Assessing multi-temporal remote sensing imagery for discriminating savannah tree species

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Declaration 1

This research work was conducted in fulfilment of the academic requirements for the Masters of Science degree in the Discipline of Geography and represents the original work of the author. Any work sourced from other researchers and organization is duly acknowledged within text and in the reference list.

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Details of contribution to publications (i.e. publications in preparation, submitted, in press or published and contribution of each author in the experimental work and writing of each publication) that form part of the research work presented include:-

Publication 1: Madonsela, S.[1,2], Cho, M.[1,2], Mathieu, R.[2] and Mutanga, O.[1] (*in preparation*). Evaluating the utility of object-based image analysis (OBIA) for mapping savannah tree species using Worldview-2 image.

This research work was conducted by the first author under the guidance and supervision of the second, third and fourth authors.

Publication 2: Madonsela, S.[1,2], Mathieu, R.[2], Cho, M.[1,2] and Mutanga, O.[1] (*in preparation*). Multi-temporal approach towards tree species mapping in southern African savannah.

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Acronyms

BI : Brightness index

NDVI : Normalized Difference Vegetation Index

NIR-2 : Near infrared-2

OBIA : Object-based image analysis

OCA : Overall Classification Accuracy

RF : Random Forest

SAM : Spectral Angle Mapper

VHR : Very High Resolution

WV-2 : Worldview-2

Abstract

The advent of new multispectral sensors such as Worldview-2 with very high spatial resolution (VHR) has presented new opportunities for mapping vegetation at species-level. However the use of VHR data for tree species mapping is often confronted with issues of within-canopy spectral variability. The prevailing intraspecies variability in southern African savannah limits our ability to accurately map the distribution of tree species. These challenges necessitate the development of new methods for tree species mapping. This study investigated i) the utility of object-based image analysis (OBIA) for tree species mapping in the savannah environment using Worldview-2 image, ii) the spectral capability of WV-2 for species mapping and iii) the ability of multi-temporal data to enhance spectral separability between tree species in southern African savannah. Using Random Forest (RF), the study could not establish any statistically significant difference between OBIA and pixel-based approach towards savannah tree species classification ($z_{obt} < z_{crit}$). However OBIA successfully improved classification accuracy of *Sclerocharya birrea* and *Acacia nigrescens* which makes it an appropriate alternative for classifying big trees in the savannah environment using WV-2 image.

Moreover, the spectral configuration of WV-2 with the inclusion of yellow and red-edge bands enhanced the discriminatory power of WV-2 sensor. The WV-2 image achieved higher classification accuracy (74.5% with object-based and 76.4% with pixel-based) than simulated IKONOS image (58.6% with object-based and 67.9% with pixel-based). The difference was statistically significant ($z_{obt} > z_{crit}$). The use of multi-temporal data enhanced spectral variability between species and achieved the highest classification accuracy (80.4%) than March and April dates (72.9% and 76.4%, respectively). Multi-temporal data mitigated the spectral confusion between *Sclerocharya birrea* and *Dichrostachys cinerea* and achieved producer's and user's accuracy of above 60% for these tree species. The results highlight the opportunities available to biodiversity managers due to advances in remote sensing technology. The ability to accurately map tree species is the key element in the management of savannah biodiversity.

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Chapter 1: Introduction

1.1 Background

Tree species mapping at large geographic scales secures indispensable information for sound management of the savannah ecosystem (Naidoo *et al*. 2012; Cho *et al*. 2012). Large tree species play an important role in the savannah ecosystem as nutrient pumps in the system (Treydte *et al*. 2007; Ludwig *et al*. 2004), source of fuelwood and economically viable fruits for local communities (Shackleton and Shackleton, 2003) and also act as breeding sites for birds (Cho *et al*. 2012). However, the savannah ecosystem bears escalating pressure from humans and bush encroaching species. Cho *et al*. (2012) noted a widespread distribution of bush encroaching species (*Dichrostachys cinerea and Combretum appiculatum*) and over-exploitation of *Terminalia sericea* species in the southern African savannah. Therefore regular mapping of biodiversity remains critical for monitoring changes and ensuring sustainable use of ecosystem resources (Cho *et al*. 2012). In addition biodiversity mapping facilitates the assessment of management decisions implemented at a regional scale (Asner *et al*. 2009).

The challenge to biodiversity mapping has been the paucity of appropriate data in terms of accuracy, details, completeness as well as spatial and spectral resolution (Foody and Cutler, 2003). The traditional ground-based methods of biodiversity assessment lack regional-scale generalization (Asner *et al*. 2009; Foody and Cutler, 2003). Moreover, the early satellite sensors such as Landsat TM or ETM+ provides low spatial and spectral resolution data insufficient for tree species mapping (Xie *et al*. 2008; Nagendra and Rocchini, 2008). Tree species mapping with remotely sensed data necessitates the use of very high resolution data to capture and differentiate species based on their unique biochemical and biophysical properties (Cho *et al*. 2012; Clark *et al*. 2007). Therefore the use of Landsat data has been limited to habitat mapping and analysis of landcover change (Yang and Prince, 2000; Townsend and Walsh, 2001; Millington *et al*. 2003).

However, the advancement in spectral and spatial resolution of multispectral sensors presents new opportunities for species-level mapping (Foody *et al*. 2005) while also renewing the need for development of new methods for effective image classification (Cho *et al*. 2010). The latter is particularly relevant to savannah environment where open, irregular canopy shape, varying tree height, interlocking canopies and background vegetation may reduce mapping accuracy when using high resolution data (Chastain, 2008;

Naidoo *et al*. 2012). Since the pixel size of high resolution sensors is smaller than canopy size, various components of the tree canopy i.e. sunlit leaves, shaded leaves and bark will be captured including the background and this eventually leads to high within-canopy variability (Nagendra and Rocchini, 2008; Chastian, 2008). Hence deriving species identity becomes challenging due to within-canopy spectral variability (Nagendra, 2001).

Studies have progressively tapped into the utility of object-based image analysis (OBIA) to improve tree species classification using very high resolution data (Ardila *et al*. 2012; Zhang and Xie, 2012; Whiteside *et al*. 2011; Chastain, 2008). Prior to the advent of OBIA, researchers exploited per-pixel classification techniques with some degree of success. The advancement in spatial and spectral resolution of satellite sensors has enhanced the level of details attainable from earth objects (Wulder *et al*. 2004). Whilst this delivered much needed benefits to ecological application of remote sensing (Nagendra and Rocchini, 2008; Wulder *et al*. 2004), it has complicated the ability of per-pixel classifiers to produce desirable accuracy level. Per-pixel classifiers are yet to resolve adequately, the issue of within-canopy spectral variability that comes with VHR data. Their application with VHR data often leads to classification inconsistencies i.e. producing a class within a class often called salt and pepper effect (Ardila *et al.* 2012; Whiteside *et al.* 2011).

Alternatively OBIA bestow an opportunity to merge spectral, spatial and contextual information in order to close the gap between much detailed spatial data and important feature classification task (Ardila *et al*. 2012; Whiteside *et al.* 2011). First, OBIA partitions the image pixels through segmentation into image objects based on scale, colour and form parameters. The subsequent image classification uses these image objects as units of classification (Whiteside *et al*. 2011; Kim *et al*. 2009). Generally, studies have reported improved mapping accuracy with OBIA and attributed that to the consideration of spectral, spatial and contextual information altogether (Kim *et al*. 2009; Whiteside *et al*. 2011; Ardila *et al*. 2012; Zhang and Xie, 2012). Nonetheless, Robertson and King (2011) in their study comparing the performance of pixel-based and object-based classification concluded that there is no statistically significant difference between these classifiers.

In addition studies have established that multi-temporal approach enhances spectral differences between species (Hill *et al*. 2010; Gilmore *et al*. 2008). Multi-temporal data covering leaf flushing, leaf development and maturity and senescence mitigates perturbing effects such as individual image noise and enhance the spectral differences between tree species (Hill *et al.* 2010; Key *et al*. 2001; Wolter *et al*. 1995). A multi-temporal approach has been recommended for mapping savannah woody species (Cho *et al*. 2010). However none of the literature consulted have adopted a multi-temporal approach towards tree species mapping in the southern African savannah.

The primary objective of this study is to develop a classification method for mapping savannah tree species using Worldview-2 image. The first part of the study intends to investigate if OBIA is superior to pixel-based classification for mapping savannah tree species using Worldview-2 image. The assumption is that using objects with Worldview-2 spectral data will improve tree species discrimination. Worldview-2 image has 2m spatial resolution which enables it to capture individual tree canopy thus presenting an opportunity for species-level mapping. Nonetheless, exploiting such an opportunity necessitates overcoming the high intra-class spectral variability inherent to VHR data. The Worldview-2 data contains innovative bands in the yellow and red-edge spectrum, which has shown to be sensitive to subtle differences between species. The study will compare the performance of WV-2 spectral configuration to that of simulated IKONOS spectral configuration. Finally, the study will investigate the ability of Worldview-2 data captured at different seasons to enhance spectral variability amongst tree species in the savannah environment.

1.2 Research Questions

- Can object-based image classification improve tree species mapping in southern African savannah when compared to pixel-based classification?
- To what extent does the inclusion of new bands in the yellow and red-edge regions of Worldview-2 enhance its capacity to discriminate tree species in the savannah environment?
- How does the spectral separability of tree species changes in: i) individual images acquired at key points of the typical phenological development of savannah and ii) when images of different dates are combined?

1.3 Objectives

- To develop an object-based method for species-level classification of individual tree crown using their spectral information;
- To assess the capability of Worldview-2 spectral bands for tree species mapping in the complex savannah environment;
- To investigate whether a multi-temporal approach based on multi-seasonal imagery could enhance the spectral variation amongst savannah tree species compared to single image data, and improve on their classification.

1.4 Summary of Chapters

The thesis is organized into four chapters. The initial chapter deliberates on the importance of tree species inventory and monitoring and the relevance of remote sensing for addressing these tasks and outlines the research objectives. Chapter two and three are written in a paper format for publication in peer reviewed journals. Chapter two investigates the utility of object-based image analysis for tree species mapping and assess the spectral capability of Worldview-2 data compared to simulated IKONOS. Chapter three investigates the benefits of multi-temporal approach for tree species mapping. The fourth chapter presents the conclusion of the study and provides recommendation for further research. Important research findings are highlighted in relation to the research objectives.

1.5 Study area

The study site is situated between longitude 31°21'18.66" to 31°31'1.61"E and latitude 24°50'42.61" to 24°59'35.04"S in the immediate vicinity of the Kruger National Park, South Africa (**Figure 1**) and it covers approximately 265 sqkm. It falls in the South African Lowveld within the broader savannah biome which is characterized by the coexistence of continuous grassy vegetation layer and discontinuous woody vegetation. Rainfall, geology, grazing pressures (both from wild and domestic herbivores), human uses (e.g. crop, fuelwood collection) and fires dictate the vegetation structure in this biome. Savannah environment is characterized by alternating periods of dry and wet seasons. The Lowveld receives annual rainfall of between 235 and 1000 mm. The average annual temperature for the site is 22°C and frost is rare (du Toit *et al*. 2003; Eckhardt *et al*. 2000).

Two geological substrates dominate in the area with vegetation communities defined along these geological structures. The nutrient-rich gabbros substrate exhibits predominance of grassy plant formation and sketchy tree distribution. Gabbros consists of shallow to moderately deep, dark clay with nutritious high-bulk grasses and sketchy distribution of trees and shrubs particularly *Acacia spp*. Conversely the granitic substrate consist of poor-nutrient soils with gentle undulating terrain and they sustain woody deciduous broad-leaved species occupying upslope while fine-leaved species dominating at the footslope. Granite landscape with shallow to moderately deep sandy soil is characterized by high species diversity and dominance of *Combretum spp.* (Cho *et al*. 2012).The study area run across two different management regimes; the Sabi Sands Wildtuin which is a privately owned land used purely for nature conservation and the Bushbuckridge Municipality District which incorporate communal land used by neighbouring communities for livestock grazing, fuelwood harvesting and other farming activities.

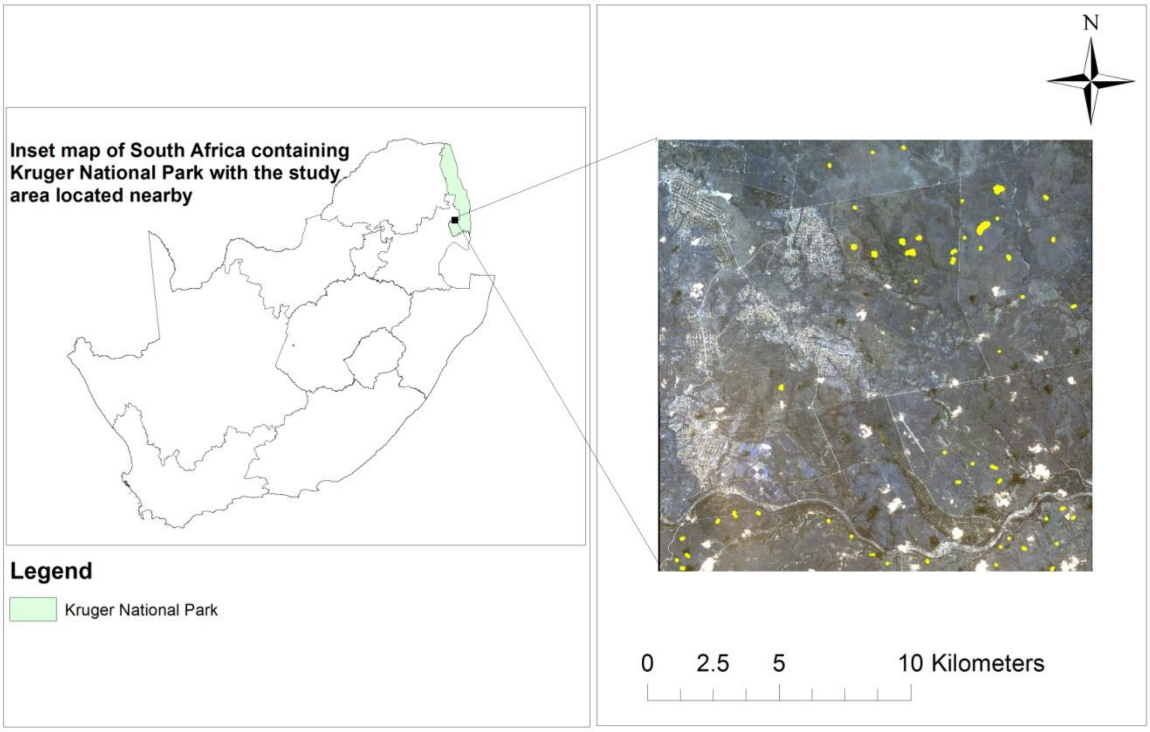

Figure 1.1 Study area and data collection sites

1.6 General methodology

A schematic representation of the research methods is presented in **Figure 1.2.** The first part of the study investigated the utility of OBIA in relation to pixel-approach, for tree species in the savannah environment using Worldview-2 image captured during the transition to senescence phonological period (April date). The second part of the study used the two Worldview-2 images to test the ability of multi-temporal data to enhance spectral separability between tree species. Detailed discussion on the pre-processing process, segmentation and classification processes is presented under method section in the subsequent chapters.

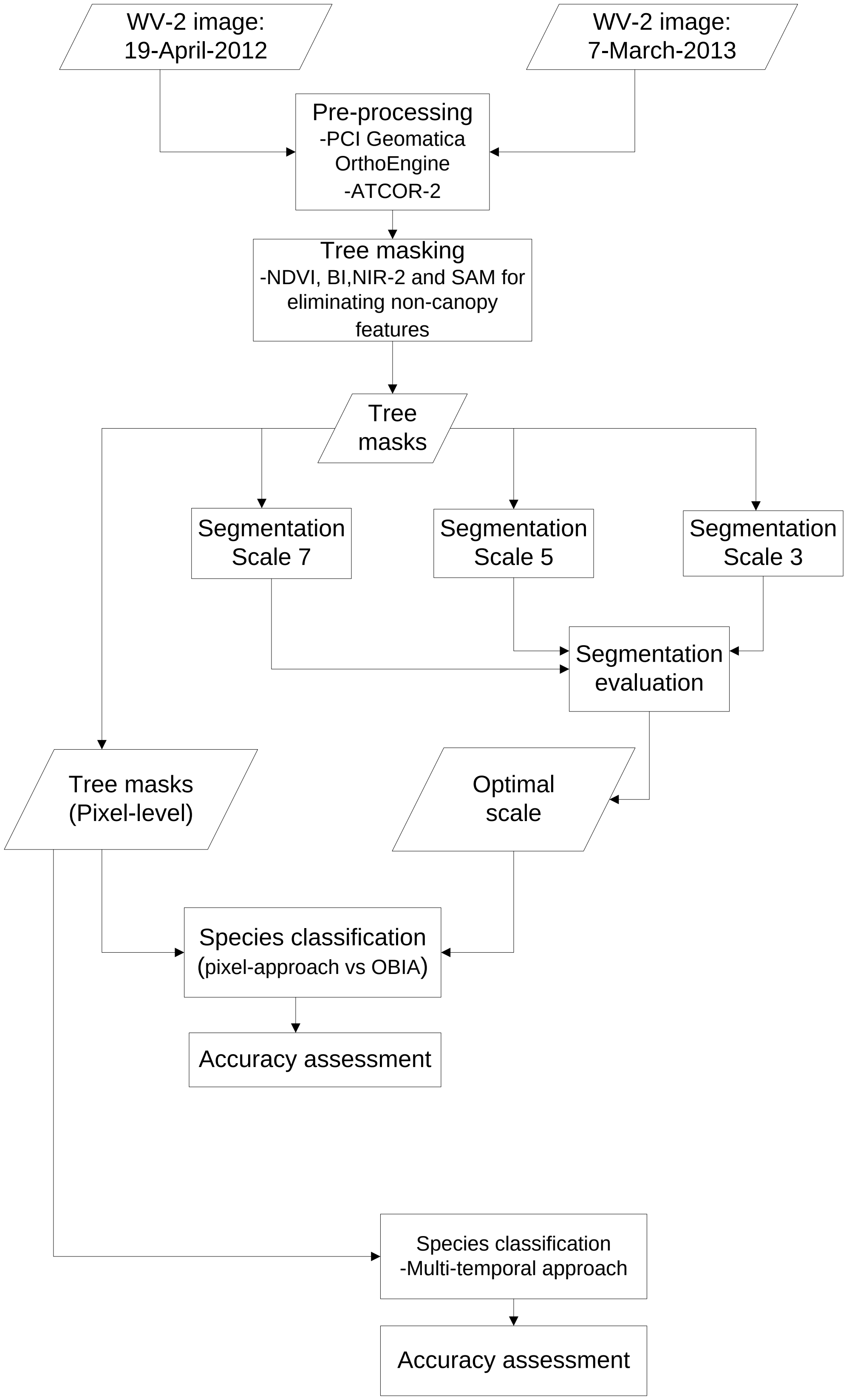

Figure 1.2 Schematic representations of the data and research methods used.

