MSc Research Report

Mapping *Eucalyptus* species using high-resolution multispectral imagery

.

Solange Nyirahagenimana

Supervisor: Dr Solomon Newete

Co-Supervisor: Dr Khaled Abutaleb

This research report is submitted in partial fulfilment of the requirements for the degree of Master of Science

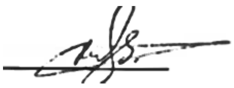
University of the Witwatersrand

School of Animal, Plant and Environmental Sciences

November 2019

Declaration

I, Solange Nyirahagenimana, declare that this research report is my own unaided work. It is being submitted for the Degree of Master of Science to the school of Animal, Plant and Environmental Sciences at the University of the Witwatersrand, Johannesburg. It has never been submitted in any form for any degree or diploma in any tertiary institution. It, therefore, represents my original work. Where use has been made of the work from other authors or organisations, it is duly acknowledged within the text or references chapter.



Signature of candidate

4 November 2019

Abstract

Although *Eucalyptus* species have several negative impacts on the environment, the management of these highly alien invasive species has been often complicated due to the socio-economic benefits that they provide. Therefore, determining the extent and distribution of these notorious alien plant species can help to prioritize resource allocation for management intervention and to mitigate the impact of their invasion on native plant diversity and water resources. Mapping *Eucalyptus* species using traditional field survey is costly, time-consuming and inconvenient for large-scale plantations. Remote sensing using low spatial and spectral resolution imagery is also complicated due to the spectral confusion between tree species. This study investigated the utility of multispectral SPOT 6 satellite imageries using Random Forest (RF) and Support Vector Machine (SVM) classification algorithms to discriminate and map *Eucalyptus* species in 'Tom Jenkins Plantation' at Rietondale, Pretoria East. The separability analysis performed to discriminate between *Eucalyptus* species using the Transformed divergence (TD) and Jeffries Matusita (JM) tests produced results ranging from 0 to 1, much lower than the benchmark values of 2 and 1.41for TD and JM, respectively. Nevertheless, at least one (the Random Forest) of the two classifiers produced a high level of overall accuracy (88.46% with a kappa coefficient of 0.87). The overall accuracy for the SVM classifier was only 55.26% (with a kappa coefficient of 0.50). The RF algorithm attained the user and producer's accuracies ranging from 67% to 95% while SVM obtained 0% user's accuracy for *Eucalyptus* classes. The study concludes that the SPOT 6 data combined with Random Forest are important in mapping invasive species and can help environmental managers to plan effective management of *Eucalyptus* species.

Dedication

I dedicate this research work to my husband Dr Meschac Rafiki and my children Shimwa Blessing Rafiki and Ashimwe Benie Rafiki.

Acknowledgement

I thank God for guiding me and for giving me strength in each step of this research journey.

I thank my family for providing the support I needed to complete this research journey. If it had not been for my husband help, this study would not have been possible.

Dr Solomon Newete and Dr Khaled Abutaleb excelled in playing their role as my supervisors. The constructive feedback they provided contributed to the success of this study in a significant way.

I thank the South Africa National Space Agency (SANSA) for providing the SPOT 6 images free of charge.

Table of content

List of Tables

List of Figures

Abbreviations and their description

GPS: Global Positioning System

SPOT: Satellite Pour l'Observation de la Terre

SANSA: South African National Space Agency

GIS: Geographic Information System

RF: Random Forest

SVM: Support Vector Machine

UTM: Universal Transverse Mercator

NDVI: Normalised Difference Vegetation Index

OOB: Out-Of-Bag

TD: Transformed Divergence

JM: Jeffries Matusita

CHAPTER ONE: INTRODUCTION

1.1 Background

The scourge of invasive alien plants is increasingly threatening the existence of the functional ecosystem and its biodiversity (Richardson & Van Wilgen, 2004). Eucalyptus and pine trees were the first alien trees brought into South Africa in 1875 (Albaugh, Dye, & King, 2013). They cover about 1.2 million hectares in South Africa, of which Eucalyptus is 515,000 ha (Albaugh et al., 2013). They are the most planted tree species because the indigenous species are not able to produce sufficient timber of good quality (Albaugh et al., 2013). Nevertheless, the introduction of these exotic tree species and their wide range plantations are not without environmental cost. There is growing concern that these species have become invasive in many riparian ecosystems and water catchments in South Africa, affecting the local water resources (South African National Biodiversity Institute, 2015).

Although South Africa is internationally well recognised for its impressive work in the management of invasive species (Musil & Macdonald, 2007), currently, little is known about the abundance and the distribution of the *Eucalyptus* species in the country outside the commercial plantations. However, such information could be important to mitigate the impact of Eucalyptus invasion on native plant diversity and water resources. Most studies on eucalyptus have focussed on its water resources impacts (Albaugh et al., 2013; Peter J. Dye, 2000; Dzikiti et al., 2016), the biological control of *Eucalyptus* species (Newete, Oberprieler, & Byrne, 2011) and the cultural problems of *Eucalyptus* as exotic species (Florence, 1986). This study, therefore, investigated the utility of Remote Sensing to map and discriminate between *Eucalyptus* species as well as from other co-existing trees. Determining the extent and distribution of this notorious alien plant and yet economically a prominent species at large scale in the natural environment can help prioritize resource allocation for management intervention. Unlike traditional field survey, mapping plant species using remote sensing is time and cost-effective and can be applied to large areas at national and regional scales without any geographical limitations or temporal data (Adam, Mutanga, Odindi, & Abdel-Rahman, 2014; Newete, Erasmus, Weiersbye, Cho, & Byrne, 2014). Mapping vegetation at species level requires high-resolution remote sensing imagery. Thus, SPOT 6 imagery was used in this study to identify between different *Eucalyptus* species at the *Eucalyptus* plantation in Reitondale, Pretoria East.

Eucalyptus, commonly known as gum tree, is the most widely spread plant worldwide with over 19 million hectares in total area coverage (Albaugh et al., 2013). The popularity of *Eucalyptus* species is attributed to its wide ecological adaptation, rapid growth and its high rate of productivity (Doughty, 2000). *Eucalyptus* can successfully grow in difficult climatic conditions such as arid, tropical and subalpine zones (Coppen, 2002). It is native to Australia and belongs to the perennial hardwood genus of *Myrtaceae*, which includes at least 800 species and subspecies (Coppen, 2002; Gilles, Zhao, An, & Agboola, 2010). Its widespread outside the natural habitat across the world is owed to its vast economic and social services. *Eucalyptus* is the major source of energy, pulp, timber, and poles (Florence, 1986). It is also used for medicine, oils and aromatic chemicals used in perfumes and soaps (Doughty, 2000). In regions receiving high annual rainfall, *Eucalyptus* trees are planted for flood and erosion control (Ghisalberti, 1996). Being the largest flowering species in the world, the trees are also used for apiculture as resources of forage for honeybees (South African National Biodiversity Institute, 2015).

Figure 1.1 Eucalyptus plantation in 'Tom Jenkins', Reitondale, Pretoria East

Despite their wide socio-economic benefits, the environmental disservices of *Eucalyptus* species are also enormous. They are known for high soil nutrient reduction rendering arable lands poor for crop production (Jagger & Pender, 2003). They contribute to water loss while producing allelopathic substances, which inhibit the growth of natural vegetation on their surrounding (Dessie, 2011). Eucalyptus tree requires 90 litres per day underwater availability and 40-50 litres per day under soil water scarcity (Palanisami & Joshi, 2011).

The Eucalyptus water use is 785litres per kg of the total biomass. This is less compared to other plants like coffee, cotton and banana with 3200 litres/kg, and maize, sorghum and potato with 1000 litres/kg (Davidson, 1993). However, because of the fast growth of eucalyptus species and their high biomass production, Eucalyptus species consume more water than any other tree species (Davidson, 1993). The introduction of many species of alien trees in South Africa has led to the increase of plantation and reduction of streamflow that provided farmers with water for irrigation (Van Wilgen, Le Maitre, & Cowling, 1998). With the increasing demand for water, energy, and wood products, it is not surprising that there is a mixed argument in the literature whether to clear or keep exotic *Eucalyptus* species.

From the South African context, *Eucalyptus* species were introduced into the country in the late 19th century to meet the country's demand for timber, mine poles, firewood, pulp, windbreaks and for bee forage (Forsyth, Richardson, Brown, & Van Wilgen, 2004). There are about 85 species of *Eucalyptus* in South Africa (South African National Biodiversity Institute, 2015). However, due to their negative impacts on the biodiversity and water supplies, the propagation of *Eucalyptus* species in riparian and catchment areas, parks, nature reserves and conservation ecosystems is strictly prohibited. According to the South African National Biodiversity Act (Act No. 10 of 2004), the species planting is only permitted in demarcated areas for commercial purposes (South African National Biodiversity Institute, 2015). However, while the country has made such effort, research indicates that Eucalyptus have continued to spread beyond demarcated areas causing enormous damage on native biodiversity and water resources (Le Maitre, Forsyth, Dzikiti, & Gush, 2016).

1.2 Rationale

There are few common species of *Eucalyptus* used in the forestry industry of South Africa mainly selected for their specific quality for provision of timber, pole or palp for paper mill. Nevertheless, not only is *Eucalyptus* an invasive species in the natural environment, but the sheer number of species in the genus and their close morphological similarities which are confounded by their ability to hybridize and produce new offspring makes it difficult to discriminate between species unless molecular analysis or fruits are used. While *Eucalyptus* is widely accepted as one of the most suitable for timber plantations in the forestry industry, its vicious consumption of water by evapotranspiration makes it one of the most controversial plants known by many conservationists. Although the plant is allowed in the country strictly for plantations, its presence in the natural environments and particularly in water catchments outside the *Eucalyptus* farms requires immediate removal. This would, however, require spatial information on the abundance and distribution of *Eucalyptus* trees in the natural environment. Traditional survey of the forest is not only time and resources demanding, but it is also inconvenient for a large-scale plant survey due to geographical constraints. Thus, remote sensing can be a suitable option of compiling such information on natural forest and exotic plant distribution for ecologists and conservationists, so that they can prioritize management intervention accordingly.

Therefore, this research investigated the utility of SPOT 6 imagery to map and discriminate between *Eucalyptus* species in the 'Tom Jenkins' plantations in Pretoria East.

1.3 Research Questions

The present study addresses the following research question:

Can the multispectral SPOT 6 imagery effectively discriminate between the different *Eucalyptus* species as well as from other co-existing plant species?

1.4 Aims and Objectives

The main aim of this study was to examine the utilities of SPOT 6 multispectral imagery in mapping the *Eucalyptus* plantation at the species level in 'Tom Jenkins' Rietondale, Pretoria-East.

The main objectives of the study were to:

- discriminate between *Eucalyptus* species using SPOT 6 satellite imagery
- map *Eucalyptus* species in 'Tom Jenkins plantation', at Reitondale, Pretoria East using SPOT 6 satellite imagery
- collect GPS points from each *Eucalyptus* species for ground-truthing of the remote sensing data

CHAPTER TWO: LITERATURE REVIEW

2.1 *Eucalyptus* in South Africa

Most invasive alien plants, including *Eucalyptus*, were brought into South Africa for timber and firewood production, for ornamental purposes, stabilizing dunes and as a barrier and hedge plants (Van Wilgen, Richardson, Le Maitre, Marais & Magadlela, 2001). *Eucalyptus* species are native to Australia and were brought to South Africa in the 19th century by the colonial forest administration of the Cape (Forsyth et al., 2004). Since then *Eucalyptus* have spread countrywide. Large plantations of eucalyptus are found in the Northern Province (Scholes et al., 1995) and Kwazulu Natal province well above 67000 hectares (Greyling, Wingfield, Coetzee, Marincowitz, & Roux, 2016).

In recent years, however, the impact of *Eucalyptus* on the biodiversity and more specifically on water resources has raised serious concerns in the country (Albaugh et al., 2013; Dye, 2000; Le Maitre et al., 2016). Nevertheless, due to their economic contributions, the government has resolved this matter by allowing their use only in demarcated areas, and removal of all *Eucalyptus* species from riparian and other catchment zones, and from protected areas such as national parks, mountain catchment and nature reserves (South African National Biodiversity Institute, 2015). *Eucalyptus camaldulensis, E. conferruminata*, *E. cladocalyx*, *E. diversicolor*, *E. grandis* and *E. tereticornis* are categorized in group two and have been declared invasive according to the biodiversity Act No. 10 of 2004 (South African National Biodiversity Institute, 2015).

2.2 *Eucalyptus* species

High growth and production of good quality wood make *Eucalyptus* economically important plants (Doughty, 2000). They provide timber for fuel, construction, firewood and charcoal (Mugunga, 2016). They also protect soils against erosion while making ecological habitat for some animal species (Dessie, 2011).

There are approximately 800 *Eucalyptus* species in the world (Coppen, 2002) of which 85 are found in South Africa (South African National Biodiversity Institute, 2015). *Eucalyptus camaldulensis* is the most common species cultivated in its native range, Australia and in other parts of the world owing to its ability to grow fast and produce fuel-wood, paper pulp, construction timber, and planting for amenity and land restoration (Butcher, McDonald, & Bell, 2009). *Eucalyptus grandis*, on the other hand, is largely planted in subtropical and warm temperate areas (Teulieres & Marque, 2007). *Eucalyptus citriodora*, which requires warmer and humid region, is planted in several countries in Africa because of its high content of citronellal oil (Coppen, 2002). *Eucalyptus nitens* and *E. macarthurii* are planted in the high altitude and colder regions of South Africa because of its resistance to severe frost, allowing meeting the increased demand of pulpwood within the country. *Eucalyptus saligna* is planted in the Broadholms in Mpumalanga and Draycott in KwaZulu-Natal provinces as it has been proven to coppice well in these areas (Little & Gardner, 2003).

