Mapping Eucalyptus trees in Johannesburg city using high resolution multispectral image

By

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Declaration

I, Shelter Mangwanya, 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. I would like to declare that the research work reported in this dissertation 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.

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Signature of candidate

…………**26th**………… day of ……**October 2018**……

Abstract

Invasive alien plants are considered as a major threat to ecological and socioeconomic systems. Nevertheless, because of the socioeconomic benefits some alien plants provide, their management is often complicated by controversies. Thus, understanding their spatial distribution and abundance facilitates management decision making processes of invasive alien species. Mapping plant species in a heterogeneous environment such as highly urbanized areas is often complicated by high spectral confusion between species. This study investigated the utility of new generation WorldView-2 (WV2) satellite imagery with both high spectral and spatial resolution in mapping eucalyptus in the historical mining area located south of Johannesburg city. It also evaluated if the medium spatial resolution satellite image SPOT-7 could be used as a cheaper alternative to map eucalyptus trees in an urban environment. Furthermore, the performances of Random Forest (RF) and Support Vector Machines (SVM) were compared to determine the most effective classification algorithms between the two methods. Both WV-2 image and SPOT-7 image attained satisfactory overall accuracies, although the WV-2 performed better than the SPOT-7 imagery. WV-2 attained accuracies of 81.67% (0.78 kappa) for RF algorithm and 80% (0.76 Kappa) for SVM algorithm, whilst SPOT-7 had overall accuracies of 72.78% (0.67 kappa) for RF and 71.11% (0.65 Kappa) for SVM. Although the overall accuracies for SPOT image was satisfactory, the user's accuracies for the eucalyptus class was very low (60% and 56.67% for RF and SVM algorithms, respectively). This suggests that WV-2, with higher user's accuracies for the eucalyptus class (73.33% and 70% for RF and SVM algorithms, respectively), is more suitable for mapping eucalyptus trees in an urban area than the SPOT data. The two classification algorithms showed high accuracy levels for both satellite data, although RF had slightly higher accuracies than SVM. The combination of WV-2 image and RF produced a more accurate map of the eucalyptus trees in the study areas. The overall accuracy was 81.67% and a kappa coefficient of 0.78 and eucalyptus class attained user's and producer's accuracies of 73.33% and 75.86%, respectively.

Dedication

I sorely dedicate this master's research project to my lovely parents Mr and Mrs Mangwanya.

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Firstly, I would like to acknowledge the Mighty God; our Father in heaven, for His love endures forever.

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Acronyms and their description

RF	Random Forest
WV-2	WorldView-2
SPOT-7	Satellite Pour l'Observation de la Terre
OOB	Out-Of-Bag
SVM	Support Vector Machine
LULC	Land use and land cover
GPS	Ground Positioning System

CHAPTER ONE: GENERAL INTRODUCTION

1.1. Background

Alien invasive plants are non-indigenous plant species living outside their native geographical range and are believed to be detrimental to the environment, human health or human economy (Richardson and Van Wilgen, 2004). The management of many invasive alien plants is often challenged by a number of controversies because of their positive and negative socio-economic and ecological impacts in the environment. For instance, timber production, and reduction of urban heat island and storm water runoff are some of the benefits to the economy and ecosystem, while pavement cracking and ground water reduction are among some of the ecosystem disservices of eucalyptus trees (Zengeya *et al*, 2017).

In South Africa, management of alien species is guided by the legislation of National Environmental Management: Biodiversity Act (NEM: BA) (Act 10 of 2004) (Zengeya *et al.*, 2017). Eucalyptus trees are listed as invasive species under category 1b, which necessitates their complete removal and control and their growth is only allowed with permission in demarcated farms for timber production lands (Department of Environmental Affairs, 2014). Eucalyptus trees are one of the abundant invasive alien plants in Johannesburg city (Buff, 2012).

Johannesburg is home to many trees and is often considered as the most forested city in the world (Schäffler and Swilling, 2013). The actual number of trees in the city has always been equivocal, but many sources suggest that it is approximately six to ten million (Maitre *et al*., 2002; Wynberg, 2002). Many of the park and street trees in the city of Johannesburg, just like in many urban areas of the developing countries, are the legacy of the former European colonist, and are predominantly exotic species largely concentrated in the affluent suburbs.

Eucalyptus species are native to Australia and they were first introduced to Johannesburg by European colonialists in late 1900s to settle dust from gold mines and for timber to support the mining industry (Carbonnier *et al*., 2004). It was the preferred species to plant around

Johannesburg, a city often referred as the ‘city of gold’, where to this day several abandoned tailings dams with eucalyptus trees are still conspicuous in the outskirt of the city. This is because of eucalyptus' fast growth rate and its adaptability to thrive in a wide range of climatic conditions including in highly contaminated soils with Acid Mine Drainage (AMD) and other metal contaminants (Carbonnier *et al*., 2004).

Ecosystem services of eucalyptus trees to the city includes regulating local climate, trapping air pollutants, reduction of noise, fixing atmospheric carbon, phytoremediation etc. (Pejchar and Mooney, 2009). Despite these ecosystem services, eucalyptus trees also have a negative impact on the urban ecosystem. Some of such disservices of eucalyptus include emission of volatile organic compounds (VOCs) (i.e. butane, monoterpenes, isoprene, ethane, propene, acetaldehyde, acetic acid, formaldehyde, and formic acid) and loss of water resource through evapotranspiration (Pejchar and Mooney, 2009). These VOCs cause air pollution which contributes to greenhouse effect and are also detrimental to the ozone layer (Gunther *et al*., 1995).

The major conflict of interest regarding eucalyptus trees is that while the country has the mandate to reduce the impact of alien invasive species, economic benefits and ecosystem services from eucalyptus cannot be ignored (Moran *et al*., 2013). Such issues complicate the management of eucalyptus trees. However, to properly manage invasive species, it is important to understand the distribution of the alien plant species. (Cho *et al*., 2015). For instance, eucalyptus forest in the outskirt of the city of Johannesburg around the historical mining waste dumps plays a vital role as phytoremediation agents as opposed to the same plantations in the inner cities such as street and park eucalyptus trees. Thus, determining their geographical distribution and abundance within the city appropriately facilitates their proper management and prioritization of resource allocation accordingly. Therefore, there is need for mapping and determining the distribution and abundance of eucalyptus trees in Johannesburg.

Identification and mapping of tree species using traditional field-based methods are tedious, time-consuming and costly (Mureriwa *et al*., 2015). However, remote sensing is capable of facilitating the acquisition of such information effectively (Akasheh *et al*., 2008). Remote sensing from airborne and or satellites platforms acquire information about objects or land surfaces on earth without physical contact (Adam *et al*., 2010). Multispectral and hyperspectral imagery have been used in mapping vegetation species in different landscapes worldwide (Lawrence *et al*., 2006). Mapping vegetation at species level using hyperspectral data is much better than multispectral data, since it has a higher spectral resolution than multispectral sensors and is capable of providing a detailed information about an object remotely acquired. However, hyperspectral data is expensive and also processing dimensional data is challenging and causes redundancy. The recent advent of high resolution multispectral imageries such as WorldView series, Sentinel series and RapidEye has made it possible to map vegetation at species level (Mutanga *et al*., 2012). Therefore, this research focused on mapping the distribution of *Eucalyptus* species around the historical mining areas located south of Johannesburg city using WorldView-2 imagery, which has a spatial resolution of 2m and eight spectral bands, and SPOT-7 which has four spectral bands with 6m spatial resolution.

1.2.Rationale

Eucalyptus trees are listed as invasive species under category 1b necessitating its growth only permitted designated lands (Department of Environmental Affairs, 2014). This is because of its unrelenting ability to compete and exclude indigenous species as well as its enormous water consumption lost by evapotranspiration (Boulet *et al*., 2015). However, these trees are also famous for their economic contributions. For example, eucalyptus produces timber upon which the forestry industry in South Africa thrives profitably. In addition, eucalyptus also offers ecosystem services such as regulating local climate, trapping air pollutants, reduction of noise, fixing atmospheric carbon, phytoremediation etc. (Schäffler and Swilling, 2013). Regardless of its positive and negative socio-economic and ecological impacts, eucalyptus continue to exist in and outside the city of Johannesburg and a proper assessment of its distribution and abundance around Johannesburg suburbs allows to formulate effective policy and legislation for appropriate management of the eucalyptus species. To understand the ecosystem services and disservices of eucalyptus trees, up-to-date spatial data about the distribution and the density of the trees among other land use and land cover types is essential. Remote sensing has been used successfully in mapping tree in different landscapes. However, mapping tree species in urban environment is challenging due to the high heterogeneity which causes spectral confusion and poor distinction between discrete and continuous cover types and lower classification accuracies (Immitzer *et al*., 2012). The use of high-resolution data such as WorldView series and advanced classification algorithms like random forest and Support Vector machines can be helpful to overcome such problems.

1.3. Research questions

a) What is the distribution and extent of eucalyptus trees in the historical mining areas located south of Johannesburg city?
b) Which algorithm performs better in classification of eucalyptus in an urban set-up between Random forest (RF) and Support Vector Machine (SMV)?
c) Can SPOT-7 imagery be used as a cost-effective method to map *Eucalyptus* species?

1.4. Aims and Objectives

The main aim of this research is to investigate the efficiency of multispectral imageries in mapping eucalyptus trees in the historical mining area located south of Johannesburg city.

The main objectives of this study are:

1. To compare the performance of WorldView-2 and SPOT-7 images in mapping eucalyptus in the historical mining area located south of Johannesburg city.
2. To evaluate the performance of Random Forest and Support Vector Machine learning algorithms in mapping eucalyptus trees using WorldView-2 and SPOT-7 imagery.
3. To identifying the contribution of WV-2 and SPOT-7 on mapping the eucalyptus trees using Random Forest variable importance measurement index.

CHAPTER TWO: LITERATURE REVIEW

2.1. Invasive alien plants in South Africa

The growing numbers of invasive species around the globe is threatening the natural ecosystem and the livelihood of local communities in the place of introduction (Richardson and Van Wilgen, 2004). The rapid spread of alien plants is accelerated by global trade and tourism (Marais *et al*., 2004). Alien plants have adverse impacts on human health, agricultural activities and the native species (Chornesky *et al*., 2003; Marais *et al*., 2004). South Africa is one of the counties that have dedicated enormous funds towards the management of invasive alien plants (Van Wilgen *et al*., 2012). The South African government has also put in place legislation that governs alien invasive species regulation. Management regulations of invasive alien plants are clearly indicated in the National Environmental Management Biodiversity Act (Act 10 of 2004) of South Africa according to the level of their socio-ecological impacts (Kraaij *et al*., 2017). The country has a long history of unwavering commitment in the management of invasive alien plants, for instance, Department of Agriculture; Plant Protection initiated biological control of invasive plants in 1930 (Richardson and Van Wilgen, 2004)

Woody alien vegetation has an impact on water resources (Le Maitre *et al*., 2000). *Pinus, Acacia* and *Eucalyptus* species are the woody species that has the highest water consumption rates and are a major concern in water strained environment like South Africa. A research by Prinsloo and Scott (1999) indicated that clearing *Eucalyptus* and *Acacia* species in Somerset West in the Western Cape increased stream flow by 12 m^3/ha/day.

2.2. Eucalyptus and its global distribution

Eucalyptus trees are evergreen plants that grow in wide geographical and climatic conditions. The fast-growing eucalyptus trees can produce significantly high amounts of biomass within a short space of time (Pulford and Dickinson, 2006). In addition, some eucalyptus species are tolerant to wide range of pH and salinity levels (Abo-Hassan *et al*., 1988). They are also known to be tolerant to high concentration of metal contaminants (Fine *et al*., 2014). The tree has a deep root system that helps it to access ground water in times of dry spells (Pulford and Dickinson, 2006).

Eucalyptus is native to Australia. However, the species are found in many parts of the world where climatic conditions are conducive for the plant. Australia has the biggest Eucalyptus natural forest, covering approximately 41 million ha (Junghans *et al*., 2003). It is the world's most cultivated hardwood and is one of the world's largest biomass source (Pua and Davey, 2007). Eucalyptus plantations are estimated to cover approximately 19 million ha in 37 countries worldwide excluding Australia (Carbonnier *et al*., 2004) and it is estimated to cover 16% of the world's forest plantations (FAO, 2000). The world's biggest eucalyptus grower is India with 8 million ha, followed by Brazil with 3 million ha (Junghans *et al*., 2003). There are approximately 700 *Eucalyptus* species. *Eucalyptus grandis* is the common species cultivated in warm subtropics and temperate regions, while *E. camaldulensis* is usually found in semi-arid and arid areas and *E. globulus* is commonly found in temperate climates that are not prone to severe frosts (Pua and Davey, 2007).