Chapter 2: The utility of Object-based image analysis (OBIA) for tree species mapping in the savannah environment using WV-2 image

2.1 Abstract

In this study, the utility of object-based image analysis (OBIA) for tree species mapping in a heterogeneous savannah environment is investigated using very high resolution Worldview-2 (WV-2) data. The spectral capability of WV-2 sensor is also compared to that of simulated IKONOS for species discrimination. Using RF as a classifier, the study could not establish any statistically significant difference between OBIA and pixel-based approach towards tree species classification ($z_{obt} < z_{crit}$) and this is attributable to complex structure of tree canopies in the savannah environment. However, OBIA minimized the effects of tree canopy edge pixels and therefore improved the classification accuracy of *Sclerocharya birrea* compared to pixel-based approach. In addition, OBIA successfully improved classification accuracy between *Sclerocharya birrea* and *Acacia nigrescens* which makes it an appropriate alternative for classifying big trees in the savannah environment using WV-2 image. The 8-bands of Worldview-2 sensor achieved higher discriminatory power than that of simulated IKONOS sensor. In particular, the yellow band (605nm) showed a statistically significant ($z_{obt} > z_{crit}$) contribution in the performance of WV-2.

Keywords: OBIA, species discrimination, savannah, Worldview-2, simulated IKONOS, yellow band

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2.2 Introduction

Regular mapping of savannah biodiversity remains critical in order to monitor changes and ensure that resource use remain within the resilience limits of the ecosystem (Cho *et al*. 2012). Large tree species are of significant ecological and economic value in the savannah ecosystem. For instance, these trees serve as breeding sites for birds, source of fuelwood and produce fruits for local communities and also act as nutrient pumps in the ecosystem (Treydte *et al*. 2007; Ludwig *et al*. 2004; Shackleton and Shackleton 2003; Archer *et al*. 2001). Previous studies noted that land use and management regimes have an impact on tree densities in southern African savannah (Wessels *et al*. 2011; Asner *et al.* 2009). Parallel to other ecosystems of the world, African savannah is subjected high pressure from humans and the burden remains with protected areas to maintain biodiversity in its pristine state (Cho *et al*. 2012; Asner *et al*. 2009). However, rigorous ecosystem management necessitates spatially detailed assessments of species richness and distribution on a regular basis (Turner *et al*. 2003).

Spaceborne remote sensing has often served as a major source of data for assessing and monitoring the earth ecosystems especially due to its extensive spatial coverage and revisit capacity (Mutanga *et al*. 2009; Foody *et al*. 2005). The recent advancement in spectral configuration and spatial resolution of spaceborne multispectral sensors has presented new opportunities for detailed examination of earth's biodiversity (Pu and Landry, 2012; Nagendra and Rocchini, 2008; Nagendra, 2001). Sensors such as Worldview-2 and Rapid-Eye, possess new bands in the yellow and red-edge spectrum when compared to well-known sensors such as SPOT or Landsat and have high spatial resolution, 2m and 5m respectively (Hamdan, 2010; Cho *et al*. 2011). These developments in spatial and spectral resolution have pushed the boundary beyond vegetation community mapping and provide opportunities for mapping vegetation at crown scale and species-level, thus enhancing the utility of multispectral data (Pu and Landry, 2012; Cho *et al*. 2012; Hamdan 2010).

Remote sensing data contain important spectral information which can be used to assess species diversity since each species possess unique spectral signature linked to its biochemical and biophysical attributes (Cho *et al*. 2012, 2010; Nagendra, 2001). The yellow and/or red-edge bands present in new multispectral sensors such as Worldview-2 and RapidEye have been shown to be sensitive to subtle differences in foliar pigments (chlorophyll and carotenoids) and therefore differences between tree species (Mutanga *et al*. 2009; Hamdan, 2010; Cho *et al*. 2011). Consistent with this, Pu and Landry (2012) used

Worldview-2 data to classify seven urban tree species with 62.93% overall accuracy and attributed this accuracy to improved spatial resolution and spectral configuration of the Worldview-2 sensor. Hamdan (2010) and Pu and Landry (2012) noted that the additional yellow, red-edge and NIR-2 bands on Worldview-2 sensor enhance our ability to spectrally discriminate different tree species with high accuracy. Moreover Cho *et al.* (2012) argued that 2m spatial resolution of Worldview-2 image is suitable for mapping tree canopy greater than 6m in diameter.

However, advances in spatial resolution of multispectral sensors also present, inadvertently new mapping challenges (Pu and Landry, 2012). High resolution datasets often capture various aspects of the tree canopy, i.e. sunlit leaves, shaded leaves, bark including background effect, and this leads to high within-canopy spectral variability. Eventually, this produces high misclassification errors when using per-pixel classification approaches (Nagendra and Rocchini, 2008; Chastain, 2008; Nagendra, 2001). Furthermore, a high intra-species spectral variability has been observed in southern African savannah setting and this originates partly from differences in within-species phenology, variation in edaphic properties and climatic conditions across the landscape (Cho *et al*. 2010; Naidoo *et al*. 2012). High intra-species spectral variability derails the assumption of unique spectral signature for each species thus calling for advanced classification approaches (Cho *et al*. 2010).

Previous studies have resorted to redesigning spectral libraries that account for intra-species variability in the spectral discrimination of tree species (Cho *et al.* 2010; Cochrane *et al*. 2000). For instance Cho *et al* (2010) developed a protocol for application of Spectral Angle Mapper (SAM) based on multiple-endmember approach and achieved higher overall accuracy compared to conventional SAM. Recent studies working on very high resolution (VHR) data have resorted to object-based image analysis (OBIA) for its ability to eliminate the effects of high within-canopy spectral variability and incorporate spectral, textural and contextual information altogether (Pu and Landry, 2012; Ardila *et al*. 2012; Zhang *et al*. 2012). OBIA addresses the disparity between detailed spatial data captured by the sensor and feature identification task; OBIA firstly runs segmentation to create meaningful objects that are internally homogeneous and uses these objects as units of classification (Pu and Landry, 2012; Ardila *et al.* 2012; Gao and Mas, 2008). Pixels representative of a tree canopy are grouped together to form an object thus eliminating within-canopy spectral variability (Devadas *et al*. 2012). During the classification process, the classifying algorithm acts on objects and the literature reviewed indicates that OBIA performs better than pixel-approach on very high resolution data (Gao and Mas, 2008; Pu and Landry, 2012; Zhang and Xie, 2012; Whiteside *et al*. 2011).

Nonetheless the performance of OBIA with VHR data in a complex scene such as presented by southern African savannah ecosystem and in the context of single-crown tree species mapping is yet to be tested. The complexity in savannah vegetation structure is centred on tree height variability, irregular or layered canopy shape and spatial arrangement of woody species (Archer *et al*. 2001; Naidoo *et al*. 2012). Such complexity in vegetation structure increases within-species spectral variability (Hill *et al*. 2010). OBIA is expected to offset this complexity through the use of tree structural attributes e.g. tree canopy delineated as objects together with Worldview-2 spectral data and that may improve tree species mapping due to the enhanced spectral configuration and spatial resolution of Worldview-2 (Cho *et al*. 2012).

The primary objective of this study is to investigate the utility of OBIA for mapping savannah tree species using Worldview-2 image. The assumption is that using objects with Worldview-2 spectral data will improve tree species discrimination compared to pixel-based classification. Worldview-2 image has 2m spatial resolution which enables it to capture individual tree canopy thus presenting an opportunity for species-level mapping. Nonetheless exploiting such an opportunity necessitates overcoming high intra-class spectral variability inherent with VHR data hence object-based classification is proposed in this study. Moreover Worldview-2 data contains new bands in the yellow and red-edge spectrum, which has shown to be sensitive to subtle differences between species and their performance will be tested against the simulated IKONOS band combination.

2.3 Data and Methods

2.3.1 Remote sensing data

The Worldview-2 (hereafter called WV-2) satellite image (DigitalGlobe, Inc., USA) was acquired on the 19th of April 2012 to capture transition to senescence phenological period prevailing at this time of the growing season (Cho *et al*. 2010). Worldview-2 is the only multispectral sensor with eight bands situated in the visible and near-infrared regions of the spectrum: coastal blue (400-450nm), blue (450-510nm), green (510-580nm), yellow (580-625nm), red (625-690nm), red-edge (705-745nm), NIR-1(770-895nm) and NIR-2(860-1040nm). It captures the image in two modes; panchromatic and multispectral. The sensor has a swath width of 16.4km, a maximum revisit period of 1.1 day and a spatial resolution of 2 m for the 8 multispectral bands. The panchromatic band (450-800nm) is acquired at spatial resolution of 0.5 m.

2.3.2 Field data collection

Field data were collected during the transition period from wet to dry season in April 2012. Eight sites distributed across the study area were sampled purposively to cover varying degrees of tree cover (low to high tree cover). These sites were selected over two geological substrates, gabbro and granite, present in the study area. In each of these sites, a 100m X 100m plot was set up and all trees with diameter at breast height greater than 10cm were sampled. In all sites big trees (N=273) located using a high precision GeoExplorer 600 series Global Positioning System (GPS), and the species were identified. One-second data from the Nelspruit reference station (90km from the study area) were used to post-process the GPS location to sub-meter accuracy. However, some of these points were located on cloud-covered parts of the image and were therefore not available for use. Additional trees and GPS points (N=62) collected in the area from previous studies (Naidoo *et al*. 2012) were also used for spectral endmember collection. A combination of these points was sufficient for maintaining representativity of each species of interest. In total 250 points representing four tree species of interest were used to train and validate the classifications. The study focused on four common tree species (i.e. *Acacia nigrescens* (AN), *Combretum spp.* (*Combretum collinum, Combretum apiculatum and Combretum herorence*) (COM), *Sclerocarya birrea* (SB) and *Dichrostachys cinerea* (DC)) that were encountered in most sampling sites in our fieldwork (**Table 2.1 for attribute information**). Additional tree attributes information, e.g. tree DBH, height, whether trees are interlocking or coppicing were also recorded.

Table 2.1 Information for the four tree species of interest in this study.

Tree species	Phenology	Attribute information
Sclerocarya birrea	Deciduous	Common tree species in SA savannah which is protected by law. Its fruits are considered important for beer-making in local communities and also a source of food for wild animals.
Acacia nigrescens	Deciduous	Important tree species for many browsers and serves as a nitrogen-fixing tree, increasing grass quality underneath its canopy.
Combretum spp.	Deciduous	Common tree species with high density in granite landscape. Often used for charcoal production and other numerous medicinal purposes
Dichrostachys cinerea	Deciduous	Shrubby tree species often considered as an encroaching species in the savannah with degrading effect on rangeland quality.

Sources: (Shackleton and Shackleton, 2003; Munyathi *et al*. 2013; Treydte *et al*. 2007; Naidoo *et al*. 2012)

2.3.3 Pre-processing steps

The WV-2 image was geometrically and atmospherically corrected. Using PCI Geomatica OrthoEngine several Rational Polynomial Coefficient (RPC) models (RPC 0^{th}, 1^{st} and 2^{nd} order correction) were tested for a rigorous orthorectification of Worldview-2 image. The accuracy of the models was assessed via a leave-one-out cross validation approach with 18 ground control points (GCPs). The GCPs were evenly distributed over the study area considering land land features available on the landscape (e.g. road intersections). A differential GeoExplorer 2008 series GPS was used to record accurate positions of the GCPs and data from Nelspruit reference station were used to post-process the data to sub-meter accuracy. The RPC 0^{th} order correction model was opted because its accuracy coincides with that of a rigorous model and it is the recommended RPC model for Worldview-2 product (Geomatica, 2013). ATCOR-2, often used for flat terrain (Richter and Schlapfer, 2012) was chosen for atmospheric correction of WV-2 image since the study area is generally flat to gentle undulating slopes.

2.3.4 Tree extraction

The image was characterized by clouds and cloud shadows, bare-ground, grass and tree canopy and therefore masking was necessary to remove unwanted features and produce a tree canopy map. Developing a tree masking method is a common practice in that it enhances the spectral separability of the target features (Pu and Landry, 2012; Pu, 2011). Vegetation indices e.g. Normalized Difference Vegetation Index and Soil Adjusted Vegetation Index enhance vegetation signals and are often used to separate vegetated areas from non-vegetated areas. NDVI in particular, is more sensitive to sparsely vegetated areas and has effectively been used to eliminate non-vegetated areas (Pu and Landry, 2012; Pu, 2011). Other studies have used textural information to separate tree canopies from non-canopy vegetation i.e. grass and shrubs (Pu and Landry, 2012; Pu, 2011). In addition, the high spatial resolution data enables the identification of tree shadows for tall trees and band thresholding has been used to facilitates the separation of shaded tree canopy from non-shaded canopy (Pu, 2011).

In this study, a tree masking method was developed in ENVI 4.8 to extract tree canopies and eliminates non-canopy features and the best method to achieve this objective relied on NDVI, Brightness index and SAM classifier. Region of interest (ROI) tool in ENVI 4.8 was used to delineate and eliminate clouds and cloud shadows. Then prior to image segmentation, a quantitative approach was developed using histogram to find optimal threshold values for elimination of non-canopy features and shaded areas. GPS points (N=72) (collected from a previous study) were used to collect NDVI values for tree canopy and grassy areas. Due to the absence of GPS reference points for bare areas, the study relied on dirt roads which were clearly discernible from the image.

An NDVI threshold value of 0.55 was used to mask tree canopies from non-canopy features. Visual inspection of the NDVI histogram (**Figure 2.1 (A)**) reveals that this threshold eliminates all pixels covering bare areas including some of the grass pixels. Shaded areas were eliminated using the brightness index. The Brightness index is often used to describe the condition of the image features with regard to overall brightness and wetness (Todd and Hoffer, 1998). The threshold value of 790 was used to separate shaded and non-shaded targets (**Figure 2.1 (B)**).

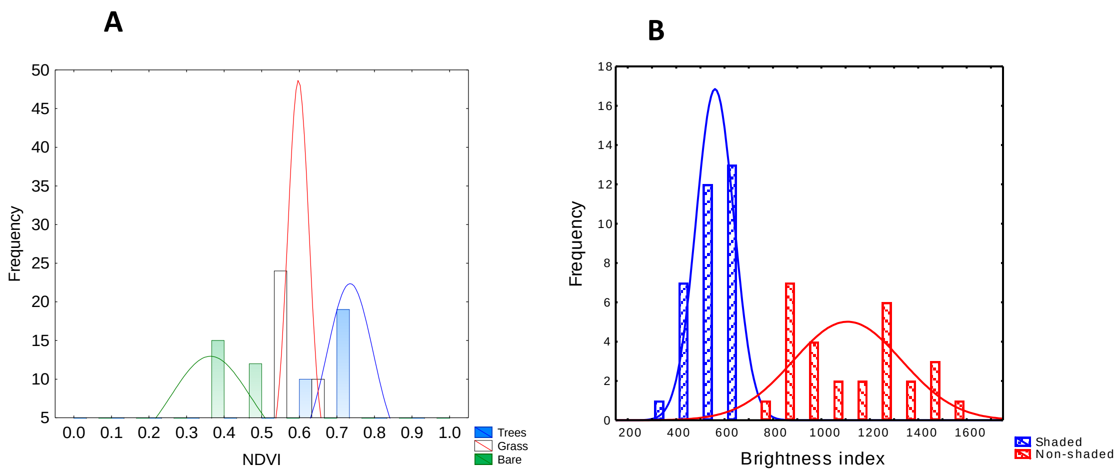


Figure 2.1 A= NDVI for separating vegetated from non-vegetated features; B= Brightness index for separating shaded areas from non-shaded.

Grassy features were not sufficiently eliminated by the NDVI thresholding and any attempt to increase the NDVI threshold beyond the histogram-derived optimum led to elimination of canopy features, especially *Acacia nigrescens*. Therefore, the study assessed the potential of textural information to eliminate grass. Grass is assumed to be a low spatial frequency feature with low variability, compared to tree canopy which has typically a rougher surface, and therefore a variance matrix was computed on a 3x3 moving window to generate a texture layer. However, this assumption was not confirmed as the variance matrix showed insensitivity to within-canopy variability. The method was unable to show textural differences between grass and tree canopy. Spectral angle mapper (SAM) was then used to classify and further eliminate grass pixels from the NDVI-based tree canopy product. SAM is a similarity measure that compares the spectral angle between the reference spectrum and the target spectrum. A small angle indicates high spectral similarity (Cho *et al* 2010; Clark *et al*. 2005). The study sets a maximum-angle threshold of 0.005 for SAM and repeatedly ran classification on the NDVI product. A smaller angle was selected to cater for the spectral similarity that exists between grass and *Acacia nigrescens*. This section generated the tree products which were subsequently used for segmentation and tree classification (**Figure 2.2**).

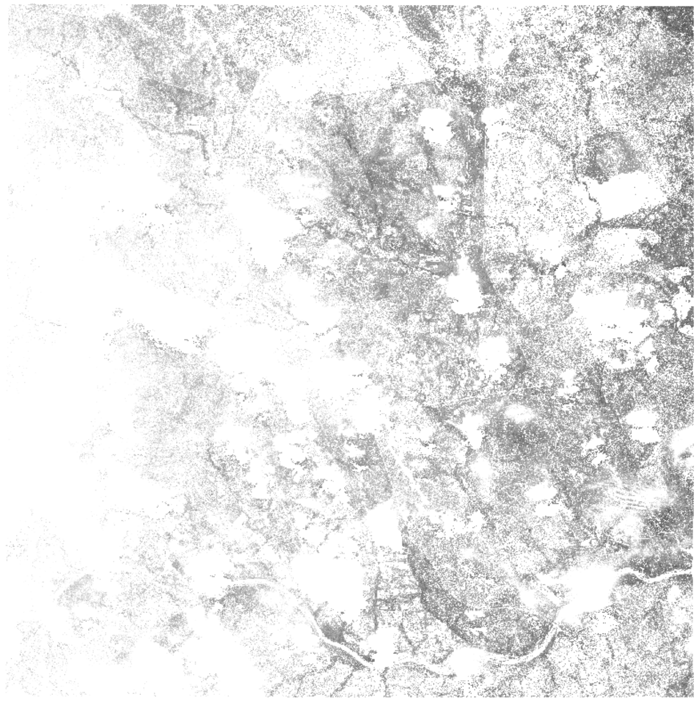


Figure 2.2 Tree mask produced from WV-2 scene with the dark colour representing the mask and the light colour representing the background.

