tropical rain forest tree species at leaf to crown scales." Remote Sensing of Environment **96**(3): 375-398.

Colgan, M. S., et al. (2012). "Mapping savanna tree species at ecosystem scales using support vector machine classification and BRDF correction on airborne hyperspectral and LiDAR data." Remote Sensing **4**(11): 3462-3480.

Congalton, R. G. and K. Green (2008). Assessing the accuracy of remotely sensed data: principles and practices, CRC press.

Connette, G., et al. (2016). "Mapping distinct forest types improves overall forest identification based on multi-spectral Landsat imagery for Myanmar's Tanintharyi Region." Remote Sensing **8**(11): 882.

Dabrowska-Zielinska, K., et al. (2016). "Assessment of carbon flux and soil moisture in wetlands applying Sentinel-1 Data." Remote Sensing **8**(9): 756.

Davidson, S. J., et al. (2016). "Mapping Arctic tundra vegetation communities using field spectroscopy and multispectral satellite data in North Alaska, USA." Remote Sensing **8**(12): 978.

Dube, T., et al. (2018). "Estimating forest standing biomass in savanna woodlands as an indicator of forest productivity using the new generation WorldView-2 sensor." Geocarto international **33**(2): 178-188.

Dube, T., et al. (2016). "Estimating forest standing biomass in savanna woodlands as an indicator of forest productivity using the new generation WorldView-2 sensor." Geocarto International: 1-11.

Dube, T. and O. Mutanga (2015). "Investigating the robustness of the new Landsat-8 Operational Land Imager derived texture metrics in estimating plantation forest aboveground biomass in resource constrained areas." ISPRS Journal of Photogrammetry and Remote Sensing **108**: 12-32.

Dube, T., et al. (2014). "Intra-and-inter species biomass prediction in a plantation forest: testing the utility of high spatial resolution spaceborne multispectral rapideye sensor and advanced machine learning algorithms." Sensors **14**(8): 15348-15370.

DWAF (2005). Commercial Timber Resources and Primary Roundwood Processing in South Africa 2003/2004, Department of Water Affairs and Forestry.

El-Askary, H., et al. (2014). "Change detection of coral reef habitat using Landsat-5 TM, Landsat 7 ETM+ and Landsat 8 OLI data in the Red Sea (Hurghada, Egypt)." International journal of remote sensing **35**(6): 2327-2346.

Fagan, M. E., et al. (2015). "Mapping species composition of forests and tree plantations in Northeastern Costa Rica with an integration of hyperspectral and multitemporal Landsat imagery." Remote Sensing **7**(5): 5660-5696.

Farrés, M., et al. (2015). "Comparison of the variable importance in projection (VIP) and of the selectivity ratio (SR) methods for variable selection and interpretation." Journal of Chemometrics **29**(10): 528-536.

Franklin, S., et al. (2000). "Incorporating texture into classification of forest species composition from airborne multispectral images." International Journal of Remote Sensing **21**(1): 61-79.

Fuchs, H., et al. (2009). "Estimating aboveground carbon in a catchment of the Siberian forest tundra: Combining satellite imagery and field inventory." Remote Sensing of Environment **113**(3): 518-531.

Geldenhuys, C.J., 2000. Classification and distribution of forest and woodlands in South Africa, fourth ed. In: Owen, D.L., Vermeulen, W.J. (Eds.), South African Forestry Handbook fourth ed., vol. 2 South African Institute of Forestry, Pretoria.

German, G., et al. (1999). Statistical and aI techniques in GIS Classification: a Comparison. Proc. of the 11th Annual Colloquium of the Spatial Information Research Centre, Citeseer.

Geudtner, D., et al. (2014). Sentinel-1 system capabilities and applications. Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International, IEEE.

Goldblatt, R., et al. (2017). "High Spatial Resolution Visual Band Imagery Outperforms Medium Resolution Spectral Imagery for Ecosystem Assessment in the Semi-Arid Brazilian Sertão." Remote Sensing **9**(12): 1336.

Govender, M., et al. (2008). "A comparison of satellite hyperspectral and multispectral remote sensing imagery for improved classification and mapping of vegetation." Water SA **34**(2): 147-154.

Govender, M., et al. (2007). "A review of hyperspectral remote sensing and its application in vegetation and water resource studies." Water Sa **33**(2): 145-151.