2.3 Morphological similarity of *Eucalyptus* species

Generally, *Eucalyptus* species are fast-growing trees. Most of them develop lignotuber and produce smooth and rough barks (Dessie, 2011). Mature crown of most *Eucalyptus* species carries adult leaves, which could be either lanceolate, petiolate or alternate, although many of the *Eucalyptus* seedlings have opposite leaf arrangement. They provide oil used as an insect repellent or for other medicinal purposes (Coppen, 2002). It is difficult to differentiate *Eucalyptus* species just by looking at their bark. A large number of species shed the out bark each year whilst others keep the dead ones (Coppen, 2002). However, the seeds of *Eucalyptus* trees have the unique morphological appearance and thus, they are often helpful to identify between species (South African National Biodiversity Institute, 2015). To be able to identify *Eucalyptus* species, you need to find dry fruit and flower buds below the tree. You can also look at the fresh and mature flower buds on the tree (South African National Biodiversity Institute, 2015) and the seedlings as some *Eucalyptus* species have the seedlings characters that are dissimilar from each other (Ladiges, Gray, & Brooker, 1981).

2.4 Hybridization problem

The increase in timber demand for pulp and paper industry has raised the increase of forests productivity as well as wood improvement though hybridization practices (de Assis, 2000). *Eucalyptus* hybrids are important in forestry plantations, especially in subtropical and tropical regions (Potts & Dungey, 2004). Hybridization enables to breed a strong and highly productive tree species (Potts and Dungey, 2004). The combinations of diverse characters from different species make the hybrids vigorous (de Assis, 2000). However, this may not sometimes be achievable due to the poor performance of the hybrids (de Assis, 2000). Hybrids are likely to be more vulnerable to pests than their pure species (Potts, Hamilton, & Blackburn, 2011; Potts & Dungey, 2004). Comparing to the parent species, hybrid growth is costly due to their susceptibility and inviability (unable to survive); therefore, they require more assessment during deployment and development stage (Potts & Dungey, 2004; Potts, Volker, Tilyard, & Joyce, 2000).

Hybrid trees support a large number of dependent taxa that make them more susceptible to pests (Potts and Dungey, 2004). Dungey and Potts (2002) reported three separate field trials, which showed more susceptibility of hybrids to browsing by Australian pests (brushtail possum) than resistant parental species. The hybrid tree produces fewer seeds per capsule than parental trees (Potts & Reid, 1983). Hybridization also results in the expansion of plantation areas, which leads to an increase in drier regions due to high water consumption (Dungey & Potts, 2002). The spread of hybrid population can replace or reduce the growth of native species, and this can lead to the extinction of the indigenous species (Vilà, Weber, & Antonio, 2000). The increase of hybridization rate in the area may result in a decrease of native plant species and promote the local loss of rare species. This may cause both demographic and genetic disruptions within a site (Field, Ayre, Whelan, & Young, 2008).

2.5 Hyperspectral and Multispectral Sensors

The traditional methods of plant survey have for many years been the main source of information for ecologist and environmental conservationist. Its high cost and geographical restrictions that require a tedious work and recurrent field visits (Govender, Chetty, Naiken, & Bulcock, 2008) have given way to the development of remote sensing and the aerial photography was used as first remote sensing technique for mapping and monitoring wetland vegetation (Shima, Anderson, & Carter, 1976). Even this was not very effective in plant survey. It was still costly and time-consuming, and it was only later with progressive improvement of the remote sensing technology that the wide use of the tool for mapping vegetation became popular (Govender et al., 2008). Multispectral sensors were used for mapping vegetation, but they could not provide the required information because they record data within limited broad spectral bands. Hyperspectral sensors were developed to reduce the limitations of multispectral sensors (Govender et al., 2008). Hyperspectral sensors acquire a large number of narrow bands of up to 200 or more spectral bands (Campbell & Wynne, 2011; Turner et al., 2003). The improved spatial and fine spectral resolution of hyperspectral sensors provide greater potential for mapping vegetation. Due to a large number of wavebands, the sensors can detect detailed information on the biochemical and anatomic structure of plants (Underwood, Ustin, & DiPietro, 2003). Their massive data create redundancy and consume a lot of storage spaces and analysis time, but more importantly, it is expensive and often with limited access for researchers. Thus, the advancement in the multispectral remote sensors such as WorldView2, Sentinel 2, Landsat and Spot can resolve this problem since they have a better resolution. Nelson (2017) reported that Sentinel-2 data has the capability of classifying forest types. Immitzer, Vuolo, and Atzberger (2016) and Nelson (2017) used Sentinel-2 for mapping tree species and forests and their results showed accuracy levels of 65% and 85.3%, respectively indicating its importance in forest mapping. Harvey and Hill (2001) compared aerial photography, Landsat TM and SPOT XS satellite imagery to map the vegetation of a tropical freshwater swamp in the Northern Territory, Australia. They obtained accuracy levels for Landsat TM 86% and 90% using both ISODATA algorithms and minimum distance to mean respectively, for SPOT XS 85% and 82% using both ISODATA algorithms and minimum distance to mean respectively. Odindi, Adam, Ngubane, Mutanga, and Slotow (2014) achieved the overall classification accuracies of 84.72% and 72.22% for WordView-2 and SPOT-5 imageries respectively when he compared the WordView-2 and SPOT-5 images in mapping the bracken fern using Random forest classifier.

2.5.1 SPOT 6 Sensors

SPOT 6 is a recently launched SPOT product financed by the Airbus Defence and Space. This new generation satellite system was designed to improve the wide range needs of product users including monitoring of operational land services (Sertel & Alganci, 2016). It has multispectral bands with a spatial resolution of 6m and panchromatic band of the high spatial resolution of 1.5m, five spectral bands that are superimposable as they are acquired at the same time, a large swath of 60 km, high spacecraft agility and high ability of recovering large area of 6 million square kilometres on earth. This allows SPOT 6 to transmit information from different countries rapidly (ASTRIUM, 2015; Sertel & Alganci, 2016). The satellite was enhanced to provide continuity as well as an improvement to the SPOT-4 and SPOT-5 services and deliver high-quality information to the user (Hellmann & Rathgeber, 2015). The advanced features such as wide swath, high spatial resolution, 6m spatial resolution for multispectral bands and 1.5m spatial resolution for panchromatic band, and large coverage capacity of 3 to 4 days revisit time (Hellmann & Rathgeber, 2015) make SPOT 6 sensor capable of detecting weeds on large scale providing more detailed information than the previous generation of the multispectral sensors. Numerous studies have shown the utility of SPOT 6 imagery in detecting and mapping alien invasive species (Forsyth, Gibson, & Turner, 2014; Kganyago, Odindi, Adjorlolo, & Mhangara, 2018; Oumar, 2016). Kganyago et al. (2018) proved the utility of Landsat 8 OLI and SPOT 6 images in mapping the alien invasive species *Parthenium hysterophorus* in the African Savanna landscape with the overall classification accuracies of 83% and 86% using the Support Vector Machine algorithm. Oumar (2016) showed the capability of SPOT 6 multispectral imagery in detecting and mapping *Lantana camara* for a community-clearing project in KwaZulu-Natal, South Africa with an overall accuracy of 75%. Forsyth et al., (2014) also showed the utility of SPOT 6 multispectral imagery in mapping the alien invasive *Pinus* spp. in a mountainous area of the Western Cape, South Africa, with an overall accuracy of 84%. With SPOT 6 high spatial resolution and well- placed spectral bands, this satellite provides the potential for detecting and mapping the *Eucalyptus* species in the 'Tom Jenkins' plantations in Pretoria East.

Furthermore, studies such as (Kganyago et al., 2018; Khare, Latifi, Rossi, & Ghosh, 2019; Odindi et al., 2014) proved the limitations and success of SPOT 6 sensor in discriminating and mapping vegetation species. Rudiastuti, Yuwono, and Hartini (2018) showed the utility of SPOT 6 in mapping Mangrove at East Lombok Indonesia with the overall accuracy >85%. Khare et al. (2019) also showed SPOT 6 and RapidEye capacity in identifying and mapping invasive plant species *Lantana* with overall accuracies of 87.38% and 85.27%, respectively. However, Odindi et al. (2014) proved the incapability of SPOT-5 image in separating the bracken fern due to its traditional bands compared to WorldView-2. The latter has additional bands capable of discriminating plant species. Kganyago et al. (2018) also reported the inefficiency of SPOT 6 in discriminating *Parthenium hysterophorus* and coexisting species because of spectral overlaps between the species. This is due to SPOT 6 broad bandwidths found especially in the Blue and NIR bands. Odindi et al. (2014) and Kganyago et al. (2018) used SPOT 5 and SPOT 6 respectively with RF or SVM classifiers and found poor results of discrimination between invasive species and coexisting species. To address the poor results shown by studies in the literature, the present study used the classification of SPOT 6 image using the RF and SVM algorithms in mapping and discriminating between the eucalyptus species.

CHAPTER THREE: METHODOLOGY

3.1 Study Site

The study site was ‘Tom Jenkins’ *Eucalyptus* plantation in Rietondale, Pretoria East. Pretoria is situated in the northern part of Gauteng Province in South Africa (Figure 3.1). It covers about 687, 54 square kilometres. It has an elevation of about 1,339 m above sea level. Its average annual temperature is high (about 18.7°C); despite its low altitude of 1350 m. It is commonly known as the ‘City of Jacaranda’ due to many jacaranda trees lining its streets (“Pretoria Geography-Information, climate and weather in Pretoria,”). *Eucalyptus* species are also planted in the city, but their distribution is currently unknown. This work focused on the *Eucalyptus* plantation belonging to the National Zoological Gardens in Pretoria. *Eucalyptus* species in this plantation were of a known species planted as forage for the Koala bear in the National Zoological Gardens in Pretoria. The land cover in the area consists of built-up, grassland, natural tree species, and *Eucalyptus* species.

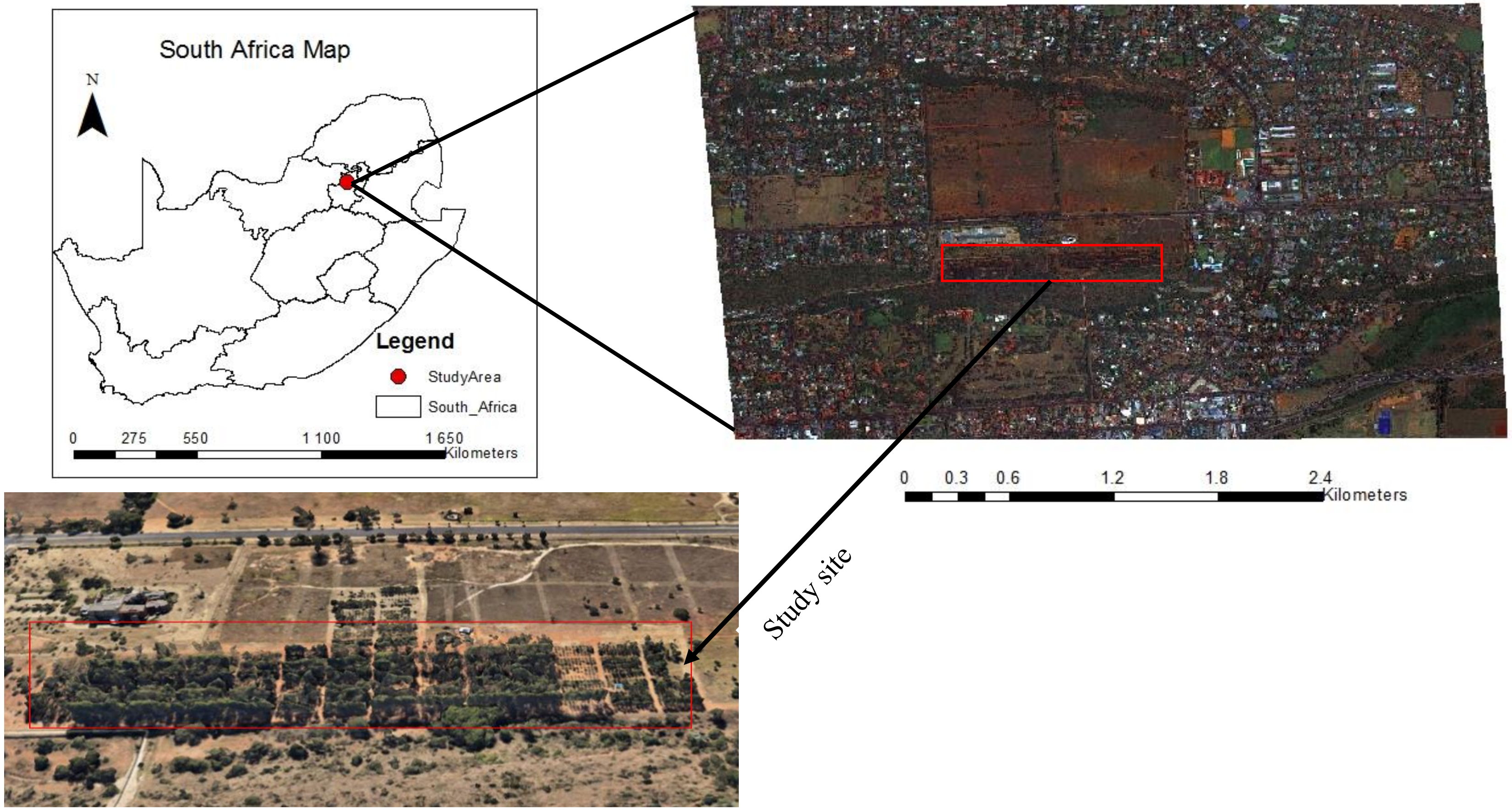


Figure 3. 1 Location of the study area with Eucalyptus plantation in ‘Tom Jenkins’, Rietondale (Pretoria East).

3.2 Materials

High-resolution multispectral data from SPOT 6 imagery were used to map eucalyptus trees and other land covers in the study area. Ground truth data were collected using a GPS (Global Positioning System) device and were used for ground-truthing of satellite imagery.

3.3 Image acquisition and processing

SPOT6 multispectral imagery provides a high resolution, 60 km swath width with five spectral bands (Panchromatic, Red, Green, Blue and NIR) acquiring 6 million square km per day. It has four multispectral bands with 6 meters spatial resolution and a panchromatic band with a spatial resolution of 1.5m (ASTRIUM, 2015; Sertel and Alganci, 2016). The sensor's characteristics are summarized in Table 3.1. In this study, SPOT6 data were acquired on 8 November 2017 from the South African National Space Agency (SANSA). The images received were Ortho-rectified (radiometrically and atmospherically corrected) and projected to the UTM Zone by the supplier, SANSA. The high-resolution panchromatic band in SPOT 6 allows the enhancement of the SPOT 6 sensor from a multispectral spatial resolution of 6m to pan-sharpened panchromatic resolution of 1.5 meters, which is more robust for tree discrimination at the species level (Pohl & Van Genderen, 1998).