2.3.5 Image segmentation

The tree mask product was partitioned into image objects (IO) resembling tree canopies and this was done via segmentation in eCognition 8.6 using a multi-resolution algorithm. This algorithm uses a bottom-up approach that begins with one pixel and fuses similar neighbouring pixels to form image objects. The average size of IOs is determined by the scale parameter which dictates the maximum spectral heterogeneity allowed within an object (Johnson and Xie, 2012; Gao and Mas, 2008). A high value for the scale parameter increases the heterogeneity threshold with consequent amalgamation of a higher number of pixels within one segment. The choice of the scale parameter is critical as it can result in over- or under-segmentation (Espindola *et al.* 2006). Other segmentation parameters include colour/shape and compactness/smoothness. Previous studies often place more weight on colour for the creation of meaningful IOs (Whiteside et al. 2012; Johnson and Xie 2012). Colour criterion determines the weight of spectral information in the segmentation process while compactness /smoothness enhances IOs with compact and smooth shape respectively (Gao and Mas, 2008).

In this study, image segmentation were conducted with various scale parameters (20, 18, 16, 14, 12, 10, 7, 5 and 3) and with higher weights placed on shape (colour 0.3; shape 0.7). High resolution dataset often show high within-canopy variability (Nagendra and Rocchini, 2008; Chastain, 2008; Nagendra, 2001) and therefore this study placed high weight on shape to minimize the possibility of over-segmented tree canopy. Smoothness/ compactness were assigned equal weights. Preliminary visual inspection assessed the extent to which image objects corresponds to tree canopies on the image. A subset of three scale parameters (7, 5 and 3) with visibly optimal segmentation results were selected for further assessment using reference data.

2.3.6 Segmentation evaluation

Segmented images were exported as shapefiles to ArcGIS 10 for assessing dimensional accuracy of IOs. Dimensional accuracy indicates, quantitatively, the degree at which the shape and dimension of IOs corresponds to real tree canopies. Literature suggests that different methods exist for assessing dimensional accuracy. Ardila *et al*. (2012) and Pu and Landry (2012) used a metric that measures both topological and geometric accuracy. The metric measures the relative area of overlap between a segmented object and a reference object and their positional discrepancy. In this study, points (N= 45) were randomly generated over the segmented IOs in order to select samples for dimensional accuracy assessment. The assessment was conducted by comparing the dimension of IOs (predicted) with the dimension of the corresponding reference canopies (observed) manually digitized from the WV-2 panchromatic image (**Figure 2.3**) with 0.5m spatial resolution. The Root-mean-square-error (RMSE) was calculated (equation 1) to determine the degree at which the segmented objects deviate from the reference objects. A 1:1 line was used to assess the distribution of segmented IOs. The points closest to the 1:1 line are indicative of high agreement with the reference objects while those further away from the 1:1 line indicates high deviation from the reference objects due to under-segmentation (above the line) or over-segmentation (below the line).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \qquad \text{Equation 1}$$

where X_{obs} is observed values and X_{model} is modelled values

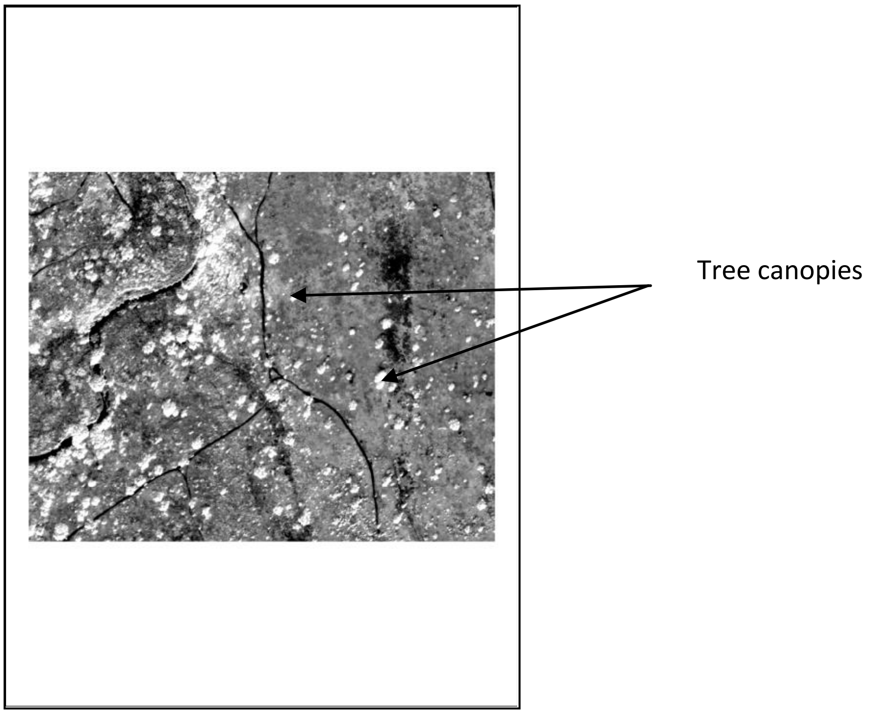


Figure 2.3 Worldview-2 panchromatic image showing examples of tree canopies used as reference polygons for segmentation assessment

The scale parameter of 5 provided the smallest RMSE of 16.7 compared to the scale of 3 and that of 7 (**Figure 2.4**). The assessment result indicates the scale parameter of 5 as optimal for tree canopy delineation in southern African savannah using Worldview-2 image acquired during the transition to senescence period (April).

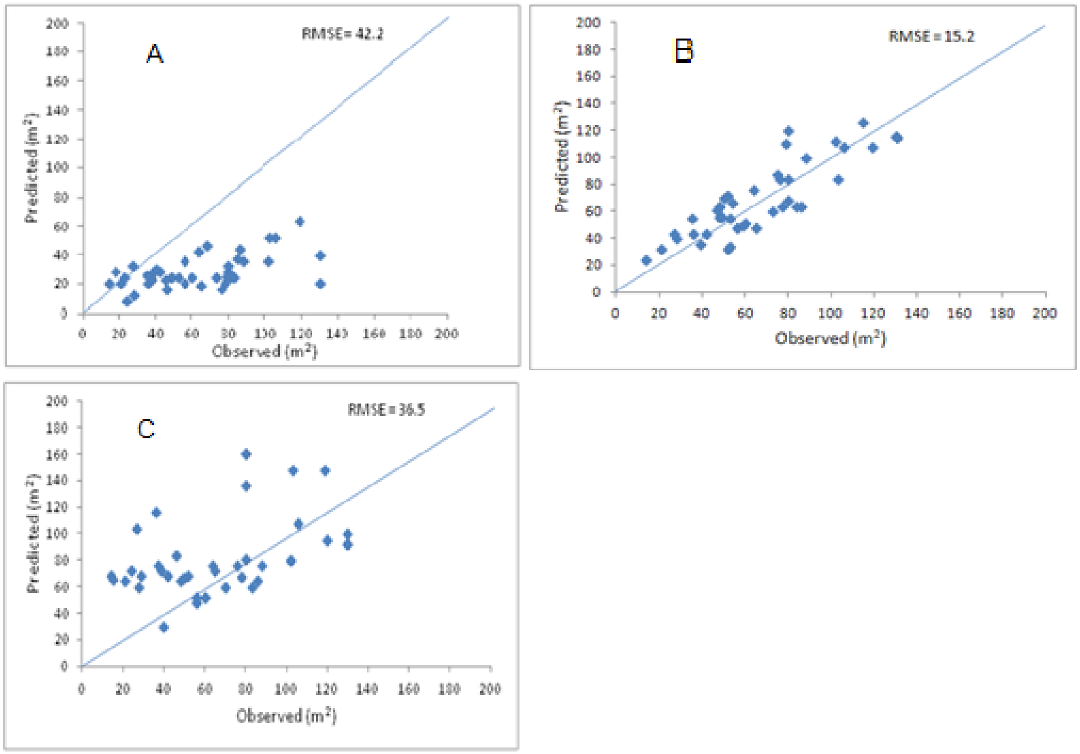


Figure 2.4 Scatterplots and RMSE for the dimensional accuracy of the segmented image objects: (A) scale parameter of 3, (B) scale of 5 and (C) scale of 7.

2.3.7 Training and validation samples

The GPS coordinates of the tree species collected in the field were used for training and validation of the pixel-based and object-based classification. The GPS data guided the collection of spectral endmembers using regions of interest (ROI) in ENVI 4.8. Table 2.2 summarizes the number of samples used for training and validation corresponding to both object-based and pixel-based classifications. ROIs collection procedure followed different formats; for pixel-based classification a minimum of two to four pixels representing a tree canopy was collected while single object was collected for object-based classification. However the validation process necessitated the use of equal validation points between OBIA and pixel-approach to be able to compare results using McNemar test. Therefore, number of pixels within an object was adjusted to be similar to those from pixel-approach.

Table 2.2 Training and validation data used for tree species classification

	April image			
	Object-based		**Pixel-based**	
	Training	**Validation**	**Training**	**Validation**
AN	30	118	119	118
COM	31	110	98	110
DC	31	108	112	108
SB	35	92	123	92

2.3.8 Spectral data analysis

This study evaluated the spectral variability within- and between-species using the Spectral Angle Mapper (SAM). SAM is a similarity measure that quantifies the level of similarity between two spectra and is insensitive to illumination-induced differences among spectra. It quantifies the angle between two spectra $s_i = s_{i1} \ldots \ldots s_{iL}$ and $s_j = s_{j1} \ldots \ldots . s_{jL}$

$$SAM\ (s_i, s_j) = \theta(s_i, s_j) = cos^{-1}\left(\frac{\sum_{l=1}^{L} s_{il}s_{jl}}{[\sum_{l=1}^{L} s_{il}^2]^{1/2}[\sum_{l=1}^{L} s_{jl}^2]}\right) \qquad \text{Equation 2}$$

where L is the number of bands. A high angle between spectra indicates that the two species are spectrally separable (Cho *et al.* 2010; Clark *et al*. 2005). In our application of intra-species SAM the angle between each spectrum of a species was computed. The application of inter-species SAM followed the same approach as the intraspecies one; the angle between each spectrum to every other species spectrum was computed. Two band combinations (all WV-2 bands and simulated IKONOS bands (blue, green, red, NIR1)) were tested at both pixel- and object-level to establish the band combination that magnifies the spectral separability between species.

In addition, we subjected the individual spectral bands of WV-2 data to further scrutiny through the use of band-add-on (BAO) procedure to establish the discriminatory ability of each band. The BAO procedure is often used on hyperspectral data with high data dimensionality (Keshava, 2004). This procedure iteratively selects bands that optimize angular separation between spectra. The procedure adds on pairs of bands and selects those with the highest average SAM. The process is repeated until no band contributes further to the discriminatory power (Keshava, 2004; Naidoo *et al*. 2012; Cho *et al*. 2010). The application of BAO, whilst identifying spectral bands that increases angular separation, also identifies band redundancy. The BAO procedure was run on WV-2 bands eight times with one band excluded each time and this enabled the identification of the spectral bands with the highest discriminatory power for the species in question.

2.3.9 Tree species classification

We conducted tree species classification at both pixel-level and object-level using Random Forest (RF). RF has been successfully applied to classify savannah tree species using hyperspectral data (Naidoo *et al*. 2012). Chan and Paelinckx (2008) argued that RF remains the most robust machine learning algorithm. RF is a tree-based classifier that assembles hundreds of decision trees using random subsets of training data. These decision trees are evaluated using out-of-bag estimates to establish the importance of each input (Naidoo *et al*. 2012; Chan and Paelinckx, 2008). Similar to Adelabu *et al* (2013) this study used the RF algorithm based on EnMap box to classify four tree species (*Acacia nigrescens, Combretum spp., Sclerocharya birea and Dichrostachys cinerea*). Eight WV-2 bands were submitted into RF procedure as predictor variables. Classification results are presented in a confusion matrix depicting user's and producer's accuracy for each species and the overall accuracy.

2.3.10 Comparing Object-based and Pixel-based classification

Performance assessment of object-based classification versus pixel-based is very important as it reveals the strengths and weakness of each classification approach. The McNemar test is preferred for such assessment since it provides detailed information on performance discrepancies between classification approach (Bostanci and Bostanci, 2013). Moreover, the classification tests employed the same samples to avoid differences induced by sampling variability and therefore these are not independent as required for the Kappa difference test (Foody, 2004). The McNemar test is a parametric test based on confusion matrices. The McNemar test employs a *z* score (Equation 2) to quantify the difference between the two classifications.

$$z = \frac{(f_{12} - f_{21} - 1)}{\sqrt{(f_{12} + f_{21})}} \qquad \text{Equation 2}$$

where f_{12} denotes the number of instances that were wrongly classified at object-based but correctly classified at pixel-based and f_{21} denotes the number of instances that were correctly classified at object-based but wrongly classified at pixel-based. Additional f_{11} and f_{22} were included for instances that were wrongly classified at both levels and the number of instances that were correctly classified at both levels respectively.

2.4 Results

2.4.1 Spectral Variability: Intra- and Inter-species

The summary of intra- and inter-species spectral variability is presented in Figure 2.5 to 2.10. The canopy reflectance collected from the April image (transition period to senescence phenological stage) for each tree species exhibit patterns of high intraspecies variability (**Figure 2.5 and 2.6**). Intraspecies species spectral variability is more pronounced in the red region which is a region associated with chlorophyll absorption (Datt, 1999). The spectral profile of each tree species showed the expected increase in the canopy reflectance at the 545nm and increase in the absorption at the 660nm due to chlorophyll within leaves. High canopy reflectance is also observed in the leaf-water-sensitive NIR region particularly for *Combretum spp*.

Acacia nigrescens showed a relatively high reflectance at the 605nm compared to other tree species which showed a more pronounced absorption. This is a region sensitive to carotenoid presence in leaves (Gitelson *et al*. 2002) and it indicates that *Acacia nigrescens* was already in the senescence stage in April. *Acacia nigrescens* displays the highest intraspecies-SAM (**Figure 2.7 A** and **B**) which may be attributable to between sites phenological differences. *Acacia nigrescens* found on gabbro soils often shows higher reflectance in the yellow to red band region compared to those found on granite soils (**Figure 2.8**), ANOVA results indicates that the difference is statistically significant ($F_{obt} > F_{crit}$) when 95% confidence level is used. This indicates the existence of between sites phenological differences due to geological variations. Coarse-textured granite soils have lower water holding-capacity than fined-textured gabbro soils (Venter *et al.* 2003). However, during the drying phase the water is more tightly bound to clay particles and becomes less accessible to plants while granite soils deep water reserves remain undiminished (Colgan *et al*. 2012). Hence it may explain that senescence occurs early on *Acacia nigrescens* found on gabbro soils.

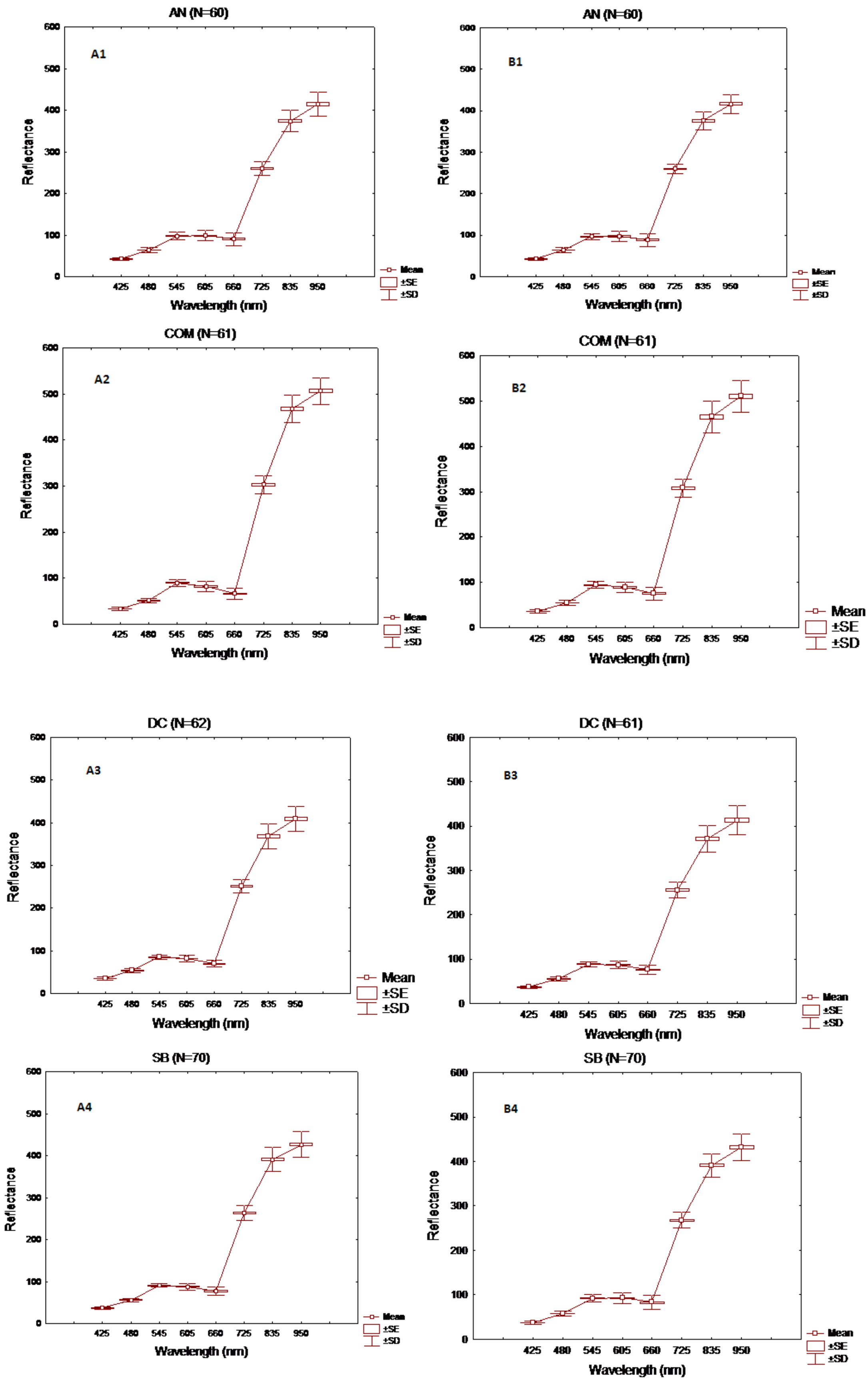


Figure 2.5 Spectral profile of the four tree species. AN= *Acacia nigrescens*; COM=*Combretum collinum*; DC=*Dichrostachys cinera*; SB=*Sclerocharya birea*. A1-A4 object-based spectra and B1-B4 pixel-based spectra