Haack, B. N., et al. (2000). "Radar and optical data integration for land-use/land-cover mapping." Photogrammetric Engineering and Remote Sensing **66**(6): 709-716.

Haghighat, M., et al. (2016). Discriminant correlation analysis for feature level fusion with application to multimodal biometrics. Acoustics, Speech and Signal Processing (ICASSP), 2016 IEEE International Conference on, IEEE.

Haghighat, M., et al. (2016). "Discriminant correlation analysis: Real-time feature level fusion for multimodal biometric recognition." IEEE Transactions on Information Forensics and Security **11**(9): 1984-1996

Hamideh Nouri 1, *, Simon Beecham 2, Sharolyn Anderson 2,3 and Pamela Nagler 4 2014 High Spatial Resolution WorldView-2 Imagery for Mapping NDVI and Its Relationship to Temporal Urban Landscape Evapotranspiration Factors. Remote Sens. 2014, 6, 580-602.

Hashemi, S. A. (2016). "Evaluation of deciduous broadleaf forests mountain using satellite data using neural network method near Caspian Sea in North of Iran." Anais da Academia Brasileira de Ciências **88**(4): 2357-2362.

Honnay, O., et al. (1999). "Effects of area, age and diversity of forest patches in Belgium on plant species richness, and implications for conservation and reforestation." Biological conservation **87**(1): 73-84.

Hossain, F. (2016). Earth Science Satellite Applications: Current and Future Prospects, Springer.

Immitzer, M., et al. (2016). "First experience with Sentinel-2 data for crop and tree species classifications in central Europe." Remote Sensing **8**(3): 166.

Ismail, R., Mutanga, O., 2010. Acomparison of regression tree ensembles: predicating Sirex noctilio induced water stress in Pinus patula forest of KwaZulu–Natal, South Africa. International Journal of Applied Earth Observation and Geoinformation **12**, 45–51.

Jha, C.S., Goparaju, L., Tripathi, A., Gharai, B., Raghubanshi, A.S., Singh, J.S., 2005. Forest fragmentation and its impact on species diversity: an analysis using remote sensing and GIS. Biodiversity and Conservation **14** (7),1681–1698.

Karlson, M., et al. (2015). "Mapping tree canopy cover and aboveground biomass in Sudano-Sahelian woodlands using Landsat 8 and random forest." Remote Sensing **7**(8): 10017-10041.

Ke, Y. and L. J. Quackenbush (2007). Forest species classification and tree crown delineation using QuickBird imagery. Proceedings of the ASPRS 2007 Annual Conference.

Keredin Temam Siraj1 * and Beka Benti Teshome2 (2017). Potential Difference of Tree Species on Carbon Sequestration Performance and Role of Forest Based Industry to the Environment (Case of Arsi Forest Enterprise Gambo District), Environ Pollut Climate Change, **1**(3) 2-10.

Korhonen, L., et al. (2017). "Comparison of Sentinel-2 and Landsat 8 in the estimation of boreal forest canopy cover and leaf area index." Remote Sensing of Environment **195**: 259-274.

Forkuor, G., et al. (2018). "Landsat-8 vs. Sentinel-2: examining the added value of sentinel-2's red-edge bands to land-use and land-cover mapping in Burkina Faso." GIScience & Remote Sensing **55**(3): 331-354.

Kor, S. and U. Tiwary (2004). Feature level fusion of multimodal medical images in lifting wavelet transform domain. Engineering in Medicine and Biology Society, 2004. IEMBS'04. 26th Annual International Conference of the IEEE, IEEE.

Lee, K.-S., et al. (2004). "Hyperspectral versus multispectral data for estimating leaf area index in four different biomes." Remote Sensing of Environment **91**(3-4): 508-520.

Le Maire, G., et al. (2011). "MODIS NDVI time-series allow the monitoring of Eucalyptus plantation biomass." Remote Sensing of Environment **115**(10): 2613-2625.

Lennartz, S. P. and R. G. Congalton (2004). Classifying and mapping forest cover types using Ikonos imagery in the northeastern United States. Proceedings of the ASPRS 2004 Annual Conference.

Li, T., et al. (2006). "Using discriminant analysis for multi-class classification: an experimental investigation." Knowledge and information systems **10**(4): 453-472.