2.3. History of Eucalyptus in South Africa

The introduction of alien trees in South Africa began in the 1800s. British colonialists believed that planting trees can increase rainfall in dry environments and they also wanted trees for timber and shelter from the wind and the sun (Carbonnier *et al*., 2004). Botanists started to investigate on exotic species that grows best under South African conditions. Species from Australia, which include the *Eucalyptus* and *Acacia* species, were found to be suitable for the South African environment. British colonialist started to import and plant *Acacia* and *Eucalyptus* species in the 1820s (Carbonnier *et al*., 2004). Colonial history suggests that the governor, Sir Galbraith Lowry Cole, introduced *Eucalyptus globulus* (blue gum) from Mauritius into the Cape in 1828 (Carbonnier *et al*., 2004). By 1890s, *Eucalyptus* species' economic value increased and the species spread to most parts of the county, especially in Mpumalanga and KwaZulu-Natal. In the present-day Eucalyptus covers approximately 500 thousand ha in South Africa (Dzikiti *et al*., 2016). Eucalyptus quickly spread within the country because of its economic value, fast growth rate and its biological ability to adapt and thrive in a wide range of environmental conditions of the country (Dzikiti *et al*., 2016). In addition, its fast spread in many parts of the country was attributed to the fact that eucalyptus is also believed to prevent malaria and other tropical diseases, largely associated to its ability to drain swampy areas and its secretion of strongly scented oils (Carbonnier *et al*., 2004).

2.4. Eucalyptus in Johannesburg

Although the contemporary city of Johannesburg is known as one of the cities with the highest tree density in the world, it was initially a bare city until the discovery of gold (Buff, 2012). It was a typical savannah grassland system with scattered shrubs. After gold was discovered in 1886, mining companies needed strong wood for their shafts and trees to settle dust particles (Turton *et al*., 2006). A tree nursery was developed at Zoo Lake Horticultural training center where experiments were tested for their suitability as mine props (Buff, 2012). *Eucalyptus globulus* was found to be among the most suitable species for the aforementioned purposes and therefore, a large number of this species were planted in areas like Fairlands, Parktown, Saxonwold, Langlaagte and Craighall (Buff, 2012). Eucalyptus is now one of the most abundant exotic trees in Johannesburg.

2.5. Controversies around eucalyptus

The general perception about invasive alien species like eucalyptus is that they have negative impacts on the ecosystem and the natural environment. However, eucalyptus trees also have benefits that they can offer.

2.5.1. Socio-economic importance of Eucalyptus.

Characteristic properties of eucalyptus such as its ability to grow fast, and its high production of quality wood make it a tree of high economic importance in many countries. It is the main source of timber and is used for energy, charcoal, housing, furniture, pulp and paper production (FAO, 2000). Some of the factors that have contributed to the popularity of eucalyptus include; its ability to grow in a wide range environment, high biomass production, quality of wood and its fast growth rate (Labate *et al*., 2009). *Eucalyptus* species are the most dominant species in forests of which wood-based products accounts for 2% of the global gross domestic product and it contributes a significant amount to basic energy needs (FAO, 2000).

Its timber is also widely used in construction, communications, packaging and furniture. Eucalyptus trees are also important in the beehive industry. In rural areas of developing countries, wood is the main source of energy and most of the indigenous trees have been exhausted. In such cases, growing eucalyptus trees has a comparative advantage over indigenous species because of their ability to grow fast and produce a large biomass within a short period as compared to indigenous species (Mbatha and De Wet, 2018; Turnbull, 1999).

Eucalyptus can thrive under unfavourable conditions. For instance, they can grow under saline conditions and are highly tolerant to a wide range of pH and they can also grow in highly heavy metal contaminated soils. For example, eucalyptus trees have been grown for firewood purposes in degraded soils of rural areas in southern China (Turnbull, 1999). Furthermore, eucalyptus plantations employ an enormous number of people across the world. For instance, the pine and eucalyptus plantations collectively employ about 100 000 people in South Africa (Le Maitre *et al*., 2002).

Eucalyptus trees are part of the urban green environments. There are several parks in Johannesburg and eucalyptus is one of the common tree species in these parks. Many people use parks for physical exercise which improves physical and mental health (Gidlöf-Gunnarsson and Öhrström, 2007). Urban trees are home to a number of animals which helps in keeping biodiversity in the city.

2.5.2. Ecosystem services of eucalyptus

Apart from socio-economic benefits, eucalyptus trees also offer some ecosystem services. Eucalyptus trees in urban environments are part of the urban green infrastructure. Together with other urban trees, eucalyptus trees are important in urban environments.

Microclimate regulation

Industrial processes, vehicles and high population densities in urban areas cause an increase in the urban area temperatures. Trees are known for regulating microclimate. Vailshery *et al*.

(2013) conducted a study on the effect of trees on urban microclimate in Bangalore one of the fastest growing cities in India. Results from the research indicated that the temperatures for streets with trees was 5.6 ^{o}C lower than in the streets without trees. Trees also reduce urban temperature through their shading effects and also the latent heat is absorbed during the process of evapotranspiration (Dwyer *et al*., 1992). Furthermore, eucalyptus trees act as windbreaks thereby reducing wind speed and damage to property (Bolund and Hunhammar, 1999).

Air filtration

There are many sources of air pollution in urban environments. Johannesburg is home to 40% of the country's economic activities (City of Johannesburg, 2013). There is mining, as well as a number of manufacturing industries, and millions of vehicles that releases greenhouse gases like CO, CO_2, and N_2O (Buff, 2012). Trees absorb these gases through their stomata. They can also reduce particulate matters, which is directly deposited on tree leaves, from the air by 7-28% (Kumar, 2010).

Water Flow Regulation and Runoff Mitigation

Most parts of urban areas are covered with impervious surfaces. This leads to enormous amount of water loss by runoff. Urban areas lose 40-80% of the rainfall through runoff, which can result in flooding of rivers (Schäffler and Swilling, 2013). Runoff also carries city pollutants with it, thereby polluting water surfaces. Green infrastructure enhances seepage, thereby increasing groundwater storage and reducing runoff (Bouland, 1999). Canopy cover of trees also intercepts rainfall reducing soil compaction and increasing infiltration (Bouland, 1999).

Carbon Sink

CO_2 only contributes a fraction of 0.035% to atmospheric gases, but it is of great concern because it is the most abundant gas of all the greenhouse gases, which includes nitrous oxide, ozone, methane, and CFCs (Kurz *et al*., 2008). High concentration of greenhouse gases in the atmosphere results in the overall increase of global temperatures. Governments around the world are now pursuing strategies to halt the rise in concentrations of carbon dioxide and other greenhouse gases. Trees act as carbon sinks (Kurz *et al*., 2008). Trees convert atmospheric carbon to organic carbon through the process of photosynthesis. *Eucalyptus* trees grows fast and produces huge amounts of biomass; therefore, they fix more atmospheric carbon, thereby, reducing greenhouse gases (FAO, 2000).

Noise regulation

Trees plays a great role of reducing noise levels in urban environments (Dwyer *et al*., 1992). Green infrastructure muffle noise from cars, industries, construction etc. by absorbing, reflecting and refracting sound waves (Gidlöf-Gunnarsson and Öhrström, 2007). A study showed that 33 m of forest can reduce noise by 7 dB (A) (Coder, 1996).

Phytoremediation

Phytoremediation is a cost-effective method used in the abatement of heavy metal-polluted soils (Gomes *et al*., 2012). Eucalyptus' rapid growth, tolerance to heavy metal and strong root systems makes them significant in restoration of contaminated soils. Eucalyptus is classified as a hyperaccumulator because it can extract organic and inorganic pollutants from contaminated environments and accumulate them at concentrations that are more than what can normally be found in plant tissues (Atangana *et al*., 2014). *Eucalyptus* species has been successfully utilized in reclaiming some contaminated soils as a result of heavy metal contamination from mines around the Witwatersrand basin (AngloGold, 2004).

2.5.3. Ecosystem disservices by Eucalyptus trees

Ecosystem disservices can be defined as the negative effects of some natural ecosystem on the well-being of humans (Kumar, 2010). It is therefore, of utmost importance to understand the ecosystem disservices of invasive alien plants. Among the common ecosystem disservices of eucalyptus trees in an urban environment include the emission of greenhouse gases and volatile organic compounds, and loss of ground water resources through transpiration (Livesley *et al*., 2016).

Eucalyptus is an evergreen plant and thus, loses water all year round (Turton *et al*., 2006). Afforestation programs with eucalyptus in Mpumalanga led to a complete drying-up of streams within 12 years after planting (Forsyth *et al*., 2004). Many researchers have indicated that Eucalyptus trees extract much water from the ground aquifers and lost through evapotranspiration. A study by le Maitre *et al.* (2002) indicated that invasive plants have reduced river flow in South Africa by about 6.7%. South Africa is classified as a water scarce country, with an average mean annual rainfall of 490 mm (Kruger and Nxumalo, 2017). The country is already experiencing frequent incidences of dry spells as a result of global climate change. It is therefore of utmost importance to conserve the water resources by effectively managing invasive alien plants to reduce their transpiration.

Eucalyptus trees are not only a threat to the water resource, but they also release some volatile organic compounds (VOCs) into the air, contributing to greenhouse effect (Gunther *et al*., 1995). These gases include butane, monoterpenes, isoprene, ethane, propene, acetaldehyde, acetic acid, formaldehyde, and formic acid. Eucalyptus trees also degrade the soil, out-compete native plants for water, light and nutrients, and produce allelopathic chemicals that inhibit the growth of other plants under their canopies (Mbatha and De Wet, 2018).

2.6. Mapping urban trees using remote sensing

Urban forests are an important facet of the urban environment. Management of urban trees is vital in strategic urban planning (Huang *et al*., 2007; Kong and Nakagoshi 2005). For effective management of urban green infrastructure, knowledge on tree species location and extent is important (Ardila *et al*., 2012). Urban tree survey and monitoring in the past involved tedious and expensive traditional tree counting and measuring (Shojanoori and Shafri, 2016). However, obtaining sufficient information for all the tree species in urban environment proves difficult and demands time and cost (Akasheh *et al.*, 2008; Cho *et al*., 2015). The adoption of remote sensing techniques has however, facilitated mapping and monitoring of the urban green infrastructure more effectively (Shojanoori and Shafri, 2016; Ardila *et al*., 2012).

The medium resolution multispectral imageries, MODIS and Landsat, have been widely used for mapping and monitoring of urban green infrastructure and land use and land cover (Peijun *et al*., 2010; Zheng and Qui, 2012). However, these imageries confounded by the presence of mixed pixels as a result of low spatial resolution (250-500m for MODIS and 30m for Landsat) and they are often more limited to land-use type classification. Spectral overlapping due to the effect of pixel mixing in heterogeneous urban environment leads to misclassifications problems (Shafri *et al*., 2012). Hyperspectral data can accurately discriminate between plant species.

However, its use is limited due to high cost and data dimensionality challenges which complicate its processing and analysis (Demir and Erturk, 2008; Shafri *et al*., 2012).

Nevertheless, the limitation of hyperspectral data and the use of low spatial resolution as a result of moderate resolution imageries have been improved by the development of high resolution multi-spectral satellites imageries. Hence, this has enabled mapping of urban forests using high-resolution multispectral imageries such as IKONOS, FormoSat-2, QuickBird, SPOT and WorldView series (Shafri *et al*., 2012). These are high-resolution multispectral sensors with four multispectral bands (i.e., red, blue, green, and near infrared) and a panchromatic band. These satellites are useful in detecting vegetation because of red and near-infrared bands which are sensitive to vegetation chlorophyll pigments which contain approximately 90% of the vegetation information (Li *et al*., 2010). However, urban environments are complex, and more bands might be useful in extracting information on green vegetation (Ouma and Tateishi, 2008).

Limited number of spectral bands in high-resolution images such as QuickBird and IKONOS make them unable to sufficiently classify urban vegetation at species level. WorldView-2 image can be used to overcome such problem. WorldView-2 is a high-resolution multispectral satellite launched in 2009. It is an enhanced version of high-resolution satellites.

This high-resolution imagery system employs eight spectral bands, including those that can distinguish vegetation species. The imagery consists of four traditional bands (i.e. blue, red, green and near infrared) and four newly developed bands, namely coastal (which detects chlorophyll content), yellow (which detects yellowness), red edge (which detects vegetation species and plant diseases), and near-infrared 2 (which helps in the study of biomass) (Shojanoori and Shafri, 2016). Different studies have already shown that the new bands in WorlView-2 helps in discriminating vegetation at species level (Ghosh and Joshi, 2014; Immitzer *et al*., 2012; Pu and and Landry, 2012).

CHAPTER THREE: METHODOLOGY

3.1. Study area

This study was conducted in the historical mining areas located south of Johannesburg city in Gauteng province stretching from Parktown to Rosettenville, covering areas like Crown city, Booysens and Turfontein (Figure 3.1). It is located at latitude -26.195246 and longitude 28.034088. Johannesburg has a subtropical highland climate and it receives an average rainfall of 604mm per annum (Holgate, 2007). Most of the rainfall occurs during summer. The average daily temperature is 16.6ºC during winter and 26.2ºC during summer (Holgate, 2007). It is the most populous city in South Africa (Statistics South Africa, 2016).

Johannesburg is home to approximately 10 million trees (Schäffler and Swilling, 2013) and most of which are exotic. Some of the most popular exotic trees in Johannesburg includes: Eucalyptus, Jacaranda, Oaks, Planes, Pepper trees, Black wattle and Green wattle. *Eucalyptus* species are one of the most prevalent tree species in the city, but their distribution is unknown. This study therefore, focused on mapping eucalyptus trees around historical mining areas located south of Johannesburg city. The main land use of the area is mining, industrial and residential.