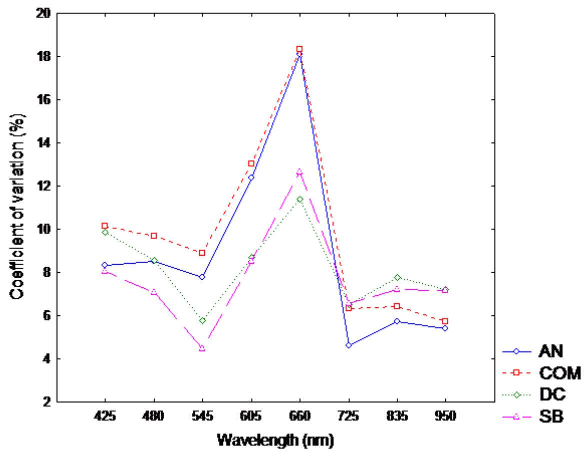


Figure 2.6 Coefficient of variation for four tree species

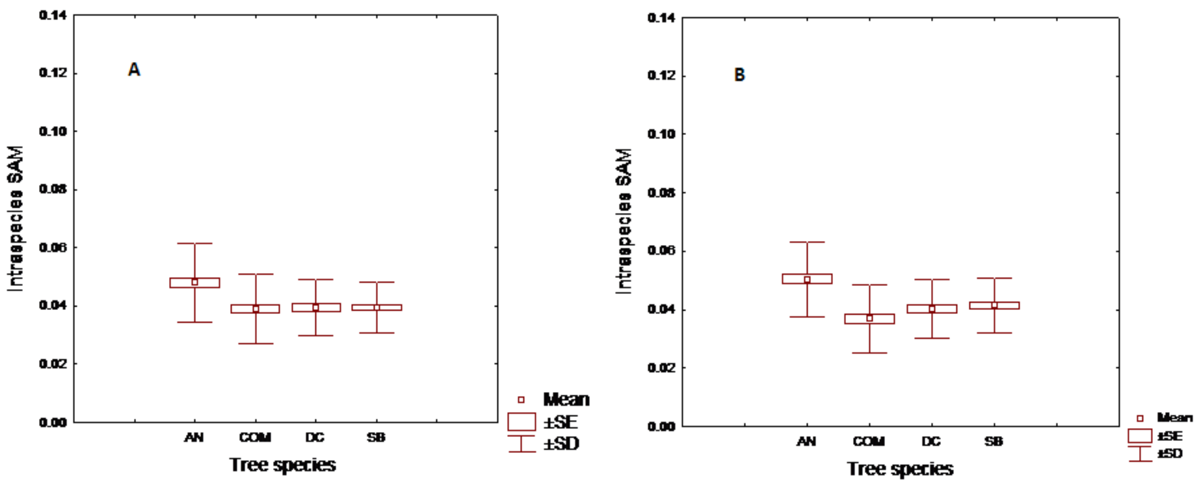


Figure 2.7 Intraspecies-SAM for four species; A=Object-based and B=Pixel-based.

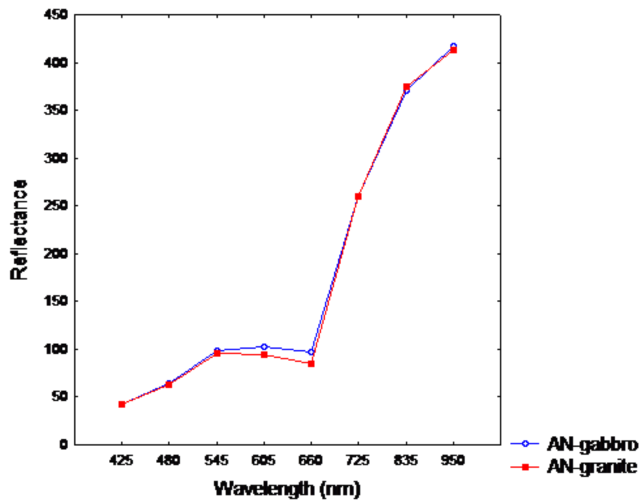


Figure 2.8 Average spectral profile of *Acacia nigrescens* collected on different geological substrates.

The interspecies SAM experiment shows a similar pattern of variability for both object-based and pixel-based spectra (**Figure 2.9**). However pixel-based spectra showed a higher average interspecies-SAM than OBIA spectra and the difference is statistically significant ($F_{obt} > F_{crit}$). Moreover, the four simulated IKONOS bands provided higher interspecies-SAM compared to WV-2 band combination (**Figure 2.9**). The BAO procedure reveals that excluding red-edge, NIR-1 and NIR-2 bands from WV-2 band combination increases the interspecies-SAM (**Figure 2.10**). The exclusion of NIR-1 and NIR-2 significantly increase interspecies-SAM ($F_{obt} > F_{crit}$) while the increase in interspecies-SAM due to exclusion of red-edge is statistically insignificant ($F_{obt} < F_{crit}$). In addition, the BAO procedure identified the yellow and red bands as the most influential bands in the discriminatory power of WV-2 during the transition period (April). The exclusion of either of the two bands significantly decreases the interspecies-SAM ($F_{obt} > F_{crit}$).

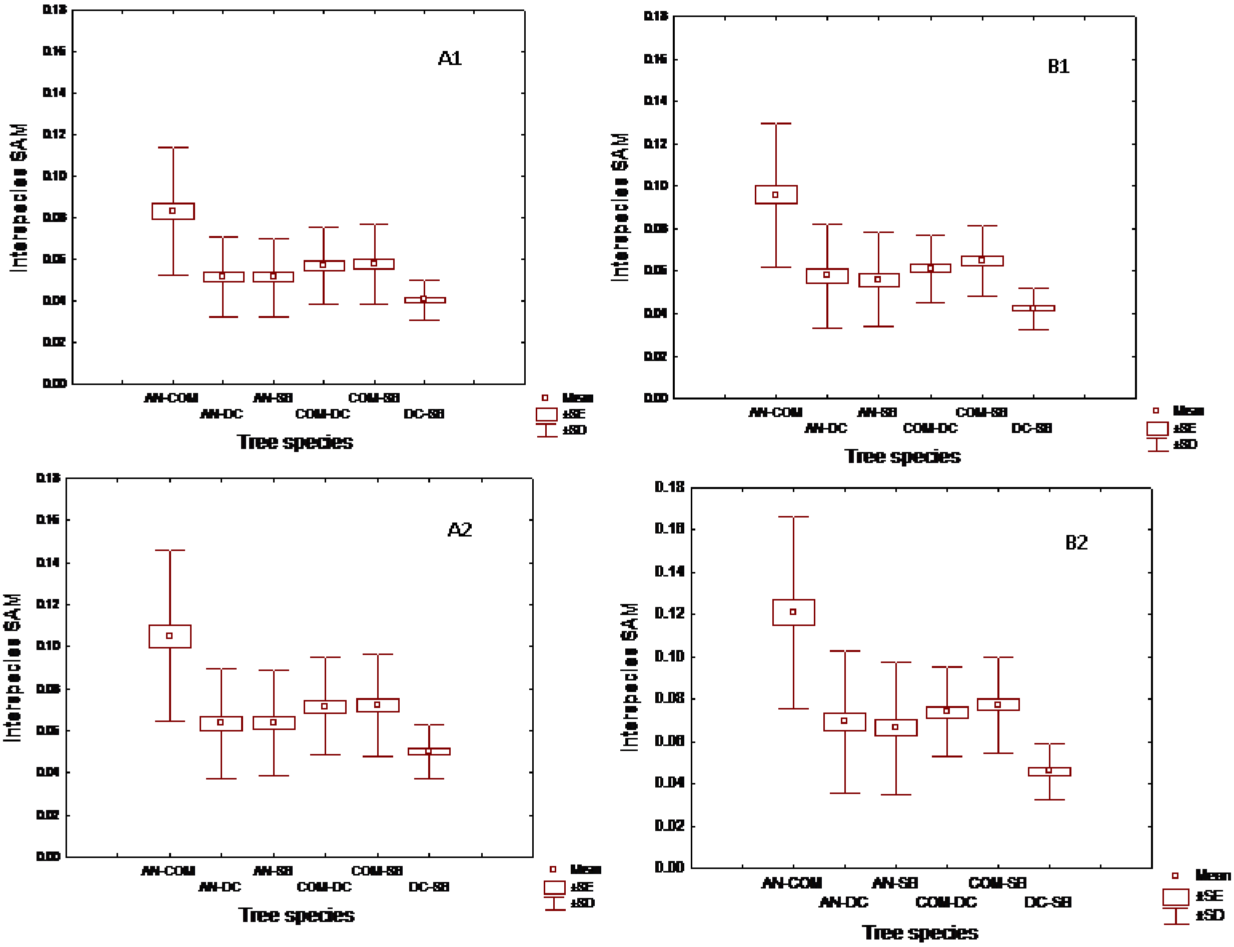
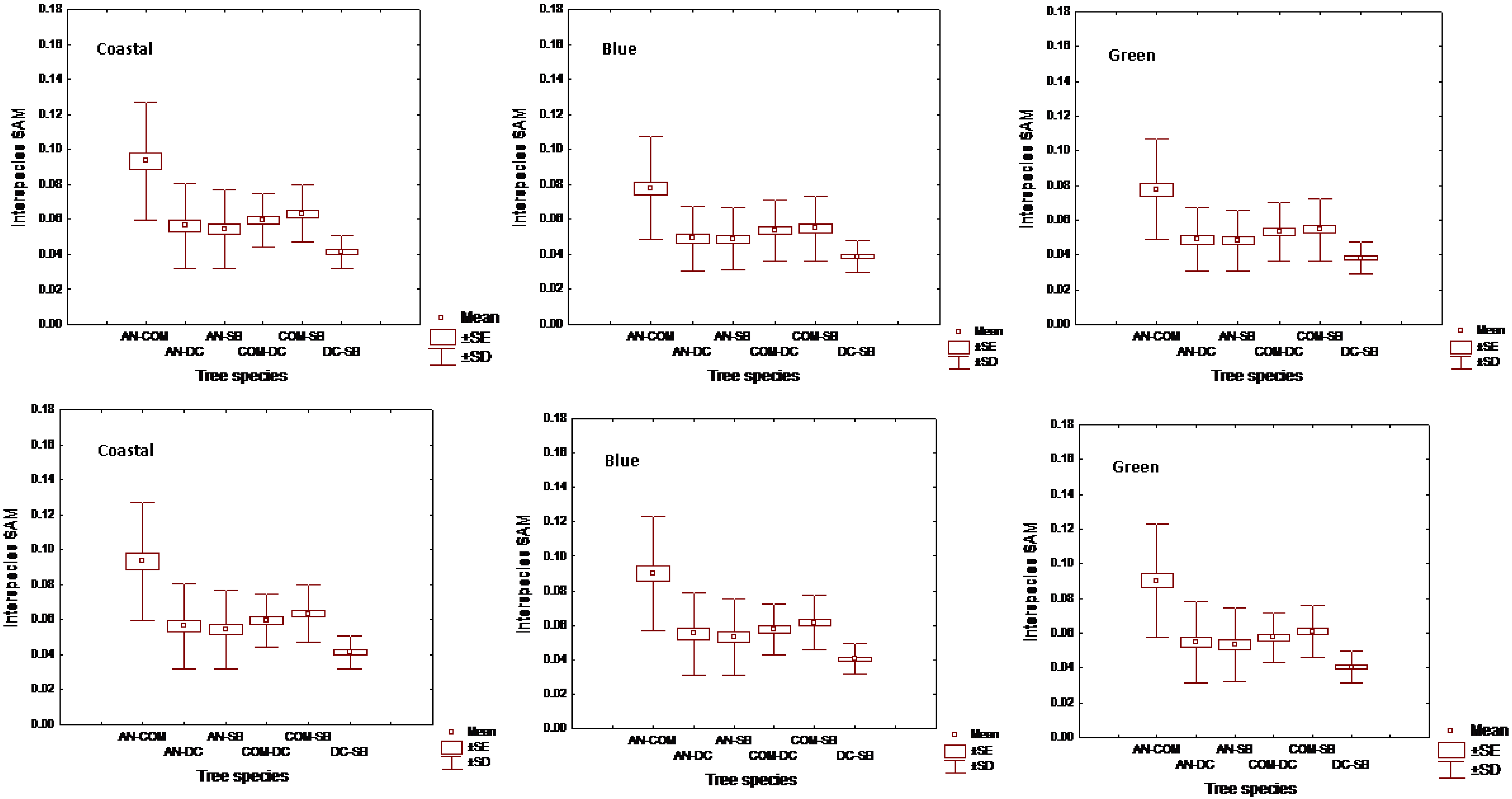
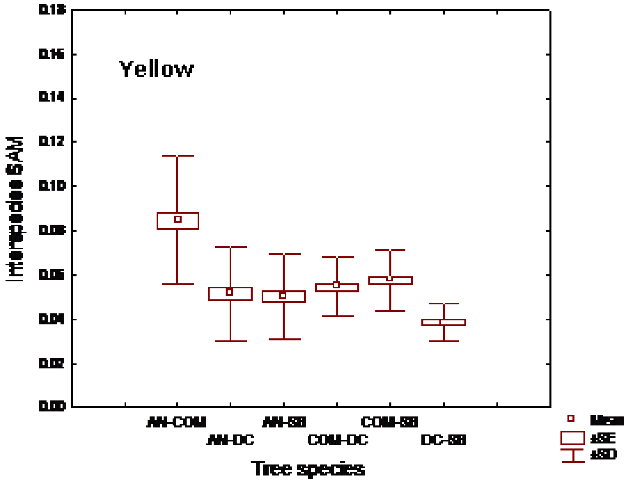
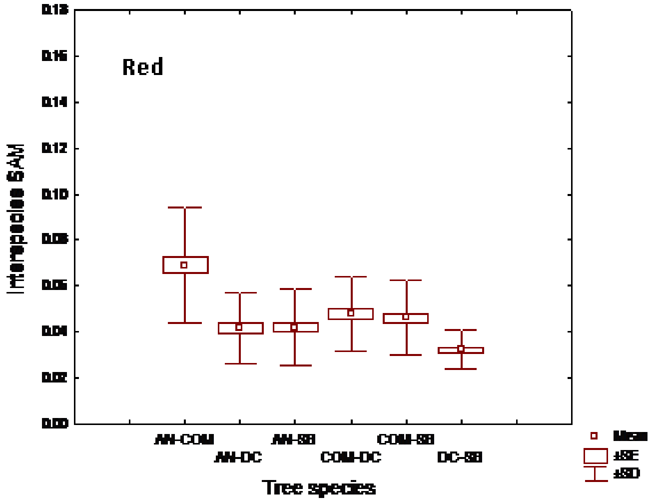
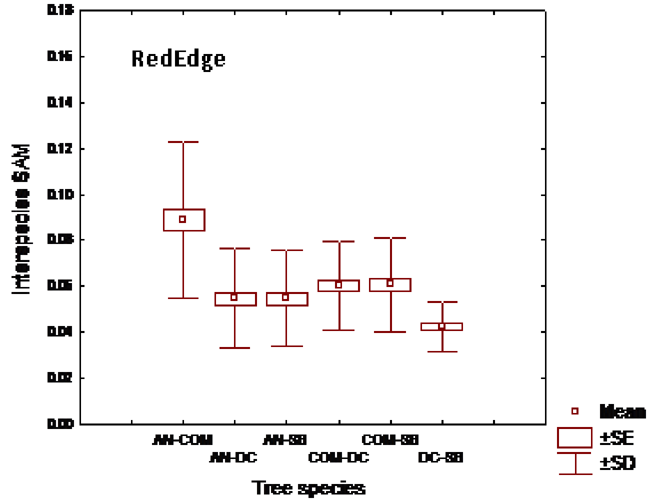


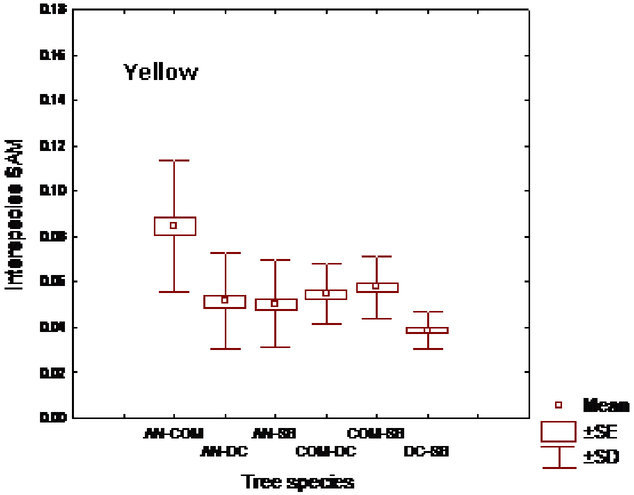
Figure 2.9 Interspecies-SAM produced with different band combinations and different classification units: A = objects and B = pixels; 1= WV-2 band combination and 2= simulated IKONOS band combination.