Lu, D. (2006). "The potential and challenge of remote sensing-based biomass estimation." International journal of remote sensing **27**(7): 1297-1328.

Lottering, R. and O. Mutanga (2012). "Estimating the road edge effect on adjacent Eucalyptus grandis forests in KwaZulu-Natal, South Africa, using texture measures and an artificial neural network." Journal of Spatial Science **57**(2): 153-173.

Mandle, L.; Bufford, J.L.; Schmidt, I.B.; Daehler, C.C (2011). Woody exotic plant invasions and fire: Reciprocal impacts and consequences for native ecosystems. Biol. Invasions, **13**, 1815–1827

Martin, M., et al. (1998). "Determining forest species composition using high spectral resolution remote sensing data." Remote Sensing of Environment 65(3): 249-254.

Matthew E. Fagan 1, *, Ruth S. DeFries 2, Steven E. Sesnie 3, J. Pablo Arroyo-Mora 4, Carlomagno Soto 4, Aditya Singh 5, Philip A. Townsend 5 and Robin L. Chazdon 6 (2015). Mapping Species Composition of Forests and Tree Plantations in Northeastern Costa Rica with an Integration of Hyperspectral and Multitemporal Landsat Imagery Remote Sens., 7, 5660-5696;

McCarthy, M. J. and J. N. Halls (2014). "Habitat mapping and change assessment of coastal environments: an examination of WorldView-2, QuickBird, and IKONOS satellite imagery and airborne LiDAR for mapping barrier island habitats." ISPRS International Journal of Geo-Information **3**(1): 297-325.

Meinzer, F. C., et al. (2011). Size-and age-related changes in tree structure and function, Springer Science & Business Media.

Moore, M. M. and M. E. Bauer (1990). "Classification of forest vegetation in north-central Minnesota using Landsat Multispectral Scanner and Thematic Mapper data." Forest Science **36**(2): 330-342.

Morris, A., Pallett, R., 2000. Pines. In: Owen, D.L. (Ed.), South African Forestry Handbook, vol. 1. South African Institute of Forestry, Pretoria.

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

Nagendra, H. (2001). "Using remote sensing to assess biodiversity". International Journal of Remote Sensing 22: 2377–2400.

Naidoo, L., et al. (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.

Omer, G., et al. (2015). "Performance of support vector machines and artificial neural network for mapping endangered tree species using WorldView-2 data in Dukuduku forest, South Africa." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 8(10): 4825-4840.

Palermo, G., et al. (2009). "Performance of PLS regression coefficients in selecting variables for each response of a multivariate PLS for omics-type data." Advances and applications in bioinformatics and chemistry: AABC 2: 57.

Peerbhay, K., et al. (2016). "Detecting bugweed (Solanum mauritianum) abundance in plantation forestry using multisource remote sensing." ISPRS journal of photogrammetry and remote sensing 121: 167-176.

Peerbhay, K. Y., et al. (2014). "Investigating the capability of few strategically placed Worldview-2 multispectral bands to discriminate forest species in KwaZulu-Natal, South Africa." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing **7**(1): 307-316.

Peerbhay, K. Y., et al. (2013). "Commercial tree species discrimination using airborne AISA Eagle hyperspectral imagery and partial least squares discriminant analysis (PLS-DA) in KwaZulu–Natal, South Africa." ISPRS Journal of Photogrammetry and Remote Sensing **79**: 19-28.

Peerbhay, K. Y., et al. (2014). "Investigating the capability of few strategically placed Worldview-2 multispectral bands to discriminate forest species in KwaZulu-Natal, South Africa." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing **7**(1): 307-316.

Peltzer, D. A., et al. (2015). "Commercial forests: Native advantage." Science **349**(6253): 1176-1176.

Raczko, E. and B. Zagajewski (2018). "Tree Species Classification of the UNESCO Man and the Biosphere Karkonoski National Park (Poland) Using Artificial Neural Networks and APEX Hyperspectral Images." Remote Sensing 10: 1111.

Rajah, P., et al. (2015). "Varietal discrimination of common dry bean (Phaseolus vulgaris L.) grown under different watering regimes using multitemporal hyperspectral data." Journal of Applied Remote Sensing **9**(1): 096050-096050.

Ramoelo, A., et al. (2015). "Potential of Sentinel-2 spectral configuration to assess rangeland quality." Journal of applied remote sensing **9**(1): 094096.