Table 3. 1 SPOT 6 satellite specifications (ASTRIUM, 2015)

Launch date	**9 September 2012**
Launch location	Satish Dhawan Space Center (India)
Orbit	Sun-synchronous
Number of spectral bands	Five spectral bands (one Panchromatic and four multispectral (blue, green, red and NIR))
Equator crossing time	10:00 am local time
Spatial Resolution	Panchromatic at 1.5 m resolution Multispectral bands (blue, green, red and near-infrared (NIR) at 6 m resolution

Spectral range	Panchromatic (0.450 µm -0.745µm) Multispectral: Blue (0.450 - 0.520 µm) Green (0.530 -0.590 µm) Red (0.625-0.695 µm) NIR (0.760-0.890 µm)
Imaging swath	60 km at Nadir
Data quantization	12-bits per pixel

3.4 Ground data collection

Field surveys were conducted on June 2018 in the *Eucalyptus* plantation in Rietondale and five major land cover classes (Bare soil, Grassland, Other woody vegetation, Built-up (white roof) and Built-up1(brown roof) were identified beside the *Eucalyptus* species (Table 3.2). Ten *Eucalyptus* of known species were identified during the field survey.

Table 3. 2 Description of main land cover classes considered in the classification process

Classes	**Class description**
Bare soil	Area no covered by vegetation and houses.
Built-up and Built-up1	All man-made construction (rooftops made from tiles) with white and brown sheets including roads.
Other woody vegetation	Other vegetation trees except for eucalyptus tree species.
Grassland	Area covered by grasses
E. camaldulensis	*Eucalyptus* tree species
E. citriodora	*Eucalyptus* tree species
E. maculata	*Eucalyptus* tree species
E. microcorys	*Eucalyptus* tree species
E. paniculata	*Eucalyptus* tree species
E. pilularis	*Eucalyptus* tree species
E. propinqua	*Eucalyptus* tree species
E. punctata	*Eucalyptus* tree species
E. sideroxlon	*Eucalyptus* tree species
E. terreticornis	*Eucalyptus* tree species

The study area had some pruned trees and others were cut down. Therefore, the trees with low or without canopy were not recorded. The data were recorded from each *Eucalyptus* tree species with a high canopy. The distribution of ground truth data is shown in figure 3.2. The GPS coordinates file containing several vegetation types were converted to GIS file to be used in the training set development, classification and accuracy assessment processes.

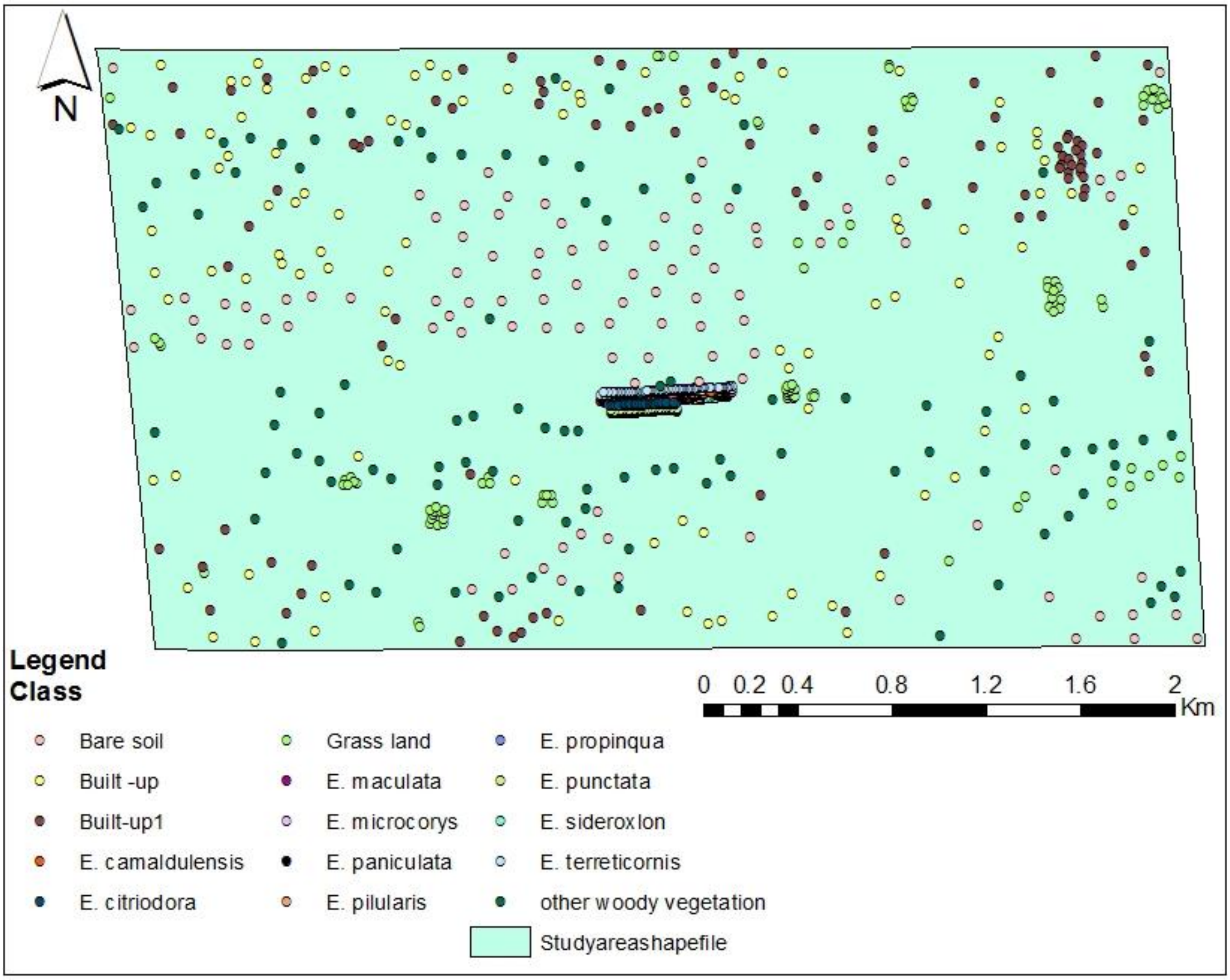


Figure 3. 2 The distribution of the ground truth points collected from the study area, 'Tom Jenkins' in Rietondale (Pretoria East). NB: the dark polygon in the middle is the Eucalyptus plantation.

The SPOT6 pan-sharpened image and google earth were used to identify some points of other Land cover classes (Grassland, Bare soil, other woody vegetation, Built-up1 (brown roof) and Built-up (white roof). A total of 988 points were recorded from the study area along with the points digitized from google earth as a training data for validation of SPOT 6 image classification using RF and SVM algorithms (Table 3.3).

Table 3. 3 Training and Test data for land cover classes of the study area

Land cover types	**Code**	**Training data (70%)**	**Test data (30%)**	**Total**
Bare soil	BS	70	30	100
Built-up	BU	70	30	100
Built-up1	BU1	70	30	100
Other woody vegetation	OWV	70	30	100
Grassland	GL	71	30	101
E. camaldulensis	E. caml	69	29	98
E. citriodora	E. citr	16	7	23
E. maculata	E. mac	14	6	20
E. microcorys	E. micr	29	12	41
E. paniculata	E. panic	32	14	46
E. pilularis	E. pilul	29	13	42
E. propinqua	E. prop	22	10	32
E. punctata	E. punct	15	6	21
E. sideroxlon	E. sider	28	12	40
E. terreticornis	E. terr	87	37	124

3.5 Data analysis

The SPOT 6 image was already radiometrically and atmospherically corrected and projected to the UTM Zone when acquired from SANSA. Separability analysis was conducted on training data to describe the spectral classes that corresponded to each of the land cover classes, including the *Eucalyptus* species in the study area to determine their spectral pattern and process the classification of the land cover map. Figure 3.3 shows the schematic flow diagram of the data analysis.

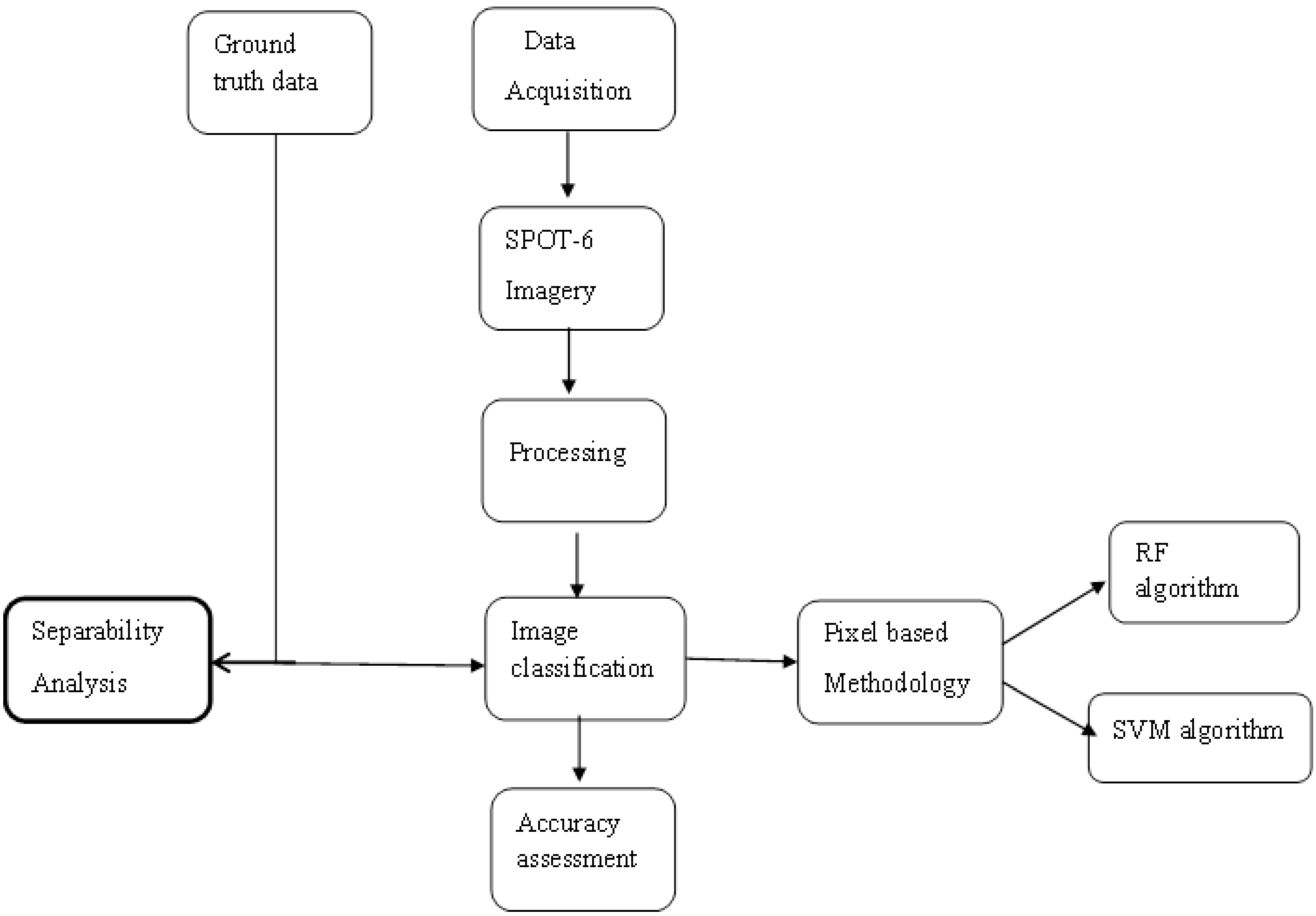


Figure 3. 3 Schematic representation of SPOT 6 image analysis

3.6 Image classification

The image was classified using pixel-based methodologies. A supervised classification was implemented to detect and discriminate between the different species in the study area. An accuracy assessment using an error matrix was performed on each of the pixel-based classifications to determine the level of accuracy in the identification of *Eucalyptus* species. Both the Random Forest (RF) and Support Vector Machine (SVM) algorithms were used for accuracy assessment of the classified.

3.6.1 Random Forest Algorithm

Random Forest (RF) is an ensemble learning technique developed by introducing the idea of bagging (bootstrapping) to decision trees (Breiman, 2001). It is commonly characterized by important parameters such as *mtry* and *ntree*, which must be optimized to increase the classification accuracy (Breiman, 2001; Gislason, Benediktsson, & Sveinsson, 2006). Random Forest algorithm combines many decision trees where each decision tree grows depending on random sampling with replacement of the primary training data (Breiman, 2001). It uses bootstrap to produce an ensemble of classification and regression tree (CART) (Gislason et al., 2006). The growth of the ensemble is controlled by the generated random vectors, which govern the growth of each tree in the ensemble (Breiman, 2001). The samples out of the bootstrap samples are called the out-of-bag (OOB) samples. These samples can be used for estimating the misclassification error and measuring the importance of each variable in the final model (Breiman, 2001). The out-of-bag (OOB) samples reduce the errors that may occur during classification (Breiman, 2001).

Random Forest provides an evaluation of the relative importance of diverse features. It has the advantage of detecting outliers and noise (Pal, 2005; Rodriguez-Galiano, Ghimire, Rogan, Chica-Olmo, & Rigol-Sanchez, 2012). Unlike Support Vector Machine, RF algorithm is a powerful classifier, which is capable of handling data with missing values (Atkinson & Tatnall, 1997; Fassnacht et al., 2016; Pal, 2005). One of the important advantages of this classifier is its capability of exploiting the strengths of a single group of classifiers while preventing the weaknesses of any individual classifier (Ghimire, Rogan, & Miller, 2010). The practical advantages of the original RF algorithm are its suitability for use in large datasets, its capacity to handle a big number of input variables, an internal unbiased estimation of the generalization error and produces important input variables (Breiman, 2001).