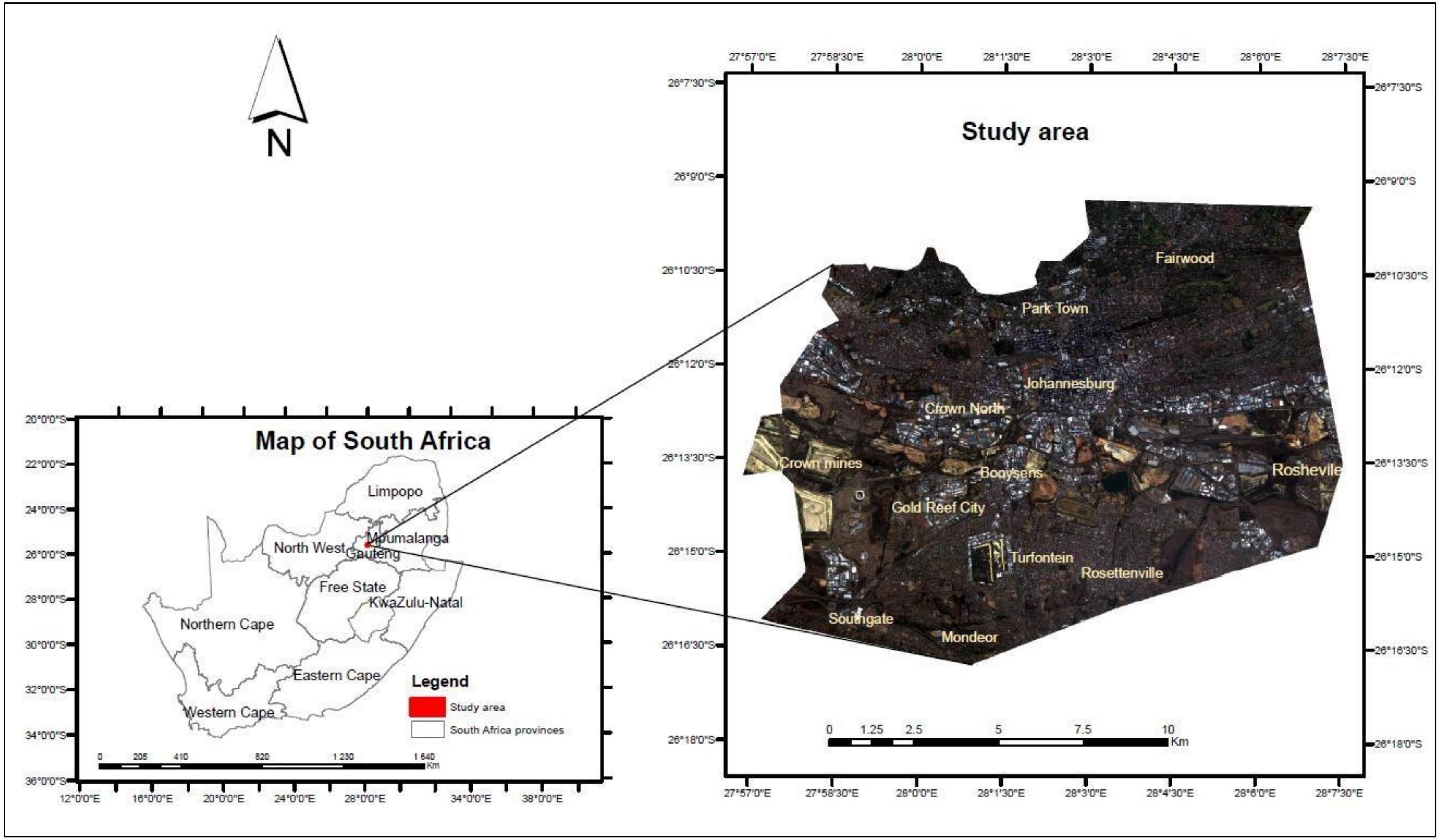

Figure 3.1: A true-colour composite SPOT-7 image showing the location of study area.

3.2. Materials

High resolution multispectral data from WorldView-2 and SPOT-7 imageries were used to map eucalyptus trees and other land use and land cover (LULC) for the study area. Ground truth data was also used for validation of satellite imageries and collected using GPS device. Classification was done using Random Forest and Support Vector Machine algorithms.

3.3. Image acquisition and processing

This study used WorldView-2 and SPOT-7 imageries. WV-2 sensor was launched on 8 October 2009 and it is the first commercial multispectral sensor with high spectral (8 bands) and spatial (2m) resolutions to be launched. The image's high spectral and spatial resolution enables it to provide detailed information such as tree species, moving vehicles, ocean depth and health of plants (DigitalGlobe, 2012). The satellite's characteristics are summarized in Table 3.1. The study site was covered by one WV-2 scene, acquired in October 2016. City of Johannesburg Corporate Geo-Informatics (DP & UM) Gauteng, South Africa provided the WorldView-2 dataset covering the study area. The image was pre-processed and ortho-rectified by the image distributor DigitalGlobe.

SPOT-7 image was launched on the 30th of June 2014 by Airbus Defence and Space. SPOT-7 image has a large swath capacity of 60 km at nadir that enables a 6 million square kilometre daily data acquisition. It has four spectral bands with a spatial resolution of 6m. Table 3.1 summarizes the image's properties. The satellite image offers remote sensing applications in mining, environmental monitoring, agriculture and coastal surveillance (Astrium, 2015). An ortho-rectified and geo-referenced SPOT-7 image was acquired from the South African Space Agency (SANSA). The image was captured in October 2017.

Table 3.1: WorldView-2 and SPOT-7 satellite specifications (Astrium, 2015; DigitalGlobe, 2012)

Satellite/Sensor properties	**WorldView-2**	**SPOT-7**
Launch date	8 October 2009	30 June 2014
Orbit	Sun synchronous	Sun synchronous
Equator crossing time	10:30 am local time	10:00 am local time
Spectral bands and spatial resolutions (HRG)	Single panchromatic band at 50 cm resolution 8 multispectral bands at 2.0 m spatial resolution (Coastal, Red, Blue, Red Edge, Green, NIR1, Yellow, NIR 2)	4 multispectral bands at 6.0 m resolution (blue, green, red, near infrared (NIR))
Spectral range (HRG)	Panchromatic (450 – 800 nm) **Multispectral** Coastal (400-450 nm), Red (630-690 nm), Blue (450-510 nm), Red Edge (705-745 nm), Green (510-580 nm), NIR1 (770- 895 nm), Yellow (585- 625 nm) and NIR2 (860-1040 nm)	Panchromatic (450 – 750 nm) **Multispectral** Blue (450 – 520 nm) Green (530 – 560 nm) Red (620 – 690 nm) NIR (760 – 890 nm)
Data quantisation	11-bits per pixel	12-bits per pixel
Imaging swath	16.4 km at nadir	60 km at nadir

3.4. Ground truth data collection

A pilot drive was done on the 1st of September 2017 around the study area to identify major land use and land cover (LULC) classes of the area. Five major LULC classes (bare soil, grassland, tailing dams, built-up area and woody vegetation) were identified as predominant in the study area along with the eucalyptus trees. Table 3.2 describes in detail each of the LULC classes. WV-2 and SPOT-7 false colour composites and Google earth were also used to identify points for LULC classes like tailing dams, bare ground, built-up area and grassland. In total, 608 training points were recorded (Table 3.2). The collected GPS points were overlaid on WV-2 and SPOT-7 map and image spectra was collected from the eucalyptus and the common LULC classes. Figure 3.2 shows the distribution of ground reference data in the study area. The ground reference data were then randomly split into 70% training and 30% validation data sets (Table 3.3).

Table 3.2: Description of major land-use classes considered during the classification of the study area (historical mining areas located south of Johannesburg city).

Class	**Description**
Bare soil	Non-vegetated soils
Built-up area	Man-made structures with rooftops made form tiles, shiny iron sheets and other material
Eucalyptus	Eucalyptus trees
Grassland	Surfaces dominated by grasses
Tailing dams	Fine shiny white earth-fill from mining operations
Woody vegetation	Other woody vegetation except for eucalyptus trees

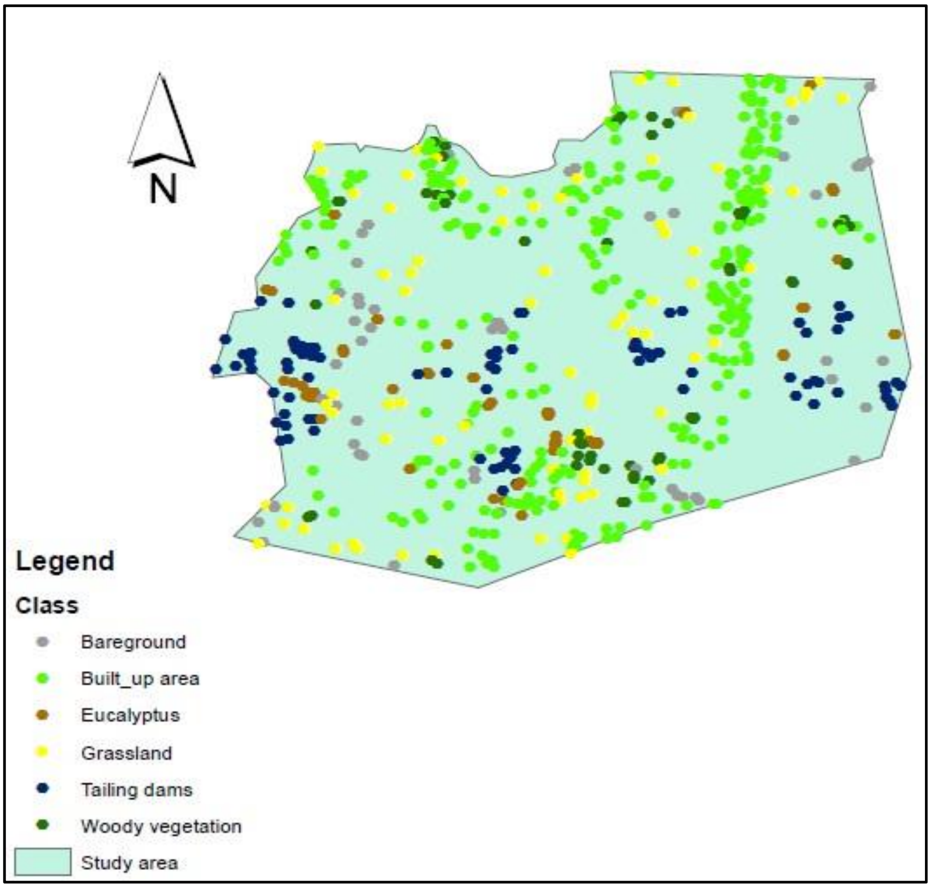

Figure 3.2: Distribution of ground truth data in the study area (historical mining areas located south of Johannesburg city).

Table 3.3: Test and training data for all land-cover classes in the study (historical mining areas located south of Johannesburg city).

Land-cover type	Test data	Training data	Total
Bare soil	30	71	101
Built-up area	30	73	103
Eucalyptus	30	70	100
Grassland	30	71	101
Tailing dams	30	73	103
Woody vegetation	30	70	100

3.5. Image classification

For the purpose of this research, two machine learning algorithms were used for classification, namely; Random Forest (RF) and Support Vector Machine (SVM).

3.5.1. Random Forest

Random Forest (RF) is a robust and user-friendly classification algorithm (Adam *et al*., 2014). The first RF algorithm was reported by Tim Kam Ho in 1995. He established that forest of trees become accurate as they grow if they are randomly constrained to be sensitive only to particular feature dimensions (Huerta *et al*., 2015). Leo Breinman (2001) further developed an extension of the RF algorithm, where he combined his idea of bagging with Ho's idea of random selection of features which enabled the construction of decision trees collection with a controlled variance. Random Forest classifier makes use of ensemble decision trees that improves classifications and regression trees in the field of machine learning (Liaw and Wiener, 2002).

Random Forest algorithm construct decision trees using bootstrap sampling based on model aggregation ideas. It starts by building several binary decision trees known as *ntree* (Breinman, 2001). This enhances diversity of classification trees created by means of several bootstrap samples with replacement drawn from original observations. Each of the decision trees contributes with a single vote in assigning class to the input data (Breinman, 2001). The number of votes from the collection of trees is the one that determines the actual classification. Out-Of-Bag (OOB) samples are the samples that are not included in the bootstrap sample. The OOB sample is the one that is used in estimating variable importance and misclassification error (Liaw and Wiener, 2002). The OOB was used to provide the variable of importance for WV-2 and SPOT-7 images.

After the construction of *ntree* variable, *mtry* (a specified number of input variables) is randomly chosen from a random subset of the features at each node. Each tree is grown without pruning on the original bootstrap sample, this improves diversity amongst trees and hence bias is reduced (Liaw and Wiener, 2002). Accuracy can be improved by optimizing random forest parameters *mtry* and *ntree* (Breiman, 2001). Random Forest algorithm measures variables importance for input dataset.

3.5.2. Support Vector Machine

Support Vector Machines are non-parametric algorithms that are used in supervised classification and regression (Otukei and Blaschke, 2010). Vapnik (1999) proposed the theory of SVM and in 1999. Support Vector Machine classification method has demonstrated superior performance among many other classification methods (Schwenker, 2000; Zhang and Liu, 2013).

The ability of the SVM algorithm to classify depends on whether the training was conducted well, the kernel that was used and the tuning parameters picked to fit the kernel (Li *et al.*, 2014; Otukei and Blaschke, 2010; Zafari *et al.*, 2017). The SVM algorithm is a binary classifier that functions by calculating separating hyperplane that provides the largest lowest distance to the training data (Li *et al*., 2014). SVM functions by projecting vectors into a high dimensional feature space by means of a kernel trick then fitting the optimal hyperplane that separates classes using an optimization function (Pouteau *et al*., 2012).