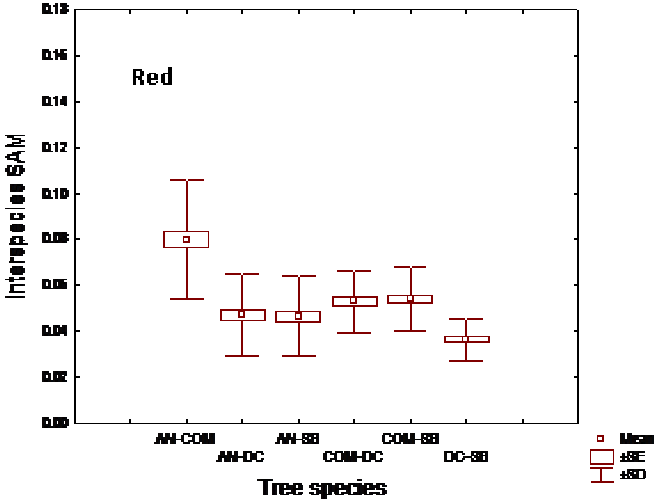

Coastal
Blue
Green
Coastal
Blue
Green
Interspecies SAM
Tree species
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
0.18
AN-COM
AN-DC
AN-SB
COM-DC
COM-SB
DC-SB
Mean
±SE
±SD

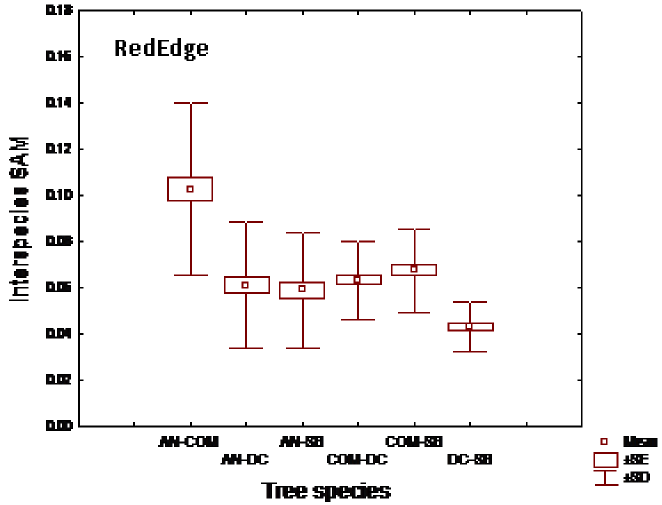

Yellow
Interspecies SAM
AN-COM
AN-DC
AN-SB
COM-DC
COM-SB
DC-SB
Tree species
Mean
±SE
±SD


Red
Interspecies SAM
AN-COM
AN-DC
AN-SB
COM-DC
COM-SB
DC-SB
Tree species
Mean
±SE
±SD


RedEdge
Interspecies SAM
AN-COM
AN-DC
AN-SB
COM-DC
COM-SB
DC-SB
Tree species
Mean
±SE
±SD


Yellow
Interspecies SAM
AN-COM
AN-DC
AN-SB
COM-DC
COM-SB
DC-SB
Tree species
Mean
±SE
±SD


Red
Interspecies SAM
AN-COM
AN-DC
AN-SB
COM-DC
COM-SB
DC-SB
Tree species
Mean
±SE
±SD


RedEdge
Interspecies SAM
AN-COM
AN-DC
AN-SB
COM-DC
COM-SB
DC-SB
Tree species
Mean
±SE
±SD

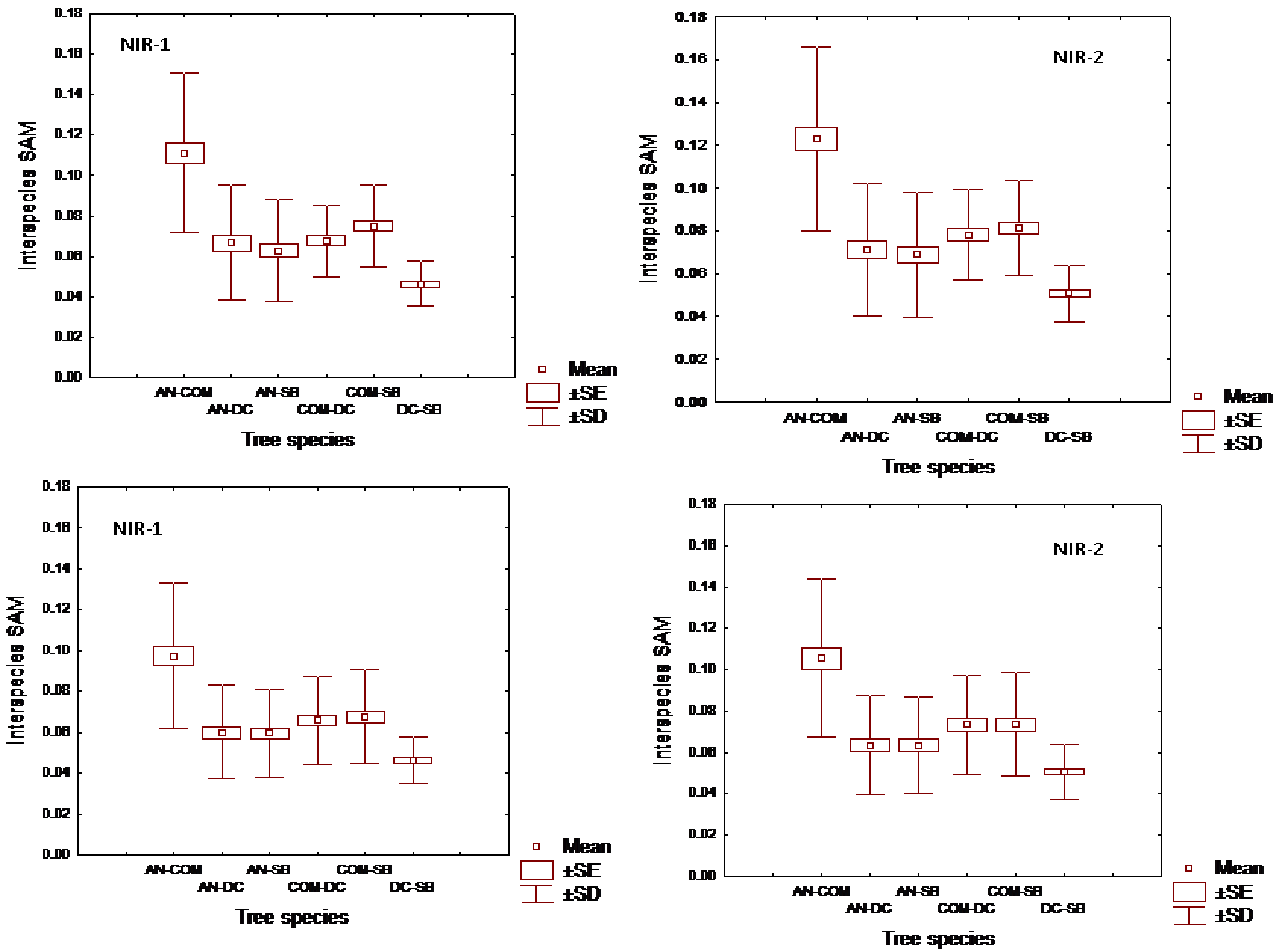


Figure 2.10 Interspecies-SAM produced with one of WV-2 bands excluded; from top to bottom = object-based to pixel-based.

2.4.2 Tree species classification results

The pixel-based classification yielded higher overall accuracy (76.4%) compared to object-based classification (74.5%) (**Table 2.3**). However the difference was not statistically significant (z_{obt} = 1.166; z_{crit} = 3.841). The producer's accuracy of *Sclerocharya birrea* was particularly lower with pixel-based classification. This was due to spectral confusion between *Sclerocharya birrea* and the three other species as 55% of *Sclerocharya birrea* was misclassified as *Combretum spp*., *Acacia nigrescens* or *Dichrostachys cinerea* (**Table 2.5**). The spectral character of *Sclerocharya birrea* may be more affected by the background such as understory and soil because of the frequent open canopy gaps that characterise the species.

However, the producer's accuracy of *Sclerocharya birrea* improved from 44.5% with pixel-based classification to 59.7% with object-based classification (**Table 2.4**). Inversely, the producer's accuracy of *Dichrostachys cinerea* decreased from 81.4% with pixel-based classification to 68.5% with the object-based classification due to spectral confusion with *Acacia nigrescens* and *Sclerocharya birrea*. The classification confusion between the *Sclerocharya birrea* and *Dichrostachys cinerea* concurs with lower SC-DC interspecies-SAM reported earlier (**Figure 2.9**). Furthermore, the high intraspecies-SAM by *Acacia nigrescens* account for classification confusion with *Dichrostachys cinerea*.

Figure 2.11 presents an example of the species maps produced using the pixel-based and object-based classifications and the WV-2 spectral configuration. The species maps are consistent with our field knowledge, *Combretum species* dominating in the granite soils while *Acacia nigrescens* dominate on gabbro soils. The pixel-based classification shows underestimation of *Sclerocharya birrea* and this is consistent with low producer's accuracy for this species.

Table 2.3 Overall accuracies achieved with WV-2 and simulated IKONOS images using Random Forest, April date.

Classification approach	WV-2	Simulated IKONOS bands
Object-5	**74.5%**	**58.6%**
Pixel	**76.4%**	**67.9%**

Table 2.4 Confusion matrix from object-based classification using Random Forest on 8-bands of Worldview-2 image April date.

Classes	Com	AN	SB	DC	Total	Producer's accuracy	User's accuracy
Com	101	6	21	3	131	91.8%	77.0%
AcNig	1	89	3	18	111	75.4%	80.1%
ScBi	6	7	55	13	81	59.7%	67.9%
DiCi	2	16	13	74	105	68.5%	70.4%
Total	110	118	92	108	428		
Overall Accuracy	74.5%						
Overall Kappa	65.9%						

Table 2.5 Confusion matrix from pixel-based classification using Random Forest on 8-bands of Worldview-2 image April date.

Classes	Com	AN	SB	DC	Total	Producer's accuracy	User's accuracy
Com	104	1	14	1	120	94.5%	86.6%
AcNig	0	94	19	14	127	79.6%	74.0%
ScBi	6	7	41	5	59	44.5%	69.4%
DiCi	0	16	18	88	122	81.4%	72.1%
Total	110	118	92	108	428		
Overall Accuracy	76.4%						
Overall Kappa	68.3%						

(Com= *Combretum spp*., AN= *Acacia nigrescens*, SB= *Sclerocharya birrea* and DC= *Dichrostachys cinerea*)

The WV-2 band combination achieved higher classification accuracy (74.5% with object-based and 76.4% with pixel-based) compared to the simulated IKONOS bands (58.6% with object-based and 67.9% with pixel-based) and the difference was statistically significant (z_{obt} = 5.833; z_{crit} = 3.841). Given that the two datasets were of the same spatial resolution and tested with same samples, the higher overall accuracy from WV-2 image demonstrates the high spectral capability of WV-2 in tree species discrimination.

To further investigate the benefits of the new bands featuring in WV-2 (coastal, yellow, red-edge and NIR-2) we ran a set of pixel-based classifications excluding these bands one by one. The following overall classification accuracies were obtained: 70.3% without coastal band centred at 425nm, 69.6% without yellow band centred at 605nm, 70.7% without red-edge band centred at 725nm and 70.3% without NIR-2 band centred at 950nm. Consistent with BAO procedure, the classification accuracy significantly decreased with the exclusion of yellow band (z_{obt} = 4.269; z_{crit} = 3.841) and this is indicative of the importance of the yellow spectral region for tree species discrimination during the transition to senescence period. The exclusion of the coastal band also led to the significant decrease in the classification accuracy (z_{obt} = 4.269; z_{crit} = 3.841). While the overall accuracy also declined when red-edge and NIR-2 were excluded the difference was not statistically significant (z_{obt} = 3.252; z_{crit} = 3.841 and z_{obt} = 3.608; z_{crit} = 3.841 respectively).

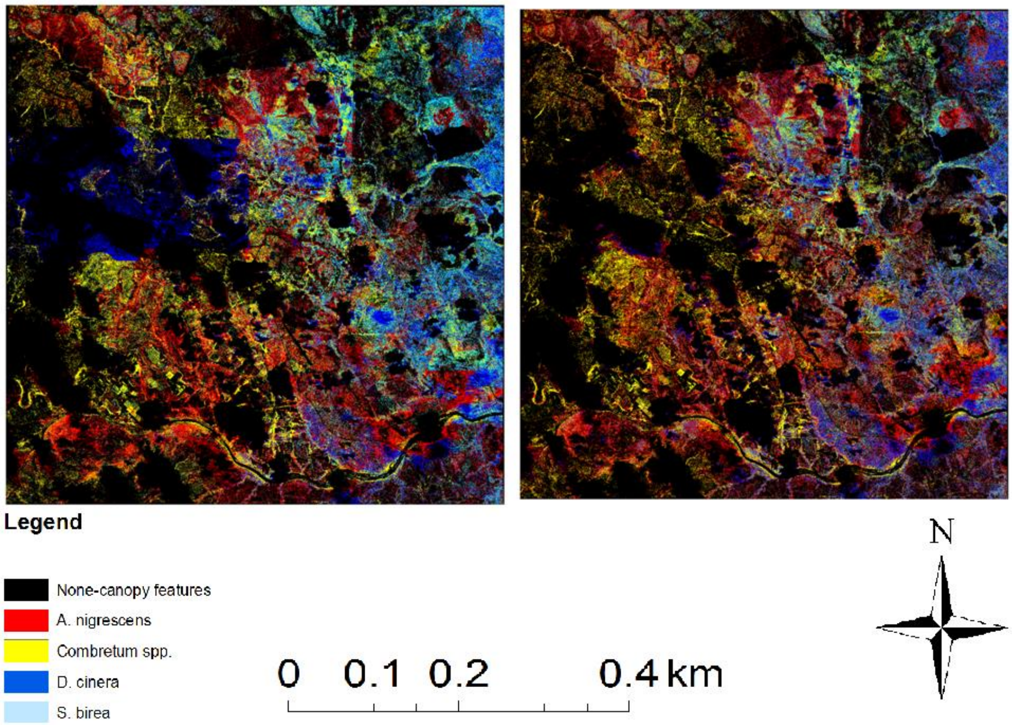


Figure 2.11 Classification produced at different units: left = object-based and right = pixel-based classification

2.4.3 McNemar Test

From **Table 2.6,** it is evident that the difference observed between object-based and pixel-based classification is statistically insignificant. Meanwhile the difference between WV-2 and simulated IKONOS image (**Table 2.7**) is statistically significant.

Table 2.6 McNemar test for object-based versus pixel-based classification: April data

f_{11}	f_{12}	f_{21}	f_{22}	Z_{obt}	Z_{crit}	Df
161	22	14	231	1.166	3.841	1

Table 2.7 McNemar test for WV-2 versus simulated IKONOS image

f_{11}	f_{12}	f_{21}	f_{22}	Z_{obt}	Z_{crit}	Df
101	36	0	291	5.833	3.841	1

2.5 Discussion

The comparative analysis of classification results from OBIA and pixel-approach shows that there is no statistically significant difference ($z_{obt} < z_{crit}$). This result does not support the suggestion in literature that spectral separability is enhanced amongst species when using objects as a basic unit of classification (Pu and Landry, 2012; Whiteside *et al*. 2011; Wang *et al*. 2004). Wang *et al*. (2004) tested the hypothesis that using objects as basic units of classification enhances spectral variability between mangrove species and subsequently achieved higher overall accuracy with objects compared to pixels. Whiteside *et al*. (2011) compared the utility of objects and pixels for mapping savannah landcover types at community level and eventually concluded that using objects minimizes spectral variability within heterogeneous landcover types of tropical savannah.

In this study the interspecies-SAM yielded similar patterns of spectral separability between objects and pixels. These results contradicts the assumption that image objects enhance tree species discrimination compared to the pixel approach (Pu and Landry 2012; Wang *et al*. 2004; Whiteside *et al*. 2011). Using both object-based and pixel-based approaches, *Acacia nigrescens* and *Combretum spp.* have shown to be highly separable with the highest interspecies-SAM while *Sclerocharya birrea* and *Dichrostachys cinerea* achieved the lowest interspecies-SAM indicative of low separability.

The interspecies-SAM results indicate that objects could not enhance spectral variability between species higher than pixels in the savannah environment. This can be associated with the averaging of pixels representing a tree canopy. Individual pixels in high resolution data captures different aspects of the tree canopy (Nagendra and Rocchini, 2008; Nagendra, 2001). Blaschke (2010) argued that averaging this information possibly reduces the purity of tree canopy spectra. Unlike mangrove forest, savannah tree canopies are highly irregular in shape with existence of canopy gaps and also have layered structure particularly for *Sclerocharya birrea* (Naidoo *et al*. 2012; Archer *et al*. 2001) therefore the spectral response from the tree is influenced by these complexities.

Despite achieving higher mapping accuracy, Whiteside *et al*. (2011) focused on broad landcover classes using ASTER data with 15m spatial resolution and therefore the effect of within-canopy variability is not as influential as it is for single-crown and species-level mapping. Our study explored the utility of objects at species-level mapping using WV-2 with 2m spatial resolution. Since tree species such as *Acacia nigrescens, Combretum spp., Sclerocharya birea and Dichrostachys cinerea* have canopy diameter greater than 2m (Cho *et* *al*. 2012), within canopy variability is inevitable. In addition, trees with small crown are often characterized by mixed edge pixels (Cho *et al*. 2012). These complexities in the savannah tree structure results in within-canopy spectral variability and therefore the aggregation of tree canopy pixels into an object is often composed of mixed pixels which reduces the purity of tree canopy spectra. Hence we observe similar patterns of spectral separability between objects and pixels.

However, object-based classification has improved the classification between big trees such as *Sclerocharya birrea* and *Acacia nigrescens*. The discrimination of *Sclerocharya birrea* from other species has also improved with object-based classification whereas pixel-based approach confused *Sclerocharya birrea* with other species (had achieved 44.5% producer's accuracy). It seems that objects minimizes the effect of tree edge pixels which are often a source of spectral confusion. Small crowns such as those of *Dichrostachys cinerea* and *Combretum spp.* are often composed of mixed pixels along the edge which increase spectral confusion with big trees (Cho *et al*. 2012) and this was observed from pixel-based classification. Exception can be made in the case involving *Sclerocharya birrea* and *Dichrostachys cinerea* which are deemed to have low spectral separability and previous studies (Naidoo *et al*. 2012; Cho *et al*. 2012) have overcome this spectral confusion with the use of structural data.