3.6.2 Support Vector Machine

Cortes and Vapnik (1995) defined Support Vector Machine (SVM) as a nonparametric binary linear algorithm where the distance of each class from the training data sets to the decision boundary or optimal hyperplane is maximized. It is an important tool capable of handling small training data sets effectively. It produces higher classification accuracy than other classical approaches such as the maximum likelihood method (Mantero, Moser, & Serpico, 2005). SVM classifier reduces classification error by constructing the optimal hyperplane separating the training data points to achieve the optimal separation among different classes

(Mills, 2008; Mountrakis, Im, & Ogole, 2011). The two support hyperplanes on the boundaries of hyperplane are called support vectors having the data points on their edges and are the ones that define the optimal hyperplane (Mountrakis et al., 2011).

Support Vector Machine uses improved algorithms to find the decision boundary or optimal hyperplane between classes (Huang, Davis, & Townshend, 2002). Therefore, the optimal hyperplane facilitates the separation of classes by maximizing the distance between classes of the data points (Huang et al., 2002; Pal, 2005). SVM requires many user-defined parameters as opposed to only two parameters in RF classifier (Pal, 2005). Support Vector Machine was used in several studies and often was more accurate than other traditional classification methodologies such as the Artificial Neural Network (ANN), and the Maximum Likelihood Classification (Foody & Mathur, 2004; Mills, 2008). However, SVM, unlike many other classifiers, requires small training data sets since it only uses the support vectors to locate the hyperplane between classes (Huang et al., 2002). The use of limited training data set in generalisation provides a chance of achieving high classification accuracies (Mills, 2008).

3.7 Accuracy assessment

Comparing ground reference test data with remote sensing classification maps is one of the commonly accepted and simplest ways of assessing the accuracy level of the results (Phinzi & Ngetar, 2017). Thus, it is important to have sufficient ground-truthing data properly collected from each class. In this project, one hundred random sample points were made using Construction Point tool (Create Random Point tool) in ArcMap 10.3. Ground reference data should preferably be collected as close as possible to the date of the image acquisition to minimize the changes in the plants biochemical, structural or phenological properties important for classification (Campbell & Wynne, 2011). Therefore, the ground truthing data and the error matrix (confusion matrix) were used to verify the accuracy of the SPOT 6 classified images. The latter is a way broadly accepted and used to express classification accuracy (Sonawane & Bhagat, 2017). Confusion matrix allows comparison between the ground-truthing reference data with the classification results (Phinzi & Ngetar, 2017). The accuracy assessments matrix produces overall accuracy, producer’s accuracy, user’s accuracy and the kappa coefficient. The Overall accuracy does not reveal the distribution of error between classes while producer and user’s accuracies are obtained by comparing the predicted data with the reference points from the field. However, the difference between them lies in the viewpoints of the map producer in the identification of pixel classification integrity on the map, and the field user determines if the map classification is represented on the ground (Congalton & Green, 2002).

3.8 Model Stacking

Model stacking was applied to improve the classification accuracy of land cover classification since the first classification had generated low overall accuracy. Model Stacking is an ensemble learning method, which consists of combining the data from different sources to improve the accuracy (Hatami & Ebrahimpour, 2007; Mutlu, Popescu, Stripling, & Spencer, 2008). In the present study, Model Stacking was applied by combining three different datasets such as NDVI image, classified image and four bands of multispectral SPOT 6 image and therefore appropriate information was obtained for better classification with improved accuracy. To achieve good results from data fusion, it is better to combine the information or data delivered from numerous sources than from only one source to reduce the inaccuracy and to improve completeness (Bloch, 1994, 1996). This technique aims to enhance overall accuracy by aggregating predictions from several models (Ting & Witten, 1999). Model stacking uses a high-level model to combine lower-level model to improve predictive accuracy (Ting & Witten, 1999; Zhai & Chen, 2018). Therefore, it is assumed as a specific case of ensemble learning that generally leads to better predictions and it performs efficiently when the base models are considerably different (Healey et al., 2018). Model stacking works as an effective ensemble technique in which the predictions that are produced from the use of diverse learning algorithms are used as inputs in a second-level learning algorithm. Therefore, the second-level algorithm is trained for optimally combining the model predictions to form a final set of predictions (Sill, Takács, Mackey, & Lin, 2009). It has to be properly completed so that the output for each model is collected into a new data set to represent every prediction of the model for better classification. This has to be completed carefully to make sure that the models are formed from a set of training data that do not contain the instance in question (Ting and Witten, 1999). Although model stacking requires several attempts to find a good model combination, it is a better technique to improve classification accuracy (Güneş, Wolfinger, & Tan, 2017).

3.9 Separability Analysis

The separability measurements such as Transformed Divergence (TD) and Jeffries Matusita (JM) distance measures were used for each SPOT 6 band and Normalised difference Vegetation Index (NDVI) to determine the spectral separability between *Eucalyptus* species.

The spectral separability of *Eucalyptus* species classes was assessed to discriminate between ten *Eucalyptus* species. TD and JM statistical measures were run in R software to quantify the *Eucalyptus* species class spectral separability for the four multispectral bands and the NDVI. The transformed divergence (TD) and Jeffries Matusita (JM) separability measures were used to reveal the spectral separability between species. TD and JM are commonly used measures. The benchmark values range between 0 and 2 and 0 and 1.41 respectively (Huang et al., 2002; Swain & Davis, 1981).

Separability test was performed on the training data to evaluate the expected errors occurring in the classification for several feature combinations. These statistical measures can also be used to determine the combination of bands between the given classes, as they are able to determine the separation between more than one features (Murakami, Ogawa, Ishitsuka, Kumagai, & Saito, 2001; Swain & Davis, 1981). To define the spectral separability between ten *Eucalyptus* classes, the multispectral response produced and shown by each *Eucalyptus* species pair were evaluated. Separability tests, Jeffries Matusita (JM) and Transformed Divergence (TD) were computed using the following equations:

The Jeffries Matusita distance for two classes i and j is given by

$$JM_{ij} = \sqrt{2(1-\exp(-\alpha))} \quad ,$$

$$\alpha = \frac{1}{8}(\mu_i - \mu_j)^T \left(\frac{c_i + c_j}{2}\right)^{-1}(\mu_i - \mu_j) + \frac{1}{2}\ln\left(\frac{|c_i + c_j|/2}{\sqrt{|c_i| X |c_j|}}\right)$$

Where:

Ci and Cj are the covariance matrices of class i and class j

T is the transposition function of matrices

$|c_i|$ and $|c_j|$ are the determinants of ci and cj, and

μ ij is the mean vector of class i and class j

The JM separability measure was applied to assess multivariate spectral separability between *Eucalyptus* species using all bands. JM distance measure was applied to an individual band to determine if *Eucalyptus* species were sufficiently discriminated between each other and from the coexisting trees species in the site. It offers a measure of the distance among all the classes in all bands and spectral index. JM separability measure offers the values bound between 0 and 1.41 where the lower value of 0 indicates identical classes and the high value of 1.41 indicates well-separated classes (Trigg & Flasse, 2001). Jeffries Matusita is commonly used for distance measure, but it requires more computation time (Swain and Davis, 1981). It assesses spectral separability of class samples with several spectral bands (Trigg and Flasse, 2001).

The transformed Divergence analysis was performed on the dataset using the data from SPOT 6 bands (Blue, Red, Green, NIR) and NDVI.

$$TD_{ij} = 2\left[1 - \exp\left(-\frac{D}{8}\right)\right],$$

$$D_{ij} = \frac{1}{2}\mathrm{tr}[(C_i - C_j)(C_i^{-1} - C_j^{-1})] + \frac{1}{2}\mathrm{tr}[(C_i^{-1} - C_j^{-1})(\mu_i - \mu_j)(\mu_i - \mu_j)^T]$$

Where:

D i j: Divergence between class i and class j

Tr is the trace function of matrices

Transformed divergence value ranges from 0 to 2. The values closer to 2 indicate good separation while the values closer to 0 indicate poor separability (Hill and Foody, 1994; Swain and Davis, 1981).

CHAPTER FOUR: RESULTS

4.1 Separability analysis

The separability test between *Eucalyptus* species produced the TD and JM values of 0.0 to 0.6 and 0.0 to 0.4 respectively, which are lower than the benchmark of 2 and 1.41 respectively, indicating a massive overlap between *Eucalyptus* species.

The blue and green bands of the SPOT 6 image used in separability analysis between *Eucalyptus* species produced inseparable results with TD and JM values lower than 0.35 (Figure 4.1) when compared to the benchmark of strong separability values of 2 and 1.41, respectively. The highest TD and JM separability values found for the Blue band were, however, between 0.25 and 0.35 in the paired species of *E. terreticornis* vs *E. maculata*, *E. terreticornis* vs *E. paniculata* and *E. terreticornis* vs *E. propinqua.* While that of the Green band was 0.2 to 0.4 and 0.2 to 0.3, respectively in the paired species of *E. sideroxlon vs E. propinqua E. sideroxlon vs E. microcorys* and *E. sideroxlon vs E. citriodora.*

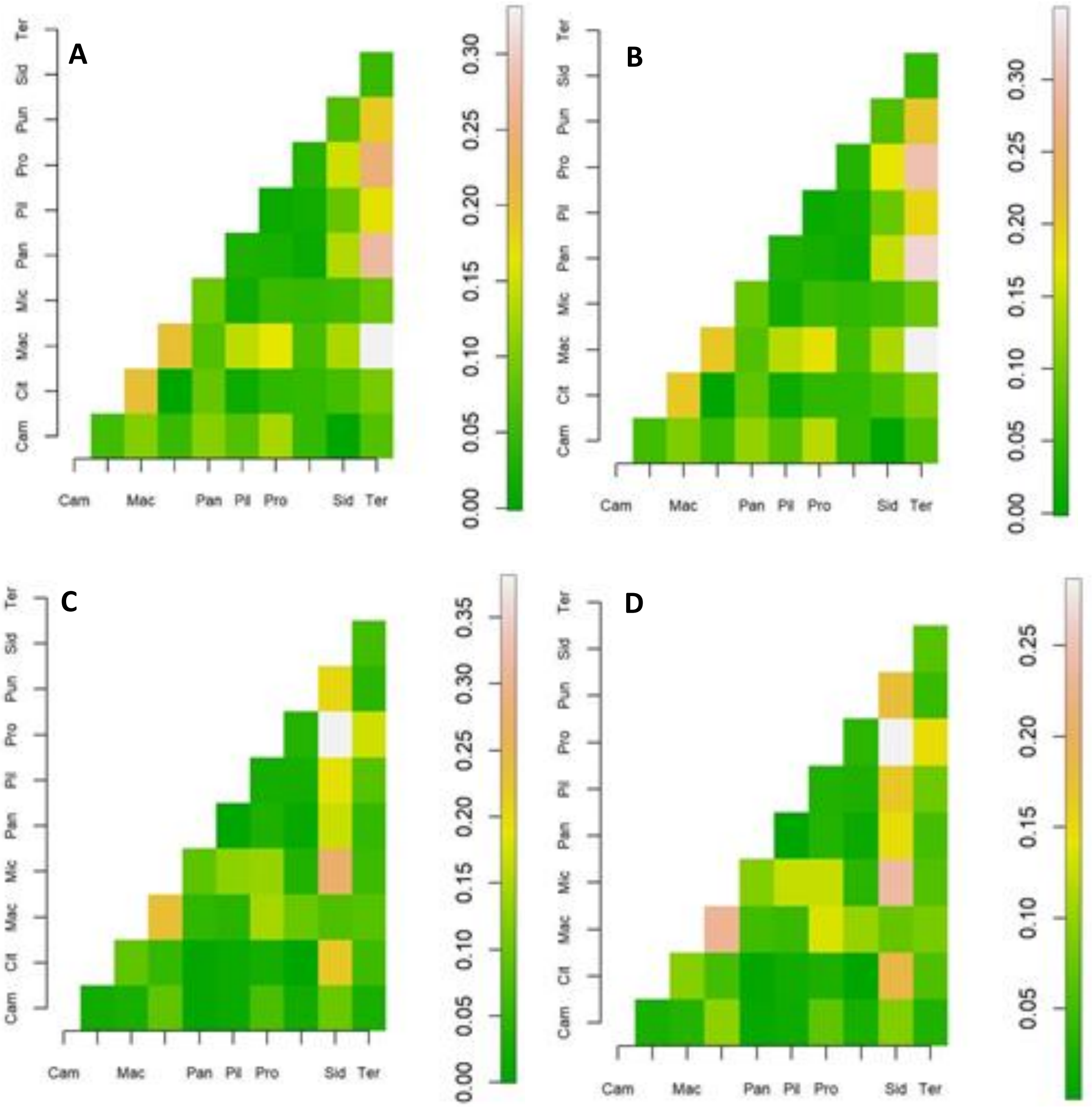


Figure 4. 1 The separability analysis of paired Eucalyptus species in Tom Jenkins' plantation in Rietondale (Pretoria East) using the Blue and Green bands from SPOT 6 image: (A) Transformed Divergence graph using the Blue band, (B) Jeffries Matusita graph using the Blue band, (C) Transformed Divergence graph using the Green band and (D) Jeffries Matusita graph using the Green band.

The Red and NIR bands of SPOT 6 image produced separability values lower than 0.4 and 0.3 respectively (Figure 4.2) compared to the TD and JM benchmarks for strong separability. The highest TD and JM results produced by the Red band were from 0.2 to 0.4 and from 0.2 to 0.3

respectively, for the paired species of *E. sideroxlon vs E. propinqua*, *E. sideroxlon vs E. microcorys* and *E. sideroxlon vs E. pilularis*. However, the high separability values of 0.15 to 2.0 were produced in the paired species of *E. microcorys* vs *E. paniculata* and *E. sideroxlon vs E. microcorys* in the NIR band for both TD and JM respectively.