This classification algorithm has four kernel types, namely: radial basis function (RBF), linear, sigmoid and polynomial (Zafari *et al.*, 2017). Data from different classes tends to overlap, in order to counter for the limitation of linear separability and to enhance classification accuracy, nonlinear polynomial can be applied (Zafari *et al.*, 2017). Radial basis function is the most used kernel method in remote sensing (Omer *et al.*, 2015). This kernel makes use of two parameters, namely, '*gamma* (γ)' and the '*cost* (C)', where *gamma* is the kernel width whilst *sigma* is the value that is used for adjusting error encountered from misclassifying training dataset values (Li *et al.*, 2014). SVM counter for the noise within the dataset by defining a distance tolerating the data scattering, thus making it easy for the algorithm to make a decision (Zhang and Liu, 2013).

3.6. **Accuracy assessment**

Accuracy is the level of closeness of results to the value that is accepted as true (Congalton, 1991). In mapping land surface features using satellite images, accuracy assessment is used to evaluate if ground truth pixels are correctly classified (Adam *et al*., 2014). In order to evaluate classification maps produced by RF and SVM algorithm classifiers on WV-2 and SPOT-7 imageries, independent dataset (30% of the ground truth data as shown in table 3.3) was used to generate confusion matrices which were used to calculate producer and user's accuracies, overall accuracy and Kappa coefficient. Both RF and SVM algorithms, were processed in R-Studio.

Overall accuracy is the probability that a point that is selected randomly has been correctly classified (Rodriguez-Galiano *et al.*, 2012). It was calculated as follows:

$$\text{Overall accuracy} = \frac{\Sigma\ (classes\ correctly\ classified\ along\ diagonal)}{\Sigma(Row\ total\ or\ Column\ total)}$$

User's accuracy is the probability that a pixel labelled as a specific feature is classified as such on the classification map (Mutanga *et al*., 2012). It was calculated as follows:

$$\text{User's accuracy} = \frac{\text{Correctly classified number of item in a row}}{\text{Verified items total number in that row}}$$

Producer's accuracy shows the percentage of specific class on the ground is labelled as such on the classified map (Rodriguez-Galiano *et al.*, 2012).

$$\text{Producer's accuracy} = \frac{\text{Number of the correctly classified class in a column}}{\text{Verified items total number in that column}}$$

Kappa coefficient measures the difference between classes and the agreement that would have been expected by chance. The kappa value lies between 0 and 1, where a value 1 indicates prefect agreement between classification and ground truth pixels and 0 shows no agreement. Kappa coefficient was calculated using the following formula: (Foody, 2002)

$$k = \frac{\mathrm{N}\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i\ C_i)}{N^2 - \sum_{i=1}^{n}(G_i\ C_i)}$$

where; **i** represents the class number, **N** is the total number of the pixels classified that are being compared to ground truth **mi, i** represents the pixels that belong to the ground class **i**, that have also been classified with a class **i** (refers to the values that are found diagonally in a confusion matrix), **Ci** represents the number in total of classified pixels that belong to class **i** and **Gi** represents the number in total of ground truth pixels that belong to class **i**.

CHAPTER FOUR: RESULTS

4.1. Optimization of RF parameters

A 10-fold grid search method was used to optimize Random Forest parameters (*ntree* and *mtry*) for both WV-2 and SPOT-7 datasets to produce the best performing parameters that will be used to train the algorithm for eucalyptus discrimination from other land cover types. The combination of parameters that had the lowest error was the one which was chosen to train the algorithm. From the grid search of random forest, the default *mtry* value of four combined with a *ntree* value of 3500 produced the lowest OOB error rate (0.218) for WV-2 and the *mtry* value of 2 *ntree* 6500 produced the lowest OOB error rate of 0.23 for SPOT-7 (Figure 4.1).

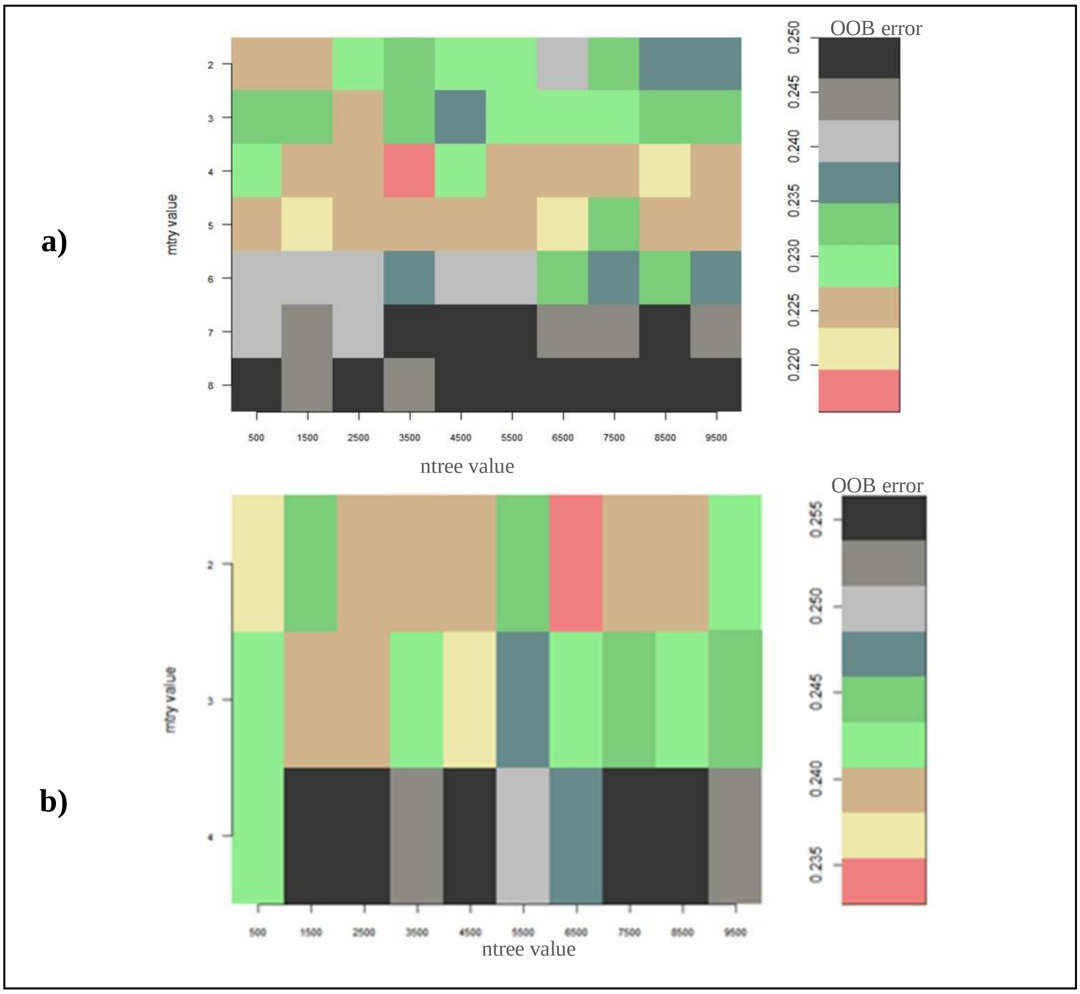

Figure 4.1: Optimization of Random Forest parameters (*mtry* and *ntree*) using the 10-fold grid search method for (a) WV-2 and (b) SPOT-7 images.

4.2. Optimization of SVM parameters

Support Vector Machine parameters (*gamma* and *cost*) were optimized for the different data sets using a 10-fold grid search approach. The combination of parameters that had the lowest error was the one which was chosen to train the algorithm. The combination *gamma* value of 0.1 and *cost* value of 1000 yielded the best performance for WV-2 with an error of 0.138 and the combination of *gamma* value of 1 and *cost* value 100 yielded the best performance for SPOT-7 with an error of 0.194 (Figure 4.2).

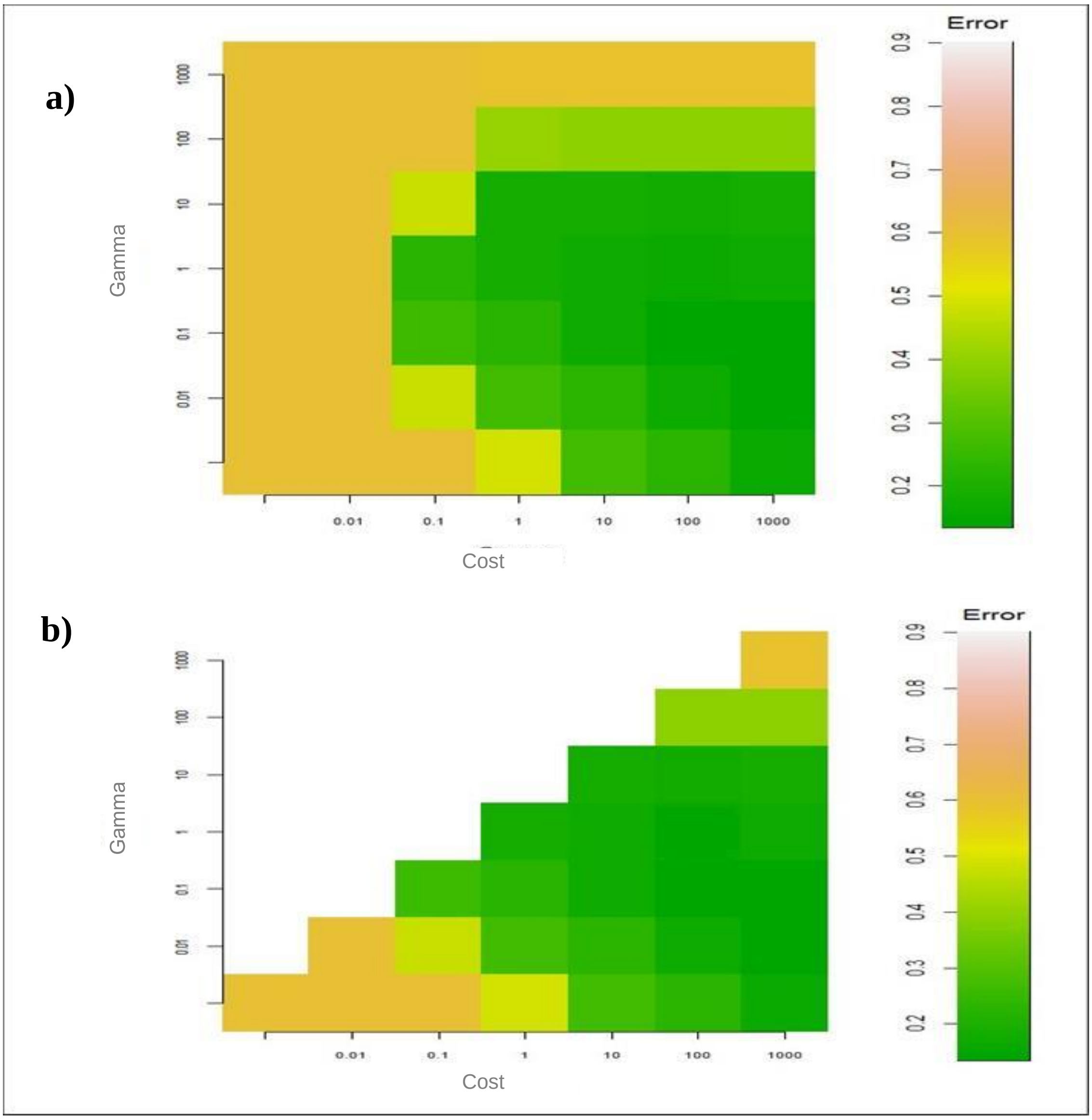

Figure 4.2: Optimization of Support Vector Machine parameters (*gamma* and *cost*) using the 10-fold grid search method for a) WV-2 and b) SPOT-7 image.

4.3. Variable Importance Measurement

Random Forest algorithm provided the bands of importance in the classification process for WV-2 and SPOT-7 datasets (Figure 4.3). In this study, the variables were the eight bands of WV-2 imagery (costal, blue, green, yellow, red, red edge, near-infrared1 and near-infrared2) and four bands of SPOT-7 imagery (blue, green, red and near-infrared). The most important variable was indicated by the highest mean decrease in accuracy. The most important spectral bands for WV-2 were B3 (green), B5 (red) and B8 (NIR-2), while B1 (blue) and B4 (NIR) were the most important bands for SPOT-7 dataset.