Our findings have also confirmed the importance of the new additional bands of WV-2 for discriminating tree species as observed by Pu and Landry (2012) and Cho *et al*. (2012). The yellow band (605 nm) and coastal blue (425 nm) in particular have a significant influence on the discriminatory ability of WV-2 compared to the red-edge and NIR-2. The higher performance from the yellow band may be reinforced by the phenological period at which the image was acquired (transition to senescence stage). The yellow and red-edge bands are sensitive to variation in leaf pigment concentration (Pu and Landry, 2012) and the transition to senescence period is characterized by a growing concentration of carotenoid (Gitelson *et al*. 2002; Zur *et al*. 2000) which is detectable in the yellow region.

It is therefore not surprising that the yellow band contributes significantly in tree species discrimination given the variation in the rate of phenological change between species. A statistically significant contribution could be expected from the red-edge band for data captured at the start of the growing season when leaf chlorophyll concentration is high. The presence of yellow and red-edge bands distinguish WV-2 sensor from IKONOS in terms of ability to discriminate spectrally different tree species. In addition, the significant decline in overall accuracy with simulated IKONOS image indicates the importance of all four additional bands in the overall performance of WV-2 image.

2.6 Conclusion

The results of this study shows that there is no statistically significant difference between OBIA and pixel-based approach towards savannah tree species mapping and this is attributed to complexities in tree canopy structure. The interspecies-SAM experiment showed similar patterns of spectral variability between objects and pixels. However, OBIA improved the classification accuracy between *Sclerocharya birrea* and *Acacia nigrescens* and this makes OBIA more appropriate for classifying big trees in the savannah environment using WV-2 data. This study has also established that the eight-band WV-2 data have higher discriminatory power than simulated IKONOS. The yellow band (605nm) in particular has shown significant contribution in the performance of WV-2. This indicates that the additional bands in the WV-2 sensor enhances it capacity to differentiate between different species.

Chapter 3: Multi-temporal approach towards tree species mapping in the savannah environment

3.1 Abstract

In southern African savannah, intraspecies spectral variability remains a difficulty that challenges accurate discrimination of tree species. Our ability to accurately discriminate tree species using remote sensing data relies on high spectral differences between them. Earlier studies have shown that multi-temporal data covering different phenological events enhances spectral differences between species. In this study two images of different phenological periods were used to investigate the importance of multi-temporal data for tree species discrimination in the savannah environment. Using interspecies-Spectral Angle Mapper (SAM) the multi-temporal data showed higher spectral variability between species than individual images and the difference was statistically significant ($z_{obt} > z_{crit}$). These results reaffirm the assertion that multi-temporal data enhances spectral separability between species. Multi-temporal data mitigated the long established spectral confusion between *Sclerocharya birrea* and *Dichrostachys cinerea* and achieved higher classification accuracy (OCA 80.4 %) compared to individual images (76.4% for April and 72.9% for March). Moreover, the higher classification accuracy from April date compared to March indicates that the transition to senescence as the most ideal phenological period for tree species mapping using single image.

Keywords: Multi-temporal, interspecies-SAM, phenology, Worldview-2, senescence

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3.2 Introduction

The ability to map big trees contributes towards biodiversity assessment and conservation in southern African savannah (Cho *et al*. 2012; Asner *et al*. 2008). Mapping tree species provides an insight on the spatial distribution and abundance of species which is key information for biodiversity assessment (Turner *et al*. 2003). In the savannah ecosystem, large tree species play important ecological and economic functions as breeding sites for birds, nutrient pumps in the ecosystem, sources of fuelwood and fruits for local communities (Treydte *et al*. 2007; Ludwig *et al*. 2004; Cho *et al*. 2012). A study by Treydte *et al*. (2007) established that the quality of grass is improved underneath tree canopies particularly in drier parts of savannah and this impact positively on grazing ungulates. The N-fixing *Acacia spp* increase soil nutrients creating islands of fertility in the landscape (Lugwid *et al.* 2004; Treydte et al. 2007). Furthermore Shackleton and Shackleton (2003) established that local communities benefit financially from *Sclerocharya birrea* which yields fruits often used for Marula-beer brewing. However Wessels *et al*. (2011) noted a declining distribution of trees below 4m due to prescribed long-term fires in protected areas and clearing in communal land.

In addition Cho *et al*. (2012) noted a pervasive occurrence of bush encroaching species such as *Dichrostachys cinerea* and *Combretum apiculatum*. This threatens the diversity of herbaceous vegetation in the savannah landscape and the distribution of palatable grass (Archer *et al*. 2001). Bush encroachment remains a big concern to the integrity of savannah ecosystems ubiquitously (Archer *et al*. 2001). These instances highlight the importance of large tree species in the functioning of savannah ecosystem, the imminent threats to palatable grass and also the necessity for regular monitoring of changes in savannah vegetation patterns. However regular monitoring of changes would necessitate frequent and detailed information on the abundance and distribution of species (Turner et al. 2003). The paucity of appropriate data in terms of accuracy, details, completeness as well as spatial and spectral resolution remains a challenge for biodiversity assessment at landscape level (Foody and Cutler, 2003). The ground-based measurement of species composition coupled by ancillary data provides information in field plots less than a hectare (Yang and Prince, 2000; Foody and Cutler, 2003). The field plot information is hardly sufficient for making landscape scale generalization about the state of biodiversity particularly in the heterogeneous savannah environment (Asner *et al*. 2008; Foody and Cutler, 2003).

Alternatively remote sensing techniques present timely information on the spatial distribution of species and species richness over large surface in a consistent manner (Nagendra 2001; Foody and Cutler, 2003; Yang and Prince, 2000; Adam *et al*. 2010). The recent availability of high resolution data from spaceborne sensors such as Worldview-2 and Rapid-Eye (2m and 5m spatial resolution respectively) and airborne sensors such as Compact Airborne Spectrographic Imager (CASI) has renewed interests in forest monitoring at species-level (Foody *et al*. 2005; Nagendra and Rocchini, 2008). The high spatial and high spectral resolution of the recent satellite and airborne sensors enables fine scale mapping of biodiversity on the basis of biochemical and biophysical differences between species (Cho *et al*. 2010; Pu and Landry, 2012; Nagendra and Rocchini, 2008). Cho *et al*. (2012) argued that the 2m spatial resolution of Worldview-2 image would be ideal for mapping tree species in the savannah ecosystem. Foody *et al*. (2005) used hyperspectral data from CASI to map the distribution of invasive *Acer pseudo-platanus* in ancient woodland in the United Kingdom in order to understand its ecology. Naidoo *et al* (2012) used hyperspectral data from Carnegie Airborne Observatory in conjunction with LiDAR data to map the eight savannah tree species.

However the use of spectral data for tree species discrimination can be problematic particularly in southern African savannah due to high intra-species variability arising from within-species phenological differences, variation in edaphic properties and climatic conditions across landscape (Cho *et al*. 2010; Asner *et al*. 2009). Such variability derails the assumption of unique spectral signature per species (Cho *et al*. 2010) and often produces spectral similarities between species (Cochrane, 2000). Studies (Hill *et al*. 2010; Gilmore *et al*. 2008; Key *et al*. 2001) have alternatively used multi-temporal data covering different phenological periods for purpose of tree species discrimination. Phenological changes occur throughout the growing season at different rates amongst species and data that captures these changes amplify the spectral variability between deciduous species (Hill *et al*. 2010; Key *et al*. 2001). This makes a multi-phenological approach towards tree species mapping in the savannah environment a more topical research question.

Few studies (Chidumayo 2001; Archibald and Scholes, 2007) have been conducted on the relationship between leaf phenology and climatic variables to develop empirical models that can serves as a proxy for changing climatic conditions. However none in our knowledge have investigated the importance of multi-phenological approach in southern African savannah for tree species mapping despite the overwhelming dominance of deciduous species. This study use Worldview-2 data to investigate how the spectral separability of tree species changes in individual images acquired at key points of the typical phenological development of savannah and when images of different dates are combined.

3.3 Data and Methods

3.3.1 Remote sensing data

Two Worldview-2 (hereafter called WV-2) satellite images (DigitalGlobe, Inc., USA) were acquired on different dates: i) 19th of April 2012 and ii) 7th of March 2013 to capture different phenological periods. In the savannah March period is characterized as the end of the rainy season with tree canopies at their maximum foliation while the April period constitutes a transition to senescence (Cho *et al*. 2010). Worldview-2 is the only multispectral sensor with eight bands situated in the visible and near-infrared regions of the spectrum: coastal blue (400-450nm), blue (450-510nm), green (510-580nm), yellow (580-625nm), red (625-690nm), red-edge (705-745nm), NIR-1(770-895nm) and NIR-2(860-1040nm). It captures the image in two modes; panchromatic and multispectral. The sensor has a swath width of 16.4km, a maximum revisit period of 1.1 day and a spatial resolution of 2 m for the 8 multispectral bands. The panchromatic band (450-800nm) is acquired at spatial resolution of 0.5 m.

3.3.2 Field data collection

Field data were collected during the transition period from wet to dry season in April 2012. Eight sites distributed across the study area were sampled purposively to cover varying degrees of tree cover (low to high tree cover). These sites were selected over two geological substrates, gabbro and granite, present in the study area. In each of these sites, a 100m X 100m plot was set up and all trees with diameter at breast height greater than 10cm were sampled. In all sites big trees (N=273) located using a high precision GeoExplorer 600 series Global Positioning System (GPS), and the species were identified. One-second data from the Nelspruit reference station (90km from the study area) was used to post-process the GPS location to sub-meter accuracy. However, some of these points were located on cloud-covered parts of the image and were therefore not available for use. Additional trees and GPS points (N=62) collected in the area from previous studies (Naidoo *et al*. 2012) were also used for spectral endmember collection. A combination of these points was sufficient for maintaining representativity of each species of interest. In total 250 points representing four tree species of interest were used to train and validate the classifications. The study focused on four common tree species (i.e. *Acacia nigrescens* (AN), *Combretum spp*, (*Combretum collinum, Combretum apiculatum and Combretum herorence*) (COM), *Sclerocarya birrea* (SB) and *Dichrostachys cinerea* (DC)) that were encountered in most sampling sites in our fieldwork (**Table 3.1 for attribute information**). Additional tree attributes information, e.g. tree DBH, height, whether trees are interlocking or coppicing were also recorded.

Table 3.1 Information for the four tree species of interest in this study.

Tree species	Phenology	Attribute information
Sclerocarya birrea	Deciduous	Common tree species in SA savannah which is protected by law. Its fruits are considered important for beer-making in local communities and also a source of food for wild animals.
Acacia nigrescens	Deciduous	Important tree species for many browsers and serves as a nitrogen-fixing tree, increasing grass quality underneath its canopy.
Combretum spp.	Deciduous	Common tree species with high density in granite landscape. Often used for charcoal production and other numerous medicinal purposes
Dichrostachys cinerea	Deciduous	Shrubby tree species often considered as an encroaching species in the savannah with degrading effect on rangeland quality.

Sources: (Shackleton and Shackleton, 2003; Munyathi *et al*. 2013; Treydte *et al*. 2007; Naidoo *et al*. 2012)

3.3.3 Pre-processing steps

The WV-2 images were geometrically and atmospherically corrected. Using PCI Geomatica OrthoEngine several Rational Polynomial Coefficient (RPC) models (RPC 0^{th}, 1^{st} and 2^{nd} order correction) were tested for a rigorous orthorectification of Worldview-2 image. The accuracy of the models was assessed via a leave-one-out cross validation approach with 18 ground control points (GCPs). The GCPs were evenly distributed over the study area considering land land features available on the landscape (e.g. road intersections). A differential GeoExplorer 2008 series GPS was used to record accurate positions of the GCPs and data from Nelspruit reference station were used to post-process the data to sub-meter accuracy. The RPC 0^{th} order correction model was opted because its accuracy coincides with that of a rigorous model and it is the recommended RPC model for Worldview-2 product (Geomatica, 2013). ATCOR-2, often used for flat terrain (Richter and Schlapfer, 2012) was chosen for atmospheric correction of WV-2 images since the study area is generally flat to gentle undulating slopes.

3.3.4 Tree extraction

The images were characterized by clouds and cloud shadows, bare-ground, grass and tree canopy and therefore masking was necessary to remove unwanted features and produce a tree canopy map. Developing a tree masking method is a common practice in that it enhances the spectral separability of the target features (Pu and Landry, 2012; Pu, 2011). Vegetation indices e.g. Normalized Difference Vegetation Index and Soil Adjusted Vegetation Index enhance vegetation signals and are often used to separate vegetated areas from non-vegetated areas. NDVI in particular, is more sensitive to sparsely vegetated areas and has effectively been used to eliminate non-vegetated areas (Pu and Landry, 2012; Pu, 2011; Jackson and Huete, 1991). Other studies have used textural information to separate tree canopies from non-canopy vegetation i.e. grass and shrubs (Pu and Landry, 2012; Pu, 2011). The high spatial resolution data enables the identification of tree shadows for tall trees and band thresholding facilitates the separation of shaded tree canopy from non-shaded canopy (Pu, 2011).

In this study, a tree masking method was developed in ENVI 4.8 to extract tree canopies and eliminate non-canopy features. The best method to achieve this objective relied on NDVI, Brightness index, NIR-2 thresholding and SAM classifier. Region of interest (ROI) tool in ENVI 4.8 was used to delineate and eliminate clouds and cloud shadows. Then prior to image segmentation, a quantitative approach was developed using histogram to find optimal threshold values for elimination of non-canopy features and shaded areas. GPS points (N=72) (collected from a previous study) were used to collect NDVI values for tree canopy and grassy areas. Due to the absence of GPS reference points for bare areas, the study relied on dirt roads which were clearly discernible from the image.

For April image, an NDVI threshold value of 0.55 was used to mask tree canopies from non-canopy features. Visual inspection of the NDVI histogram (**Figure 3.1 (A)**) reveals that this threshold eliminates all pixels covering bare areas including some of the grass pixels. Shaded areas were eliminated using the brightness index. The Brightness index is often used to describe the condition of the image features with regard to overall brightness and wetness (Todd and Hoffer, 1998). The threshold value of 790 was used to separate shaded and non-shaded targets (**Figure 3.1 (B)**).

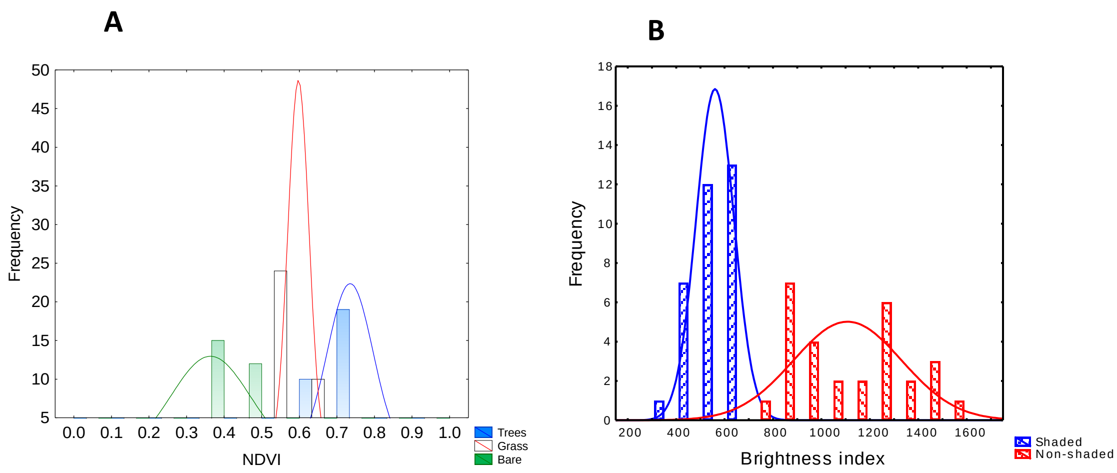

Figure 3.1 A= NDVI for separating vegetated from non-vegetated features; B= Brightness index for separating shaded areas from non-shaded. April image.

For March data, an NDVI threshold value of 0.65 was observed from the NDVI histogram (**see Figure 3.2 Left**) as the most optimal for eliminating pixels representing non-canopy features. Moreover NIR-2 thresholding was used to eliminate shaded pixels. Visual inspection of NIR-2 histogram (**Figure 3.2 Right**) indicates that a threshold value of 250 was sufficient to eliminate shaded pixels.

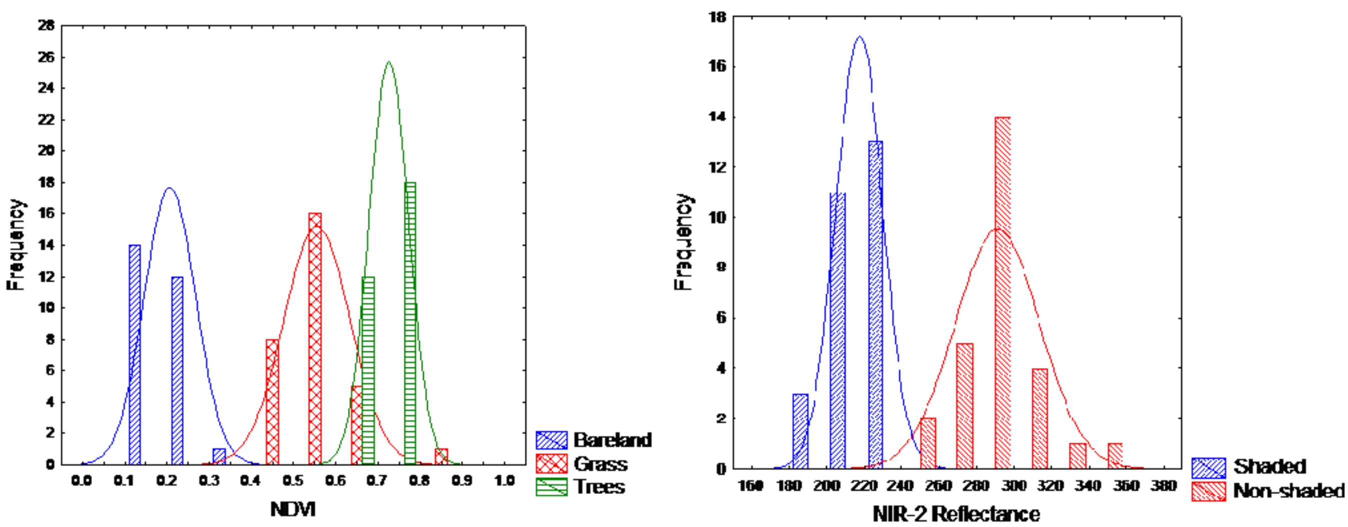

Figure 3.2 Left= NDVI for separating vegetated from non-vegetated features; Right= NIR-2 reflectance for separating shaded areas from non-shaded. March image.