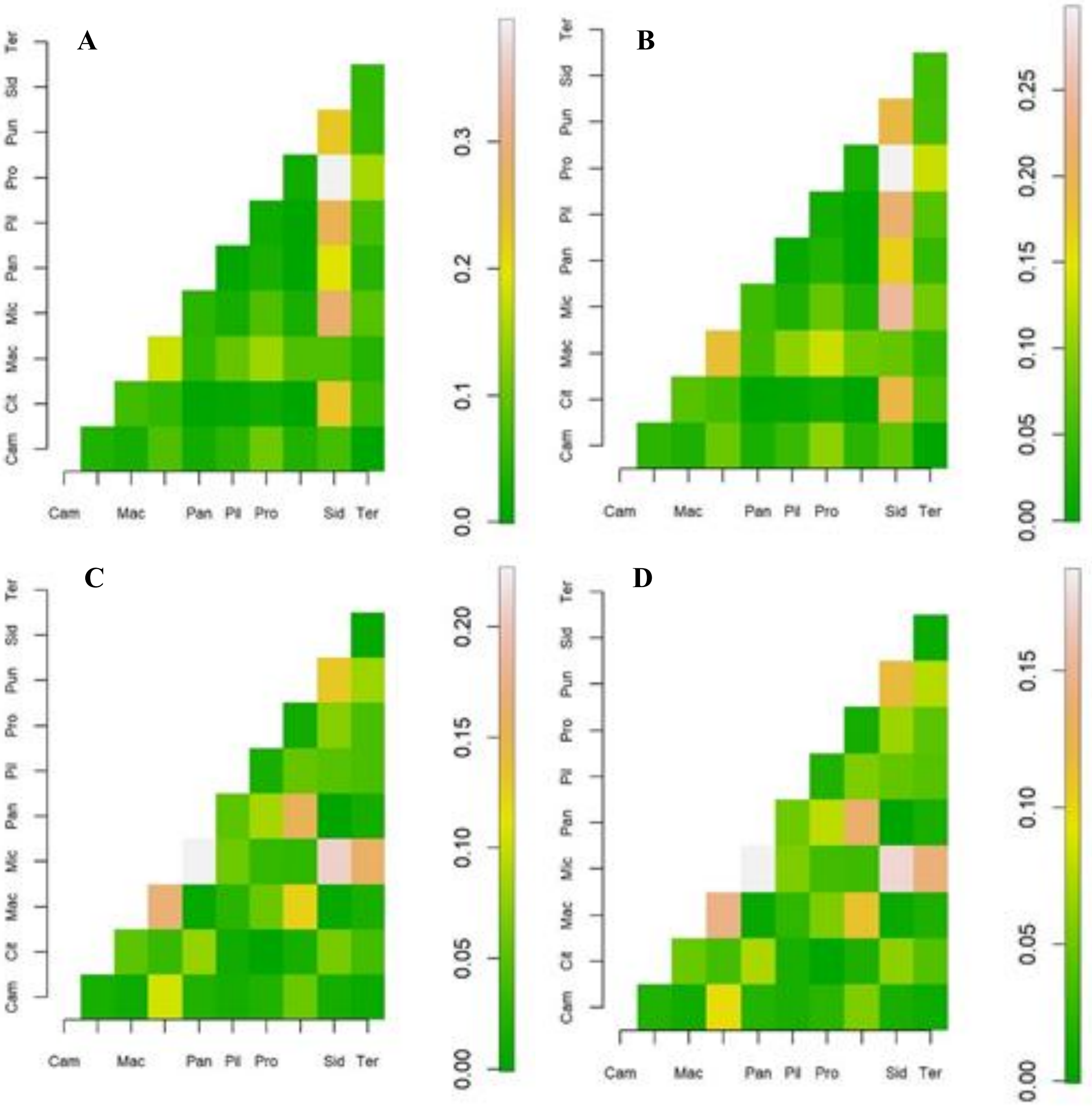


Figure 4. 2 The separability analysis of paired Eucalyptus species in Tom Jenkins' plantation in Rietondale (Pretoria East) using the Red and NIR bands from SPOT 6 image:(A) Transformed Divergence graph using the Red band, (B) Jeffries Matusita graph using the Red band, (C) Transformed Divergence graph using the NIR band and (D) Jeffries Matusita graph using the NIR band**.**

The vegetation index (NDVI) exhibited high separability value of 0.6 and 0.4 in the paired species of *E. sideroxylon* vs *E. citriodora* and *E. sideroxylon* vs *E. punctata* when compared to those produced by other bands in SPOT 6 imagery. Nevertheless, these results were far too small to suggest any strong separability between the *Eucalyptus* species when compared to the TD and JM benchmarks for dissimilarity (Figure 4.3).

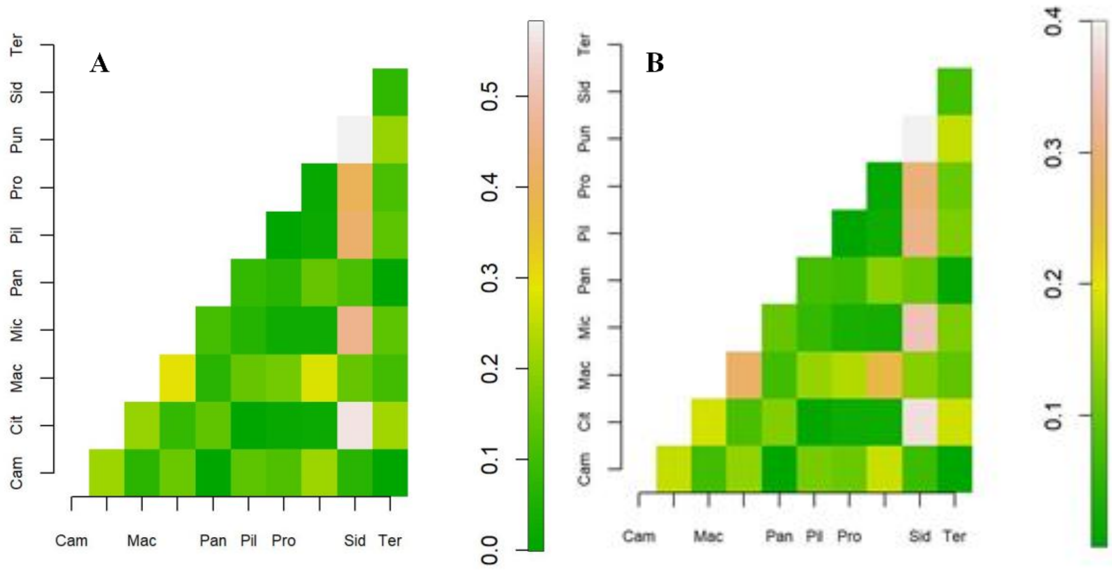
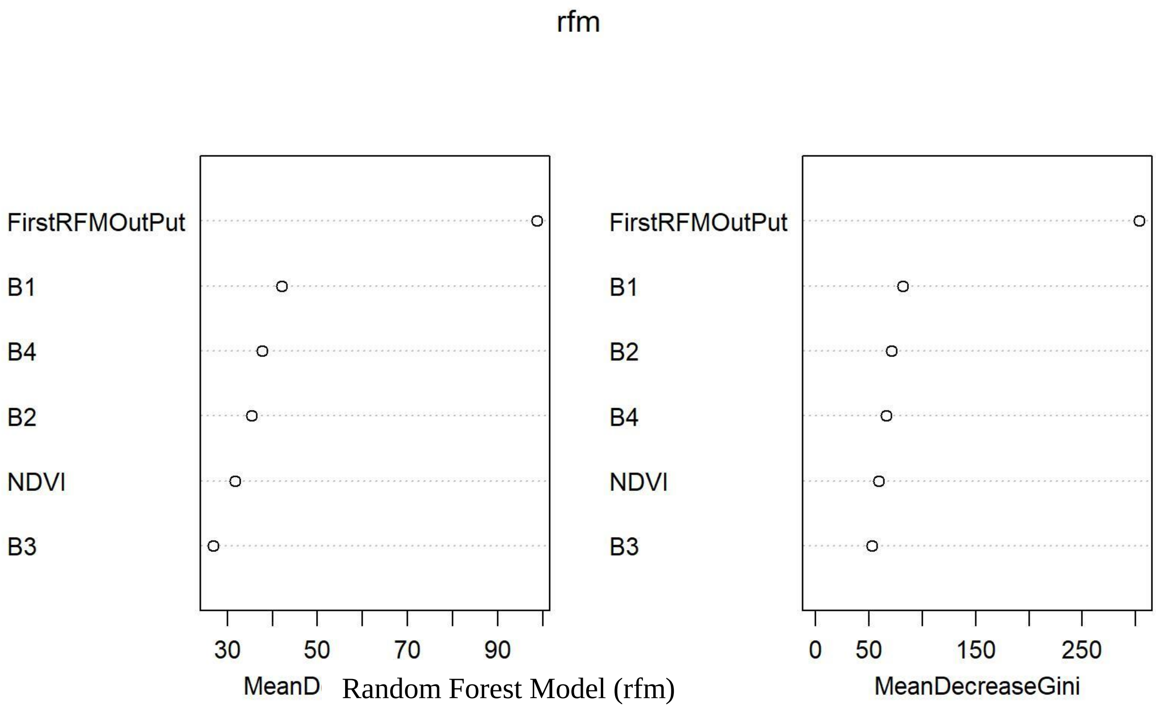


Figure 4. 3 The separability analysis of paired Eucalyptus species in Tom Jenkins' plantation in Rietondale (Pretoria East) using NDVI: (A) Transformed Divergence graph and (B) Jeffries Matusita graph using NDVI.

4.2 Random Forest parameters

4.2.1 Measurement of Variable Importance using the Mean Decrease in Accuracy and Mean Decrease in Gini

The RF algorithm determined important variables used in the classification of SPOT 6 imagery. These include the NDVI image, FirstRFMoutPut (classified image resulted from the first classification) and the four bands (blue, green, red and near-infrared) of the multispectral SPOT 6 imagery (Figure 4.4). The most essential high variable importance is that with the highest Mean Decrease in Accuracy and highest Mean Decrease in Gini. A high mean decrease in Accuracy means high variable importance. The same was true for high Mean Decrease in Gini. Thus, the FirstRFMoutPut (classified image) showed the most important variables for classification of *Eucalyptus* species (Figure 4.4).



Random Forest Model (rfm)

Figure 4. 4 The importance of SPOT 6 bands, NDVI and FirstRFMOutPut in discriminating between land cover classes.

4.2.2 The Out-of-Bag Error

The Out-of-Bag (OOB) Error is one of the classification empirical results obtained from the analysis of SPOT 6 image using Random Forest classifier. Five hundred trees were used in the analysis and the OOB errors for each class were determined. The lowest OOB error rate of 10% was produced from approximately a hundred trees while the high OOB error rate of 38% was produced from approximately 20 trees (Figure 4.5).

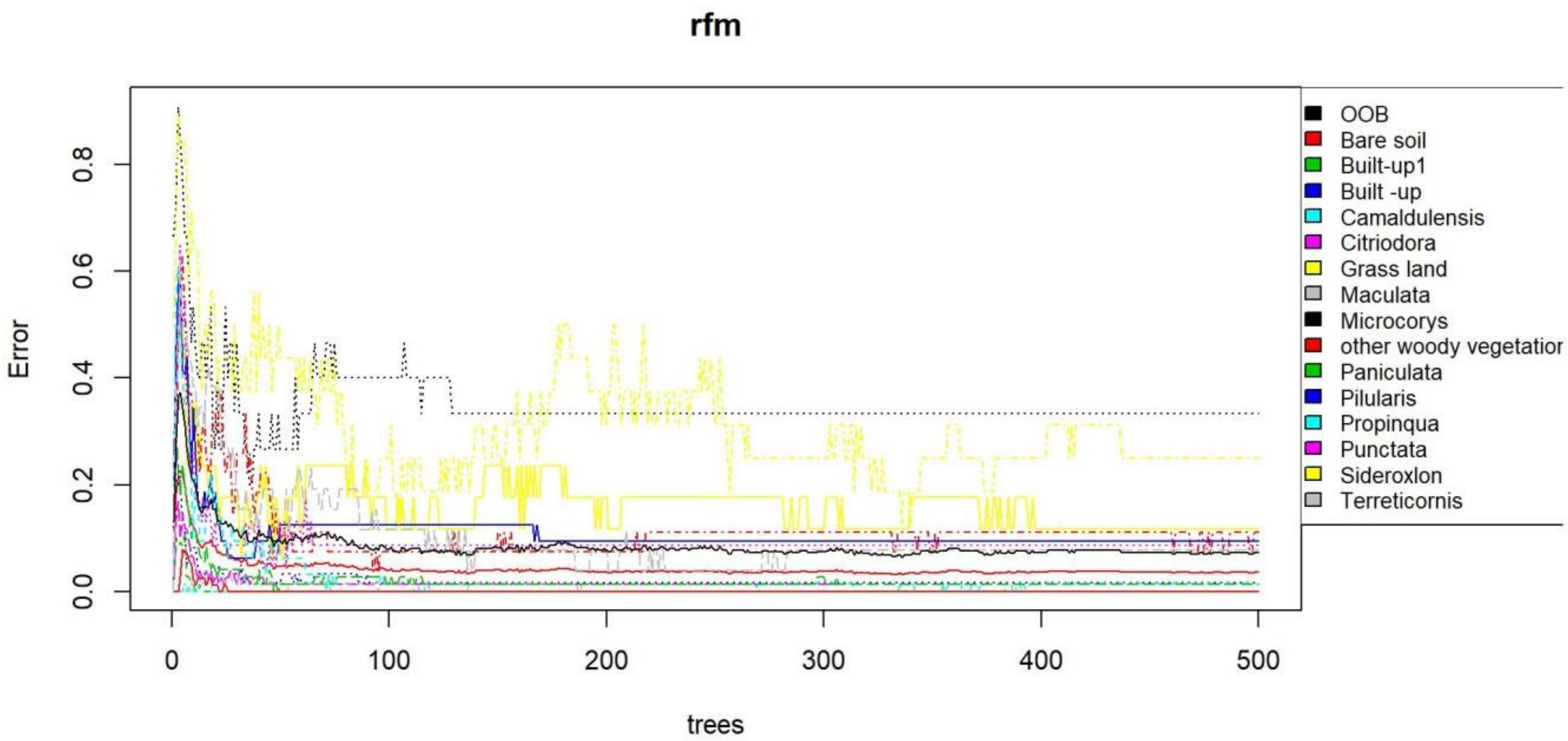


Figure 4. 5 Estimates of Out-of-Bag Error for a number of trees in the 'Tom Jenkins' Eucalyptus Plantation in Rietondale (Pretoria East).