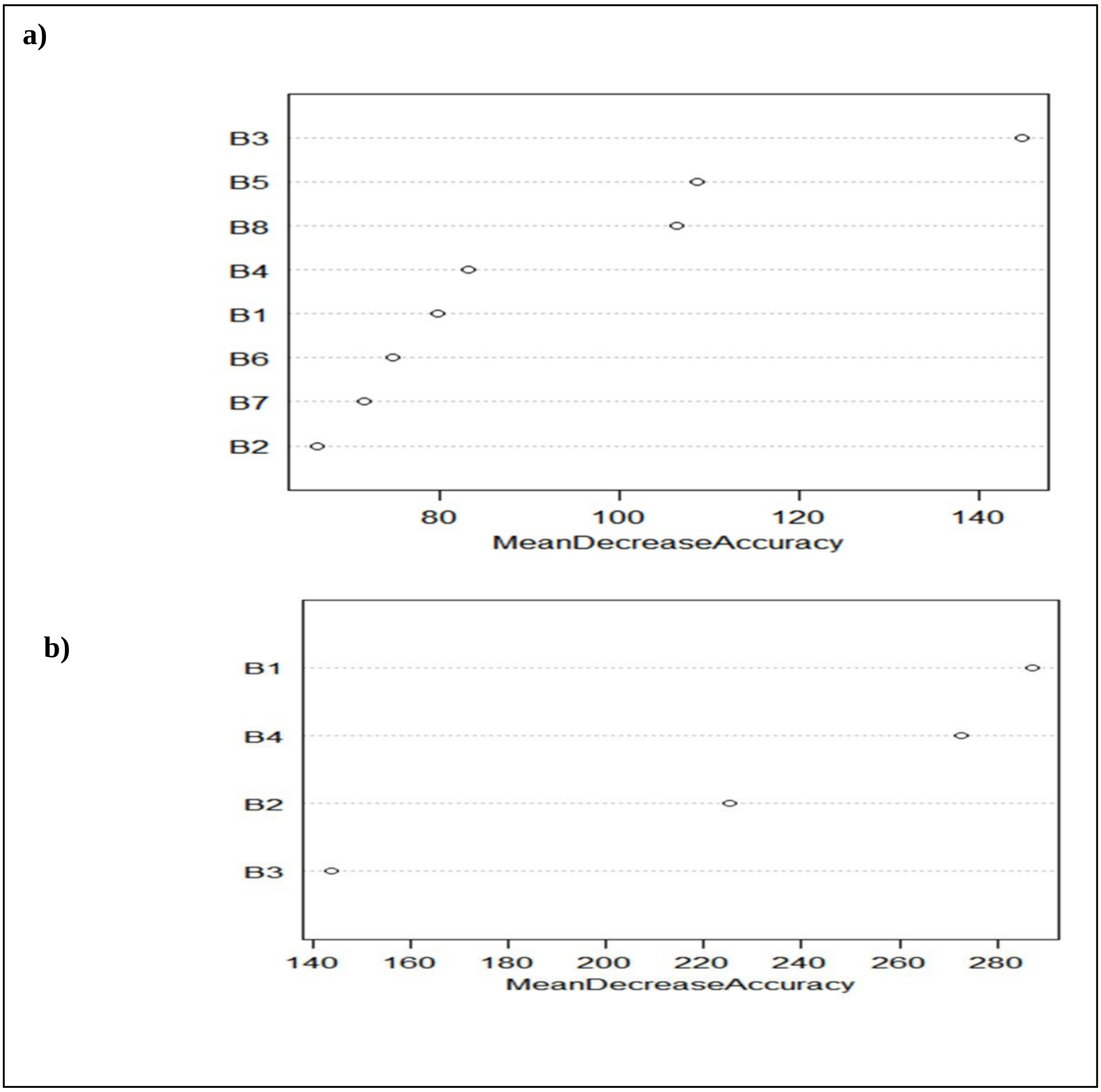

Figure 4.3: The importance of (a) WV-2 and (b) SPOT-7 bands in discriminating between different land use and land cover (LULC) classes as measured by Random Forest classifier.

4.4. Variable of importance in the classification of eucalyptus and other LULC classes

From figure 4.4, it can be noted that NIR-2, green, red and yellow bands were the most important bands in classifying vegetation classes (i.e. eucalyptus, grassland and woody vegetation) when using the WV-2 dataset, while the Blue, Near-IR and green bands were the most important variables in classifying vegetation classes for SPOT-7 dataset (Figure 4.4).

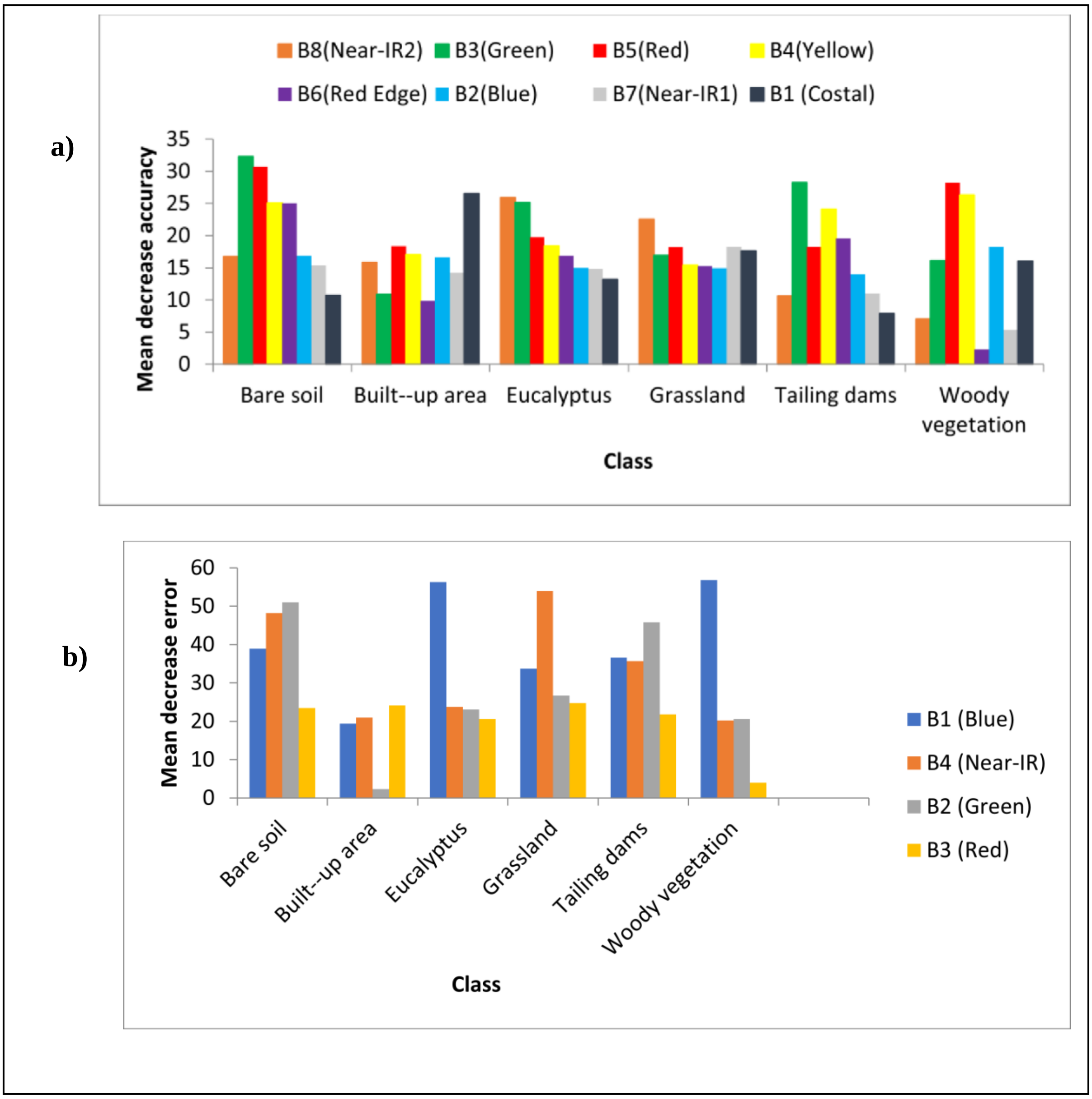

Figure 4.4: The relationship between each individual land-cover class and the importance of the (a) WV-2 and (b) SPOT-7 bands. The highest mean decrease in accuracy shows the most important band.

4.5. Accuracy assessment

4.5.1. WV-2 versus SPOT-7

An independent test dataset was utilised to assess the performance of RF and SVM on classifying land cover using WV-2 and SPOT-7 datasets. Both RF and SVM algorithms obtained higher accuracies for WV-2 image as compared to accuracies obtained for SPOT-7. For instance, RF classifier produced an overall accuracy of 81.67% and a kappa coefficient of 0.78 for WV-2 while SPOT-7 generated an overall accuracy of 72.78% and 0.67 kappa coefficient (Table 4.1). For WV-2, it can be noted that the Random Forest classifier generated user's and producer's accuracies that ranged from 80% to 90% for all other classes except for eucalyptus and other woody vegetation, whilst the same classification algorithm generated user's and producer's accuracies that ranged from 72.22% to 86.67% for all other classes except for eucalyptus and woody vegetation for SPOT-7 imagery. Eucalyptus and woody vegetation have user's accuracies of 73.33% and 70%, respectively, for WV-2 image whilst SPOT-7 attained user's accuracies of 60% and 56.67%, respectively when using RF algorithm. From the confusion matrices (Table 4.1 and 4.2), it can also be noted that there was much spectral confusion between the eucalyptus class and other woody vegetation class for both images. However, WV-2 image performed better in terms of separating these classes as indicated by the high accuracies obtained from the WV-2 dataset.

4.5.2. Random Forest algorithm versus Support Vector Machines algorithm

On the other hand, accuracies from SVM classifier were slightly lower than those for random forest. The SVM classifier had an overall accuracy of 80% (kappa value of 0.76) for WV-2 and 71.11% (kappa value of 0.65) for SPOT-7, whilst RF generated an overall accuracy of 81.67% (kappa coefficient of 0.78) for WV-2 and 72.78% (0.67 kappa coefficient) for SPOT7. RF also yielded higher accuracies for land use classes than SVM for both images. For instance, RF algorithm generated user's accuracies of 73.33% and 70% for eucalyptus and other woody vegetation respectively for WV-2 whilst SVM generated user's accuracies of 70% for eucalyptus and 66.67% for woody vegetation. The same applies to SPOT-7 image.

RF generated higher accuracies as compared to SVM. RF algorithm generated user's accuracies of 60% and 56.67% for eucalyptus and other woody vegetation, respectively for WV-2 whilst SVM generated user's accuracies of 56.67% for eucalyptus and 53.33% for woody vegetation.

Table 4.1: The confusion matrix (generated using RF algorithm) of classification error obtained for discriminating eucalyptus (EC) and other land cover types, including bare soil (BS), grassland (GL), woody vegetation (WV), built-up area (BA), and tailing dams (TD). The confusion matrix includes producer's accuracy (PA), user's accuracy, overall accuracy and kappa coefficient.

Confusion matrix generated using Random Forest algorithm

Using WorldView-2 spectral bands

	BS	BUA	EC	GL	TD	WV	Row total	PA
BS	26	4	0	0	3	0	33	**78.79%**
BUA	3	24	0	0	0	0	27	**88.89%**
EC	0	0	22	1	0	6	29	**75.86%**
GL	0	2	2	27	0	3	34	**79.41%**
TD	1	0	0	0	27	0	28	**96.43%**
WV	0	0	6	2	0	21	29	**72.41%**
Column total	30	30	30	30	30	30	180	
UA	**86.67%**	**80%**	**73.33%**	**90%**	**90%**	**70%**		

Overall accuracy = 81.67%

Kappa = 0.78

Using SPOT 7 spectral bands

	BS	BUA	EC	GL	TD	WV	Row total	PA
BS	23	3	0	2	3	0	31	**74.19%**
BUA	2	22	0	1	1	0	26	**84.62%**
EC	0	0	18	1	0	10	29	**62.07%**
GL	2	2	3	26	0	3	36	**72.22%**
TD	3	3	0	0	25	0	31	**80.65%**
WV	0	0	9	0	1	17	27	**62.96%**
Column total	30	30	30	30	30	30	180	
UA	**76.67%**	**73.33%**	**60%**	**86.67%**	**83.33%**	**56.67%**		

Overall accuracy = 72.78

Kappa = 0.67

Table 4.2: The confusion matrix (generated using SVM algorithm) of classification error obtained for discriminating eucalyptus (EC) and other land cover types, including bare soil (BS), grassland (GL), woody vegetation (WV), built-up area (BA), and tailing dams (TD). The confusion matrix includes producer's accuracy (PA), user's accuracy, overall accuracy and kappa coefficient.

Confusion matrix generated using Support Vector Machine algorithm

Using WorldView-2 spectral bands									Using SPOT-7 spectral bands								
	BS	BUA	EC	GL	TD	WV	Row total	PA		BS	BUA	EC	GL	TD	WV	Row total	PA
BS	25	3	0	1	3	0	32	78.13%	BS	23	3	0	2	3	0	31	74.19%
BUA	3	25	0	0	0	0	28	89.29%	BUA	2	23	0	1	1	0	27	85.19%
EC	0	0	21	1	0	7	29	72.41%	EC	0	0	17	1	0	10	28	60.71%
GL	0	2	2	26	0	3	33	78.79%	GL	2	2	3	24	0	4	35	68.57%
TD	2	0	0	0	27	0	29	93.10%	TD	3	2	0	0	25	0	30	83.33%
WV	0	0	7	2	0	20	29	68.97%	WV	0	0	10	2	1	16	29	55.17%
Column total	30	30	30	30	30	30	180		Column total	30	30	30	30	30	30	180	
UA	83.33%	83.33%	70%	86.67%	90%	66.67%			UA	76.67%	76.67%	56.67%	80.00%	83.33%	53.33%		
Overall accuracy = 80%									Overall accuracy = 71.11%								
Kappa = 0.76									Kappa = 0.65								

4.6. Classification maps for study area.

RF and SVM algorithms managed to generate classification maps for WV-2 and SPOT-7 images (Figure 4.7 and 4.8).