Grassy features were not sufficiently eliminated by the NDVI thresholding and any attempt to increase the NDVI threshold beyond the histogram-derived optimum led to elimination canopy features, especially *Acacia nigrescens*. Therefore, the study assessed the potential of textural information to eliminate grass. Grass is assumed to be a low spatial frequency feature with low variability, compared to tree canopy which has typically a rougher surface, and therefore a variance matrix was computed on a 3x3 moving window to generate a texture layer. However, this assumption was not confirmed as the variance matrix showed insensitivity to within-canopy variability. The method was unable to show textural differences between grass and tree canopy. Spectral angle mapper (SAM) was then used to classify and further eliminate grass pixels from the NDVI-based tree canopy product. SAM is a similarity measure that compares the spectral angle between the reference spectrum and the target spectrum. A small angle indicates high spectral similarity (Cho *et al* 2010; Clark *et al*. 2005). The study sets a maximum-angle threshold of 0.005 for SAM and repeatedly ran classification on the NDVI product. A smaller angle was selected to cater for the spectral similarity that exists between grass and *Acacia nigrescens*. This section generated the tree products which were subsequently used for segmentation and tree classification (**Figure 3.3**).

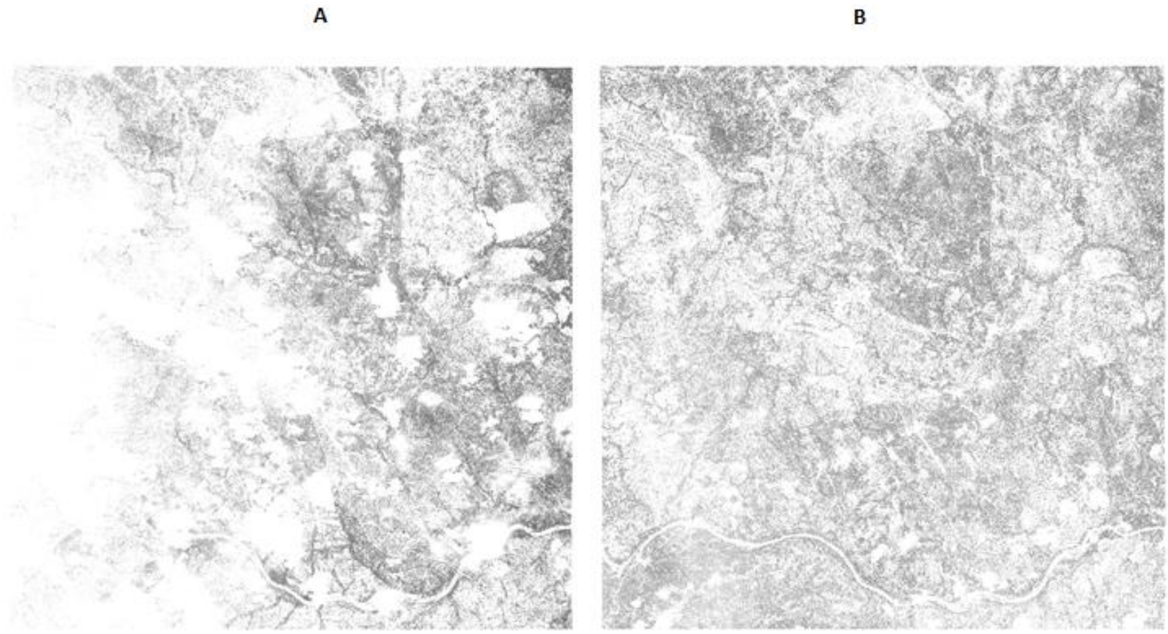

Figure 3.3 Tree mask produced from WV-2 scene with dark colour representing mask and light colour representing the background: A April and B March data

3.3.7 Training and validation samples

The GPS coordinates of the tree species collected in the field were used for training and validation of the pixel-based and object-based classification. The GPS data guided the collection of spectral endmembers using regions of interest (ROI) in ENVI 4.8. Table 3.2

summarizes the number of samples used for training and validation. ROIs collection procedure followed the similar formats for both images.

Table 3.2 Training and validation data used for tree species classification

	April data		**March data**	
	Training	**Validation**	**Training**	**Validation**
AN	119	118	102	108
COM	98	110	123	96
DC	112	108	137	113
SB	123	92	87	103

3.3.8 Spectral data analysis

This study evaluated the spectral variability within- and between-species using the Spectral Angle Mapper (SAM). SAM is a similarity measure that quantifies the level of similarity between two spectra and is insensitive to illumination-induced differences among spectra. It quantifies the angle between two spectra $s_i = s_{i1} \dots \dots s_{iL}$ and $s_j = s_{j1} \dots \dots . s_{jL}$

$$SAM\ (s_i, s_j) = \theta(s_i, s_j) = cos^{-1}\left(\frac{\sum_{l=1}^{L} s_{il}s_{jl}}{[\sum_{l=1}^{L} s_{il}^2]^{1}/_{2}[\sum_{l=1}^{L} s_{jl}^2]}\right) \qquad \text{Equation 2}$$

where L is the number of bands. A high angle between spectra indicates that the two species are spectrally separable (Cho *et al.* 2010; Clark *et al*. 2005). In our application of intra-species SAM the angle between each spectrum of a species was computed. The application of inter-species SAM followed the same approach as the intraspecies; the angle between each spectrum to every other species spectrum was computed. Two band combinations (all WV-2 bands and simulated IKONOS bands (blue, green, red, NIR1)) were tested at both pixel- and object-level to establish the band combination that magnifies the spectral separability between species.

In addition, we subjected the individual spectral bands of WV-2 data to further scrutiny through the use of band-add-on (BAO) procedure to establish the discriminatory ability of each band. The BAO procedure is often used on hyperspectral data with high data dimensionality (Keshava, 2004). This procedure iteratively selects bands that optimize angular separation between spectra. The procedure adds on pairs of bands and selects those with the highest average SAM. The process is repeated until no band contributes further to the discriminatory power (Keshava, 2004; Naidoo *et al*. 2012; Cho *et al*. 2010). The application of BAO, whilst identifying spectral bands that increases angular separation, also identifies band redundancy. The BAO procedure was run on WV-2 bands eight times with one band excluded each time and this enabled the identification of the spectral bands with the highest discriminatory power for the species in question.

3.3.9 Tree species classification

We conducted tree species classification using Random Forest (RF). RF has been successfully applied to classify savannah tree species using hyperspectral data (Naidoo *et al*. 2012). Chan and Paelinckx (2008) argued that RF remains the most robust machine learning algorithm. RF is a tree-based classifier that assembles hundreds of decision trees using random subsets of training data. These decision trees are evaluated using out-of-bag estimates to establish the importance of each input (Naidoo *et al*. 2012; Chan and Paelinckx, 2008). Similar to Adelabu *et al*. (2013) this study used the RF algorithm based on EnMap box to classify four tree species (*Acacia nigrescens, Combretum spp., Sclerocharya birrea* and *Dichrostachys cinerea*). The spectral endmembers collected from the April and March images were combined into hybrid spectral data to run multi-temporal classification in R Studio using RF modelling procedure.

3.4 Results

3.4.1 Spectral variability: interspecies-SAM

The interspecies-SAM experiment shows that overall tree species are more separable during the transition to senescence period (April) compared to the peak of productivity period (March) (**Figure 3.7**). The March data shows a relatively similar average interspecies-SAM for all species tested and this is typical of productivity period (Cho *et al*. 2012). *Acacia nigrescens* and *Combretum spp.* showed a high spectral separability due to the earlier senescence of *Acacia nigrescens* in April. However *Sclerocharya birrea* and *Dichrostachys cinerea* showed a lower spectral separability during April compared to the end of the rainy season (March). The multi-temporal data achieved higher interspecies-SAM for all tree species than single dates and the difference was statistically significant ($z_{obt} > z_{crit}$).

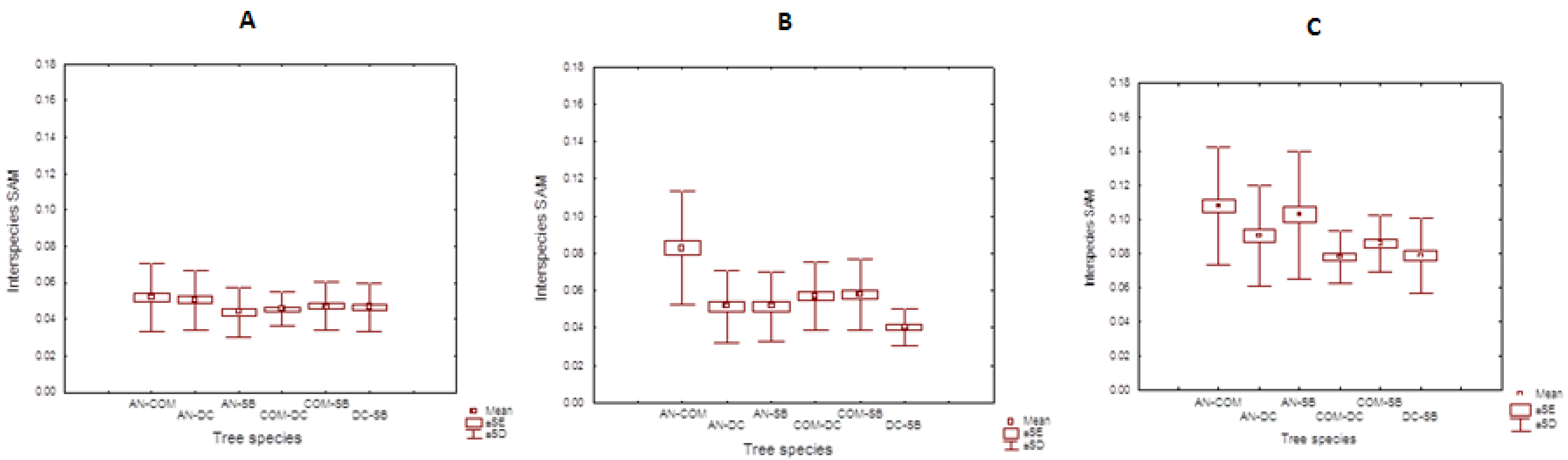

Figure 3.4 Interspecies-SAM for single dates and time-series data: A = March image, B = April image and C = combination of the two dates.

3.2.2 Tree species classification

The assessment of classification was based on a scenario which considers two datasets: multi-temporal data (March-April combination) and single dates. Using RF, the March-April combination achieved the highest overall accuracy for pixel-based classification than each of the single dates (**Table 3.3**). The higher overall accuracy concurs with the higher average interspecies-SAM achieved above (**Figure 3.4**) suggesting an amplified spectral differences between tree species. Amongst single dates April data achieved higher overall accuracy compared to March data and which is also consistent with the observed interspecies-SAM (**Figure 3.4**).

Table 3.3 Overall classification accuracies for time-series data and single dates

Classification unit	**Overall classification accuracy**		
	April 2012	**March 2013**	**Time-series data (April 2012 & March 2013)**
Pixel-based	76.4%	72.9%	80.4%

Classification with multi-temporal data achieved the producer's and user's accuracy of above 60% for all species including *Sclerocharya birrea* and *Dichrostachys cinerea* (**Table 3.4**) which are often difficult to discriminate using spectral data alone (Naidoo *et al*. 2012) and were also difficult to discriminate with single dates. The producer's accuracy of *Acacia nigrescens* has also improved with the use of time-series data.

Table 3.4 Producer's and user's accuracies for time-series and single dates: pixel-based approach

	April data		**March data**		**Time-series data**	
Classes	**Producer's accuracy**	**User's accuracy**	**Producer's accuracy**	**User's accuracy**	**Producer's accuracy**	**User's accuracy**
Com	94.50%	86.60%	83.60%	81.40%	96.50%	100%
AN	79.60%	74.00%	65.20%	76.20%	95.00%	80.80%
SB	44.50%	69.40%	55.40%	68.00%	66.60%	61.50%
DC	81.40%	72.10%	79.60%	61.80%	60.00%	77.70%

(Com= *Combretum spp*., AN= *Acacia nigrescens*, SB= *Sclerocharya birrea* and DC= *Dichrostachys cinerea*)

3.5 Discussion

The spectral properties of tree species and separability between species originate from variation in leaf pigments, water content and other biophysical properties (e.g. leaf size and structure) that varies throughout the growing season (Gilmore *et al*. 2008). At a single date the highest spectral variability between the four species was found to be in April which captured the transition to senescence phenological stage. The rate of phenological change varies between species (Gilmore *et al.* 2008) and our results (interspecies-SAM) indicates that the rate of transition to senescence varies between species hence pronounced spectral differences were observed in April data. March data captures the peak of productivity and this seems to represent minor differences in tree phenological states. The peak of productivity is associated with less interspecies separability (Cho *et al*. 2012) and our results revealed a similar average interspecies-SAM with the March data. These observations authenticate the assertion made by Hill *et al*. (2010) that the ability to discriminate tree species is higher on the data captured at the start or end of the growing than mid-summer which is reported to have low interspecies separability (Cho *et al*. 2012). It would be interesting to test the performance of WV-2 data captured at the start of the growing for savannah tree species discrimination given that the yellow band had outperformed the red-edge band during the senescence period.

This study showed the importance of identifying phenological period when tree species would achieve high spectral differences between them particularly in the deciduous woodland. The results of the study indicate April period as the most optimal time to acquire single spectral data for tree species discrimination in savannah. Differences in leaf pigments and other structural attributes between tree species seem to have been high during April period and this enhanced the discriminatory power of Worldview-2 image. However data collection during this period is often hampered by natural constraints such as cloudy weather condition.

The March data did not exhibit high interspecies-SAM between species. However, combining data from March and April dates enhanced the spectral differences between species. The higher interspecies-SAM from multi-temporal data compared to individual images concurs with the literature that variations in spectral reflectance of deciduous species throughout the growing season enhances species separability (Hill *et al*. 2010; Gilmore *et al*. 2008). Throughout the growing season, deciduous tree species undergo phenological changes and multi-temporal data capturing these changes enhance the spectral differences between species (Hill *et al* 2010; Gilmore *et al.* 2008). The two dates obviously captures different stages of phenological changes which also occur at different rates between deciduous tree species in the savannah. Therefore the compounded interspecies-SAM with multi-temporal data indicates the importance of multi-seasonal approach for discriminating numerous tree species in the savannah. Moreover multi-temporal data mitigated the well-established spectral confusion between *Sclerocharya birrea* and *Dichrostachys cinerea* often neutralised with the use of LiDAR data. Such improvement indicates that multi-temporal data is able to offset the effect of mixed pixels bordering the crowns of small trees. Therefore in the absence of LiDAR data, time-series data may also serves as an alternative.

3.6 Conclusion

This study concludes that the multi-temporal approach towards tree species increase the spectral differences between species. Multi-temporal data used to classify tree species in this study achieved higher interspecies-SAM and higher classification accuracy than individual images. Moreover, the study showed transition to senescence period to be an optimal period for spectral discrimination of savannah tree species using WV-2 data.

Chapter 4: Conclusion

4.1 Objectives review and concluding remarks

The advent of new multispectral sensors such as Worldview-2 with high spatial resolution and innovative bands in the yellow and red-edge regions of the electromagnetic spectrum provides opportunities for species-level mapping of biodiversity (Pu and Landry, 2012; Omar, 2010; Nagendra and Rocchini, 2008). However species-level mapping of biodiversity in the savannah environment is often challenged by intraspecies spectral variability arising from within-species phenological differences, driven by variation in edaphic and climatic conditions across landscape (Cho *et al*. 2010; Naidoo *et al*. 2012). While the data from new multispectral sensors delivers the necessary spatial and spectral details for biodiversity estimation, its use for tree species mapping has often been challenged by within-canopy variability (Pu and Landry, 2012; Nagendra and Rocchini, 2008). This study has showed that developing methods for exploiting high resolution data will improve our ability to map biodiversity in the savannah environment. The main objectives of the study were to i) investigate the utility of OBIA for mapping savannah tree species using WV-2 data, ii) investigate and compare the spectral capability of WV-2 sensor to that of simulated IKONOS and iii) investigate the ability of multi-temporal data to enhance spectral variability amongst tree species in the savannah environment using Worldview-2 imagery captured in different seasons. The following concluding remarks were drawn from our findings in relation to the objectives of the study:

4.1.1 Investigate the utility of OBIA for mapping savannah tree species using WV-2 image

This study concludes that there is no statistically significant difference between OBIA and pixel-approach towards savannah tree species mapping. The assumption that using objects with Worldview-2 spectral data improves tree species mapping could not be verified and this may be attributed to complexities in the savannah tree structure. Nonetheless, OBIA minimized the effects of tree canopy edge pixels and therefore improves the classification accuracy of *Sclerocharya birrea* compared to a pixel-based approach. OBIA improved the classification accuracy between *Sclerocharya birrea* and *Acacia nigrescens* and this makes OBIA an appropriate alternative for classifying big trees in the savannah environment using WV-2 image. In addition mapping savannah tree species at 74.5% overall accuracy compares positively with other studies that have used OBIA for species-level mapping.

4.1.2 Investigate and compare the spectral capability of WV-2 sensor to that of simulated IKONOS

The higher classification accuracy produced using WV-2 image demonstrates the improved capability of WV-2 spectral bands over that of IKONOS. Our results provide evidence that accurate mapping of savannah tree species is possible with WV-2 data. WV-2 image improved the overall accuracies of the classification of the four species from up to 15.9% and 8.5% higher than the simulated IKONOS using OBIA and pixel-based approach respectively. This may be attributable to the yellow band (605 nm) not present in most multispectral sensors such as IKONOS. The results in this study reiterate Pu and Landry (2012) conclusion that increasing spectral resolution of multispectral sensors will improve their ability to discriminate tree species spectrally.

4.1.3 Multi-temporal approach towards tree species in the savannah environment using WV-2 data

The enhanced spectral difference with the use of multi-temporal data stresses the ease at which tree species can be classified with multi-temporal approach. The multi-temporal data achieved higher interspecies-SAM compared to individual images. In addition a higher overall classification accuracy was produced from multi-temporal data (80.4%) compared to individual images (76.4% and 72.9% April and March respectively). Deciduous tree species undergo phenological changes throughout the growing season (Hill *et al*. 2010; Gilmore *et al*. 2008) and developing multi-temporal framework using WV-2 imagery with innovative bands in the yellow and red-edge regions improves our ability to discriminate tree species. The level of classification accuracy achieved in this study with multi-temporal data indicates the need to move towards multi-temporal approach if our work is to feed into biodiversity management. Accurate mapping of tree species distribution is essential for sound management of biodiversity (Turner *et al*. 2003). Moreover, the classification result shows the April period as the optimal period for discriminating tree species using spectral data.