4.3 Accuracy assessment

Sequences of classifications and accuracy assessment were performed using the independent test dataset with Random Forest and Support Vector Machine algorithms to classify land cover types using the SPOT 6 dataset. Both RF and SVM algorithms obtained lower accuracies for multispectral SPOT 6 image compared to the accuracies produced for SPOT6 bands-NDVI-FirstoutPut (classified image) stack image. With the multispectral SPOT 6 image, the RF algorithm produced an overall accuracy of 61.09% and a Kappa coefficient of 0.57. The SVM classifier produced an overall accuracy of 53.34% and kappa coefficient of 0.49, while with SPOT6 bands-NDVI-FirstoutPut stack image, RF and SVM algorithms produced an overall accuracy of 88.46% and Kappa coefficient of 0.87 and overall accuracy of 55.26% and kappa coefficient of 0.50, respectively.

The performance of RF and SVM algorithms was evaluated using the test dataset (Table 3.3). The Random Forest classifier produced higher accuracy levels than Support Vector Machine classifier. The overall accuracy produced using RF classifier was 88.46% with a kappa coefficient of 0.87. Random Forest classifier generated the highest user's and producer's accuracy ranging from 91% to 100% for Land cover classes like Bare soil (BS), Built-up (BU), Built-up1 (BU1), Grassland (GL) and Other woody vegetation (OWV) and 67% to 95% for *Eucalyptus* species (Table 4.1). Spectral confusion occurred in all *Eucalyptus* species (*E. camaldulensis*, *E. citriodora*, *E. maculata*, *E. microcorys*, *E. paniculata*, *E. pilularis*, *E. propinqua*, *E. punctata*, *E. sideroxlon* and *E. terreticornis*). However, the strongest spectral confusion was observed between *E. camaldulensis* (*E. caml*) and *E. terreticornis* (*E. terr*) with a user accuracy of 83.67% and producer accuracy of 67.21% for *E. camaldulensis* (*E. caml*) while *E. terreticornis* (*E. terr*) obtained the user accuracy of 88.71% and producer accuracy of 80.88% (Table 4.1).

Table 4. 1 Confusion matrix produced using Random Forest algorithm for Grassland (GL), Bare soil (BS), other woody vegetation (OWV), Built-up1 (BU1), Built-up (BU) and ten Eucalyptus species which are *E. camaldulensis* (*E.caml*), *E. citriodora (E. citr)*, *E. maculate (E. mac)*, *E. microcorys (E. micr)*, *E. paniculata (E. panic)*, *E. pilularis (E. pilul)*, *E. propinqua (E. prop)*, *E. punctate (E. punct)*, *E. sideroxlon (E. sider*), *E. terreticornis (E. terr).* The confusion matrix (error matrix) includes the Producer's accuracy (PA), User's accuracy (UA), Overall accuracy (OA) and the Kappa coefficient (KA) developed on the test dataset.

Land cover types	**BS**	**BU1**	**BU**	**E. caml**	**E. citr**	**GL**	**E. mac**	**E. micr**	**OWV**	**E. panic**	**E. pilul**	**E. prop**	**E. punct**	**E. sider**	**E. terr**	**Row total**	**PA (%)**
BS	**97**	1	0	0	0	0	0	0	1	0	0	0	0	0	4	103	94.18
BU1	1	**98**	**0**	0	0	0	0	0	0	0	0	0	0	1	0	100	98
BU	0	0	**100**	0	0	0	0	0	0	0	0	0	0	0	0	100	100
E. caml	0	0	0	**82**	2	0	2	5	3	4	5	3	2	6	8	122	67.21
E. citr	0	0	0	0	**17**	0	0	0	0	0	0	0	0	0	1	18	94.44
GL	0	0	0	0	0	**97**	0	0	1	0	0	0	0	0	0	98	98.98
E.mac	0	0	0	1	0	0	**15**	0	0	0	0	1	0	0	0	17	88.24
E. micr	0	0	0	1	0	0	0	**28**	1	2	0	0	0	0	0	32	87.5
OWV	0	1	0	2	0	4	0	1	**91**	1	0	0	0	0	0	100	91
E. panic	0	0	0	1	1	0	0	1	1	**36**	0	1	0	0	1	42	85.71
E. pilul	0	0	0	0	0	0	1	0	0	1	**36**	0	2	0	0	40	90
E. prop	0	0	0	1	1	0	1	1	0	1	0	**23**	1	0	0	29	79.31
E. punct	0	0	0	0	1	0	1	1	2	0	0	0	**16**	0	0	21	76.19
E. sider	0	0	0	1	0	0	0	0	0	0	0	1	0	**28**	0	30	93.33
E. terr	2	0	0	9	1	0	0	4	0	1	1	3	0	5	**110**	136	80.88
Column total	100	100	100	98	23	101	20	41	100	46	42	32	21	40	124	988	
UA (%)	97	98	100	83.67	73.91	96.04	75	68.29	91	78.26	85.71	71.88	76.19	70	88.71		

Overall accuracy = 88.46%, Kappa = 0.87

Compared to RF, the SVM classifier produced a lower overall accuracy of 55.26% with a kappa coefficient of 0.50 (Table 4.2). SVM classifier produced user's and producer's accuracies ranging from 70% to 100% for the other land cover classes in the area. Noticeably, the SVM algorithm generated a user's accuracy of 0% for *Eucalyptus* species classes, except for *E. terreticornis* with 87.10%. This was also true for the producer's accuracy where *Eucalyptus* species were misclassified, except for *E. terreticornis,* which had the producer's accuracy of 23.08%. Also, the major spectral confusion occurred between other *Eucalyptus* species (*E. camaldulensis, E. citriodora, E. maculata, E. microcorys, E. paniculata, E. pilularis, E. propinqua, E. punctata, E. sideroxlon*) and *E. terreticornis* (*E. terr*). This was due to the close morphological similarity between most *Eucalyptus* species resulting in spectral mix up between them (Table 4.2).

Table 4. 2 Confusion matrix produced using Support Vector machine algorithm for Grassland (GL), Bare soil (BS), other woody vegetation (OWV), Built-up1 (BU1), Built-up (BU) and ten Eucalyptus species such as *E. camaldulensis (E.caml), E. citriodora (E. citr), E. maculate (E. mac), E. microcorys (E. micr), E. paniculata (E. panic), E. pilularis (E. pilul), E. propinqua (E. prop), E. punctate* (*E. punct*), *E. sideroxlon (E. sider*), *E. terreticornis (E. terr).* The confusion matrix (error matrix) includes the Producer's accuracy (PA), User's accuracy (UA), Overall accuracy (OA) and the Kappa coefficient (KA) developed on the test dataset.

Land cover types	**BS**	**BU1**	**BU**	**E. caml**	**E. citr**	**GL**	**E.mac**	**E. micr**	**OWV**	**E. panic**	**E. pilul**	**E. prop**	**E. punct**	**E. sider**	**E. terr**	**Row total**	**PA (%)**
BS	**82**	10	0	6	1	0	0	2	1	0	0	0	0	3	16	121	67.77
BU1	7	**88**	0	1	0	0	0	0	0	0	0	0	0	0	0	96	91.67
BU	0	1	**100**	0	0	0	0	0	0	0	0	0	0	0	0	101	99.01
E.caml	0	0	0	**0**	0	0	0	0	0	0	0	0	0	0	0	0	no data
E.citr	0	0	0	0	**0**	0	0	0	0	0	0	0	0	0	0	0	no data
GL	2	0	0	0	0	**95**	0	0	5	0	0	0	0	0	0	102	93.14
E.mac	0	0	0	0	0	0	**0**	0	0	0	0	0	0	0	0	0	no data
E.micr	0	0	0	0	0	0	0	**0**	0	0	0	0	0	0	0	0	no data
OWV	0	0	0	8	0	6	4	0	**73**	6	1	1	1	0	0	100	73
E.panic	0	0	0	0	0	0	0	0	0	**0**	0	0	0	0	0	0	no data
E.pilul	0	0	0	0	0	0	0	0	0	0	**0**	0	0	0	0	0	no data
E.prop	0	0	0	0	0	0	0	0	0	0	0	**0**	0	0	0	0	no data
E.punct	0	0	0	0	0	0	0	0	0	0	0	0	**0**	0	0	0	no data
E.sider	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**	0	0	no data
E.terr	9	1	0	83	22	0	16	39	21	40	41	31	20	37	**108**	468	23.08
Column total	100	100	100	98	23	101	20	41	100	46	42	32	21	40	124	988	
UA (%)	82	88	100	0	0	94.06	0	0	73	0	0	0	0	0	87.10		

Overall accuracy = 55.26%, Kappa = 0.50

4.6 Classified maps of the study area

The Random Forest algorithm was able to classify the spatial distribution of fifteen classes, the bare soil, grassland, built-up, other woody vegetation, built-up1 and ten classes of *Eucalyptus* species (Figure 4.6). The RF classification image resulted in bare soil and other woody vegetation as dominant land cover classes followed by built up, builtup1 and grassland, while the ten *Eucalyptus* species occupied smaller area of 0.712km^2 for *E. microcorys,* 0.512km^2 for *E. camaldulensis,* 0.047km^2 for *E. citriodora,* 0.104km^2 for *E. maculate,* 0.197km^2 for *E. paniculata,* 0.160km^2 for *E. pilularis,* 0.088km^2 for *E. propinqua,* 0.074km^2 for *E. punctate,* 0.207km^2 for *E. sideroxylon,* and 0.690km^2 for *E. terreticornis*.

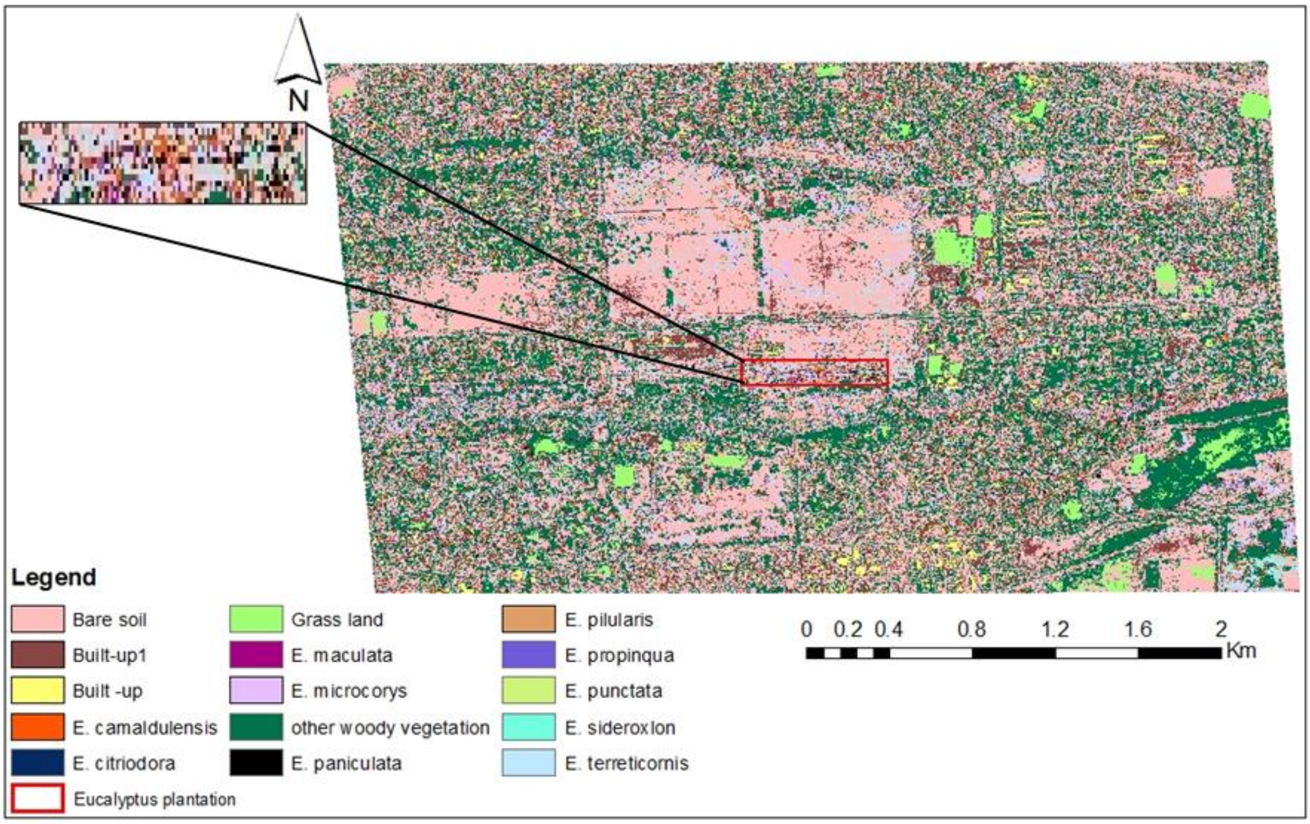


Figure 4. 6 Classified map of 'Tom Jenkins' Eucalyptus plantation in Rietondale, Pretoria East, produced from SPOT 6 image using Random Forest classification algorithm.

A SPOT 6 image was classified using Support Vector Machine to produce a map with six classes of bare soil, grassland, built-up, other woody vegetation, built-up1 and one class of *Eucalyptus* species (*E. terreticornis*) (Figure 4.7). Like RF classification image, bare soil and other woody vegetation were the most dominant land cover types in the SVM classification image. Built-up, builtup1 and grassland occupied relatively smaller areas. One *Eucalyptus* species (*E. terreticornis)* occupied the smallest area. Figure 4.7 shows the overlap between other *Eucalyptus* species and *E. terreticornis*, which resulted in the spectral confusion between them. The SVM algorithm effectively classified all other land cover types except *Eucalyptus* species. This indicated the SVM incapability to distinguish the species, which are morphologically as well as spatially close to each other.