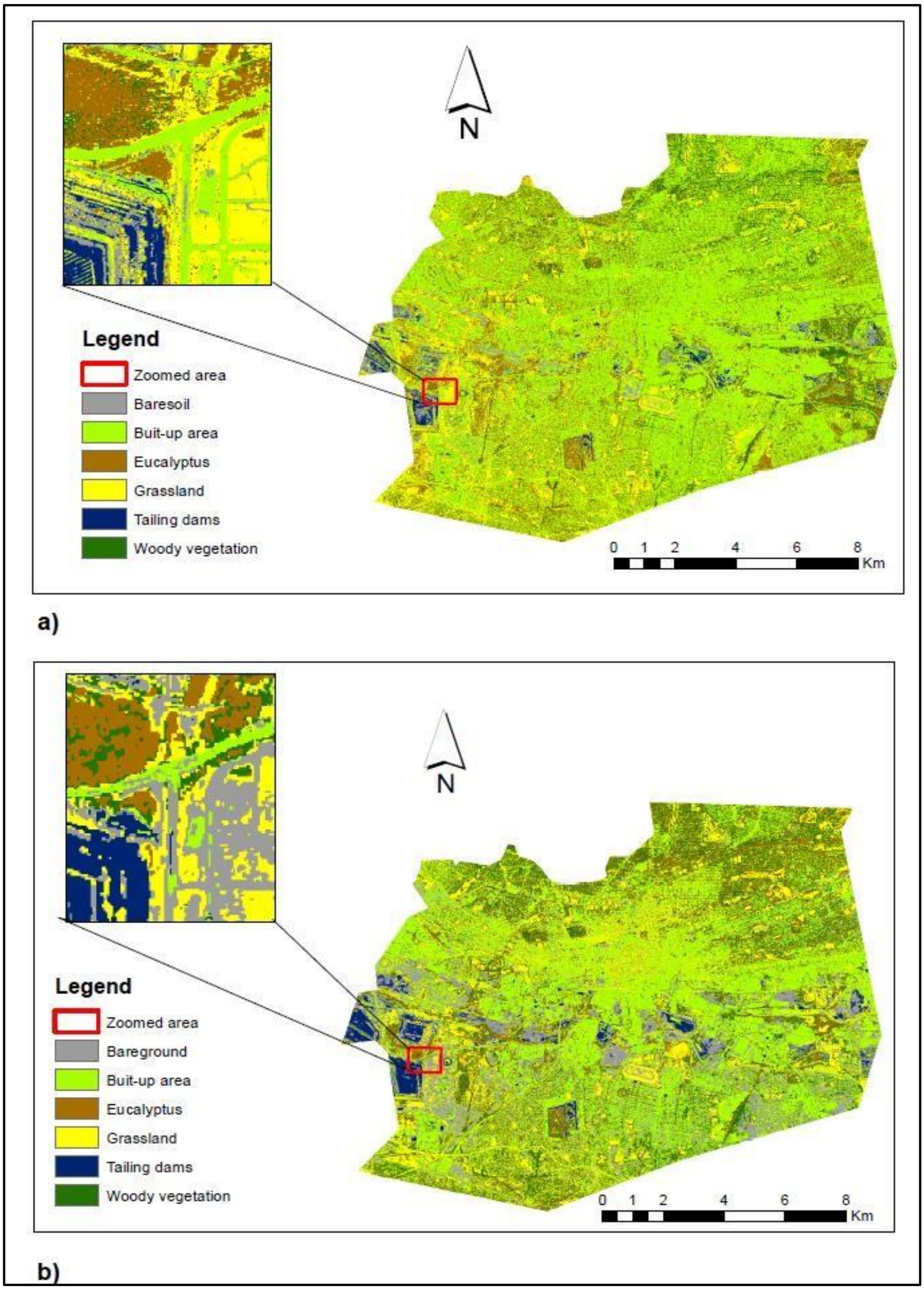

Figure 4.5: Classification maps obtained using Random Forest classification algorithm and (a) WV-2 image (b) SPOT-7 image.

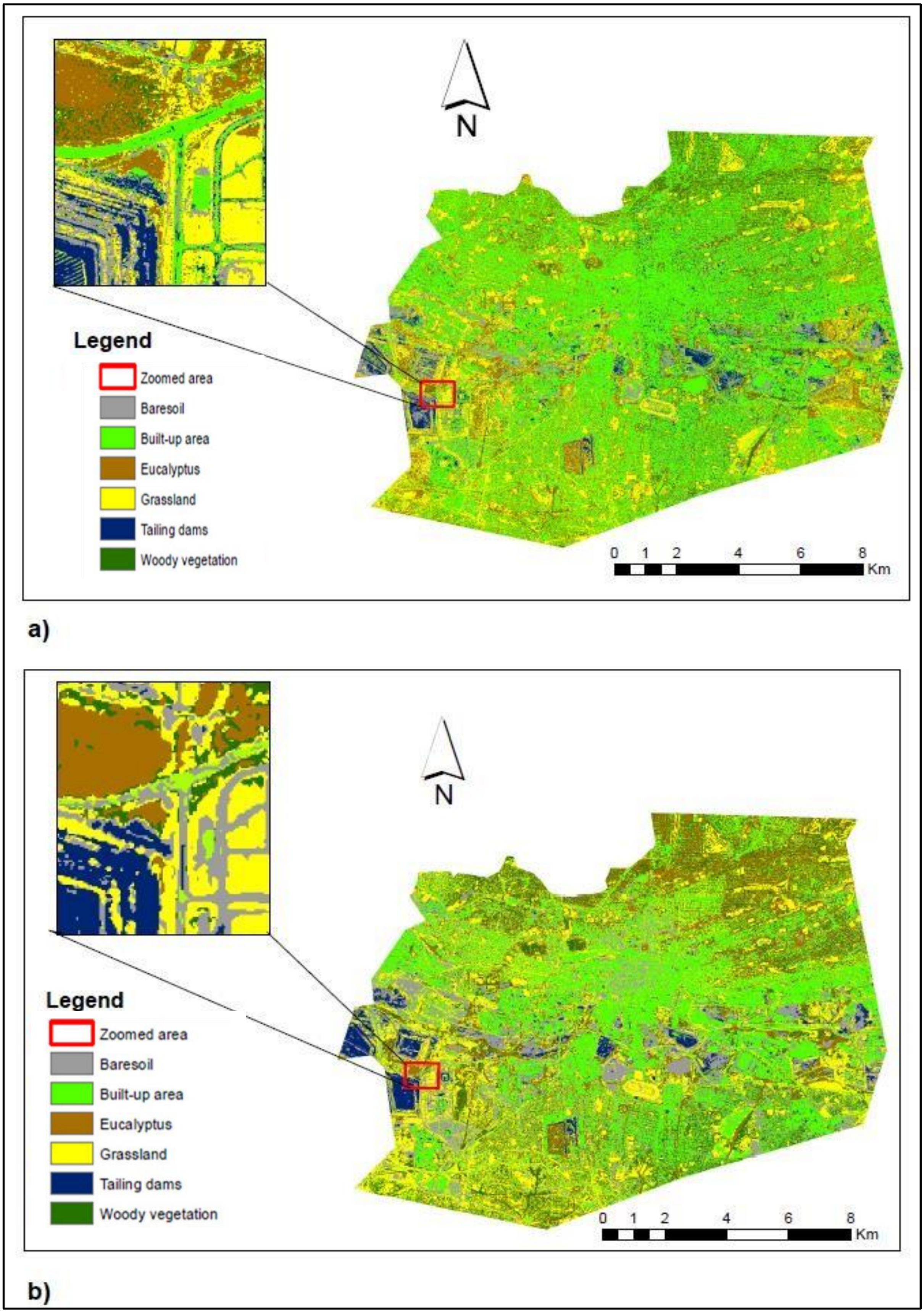

Figure 4.6: Classification maps obtained using Support Vector Machine classification algorithm and (a) WV-2 image. (b) SPOT-7 image

4.7. Final classification map for eucalyptus distribution in historical mining areas located south of Johannesburg city

WV-2 image and RF algorithm classified eucalyptus effectively in historical mining areas located south of Johannesburg city. The overall accuracy was 81.67% and 0.78 kappa coefficient. The user's and producer's accuracies for the eucalyptus class were 73.33% and 75.86%, respectively. From this map it can be noted that eucalyptus trees are dominant in historical mining sites, where tailing dams are dominant (Figure 4.7). This includes areas like the Crown city and Booysens. Table 4.3 shows the total area and proportion of eucalyptus class and other LULC classes obtained from WV-2 image and Random Forest classifier.

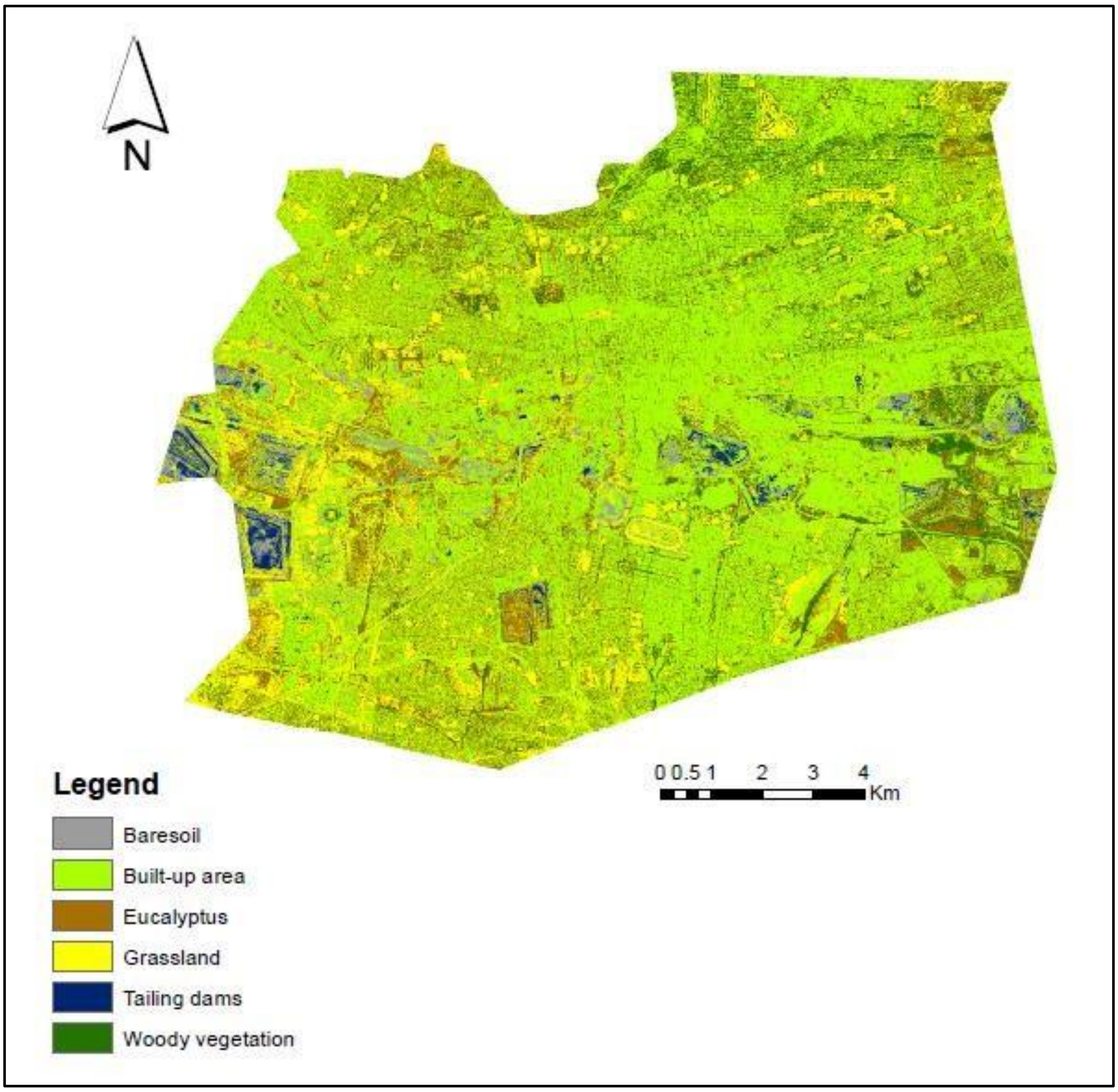

Figure 4.7: Map for eucalyptus distribution in the historical mining areas located south of Johannesburg city.

Table 4.3: Area covered by *Eucalyptus* species and other land cover class obtained by WorldView-2 image and Random Forest classifier.