Ramoelo, A., et al. (2013). "Non-linear partial least square regression increases the estimation accuracy of grass nitrogen and phosphorus using in situ hyperspectral and environmental data." ISPRS journal of photogrammetry and remote sensing **82**: 27-40.

Rapinel, S., et al. (2014). "Identification and mapping of natural vegetation on a coastal site using a Worldview-2 satellite image." Journal of environmental management **144**: 236-246.

Roberts, J., et al. (2007). "Forest structural assessment using remote sensing technologies: an overview of the current state of the art." Southern Hemisphere Forestry Journal **69**(3): 183-203.

Schmidtlein, S., et al. (2007). "Mapping the floristic continuum: Ordination space position estimated from imaging spectroscopy." Journal of Vegetation Science **18**(1): 131-140.

Shang, X. and L. A. Chisholm (2014). "Classification of Australian native forest species using hyperspectral remote sensing and machine-learning classification algorithms." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing **7**(6): 2481-2489.

Sheeren, D., et al. (2015). Tree species discrimination in temperate woodland using high spatial resolution Formosat-2 time series. Analysis of Multitemporal Remote Sensing Images (Multi-Temp), 2015 8th International Workshop on the, IEEE.

Sibanda, M., et al. (2016). "Comparing the spectral settings of the new generation broad and narrow band sensors in estimating biomass of native grasses grown under different management practices." GIScience & Remote Sensing **53**(5): 614-633.

Siddiqui, M. D. and A. Z. Zaidi (2016). "Worldview-2 and Landsat 8 Satellite Data for Seaweed Mapping along Karachi Coast." Pakistan Journal of Engineering, Technology & Science **5**(2).

Skidmore, A. K., et al. (2010). "Forage quality of savannas—Simultaneously mapping foliar protein and polyphenols for trees and grass using hyperspectral imagery." Remote Sensing of Environment **114**(1): 64-72.

Sliney, D. (2016). What is light? The visible spectrum and beyond, Nature Publishing Group.

Sothe, C., et al. (2017). "Evaluating sentinel-2 and Landsat-8 data to map sucessional forest stages in a subtropical forest in Southern Brazil." Remote Sensing **9**(8): 838.

Steppe, K., et al. (2011). Tree size-and age-related changes in leaf physiology and their influence on carbon gain. Size-and age-related changes in tree structure and function, Springer: 235-253.

Tagliabue, G., et al. (2016). "Forest species mapping using airborne hyperspectral APEX data." Miscellanea Geographica **20**(1): 28-33.

Tharwat, A., et al. (2017). "Linear discriminant analysis: A detailed tutorial." AI Communications **30**(2): 169-190.

Thenkabail, P. S., et al. (2013). "Selection of hyperspectral narrowbands (HNBs) and composition of hyperspectral twoband vegetation indices (HVIs) for biophysical characterization and discrimination of crop types using field reflectance and Hyperion/EO-1 data." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing **6**(2): 427-439.

Torabzadeh, H., et al. (2013). "Mapping forest species composition using imaging spectrometry and airborne laser scanner data." ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (**3**): 437-440.

Van Aardt, J. and M. Norris-Rogers (2008). "Spectral–age interactions in managed, even-aged Eucalyptus plantations: application of discriminant analysis and classification and regression trees approaches to hyperspectral data." International Journal of Remote Sensing **29**(6): 1841-1845.

Wang, Z., et al. (2004). "Prediction of grain protein content in winter wheat (Triticum aestivum L.) using plant pigment ratio (PPR)." Field Crops Research **90**(2-3): 311-321.

Waser, L. T., et al. (2014). "Evaluating the potential of WorldView-2 data to classify tree species and different levels of ash mortality." Remote Sensing **6**(5): 4515-4545.

Wicaksono, P. and F. Adhimah (2017). "Accuracy assessments of pan-sharpened image for benthic habitats mapping." Geoplanning: Journal of Geomatics and Planning **4**(1): 27-40.

Wittwer, R. F., et al. (2004). Even and uneven-aged forest management, Division of Agricultural Sciences and Natural Resources, Oklahoma State University.

Wulder, M. A., et al. (2005). "Remote sensing and GIS in forestry." Remote sensing for GIS managers. ESRI Press, Redlands: 351-362.