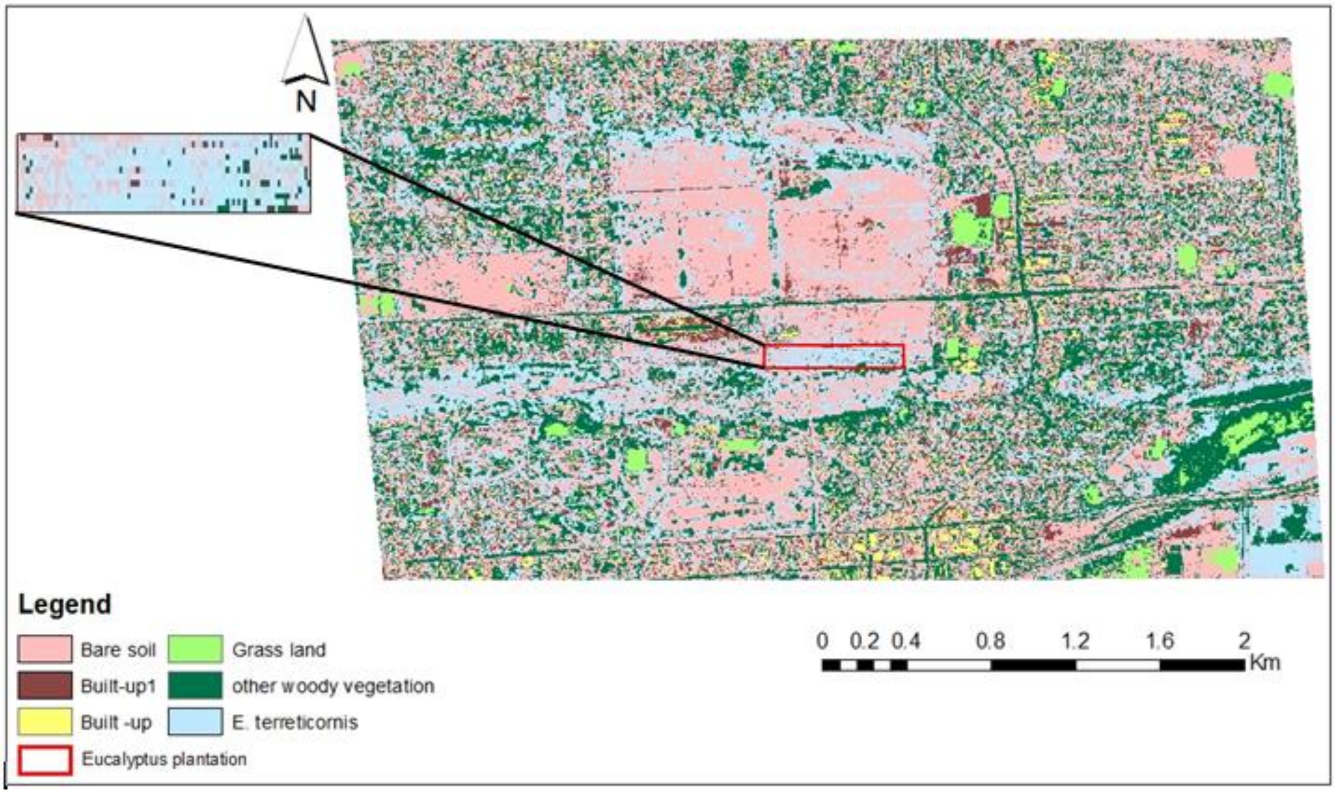


Figure 4. 7 Classified map of ‘Tom Jenkins’ Eucalyptus plantation in Rietondale, Pretoria East, produced from SPOT 6 image using Support Vector Machine algorithm.

The largest area (3.54 km^2) of the study site was open land, followed by woody vegetation. *Eucalyptus* species occupied 32.69% (3.09 km^2) of the total area of the study site (Table 4.3). The other classes (Builtup1, Built-up and Grassland) occupied 0.96 km^2, 0.21 km^2 and 0.23 km^2, respectively. The classes representing *Eucalyptus* species had the smallest area coverage ranging between 0.04 km^2 and 0.71 km^2 (Table 4.3).

Table 4. 3 Area covered by land cover class obtained using SPOT 6 image and Random

Land cover classes	**Area (km^2)**	**Proportion (%)**
Bare soil	3.54018825	32.665
Builtup1	0.96058125	8.863
Builtup	0.21389175	1.974
E. camaldulensis	0.51226425	4.727
E. citriodora	0.0473895	0.437
Grassland	0.2348235	2.167
E. maculate	0.1044045	0.963
E. microcorys	0.7123545	6.573
Other Woody Vegetation	3.0954915	28.562
E. paniculata	0.19728675	1.82
E. pilularis	0.16038225	1.48
E. propinqua	0.087876	0.811
E. punctate	0.073782	0.681
E. sideroxlon	0.20666025	1.907
E. terreticornis	0.69047775	6.371
Total	**10.837854**	**100**

CHAPTER FIVE: DISCUSSION AND CONCLUSION

5.1 Discussion

Eucalyptus is unarguably one of the most economically important tree species in the forest industry. It plays a driving role in the supply of timber and provides a variety of other services such as recreation, landscape, carbon sequestration, watershed protection, and protection from soil erosion (Lopes, 2013). However, *Eucalyptus* has also destructive environmental impact like groundwater depletion. The Biodiversity Act (Act No. 10 of 2004) declares *Eucalyptus* species as category 2 weed, which only allows propagation of eucalyptus in demarcated areas with special permission (South African National Biodiversity Institute, 2015). However, the management of eucalyptus has often been contentious (Newete, 2011) and its removal leads to a conflict of interest in many parts of the country, where the tree species were grown for different socio-economic purposes (Forsyth et al. 2004). Currently, South Africa is experiencing a water crisis due to climate change; therefore, it is of utmost importance to develop effective management of this alien species to conserve existing water resources. Reliable and accurate information about its spatial distribution is essential to containing its spread.

This study investigated the utility of the multispectral image SPOT 6 using Random Forest and Support Vector Machines classifiers to map and discriminate between *Eucalyptus* tree species and other co-existing trees in Tom Jenkins' *Eucalyptus* plantation in Rietondale, Pretoria East. The *Eucalyptus* species were not discriminated using SPOT 6 multispectral images. The separability test conducted using the two methods, Transformed Divergence (TD) and Jeffries Matusita (JM), to effectively discriminate between the different *Eucalyptus* species produced values ranging from 0.0 to 0.6 and 0.0 to 0.4 respectively, indicating poor separability between the species compared to the respective benchmark values of 2 and 1.41, to suggest strong separability. This was due to SPOT 6 incapability in detecting spectral signatures within structurally similar types of vegetation. Therefore, SPOT 6 sensor had limited success in discriminating *Eucalyptus* at the species level, because of its spectral and spatial resolutions limitations. The findings in this study agree with those from the literature. Kganyago et al. (2018) found that SPOT 6 images were incapable of discriminating between *Parthenium hysterophorus* and co-existing species due to spectral overlaps. Odindi et al. (2014) also found that the traditional bands of SPOT-5 sensor were incapable of distinguishing the bracken fern from others. Harvey and Hill (2001) asserted that lower spectral resolution of SPOT imageries contributes to ineffective discrimination between different vegetation types.

In the present study, the classification of the multispectral SPOT 6 imagery using the RF and SVM algorithms produced overall accuracies of 61.09% (Ka = 0.57) and 53.34% (Ka = 0.49), respectively. However, when the model stacking was applied by combining the SPOT 6 four bands and the NDVI-classified image, the overall accuracies were improved to 88.46% (Ka = 0.87) and 55.26% (Ka = 0.50) for both RF and SVM classifier respectively. Similar results were obtained by Mutlu et al. (2008) who combined QuickBird data with airborne LIDAR data and produced an overall accuracy of 90.10% compared to 76.52% overall accuracy using QuickBirg imagery only. The improved overall accuracy of 88.46% obtained for the Random Forest algorithm is similar to those found in previous studies. Forsyth et al. (2014) assessed the utility of SPOT 6 imagery in mapping the invasive alien plant *Pinus* spp. in mountainous area of the Western Cape, and achieved the overall accuracy of 84%. Oumar (2016) also found an overall accuracy of 75% in mapping *Lantana camara* in a community-clearing project in KwaZulu-Natal using the multispectral SPOT 6 imagery.

The mage generated using RF and SVM algorithms produced high producer's and user's accuracy for other land cover classes except for *Eucalyptus* species, which showed spectral confusion between the species, particularly between *E. camaldulensis* (*E. caml*) and *E. terreticornis* (*E. terr*). The user's accuracy and producer accuracy for *Eucalyptus camaldulensis* obtained was 83.67% and 67.21%, while those of *E. terreticornis* were 88.71% and 80.88% respectively. This was due to similar morphology in *E. camaldulensis* and *E. tereticornis* subspecies (Slee et al., 2006). Brooker and Kleinig (2004) and Slee et al. (2006) found that *E. camaldulensis* and *E. terreticonris* subspecies are morphologically very similar, the identical bud shapes in particular.

Even though the classification of SPOT 6 image and RF algorithm produced satisfactory user's and producer's accuracies levels for *Eucalyptus* species, the SVM classifier performed poorly with many species inaccurately classified in a different group. The spectral misclassification of the *Eucalyptus* classes resulted from the high spectral confusion among the species in this genus due to the similarity in their spectral signatures. This was also because most *Eucalyptus* trees canopies were closely overlapping. Thus, the SVM algorithm was found unsuitable for classification of *Eucalyptus* species in dense population.

Random Forest (RF) and Support Vector Machine (SVM) are the common algorithms used in classifying land cover types (Huang et al., 2002; Rodriguez-Galiano et al., 2012; Thanh Noi & Kappas, 2018). Random Forest algorithm produced acceptable overall accuracy while the Support Vector Machine algorithm produced slight accuracy for SPOT 6 imagery. However, the Random Forest algorithm, with 88.46%, achieved higher overall accuracy than the SVM algorithm (55.26%). This concurs with Pal (2005) who, when comparing these two algorithms, found that RF classifier outperformed the SVM classifier. The advantage of using the RF algorithm is that it allows combining many decision trees to optimize the classification and regression trees approach (Breiman, 2001). This makes it a robust classifier capable of dealing with errors or outliers. Thus, the classification accuracy was higher in the RF than in SVM. Sesnie et al. (2010) also reported good performance of RF than SVM classifiers with 86.7% and 84.3% respectively, which is very close to the Random Forest results obtained in this study. This present study proved the robustness of the RF algorithm in identifying the important variables, which improved the classification results.

The combination of the multispectral SPOT 6 image and Random Forest classification algorithm successfully enhanced the mapping of *Eucalyptus* species and its distribution in 'Tom Jenkins' plantation, at Reitondale, Pretoria East. Random Forest algorithm and SPOT 6 image generated the highest accuracy levels.

5.2 Conclusion

The main aim of this study was to assess the utility of SPOT 6 multi-spectral imagery in mapping and discriminating between *Eucalyptus* species in 'Tom Jenkins' plantation, in Reitondale, Pretoria. Separability analysis was performed to examine the ability of SPOT 6 imagery in distinguishing between *Eucalyptus* species. The results of separability analysis, as revealed by the different SPOT 6 bands and the vegetative indice (NDVI), indicated that *Eucalyptus* species were inseparable indicating that the medium resolution multispectral SPOT 6 image could not effectively discriminate between the closely related *Eucalyptus* species with overlapping canopies. The Transformed Divergence (TD) and Jeffries Matusita Distance (JM) measurements, conducted in this study produced values between 0 and 1 which were lower than the benchmark values of 2 and 1.41 for TD and JM, respectively. Similarly, the Random Forest (RF) and Support Vector Machine (SVM) algorithms used for classification between the *Eucalyptus* species yielded poor results with overall accuracy levels of 61.09% (Ka = 0.57) and 53.34% (Ka = 0.49), respectively. Nevertheless, despite the evident spectral confusion and the misclassification in the RF and SVM classifiers used, the results were remarkably enhanced, particularly for RF when Model Stacking was applied by combining the four bands of SPOT 6 and the NDVI to overall accuracies of 88.46% and 55.26% (Ka = 0.50) respectively. The RF algorithm outperformed the SVM significantly, suggesting the suitability of the former classifier in Eucalyptus plantation at the species level, particularly where overlapping canopies occur.

It is recommended to investigate the object-based classification of *Eucalyptus* species in SPOT 6 imageries to effectively discriminate between *Eucalyptus* species with close morphological similarity for future studies.

Reference List

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

Albaugh, J. M., Dye, P. J., & King, J. S. (2013). Eucalyptus and water use in South Africa. *International Journal of Forestry Research*, *2013*.

ASTRIUM. (2015). *SPOT 6 | SPOT 7 Technical Features*. Retrieved from https://www.intelligence-airbusds.com/files/pmedia/public/r12317_9_spot6-7_technical_sheet.pdf [Accessed 20 May 2019]

Atkinson, P. M., & Tatnall, A. R. (1997). Introduction neural networks in remote sensing. *International Journal of Remote Sensing*, *18*(4), 699–709.

Bloch, I. (1994). Information combination operators for data fusion: A comparative review with classification. *Image and Signal Processing for Remote Sensing*, *2315*, 148–159. International Society for Optics and Photonics.

Bloch, I. (1996). Information combination operators for data fusion: A comparative review with classification. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, *26*(1), 52–67.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32.

Brooker, I., & Kleinig, D. A. (2004). *Field Guide to Eucalyptus. Melbourne: Inkata Press.*

Butcher, P. A., McDonald, M. W., & Bell, J. C. (2009). Congruence between environmental parameters, morphology and genetic structure in Australia's most widely distributed eucalypt, Eucalyptus camaldulensis. *Tree Genetics & Genomes*, *5*(1), 189.

Campbell, J. B., & Wynne, R. H. (2011). *Introduction to remote sensing*. New York & London: Guilford Press.

Congalton, R. G., & Green, K. (2002). *Assessing the accuracy of remotely sensed data: Principles and practices*. Boca Raton: CRC press.

Coppen, J. J. (2002). *Eucalyptus: The genus Eucalyptus*. New York & London: CRC Press.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, *20*(3), 273–297.

Davidson, J. (1993). Ecological aspects of Eucalyptus plantations. *Proceedings of the Regional Expert Consultation on Eucalyptus*, *1*, 35–60. RAPA/FAO, Bangkok, Thailand.

de Assis, T. F. (2000). Production and use of Eucalyptus hybrids for industrial purposes. *Hybrid Breeding and Genetics of Forest Trees. Proceedings of QFRI/CRC-SPF Symposium*, 63–74.