	Area (ha)	**Proportion (%)**
Bare soil	624.058	4.330
Built-up	8408.751	58.335
Eucalyptus	703.172	4.878
Grassland	1072.343	7.439
Tailing dams	380.817	2.642
Woody vegetation	3225.581	22.376
Total	14414.722	100

CHAPTER FIVE: DISCUSSION AND CONCLUSIONS

5.1. Discussion

In as much as there is a mandate to get rid of invasive alien plants such as eucalyptus trees because of their negative impact on natural ecosystems, the fact that eucalyptus trees also have positive impacts they cannot be ignored. This has resulted in a lot of controversies regarding management of *Eucalyptus* species. The species has been listed under category 1b of the National Environmental Management Biodiversity Act (Act 10 of 2004), which implies that the species outside permissible areas need to be removed (Department of Environmental Affairs, 2014). Therefore, knowledge on spatial distribution is a priority for successful management of the species. Knowing the spatial distribution of eucalyptus in urban environments can therefore help local authorities, governments, researchers, land management practitioners and planners to make appropriate management decisions with regards to the species. High heterogeneity in urban environments makes it difficult to discriminate vegetation species and other land uses (Pu and Landry, 2012). However, the advent of high resolution multi-spectral satellite imageries provides new opportunities for mapping plant species in urban environments (Immitzer *et al*., 2012).

This study sought to investigate the utility of medium resolution image SPOT-7 and high resolution image WV-2 together with Random Forest (RF) and Support Vector Machines (SVM) algorithms in mapping eucalyptus trees in historical mining area located south of Johannesburg city. In addition, the performances of WV-2 and SPOT-7 imageries in mapping land uses and land cover were compared to determine if the relatively cheaper SPOT-7 data could be effectively used for vegetation mapping in urban environments instead of the more expensive and less available data from WV-2 imagery.

Satisfactory overall accuracies were obtained for both WV-2 (81.67% and 80% for RF and SVM algorithms, respectively) and SPOT-7 (72.78% and 71.11% for RF and SVM algorithms, respectively). Nevertheless, these results indicate that WV-2 is superior over SPOT-7, this could be due to the fact that WV-2 has both high spatial and spectral resolutions (Odindi *et al*., 2014). This result is consistent with what other researchers found. Odindi *et al.* (2014) compared the performance of WV-2 and SPOT-5 images in mapping bracken fern in Giba

Gorge of KwaZulu-Natal province of South Africa. WV-2 attained an overall accuracy of 84.72% whilst SPOT-5 had an overall accuracy of 72.22%.

Both images produced higher user's and producer's accuracies for all other classes except for eucalyptus and other woody vegetation classes. These classes obtained lower accuracies because of the high spectral confusion between the eucalyptus and other woody vegetation classes. This might be due to a couple of factors. Firstly, there are several species of eucalyptus (which possess different anatomy) in the study area and they were all classified as one eucalyptus class for this study. Secondly, all other woody vegetation that is not eucalyptus were grouped under one collective class. Some vegetation species possess similar spectral signatures with eucalyptus.

Although the SPOT image produced satisfactory overall accuracies, the user's accuracies for the eucalyptus class was very low (60% and 56.67% for RF and SVM algorithms, respectively) which makes the image not suitable for classifying eucalyptus trees in heterogeneous environments such as urban areas. On the other hand, WV-2 attained higher user's accuracies for the eucalyptus class (73.33% and 70% for RF and SVM algorithms, respectively). This can be attributed to the fact that WV-2 has additional bands (costal blue, yellow, red-edge and NIR-2) which enhance vegetation and land use classification accuracy (Immitzer *et al*., 2012; Odindi *et al*., 2014). Furthermore, Random Forest variable importance measurement index indicated that newly developed bands in WV-2 are more effective in discriminating eucalyptus from other species. Some of the newly developed bands in WV-2 (NIR-2, yellow and red-edge) were amongst the top bands in the classification process. Hence, it can be deduced that the additional bands in WV-2 enhances classification of eucalyptus and other land cover better than the traditional bands in SPOT-7 data. These results are consistent with the findings in the literature. Omar (2010) investigated the importance of newly developed WV-2 bands in mapping forest species in Malaysia forest. His findings indicated that the additional WV-2 bands improved the classification accuracy of the forest species. A study by Chen (2011) investigated the accuracy of WV-2 and IKONOS imageries in the classification of *Myoporum sandwicense* and *Sophora chrysophylla* species on the western slope of Mauna Kea in Hawaii. He found that WV-2 had higher overall accuracies than IKONOS (6% higher using pixel-based approach and 13% higher using object-based approach). Other researches also showed that the additional red-edge and yellow band in WV-2 can make a significant difference in identifying urban area tree species (Immitzer *et al*., 2012). WV-2 has improved spatial and spectral resolution as compared to SPOT-7. WorldView-2 has eight spectral bands whilst SPOT-7 only have four spectral bands. Pu (2009) also found red-edge and yellow bands (additional bands in WV-2 image) to be important for accurately identifying urban tree species using hyperspectral measurements collected from11 urban tree species. Results from this study are also evident that the additional WV-2 bands are useful in vegetation classification at species level.

Random Forest and SVM are both robust algorithms in classifying land use and land cover (Benediktsson *et al*., 2007; Belgiu and Drăguţ, 2016; Huang *et al*., 2002; Mountrakis *et al*., 2011). This is in line with findings of this research; where both RF and SVM achieved high overall accuracies for the WV-2 and SPOT-7 imageries. However, RF had slightly higher overall accuracies than SVM. Random Forest obtained accuracies of 81.67% for WV-2 image and 72.78% for SPOT-7, whilst SVM obtained overall accuracies of 80% and 71.11% for WV-2 and SPOT-7 respectively. The SVM algorithm function by calculating separating hyperplane that provides the largest lowest distance to the training data (Li *et al*., 2014). The algorithm minimises classification error by increasing the margin between the hyperplane and data points. Accuracies obtained for SVM in this study were also as a result of the radial kernel function that was used with the optimisation of two parameters *gamma* (γ) and *cost* (C), which solves inseparability issues as a result of overlapping classes (Huang *et al*., 2002). On the other hand, Random Forest classifier makes use of decision trees and each tree contributes with a single vote for the most popular class (Pal, 2005). This makes this algorithm a robust classier because it can deal better with outliers, hence it had slightly higher accuracies than SVM. Other comparison studies also reported that RF performs better than SVM (Mureriwa *et al*., 2015).

The combination of WV-2 image and RF classification algorithms effectively improved mapping of the eucalyptus distribution in the historical mining areas located south of Johannesburg city. Worldview-2 image and Random forest classifier produced the highest classification accuracy of 81.67%. This classification also had the highest accuracy for eucalyptus class (73.33%). The final distribution map produced shows that eucalyptus trees are more dominant around the mine tailing dams, an evidence showing that these trees were intentionally planted for their phytoremediation values (AngloGold, 2004). This is because eucalyptus trees are tolerant and can thrive well in highly contaminated soils and a wide range of pH levels (AngloGold, 2004). Therefore, the concentrated eucalyptus trees found in this study in Johannesburg south where most historical mining sites are located shows the importance of the trees for soil erosion control in the mines and their services as phytoremediation agents to reduce acid mine drainage problems.

5.2. Conclusions

The main aim of this research was to investigate the importance of high-resolution multispectral imageries in mapping eucalyptus trees in Johannesburg city. The study also compared the classification efficiency of Random Forest and Support Vector Machines algorithms between the eucalyptus trees and other land uses in this historical mining areas located south of Johannesburg city and the results were as follows:

- Johannesburg city was successfully mapped using WorldView-2 and SPOT-7 imageries. However, WV-2 imagery achieved better accuracies as compared to SPOT-7 and RF algorithm attained slightly higher accuracies for both images as compared to SVM algorithm. WV-2 image achieved overall accuracies of 81.67% and 80% for RF and SVM classifiers, respectively. Overall accuracies for SPOT-7 were 72.78% and 71.11% for RF and SVM, respectively. WV-2 performed better because of its high spatial and spectral resolution.
- The extra bands of WorlView-2 enhanced the mapping of eucalyptus trees around the historical mining area located south of Johannesburg as compared to SPOT-7 image which only have four traditional bands. Thus, the combination of WorldView-2 image and Random Forest algorithm improved the eucalyptus accuracies classification levels.
- According to the RF classification algorithm for WV-2, which produced the highest accuracy level of all, most of the eucalyptus trees were predominantly concentrated on and near the tailing dams located south of the city.

5.3. Recommendations for future studies

In this study no vegetation indices were used in the classification process, and their use might help to improve discrimination of eucalyptus trees from other woody trees. The classification of the genus eucalyptus at species level might improve the classification accuracy levels since the genus has a lot of species that portrays different physical characteristics.

References

Abo-Hassan, A., Kandeel, S.A. and Kherallah, I.E., 1988. New eucalyt species introduction in the Saudi Arabia central zone. *In Proceedings of the international forestry conference, Australian Bicentenary, 5*, pp.1-16.

Adam, E., Mutanga, O. and Rugege, D., 2010. Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: a review. *Wetlands Ecology and Management*, *18*(3), pp.281-296.

Adam, E., Mutanga, O., Odindi, J. and 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), pp.3440-3458.

Akasheh, O.Z., Neale, C.M. and Jayanthi, H., 2008. Detailed mapping of riparian vegetation in the middle Rio Grande River using high resolution multi-spectral airborne remote sensing.

Journal of Arid Environments, *72*(9), pp.1734-1744.

AngloGold, A., 2004. Case studies. Woodlands Project–good progress being made with phytoremediation project.

Ardila, J.P., Bijker, W., Tolpekin, V.A. and Stein, A., 2012. Context-sensitive extraction of tree crown objects in urban areas using VHR satellite images. *International journal of applied earth observation and geoinformation*, *15*, pp.57-69.

Astrium, 2015. SP0T 6/ SPOT 7 Technical sheet. Available at: https://www.intelligencehttps://www.intelligence-airbusds.com/files/pmedia/public/r12317_9_spot6-7_technical_sheet.pdfairbusds.com/files/pmedia/public/r12317_9_spot6-7_technical_sheet.pdf. [Accessed 10 Feb. 2018]

Atangana, A., Khasa, D., Chang, S. and Degrande, A., 2014. Agroforestry for soil conservation.

In *Tropical Agroforestry* (pp. 203-216). Springer, Dordrecht.

Belgiu, M. and Drăguţ, L., 2016. Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, *114*, pp.24-31.

Benediktsson, J.A., Chanussot, J. and Fauvel, M., 2007. Multiple classifier systems in remote sensing: from basics to recent developments. *In International Workshop on Multiple Classifier Systems*, pp.501-512.

Bolund, P. and Hunhammar, S., 1999. Ecosystem services in urban areas. *Ecological economics*, *29*(2), pp.293-301.

Boulet, A.K., Prats, S.A., Malvar, M.C., González-Pelayo, O., Coelho, C.O., Ferreira, A.J. and Keizer, J.J., 2015. Surface and subsurface flow in eucalyptus plantations in north-central Portugal. *Journal of Hydrology and Hydromechanics*, *63*(3), pp.193-200.

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

Buff, A., 2012. A quick history of Joburg's trees. *Johannesburg City Parks and Zoo Tree Management Strategy*. Available at: http://www.jhbcityparks.com/index.php/treehttp://www.jhbcityparks.com/index.php/tree-planting/tree-planting-updates/1288-a-quick-history-of-joburgs-treesplanting/tree-planting-updates/1288-a-quick-history-of-joburgs-trees [Accessed 23 Aug. 2017]

Carbonnier, L., Marques, C., Coutinho, J., Madeira, M. and Tomé, M., 2004. The future of Eucalyptus plantations. *Borralho NMG PJS, IUFRO on silviculture and improvement of Eucalypts: 'Eucalyptus in a changing world'. Portugal: Aveiro*.

Chen, Q., 2011. Comparison of Worldview-2 and IKONOS-2 Imagery for Identifying Tree Species in the Habitat of an Endangered Bird Species in Hawaii; 8-Band Research Challenge. *DigitalGlobe: Longmont, CO, USA.*

Cho, M.A., Malahlela, O. and Ramoelo, A., 2015. Assessing the utility WorldView-2 imagery for tree species mapping in South African subtropical humid forest and the conservation implications: Dukuduku forest patch as case study. *International Journal of Applied Earth Observation and Geoinformation*, *38*, pp.349-357.

Chornesky, E.A. and Randall, J.M., 2003. The threat of invasive alien species to biological diversity: setting a future course. *Annals of the Missouri Botanical Garden*, pp.67-76.

City of Johannesburg, 2013. *We're living in an urban forest*. Available at: https://joburg.org.za/index.php?option=com_content&task=view&id=355&Itemid=52 [Accessed 21 Aug. 2017]

Coder, K.D., 1996. *Construction damage assessments: trees and sites*. University of Georgia.

Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote sensing of environment*, *37*(1), pp.35-46.

Demir, B. and Erturk, S., 2008. Spectral magnitude and spectral derivative feature fusion for improved classification of hyperspectral images. *Geoscience and Remote Sensing Symposium. IGARSS 2008. IEEE International*, 1020(3)

Department of Environmental Affairs, 2014. *South Africa Government Gazette*. Accessed at: http://www.sanbi.org/sites/default/files/documents/documents/nembainvasivealienspeciesregulations-12feb2014.pdf [Accessed 12 Nov. 2017]

DigitalGlobe, 2012. *The benefits of the 8 spectral bands of WorldView-2*. Available at: https://dghttps://dg-cms-uploads-production.s3.amazonaws.com/uploads/document/file/35/DG-8SPECTRAL-WP_0.pdfcms-uploads-production.s3.amazonaws.com/uploads/document/file/35/DG-8SPECTRALhttps://dg-cms-uploads-production.s3.amazonaws.com/uploads/document/file/35/DG-8SPECTRAL-WP_0.pdfWP_0.pdf (Accessed 10 Nov. 2017)

Dwyer, J.F., McPherson, E.G., Schroeder, H.W. and Rowntree, R.A., 1992. Assessing the benefits and costs of the urban forest. *Journal of Arboriculture*, *18*, pp.227-227.

Dzikiti, S., Gush, M.B., Le Maitre, D.C., Maherry, A., Jovanovic, N.Z., Ramoelo, A. and 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*, pp.69-80.

FAO, 2000. Global forest resources assessment. *FAO Forestry paper. ISSN 0258-6150* Available at: http://www.fao.org/forestry/fo/fra/main/index.jsp [Accessed 05 May. 2017]

Fine, P., Paresh, R., Beriozkin, A. and Hass, A., 2014. Chelant-enhanced heavy metal uptake by Eucalyptus trees under controlled deficit irrigation. *Science of the Total Environment*, *493*, pp.995-1005.

Foody, G.M., 2002. Status of land cover classification accuracy assessment. *Remote sensing of environment*, *80*(1), pp.185-201.

Forsyth, G.G., Richardson, D.M., Brown, P.J. and 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), pp.75-77.

Ghosh, A. and Joshi, P.K., 2014. A comparison of selected classification algorithms for mapping bamboo patches in lower Gangetic plains using very high resolution WorldView 2 imagery. *International Journal of Applied Earth Observation and Geoinformation*, *26*, pp.298-311.

Gidlöf-Gunnarsson, A. and Öhrström, E., 2007. Noise and well-being in urban residential environments: The potential role of perceived availability to nearby green areas. *Landscape and Urban Planning*, *83*(2), pp.115-126.

Gomes, M.P., Marques, T.C.L.L.S.M., Carneiro, M.M.L.C. and Soares, Â.M., 2012. Anatomical characteristics and nutrient uptake and distribution associated with the Cd-phytoremediation capacity of Eucalyptus camaldulenses Dehnh. *Journal of soil science and plant nutrition*, *12*(3), pp.481-496.

Gong, P., Pu, R. and Yu, B., 1997. Conifer species recognition: An exploratory analysis of in situ hyperspectral data. *Remote sensing of Environment*, *62*(2), pp.189-200.

Guenther, A., Hewitt, C.N., Erickson, D., Fall, R., Geron, C., Graedel, T., Harley, P., Klinger, L., Lerdau, M., McKay, W.A. and Pierce, T., 1995. A global model of natural volatile organic compound emissions. *Journal of Geophysical Research: Atmospheres*, *100*(D5), pp.88738892.

Holgate, C., 2007. Factors and actors in climate change mitigation: a tale of two South African cities. *Local Environment*, *12*(5), pp.471-484.

Huang, C., Davis, L.S. and Townshend, J.R.G., 2002. An assessment of support vector machines for land cover classification. *International Journal of remote sensing*, *23*(4), pp.725-749.

Huang, C., Shao, Y., Chen, J., Liu, J., Chen, J. and Li, J., 2007. A strategy for analyzing urban forest using Landsat ETM+ imagery. *Geoscience and Remote Sensing Symposium. IEEE International*, pp.1990-1993

Huerta, L., Huesca, J., Cabrera, N., Ruiz, J. and Hernandez, L., 2015. The Data Mining Process for Classification of Fetal Death Causes. *International Journal of Computer Science and Information Security*, *13*(8), pp.5.

Immitzer, M., Atzberger, C. and Koukal, T., 2012. Tree species classification with random forest using very high spatial resolution 8-band WorldView-2 satellite data. *Remote Sensing*, *4*(9), pp.2661-2693.

Jensen, J.R. and Lulla, K., 1987. Introductory digital image processing: a remote sensing perspective.

Junghans, D.T., Alfenas, A.C., Brommonschenkel, S.H., Oda, S., Mello, E.J.D. and Grattapaglia, D., 2003. Resistance to rust (*Puccinia psidii* Winter) in Eucalyptus: mode of inheritance and mapping of a major gene with RAPD markers. *Theoretical and Applied Genetics*, *108*(1), pp.175-180.

Kong, F. and Nakagoshi, N., 2005. Changes of urban green spaces and their driving forces: a case study of Jinan city, China. *J. Int. Dev. Cooperat.*, *11*(2), pp.97-109.

Kraaij, T., Baard, J.A., Rikhotso, D.R., Cole, N.S. and Van Wilgen, B.W., 2017. Assessing the effectiveness of invasive alien plant management in a large fynbos protected area. *BothaliaAfrican Biodiversity & Conservation*, *47*(2), pp.1-11.

Kruger, A.C. and Nxumalo, M.P., 2017. Historical rainfall trends in South Africa: 1921-2015. *Water SA*, *43*(2), pp.285-297.

Kumar, P., 2010. *The economics of ecosystems and biodiversity: ecological and economic foundations*. UNEP/Earthprint.

Kurz, W.A., Stinson, G., Rampley, G.J., Dymond, C.C. and Neilson, E.T., 2008. Risk of natural disturbances makes future contribution of Canada's forests to the global carbon cycle highly uncertain. *Proceedings of the National Academy of Sciences*, *105*(5), pp.1551-1555.

Labate, C.A., de Assis, T.F., Oda, S., de Mello, E.J., González, E.R., Zauza, E.A.V., Mori, E.S., de Moraes, M.L.T., Cid, L.P.B., Alfenas, A.C. and Foelkel, C., 2009. Eucalyptus. *Compendium of Transgenic Crop Plants*.

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

Le Maitre, D.C., van Wilgen, B.W., Gelderblom, C.M., Bailey, C., Chapman, R.A. and Nel, J.A., 2002. Invasive alien trees and water resources in South Africa: case studies of the costs and benefits of management. *Forest Ecology and management*, *160*(1-3), pp.143-159.

Le Maitre, D.C., Versfeld, D.B. and Chapman, R.A., 2000. Impact of invading alien plants on surface water resources in South Africa: A preliminary assessment.

Li, C., Wang, J., Wang, L., Hu, L. and Gong, P., 2014. Comparison of classification algorithms and training sample sizes in urban land classification with Landsat thematic mapper imagery. *Remote Sensing*, *6*(2), pp.964-983.

Li, C., Yin, J. and Zhao, J., 2010. Extraction of urban vegetation from high resolution remote sensing image. *Computer Design and Applications (ICCDA), International Conference*, 403(4)

Liaw, A. and Wiener, M., 2002. Classification and regression by Random Forest. *R news*, *2*(3), pp.18-22.

Livesley, S.J., McPherson, E.G. and Calfapietra, C., 2016. The urban forest and ecosystem services: Impacts on urban water, heat, and pollution cycles at the tree, street, and city scale. *Journal of environmental quality*, *45*(1), pp.119-124.

Marais, C., Van Wilgen, B.W. and Stevens, D., 2004. The clearing of invasive alien plants in South Africa: a preliminary assessment of costs and progress: working for water. *South African Journal of Science*, *100*(1-2), pp.97-103.

Mbatha, K.C. and De Wet, H., 2018. The importance of alien plants in the well-being of rural communities in northern Maputaland, KwaZulu-Natal, South Africa. *South African Journal of Botany*, *115*, pp.297-298.

Moran, V.C., Hoffmann, J.H. and Zimmermann, H.G., 2013. 100 years of biological control of invasive alien plants in South Africa: History, practice and achievements. *South African Journal of Science*, *109*(9-10), pp.01-06.

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

Mureriwa, N., Adam, E., Sahu, A. and Tesfamichael, S., 2015. Spectral Discrimination of *Prosopis glandulosa* (Mesquite) in Arid Environment of South Africa: Testing the Utility of in Situ Hyperspectral Data and Guided Regularized Random Forest Algorithm. *Asian Association on Remote Sensing: Manila, Philippines*.

Mutanga, O., Adam, E. and Cho, M.A., 2012. High density biomass estimation for wetland vegetation using WorldView-2 imagery and random forest regression algorithm. *International Journal of Applied Earth Observation and Geoinformation*, *18*, pp.399-406.

Odindi, J.O., Adam, E.E., Ngubane, Z., Mutanga, O. and 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), p.083527.

Omar, H., 2010. Commercial timber tree species identification using multispectral Worldview2 data. *Digital Globe® 8Bands Research Challenge*, pp.2-13.

Omer, G., Mutanga, O., Abdel-Rahman, E.M. and Adam, E., 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), pp.4825-4840.

Otukei, J.R. and Blaschke, T., 2010. Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. *International Journal of Applied Earth Observation and Geoinformation*, *12*, pp.S27-S31.

Ouma, Y.O. and Tateishi, R., 2008. Urban-trees extraction from Quickbird imagery using multiscale spectex-filtering and non-parametric classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *63*(3), pp.333-351.

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

Pouteau, R., Meyer, J.Y., Taputuarai, R. and Stoll, B., 2012. Support vector machines to map rare and endangered native plants in Pacific islands forests. *Ecological Informatics*, *9*, pp.37-46.

Peijun, D.U., Xingli, L.I., Wen, C.A.O., Yan, L.U.O. and Zhang, H., 2010. Monitoring urban land cover and vegetation change by multi-temporal remote sensing information. *Mining Science and Technology (China)*, *20*(6), pp.922-932.

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

Prinsloo, F.W. and Scott, D.F., 1999. Streamflow responses to the clearing of alien invasive trees from riparian zones at three sites in the Western Cape Province. *Southern African Forestry Journal*, *185*(1), pp.1-7.

Pu, R. and Landry, S., 2012. A comparative analysis of high spatial resolution IKONOS and WorldView-2 imagery for mapping urban tree species. *Remote Sensing of Environment*,*124*, pp.516-533.

Pu, R., 2009. Broadleaf species recognition with in situ hyperspectral data. *International Journal of Remote Sensing*, *30*(11), pp.2759-2779.

Pua, E.C. and Davey, M.R., 2007. *Transgenic crops*. Springer Science & Business Media.

Pulford, I.D. and Dickinson, N.M., 2006. Phytoremediation technologies using trees. *Trace elements in the environment: biogeochemistry, biotechnology and bioremediation*, pp.375–395.

Richardson, D.M. and 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), pp.45-52.

Rodriguez-Galiano, V.F., Ghimire, B., Rogan, J., Chica-Olmo, M. and 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*, pp.93-104.

Schäffler, A. and Swilling, M., 2013. Valuing green infrastructure in an urban environment under pressure—The Johannesburg case. *Ecological Economics*, *86*, pp.246-257.

Schwenker, F., 2000. Hierarchical support vector machines for multi-class pattern recognition. In *Knowledge-based intelligent engineering systems and allied technologies, 2000. Proceedings. Fourth international conference on* (Vol. 2, pp. 561-565). IEEE.

Shafri, H.Z., Taherzadeh, E., Mansor, S. and Ashurov, R., 2012. Hyperspectral remote sensing of urban areas: an overview of techniques and applications. *Research Journal of Applied Sciences, Engineering and Technology*, *4*(11), pp.1557-1565.

Shojanoori, R. and Shafri, H.Z., 2016. Review on the use of remote sensing for urban forest monitoring. *Arboric Urban For*,*42*(6), pp.400-17.

Statistics South Africa (StatsSA), 2010. Midyear Population Estimates. Available at:

http://www.statssa.gov.za/timeseriesdata/timeseriesdata.asp [Accessed 30 Mar. 2017].

Turnbull, J.W., 1999. Eucalyptus plantations. *New Forests*, 17: 37-52.

Turton, A., Schultz, C., Buckle, H., Kgomongoe, M., Malungani, T. and Drackner, M., 2006. Gold, scorched earth and water: the hydropolitics of Johannesburg. Water Resources Development, 22(2), pp.313-335.

Vailshery, L.S., Jaganmohan, M. and Nagendra, H., 2013. Effect of street trees on microclimate and air pollution in a tropical city. *Urban forestry & urban greening*, *12*(3), pp.408-415.

Van Wilgen, B.W., Le Maitre, D.C. and Cowling, R.M., 2012. Ecosystem services, efficiency, sustainability and equity: South Africa's Working for Water programme. *Trends in Ecology & Evolution*, *13*(9), pp.378.

Vapnik, W.N., 1999. An overview of statistical learning theory. *IEEE Transactions of Neural Networks*, *10*, pp.988–999

Wynberg, R., 2002. A decade of biodiversity conservation and use in South Africa: tracking progress from the Rio Earth Summit to the Johannesburg World Summit on Sustainable Development. *South African Journal of Science*, *98*(5-6), pp.233-243.

Zafari, A., Zurita-Milla, R. and Izquierdo-Verdiguier, E., 2017, October. Integrating support vector machines and random forests to classify crops in time series of Worldview-2 images. *Image and Signal Processing for Remote Sensing XXIII*, *10427*. International Society for Optics and Photonics.

Zengeya, T., Ivey, P., Woodford, D.J., Weyl, O., Novoa, A., Shackleton, R., Richardson, D. and van Wilgen, B., 2017. Managing conflict-generating invasive species in South Africa: Challenges and trade-offs. *Bothalia-African Biodiversity & Conservation*, *47*(2), pp.1-11.

Zhang, C. and Qiu, F., 2012. Mapping individual tree species in an urban forest using airborne lidar data and hyperspectral imagery. *Photogrammetric Engineering & Remote Sensing*, *78*(10), pp.1079-1087.

Zhang, Z. and Liu, X., 2013. Support vector machines for tree species identification using LiDAR-derived structure and intensity variables. *Geocarto International*, *28*(4), pp.364-378.