Dessie, G. (2011). *Eucalyptus in East Africa: Socio-economic and environmental issues*. International Water Management Institute.

Doughty, R. W. (2000). *The Eucalyptus: A natural and commercial history of the gum tree.* Johns Hopkins University Press.

Dungey, H. S., & Potts, B. M. (2002). Susceptibility of some Eucalyptus species and their hybrids to possum damage. *Australian Forestry*, *65*(1), 23–30.

Dye, Peter J. (2000). Water use efficiency in South African Eucalyptus plantations: A review. *Southern African Forestry Journal*, *189*(1), 17–26.

Dzikiti, S., Gush, M. B., Le Maitre, D. C., Maherry, A., Jovanovic, N. Z., Ramoelo, A., & Cho, M. A. (2016). Quantifying potential water savings from clearing invasive alien Eucalyptus camaldulensis using in situ and high resolution remote sensing data in the Berg River Catchment, Western Cape, South Africa. *Forest Ecology and Management*, *361*, 69–80.

Fassnacht, F. E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L. T., Ghosh, A. (2016). Review of studies on tree species classification from remotely sensed data. *Remote Sensing of Environment*, *186*, 64–87. https://doi.org/10.1016/j.rse.2016.08.013

Field, D. L., Ayre, D. J., Whelan, R. J., & Young, A. G. (2008). Relative frequency of sympatric species influences rates of interspecific hybridization, seed production and seedling performance in the uncommon Eucalyptus aggregata. *Journal of Ecology*, *96*(6), 1198–1210.

Florence, R. G. (1986). Cultural problems of Eucalyptus as exotics. *The Commonwealth Forestry Review*, 141–163.

Foody, G. M., & Mathur, A. (2004). Toward intelligent training of supervised image classifications: Directing training data acquisition for SVM classification. *Remote Sensing of Environment*, *93*(1–2), 107–117.

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

Forsyth, G. G., Richardson, D. M., Brown, P. J., & Van Wilgen, B. W. (2004). A rapid assessment of the invasive status of Eucalyptus species in two South African provinces: Working for water. *South African Journal of Science*, *100*(1–2), 75–77.

Ghimire, B., Rogan, J., & Miller, J. (2010). Contextual land-cover classification: Incorporating spatial dependence in land-cover classification models using random forests and the Getis statistic. *Remote Sensing Letters*, *1*(1), 45–54.

Ghisalberti, E. L. (1996). Bioactive acylphloroglucinol derivatives from Eucalyptus species. *Phytochemistry*, *41*(1), 7–22.

Gilles, M., Zhao, J., An, M., & Agboola, S. (2010). Chemical composition and antimicrobial properties of essential oils of three Australian Eucalyptus species. *Food Chemistry*, *119*(2), 731–737.

Gislason, P. O., Benediktsson, J. A., & Sveinsson, J. R. (2006). Random forests for land cover classification. *Pattern Recognition Letters*, *27*(4), 294–300.

Govender, M., Chetty, K., Naiken, V., & Bulcock, H. (2008). A comparison of satellite hyperspectral and multispectral remote sensing imagery for improved classification and mapping of vegetation. *Water SA*, *34*(2), 147–154.

Greyling, I., Wingfield, M. J., Coetzee, M. P., Marincowitz, S., & Roux, J. (2016). The Eucalyptus shoot and leaf pathogen Teratosphaeria destructans recorded in South Africa. *Southern Forests: A Journal of Forest Science*, *78*(2), 123–129.

Güneş, F., Wolfinger, R., & Tan, P.-Y. (2017). Stacked ensemble models for improved prediction accuracy. *Proc. Static Anal. Symp.*, 1–19.

Harvey, K. R., & Hill, G. J. E. (2001). Vegetation mapping of a tropical freshwater swamp in the Northern Territory, Australia: A comparison of aerial photography, Landsat TM and SPOT satellite imagery. *International Journal of Remote Sensing*, *22*(15), 2911–2925.

Hatami, N., & Ebrahimpour, R. (2007). Combining multiple classifiers: Diversify with boosting and combining by stacking. *International Journal of Computer Science and Network Security*, *7*(1), 127–131.

Healey, S. P., Cohen, W. B., Yang, Z., Brewer, C. K., Brooks, E. B., Gorelick, N., … Kennedy, R. E. (2018). Mapping forest change using stacked generalization: An ensemble approach. *Remote Sensing of Environment*, *204*, 717–728.

Hellmann, M., & Rathgeber, W. (2015). European Member States Satellite Programs. In K.-U. Schrogl, P. L. Hays, J. Robinson, D. Moura, & C. Giannopapa (Eds.), *Handbook of Space Security: Policies, Applications and Programs* (pp. 831–842). https://doi.org/10.1007/978-1-4614-2029-3_23

Huang, C., Davis, L. S., & Townshend, J. R. G. (2002). An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing*, *23*(4), 725–749.

Immitzer, M., Vuolo, F., & Atzberger, C. (2016). First experience with Sentinel-2 data for crop and tree species classifications in central Europe. *Remote Sensing*, *8*(3), 166.

Jagger, P., & Pender, J. (2003). The role of trees for sustainable management of less-favored lands: The case of eucalyptus in Ethiopia. *Forest Policy and Economics*, *5*(1), 83–95.

Kganyago, M., Odindi, J., Adjorlolo, C., & Mhangara, P. (2018). Evaluating the capability of Landsat 8 OLI and SPOT 6 for discriminating invasive alien species in the African Savanna landscape. *International Journal of Applied Earth Observation and Geoinformation*, *67*, 10–19.

Khare, S., Latifi, H., Rossi, S., & Ghosh, S. K. (2019). Fractional Cover Mapping of Invasive Plant Species by Combining Very High-Resolution Stereo and Multi-Sensor Multispectral Imageries. *Forests*, *10*(7), 540.

Ladiges, P. Y., Gray, A. M., & Brooker, M. I. H. (1981). Pattern of Geographic Variation, Based on Seedling Morphology, in Eucalyptus Ovata Labill. And E. Brookerana Am Gray [Provenances From Victoria, Tasmania and King Island] and Comparisons With Some Other Eucalyptus Species. *Australian Journal of Botany*, *29*(5), 593–603.

Le Maitre, D. C., Forsyth, G. G., Dzikiti, S., & Gush, M. B. (2016). Estimates of the impacts of invasive alien plants on water flows in South Africa. *Water SA*, *42*(4), 659–672.

Little, K. M., & Gardner, R. A. (2003). Coppicing ability of 20 Eucalyptus species grown at two high-altitude sites in South Africa. *Canadian Journal of Forest Research*, *33*(2), 181–189.

Lopes, A. F. F. (2013). *The economic value of Portuguese pine and eucalyptus forests* (PhD Thesis). National Society of Black Engineers-University of Nebraska-Lincoln.

Mantero, P., Moser, G., & Serpico, S. B. (2005). Partially supervised classification of remote sensing images through SVM-based probability density estimation. *IEEE Transactions on Geoscience and Remote Sensing*, *43*(3), 559–570.

Mills, H. (2008). Analysis of the transferability of support vector machines for vegetation classification. *Proc. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci*, *37*, 557–563.

Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *66*(3), 247–259.

Mugunga, C. (2016). *The use of Eucalyptus in agroforestry systems of southern Rwanda: To integrate of segregate* (PhD Thesis). Wageningen University.

Murakami, T., Ogawa, S., Ishitsuka, N., Kumagai, K., & Saito, G. (2001). Crop discrimination with multitemporal SPOT/HRV data in the Saga Plains, Japan. *International Journal of Remote Sensing*, *22*(7), 1335–1348.

Musil, F. C., & Macdonald, I. A. W. (2007). *Invasive alien flora and fauna in South Africa: Expertise and bibliography*.

Mutlu, M., Popescu, S. C., Stripling, C., & Spencer, T. (2008). Mapping surface fuel models using lidar and multispectral data fusion for fire behavior. *Remote Sensing of Environment*, *112*(1), 274–285.

Nelson, M. (2017). *Evaluating Multitemporal Sentinel-2 data for Forest Mapping using Random Forest*.

Newete, S. W., Erasmus, B. F., Weiersbye, I. M., Cho, M. A., & Byrne, M. J. (2014). Hyperspectral reflectance features of water hyacinth growing under feeding stresses of Neochetina spp. And different heavy metal pollutants. *International Journal of Remote Sensing*, *35*(3), 799–817.

Newete, S. W., Oberprieler, R. G., & Byrne, M. J. (2011). The host range of the Eucalyptus Weevil, Gonipterus “scutellatus” Gyllenhal (Coleoptera: Curculionidae), in South Africa. *Annals of Forest Science*, *68*(5), 1005–1013.

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

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

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

Palanisami, K., & Joshi, M. (2011). Impact of eucalyptus plantations on groundwater availability in South Karnataka. In *21st International Congress on Irrigation and Drainage, 15-23 October 2011*

Phinzi, K., & Ngetar, N. S. (2017). Mapping soil erosion in a Quaternary catchment in Eastern Cape using Geographic information system and remote sensing. *South African Journal of Geomatics*, *6*(1), 11–29.

Pohl, C., & Van Genderen, J. L. (1998). Review article multisensor image fusion in remote sensing: Concepts, methods and applications. *International Journal of Remote Sensing*, *19*(5), 823–854.

Potts, B. M., Hamilton, M. G., & Blackburn, D. P. (2011). *Genetics of Eucalyptus: Traps and opportunities*.

Potts, B. M., & Reid, J. B. (1983). Hybridization between Eucalyptus obliqua L'Herit. And E. pulchella Desf. *Australian Journal of Botany*, *31*(3), 211–229.

Potts, Brad M., & Dungey, H. S. (2004). Interspecific hybridization of Eucalyptus: Key issues for breeders and geneticists. *New Forests*, *27*(2), 115–138.

Potts, Brad M., Volker, P. W., Tilyard, P., & Joyce, K. (2000). *The genetics of hybridisation in the temperate Eucalyptus*.

Pretoria Geography Information, climate and weather in Pretoria. (n.d.). Retrieved September 15, 2019, from https://www.pretoria.com/v/geography/

Richardson, D. M., & Van Wilgen, B. W. (2004). Invasive alien plants in South Africa: How well do we understand the ecological impacts?: working for water. *South African Journal of Science*, *100*(1–2), 45–52.

Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *67*, 93–104.

Rudiastuti, A. W., Yuwono, D. M., & Hartini, S. (2018). Mangrove Mapping Using SPOT 6 at East Lombok Indonesia. *IOP Conference Series: Earth and Environmental Science*, *165*, 012005. IOP Publishing.

Scholes, R. J., Berns, J., Everard, D. A., Scott, D., Van Tienhoven, M., & Viljoen, P. (1995). The costs and benefits of forestry, case studies from Mpumalanga. *Report For–DEA 939, Environmental, CSIR, Pretoria*.

Sertel, E., & Alganci, U. (2016). Comparison of pixel and object-based classification for burned area mapping using SPOT 6 images. *Geomatics, Natural Hazards and Risk*, *7*(4), 1198–1206.

Sesnie, S. E., Finegan, B., Gessler, P. E., Thessler, S., Ramos Bendana, Z., & Smith, A. M. (2010). The multispectral separability of Costa Rican rainforest types with support vector machines and Random Forest decision trees. *International Journal of Remote Sensing*, *31*(11), 2885–2909.

Shima, L. J., Anderson, R. R., & Carter, V. P. (1976). The use of aerial color infrared photography in mapping the vegetation of a freshwater marsh. *Chesapeake Science*, *17*(2), 74–85.

Sill, J., Takács, G., Mackey, L., & Lin, D. (2009). Feature-weighted linear stacking. *ArXiv Preprint ArXiv:0911.0460*.

Slee, A. V., Brooker, H., Duffy, M., & West, J. G. (2006). EUCLID Eucalyptus of Australia. DVD edn. *Centre for Plant Biodiversity Research–CSIRO publishing Canberra*.

Sonawane, K. R., & Bhagat, V. S. (2017). Improved change detection of forests using Landsat TM and ETM+ data. *Remote Sensing of Land*, *1*(1), 18–40.

South African National Biodiversity Institute. (2015). *Gums & Beesâ: A roadmap for landowners in South Africa*.

Swain, P. H., & Davis, S. M. (1981). Remote sensing: The quantitative approach. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, (6), 713–714.

Teulieres, C., & Marque, C. (2007). II. 3 Eucalyptus. *Transgenic Crops*, *60*, 387.

Thanh Noi, P., & Kappas, M. (2018). Comparison of random forest, k-nearest neighbor, and support vector machine classifiers for land cover classification using Sentinel-2 imagery. *Sensors*, *18*(1), 18.

Ting, K. M., & Witten, I. H. (1999). Issues in stacked generalization. *Journal of Artificial Intelligence Research*, *10*, 271–289.

Trigg, S., & Flasse, S. (2001). An evaluation of different bi-spectral spaces for discriminating burned shrub-savannah. *International Journal of Remote Sensing*, *22*(13), 2641–2647.

Turner, W., Spector, S., Gardiner, N., Fladeland, M., Sterling, E., & Steininger, M. (2003). Remote sensing for biodiversity science and conservation. *Trends in Ecology & Evolution*, *18*(6), 306–314.

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

Van Wilgen, B. W., Le Maitre, D. C., & Cowling, R. M. (1998). *Ecosystem services, efficiency, sustainability and equity: South Africa's Working for Water programme*.

Van Wilgen, B. W., Richardson, D. M., Le Maitre, D. C., Marais, C., & Magadlela, D. (2001). The economic consequences of alien plant invasions: Examples of impacts and approaches to sustainable management in South Africa. *Environment, Development and Sustainability*, *3*(2), 145–168.

Vilà, M., Weber, E., & Antonio, C. M. (2000). Conservation implications of invasion by plant hybridization. *Biological Invasions*, *2*(3), 207–217.

Zhai, B., & Chen, J. (2018). Development of a stacked ensemble model for forecasting and analyzing daily average PM2. 5 concentrations in Beijing, China. *Science of the Total Environment*, *635*, 644–658.