4.2 Limitations of the study

The study could not produce a classification map from the multi-temporal approach due to pixel misalignment between images. Although the two images were corrected for geometric errors, the orientation of tree crowns between the images could not match. Therefore the study tested the concept of multi-temporal approach only without producing a classification map. In addition cloudy weather conditions distorted the image and some GPS points could not be used.

4.3 Recommendations

The transition to senescence phenological period has shown high spectral difference between tree species and produced high mapping accuracy. This period can therefore be recommended as ideal for tree species discrimination using multispectral data particularly WV-2 image. Further research on the performance of WV-2 data captured at the beginning of the growing season is necessary to establish the importance of red-edge and NIR-2 bands pioneered in WV-2 sensor. The present study has established the yellow band as significant in the overall performance of WV-2. It will therefore be insightful to investigate the performance of WV-2 captured at a season different to present study.

The study has shown improved mapping accuracy for *Sclerocharya birrea* and *Acacia nigrescens* with the use of object-based image analysis. The present study used only multi-spectral data to investigate the utility of OBIA. Research that combines multispectral data with LiDAR data may provide more insight on the utility of OBIA in tree species mapping. The use of LiDAR data will assist with the elimination of below-canopy effect and therefore makes the first part of OBIA (segmentation) more effective.

Pattern matching would be an appropriate corrective method where overlapping features are detected (Cervantes and Kang, 2006) and corrected using GPS points as a reference data. The challenge is that the two images cover different phonological periods. A study into the utility of pattern matching in the correction of pixel misalignment is warranted.

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Appendices

Appendix A: ANOVA results

Appendix A.1: One-way ANOVA results for the observed variation in the reflectance of *Acacia nigrescens* found on different geological substrates.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	14734.5	1	14734.5	148.5537	1.23E-17	4.006873
Within Groups	5752.809	58	99.18636			
Total	20487.31	59				

Appendix A.2: One-way ANOVA results for the observed interspecies-SAM between OBIA and pixel-based approach.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.006752	1	0.006752	10.33951	0.00136	3.854317
Within Groups	0.473446	725	0.000653			
Total	0.480198	726				

Appendix A.3: One-way ANOVA results for the observed interspecies-SAM between 8-bands of WV-2 and simulated bands of IKONOS sensor.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.029259	1	0.029259	27.64561	1.92E-07	3.854299
Within Groups	0.768375	726	0.001058			
Total	0.797634	727				

Appendix A.4: One-way ANOVA results for the observed interspecies-SAM between 8-bands of WV-2 and 7-bands of WV-2 with coastal blue excluded via BAO procedure.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.000466	1	0.000466	0.645458	0.422004	3.854299
Within Groups	0.524338	726	0.000722			
Total	0.524805	727				

Appendix A.5: One-way ANOVA results for the observed interspecies-SAM between 8-bands of WV-2 and 7-bands of WV-2 with blue band excluded via BAO procedure.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.002013	1	0.002013	2.877105	0.090276	3.854299
Within Groups	0.508069	726	0.0007			
Total	0.510082	727				

Appendix A.6: One-way ANOVA results for the observed interspecies-SAM between 8-bands of WV-2 and 7-bands of WV-2 with green excluded via BAO procedure.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.002037	1	0.002037	2.957948	0.085883	3.854299
Within Groups	0.499995	726	0.000689			
Total	0.502032	727				

Appendix A.7: One-way ANOVA results for the observed interspecies-SAM between 8-bands of WV-2 and 7-bands of WV-2 with yellow excluded via BAO procedure.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.008592	1	0.008592	13.53715	0.000251	3.854299
Within Groups	0.460777	726	0.000635			
Total	0.469368	727				

Appendix A.8: One-way ANOVA results for the observed interspecies-SAM between 8-bands of WV-2 and 7-bands of WV-2 with red band excluded via BAO procedure.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.018433	1	0.018433	30.80934	3.99E-08	3.854299
Within Groups	0.434355	726	0.000598			
Total	0.452787	727				

Appendix A.9: One-way ANOVA results for the observed interspecies-SAM between 8-bands of WV-2 and 7-bands of WV-2 with red-edge band excluded via BAO procedure.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.001725	1	0.001725	2.121077	0.145717	3.854299
Within Groups	0.590434	726	0.000813			
Total	0.592159	727				

Appendix A.10: One-way ANOVA results for the observed interspecies-SAM between 8-bands of WV-2 and 7-bands of WV-2 with NIR-1 band excluded via BAO procedure.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.013493	1	0.013493	15.45058	9.28E-05	3.854299
Within Groups	0.634015	726	0.000873			
Total	0.647508	727				

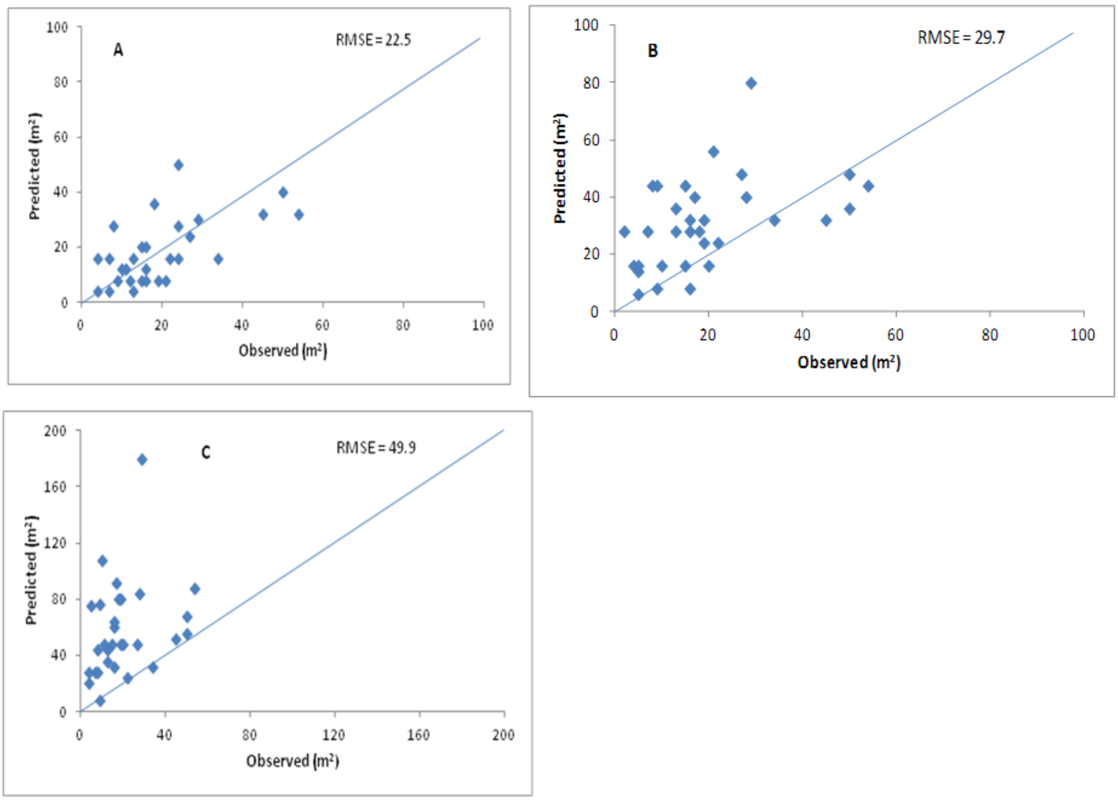
Appendix A.11: One-way ANOVA results for the observed interspecies-SAM between 8-bands of WV-2 and 7-bands of WV-2 with NIR-2 excluded via BAO procedure.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.045926	1	0.045926	46.11867	2.32E-11	3.854299
Within Groups	0.722973	726	0.000996			
Total	0.7689	727				

Appendix B: OBIA results from March Data

Segmentation scale parameter

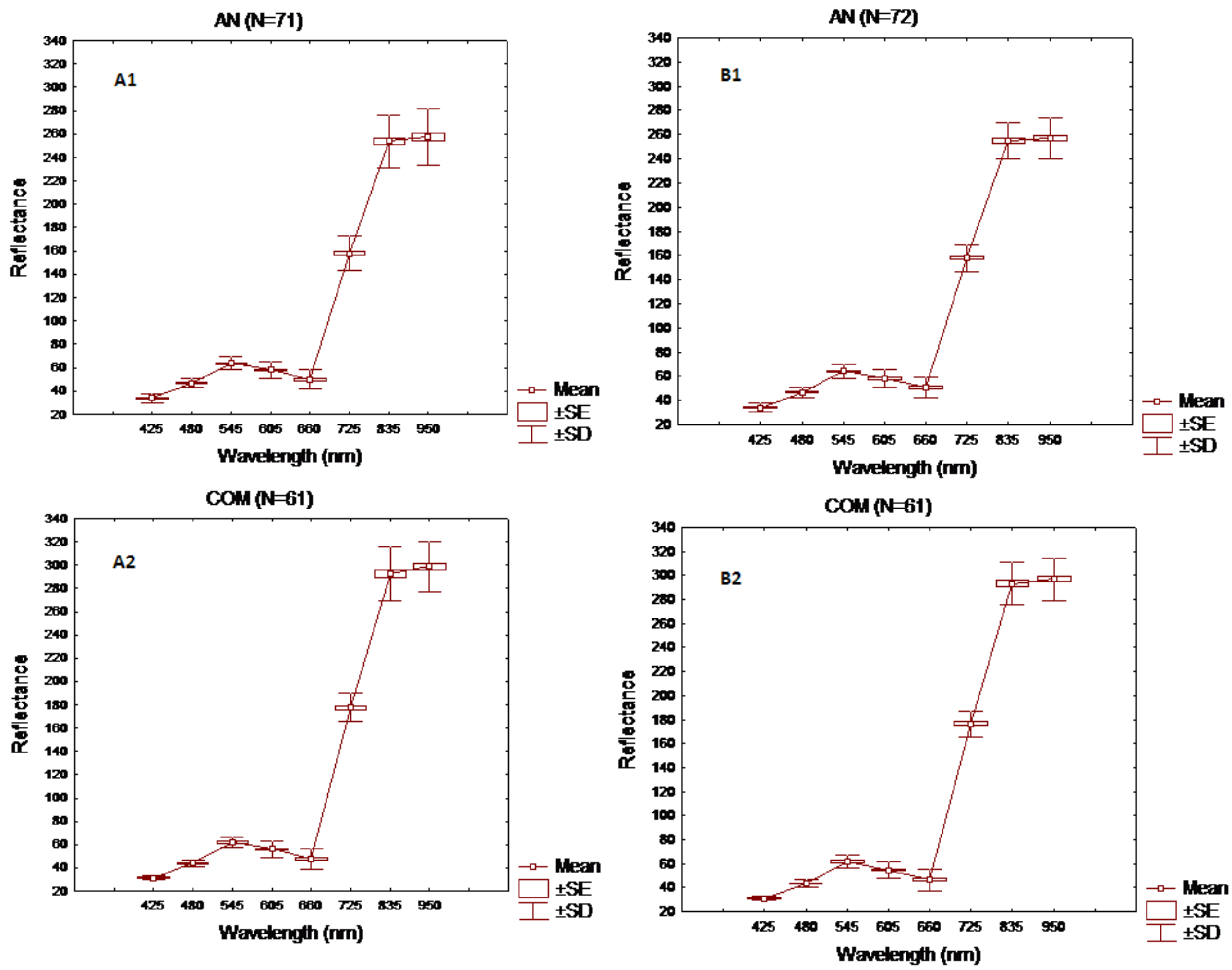
The scale parameter of 3 provided the smallest RMSE of 22.5 compared to the scale of 5 and that of 7 (**Appendix B1**). The assessment result indicates the scale parameter of 3 as optimal for tree canopy delineation in southern African savannah using Worldview-2 image acquired during the peak of productivity period (March).

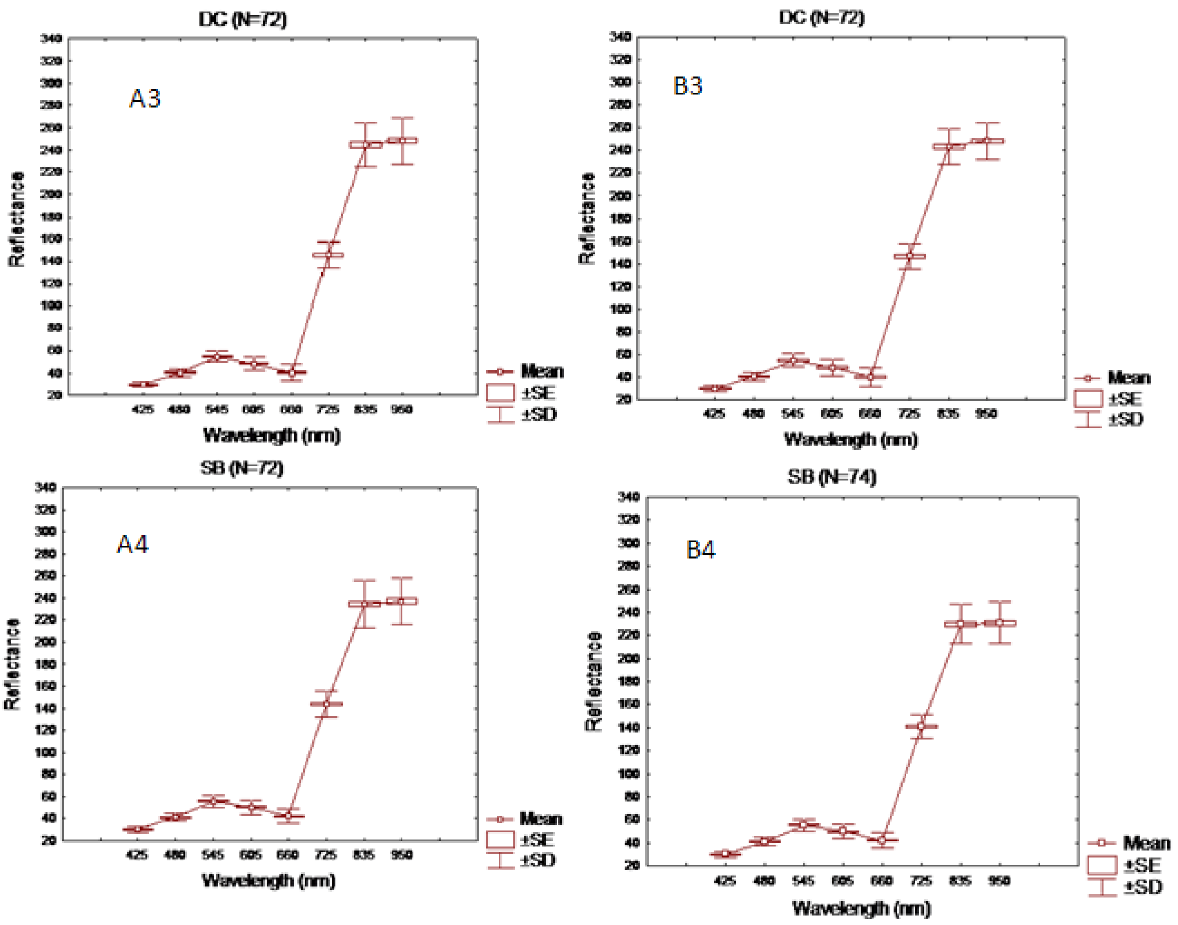


Appendix B.1 Scatterplot and Root-mean-square-error for dimensional accuracy of the segmented objects – March image; (A) segmentation scale parameter of 3, (B) scale of 5 and (C) scale of 7.

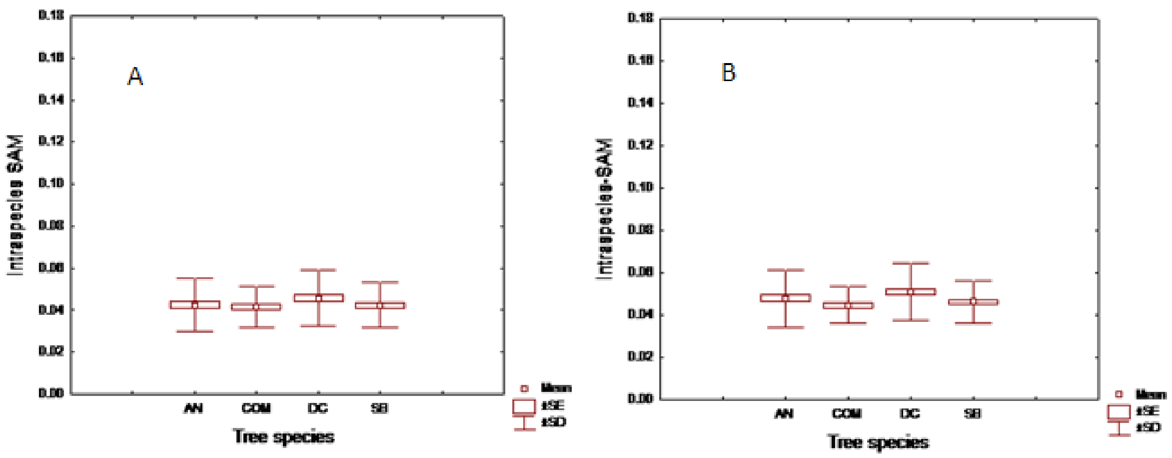
Spectral variability: intra- and interspecies

The canopy reflectance for all tree species shows a common pattern of spectral variability in the visible and near infrared regions. Intraspecies variability remains low in the visible region while a high spectral variability is observable in the near infrared region for all tree species. Moreover the spectral profile of each tree species is typical of a healthy photosynthetically active plant with high reflectance in the green region and high absorption in the red region due to the presence of leaf chlorophyll. This trend is observed for both object-based and pixel-based approaches (**Appendix B2**). The intraspecies-SAM experiment shows a high spectral variability within *Dichrostachys cinerea* (**Appendix B3**). However *Acacia nigrescens, Combretum spp*. and *Sclerocharya birea* exhibit similar patterns of intraspecies variability and this is observed for both object-based and pixel-based approaches (**Appendix B3**).

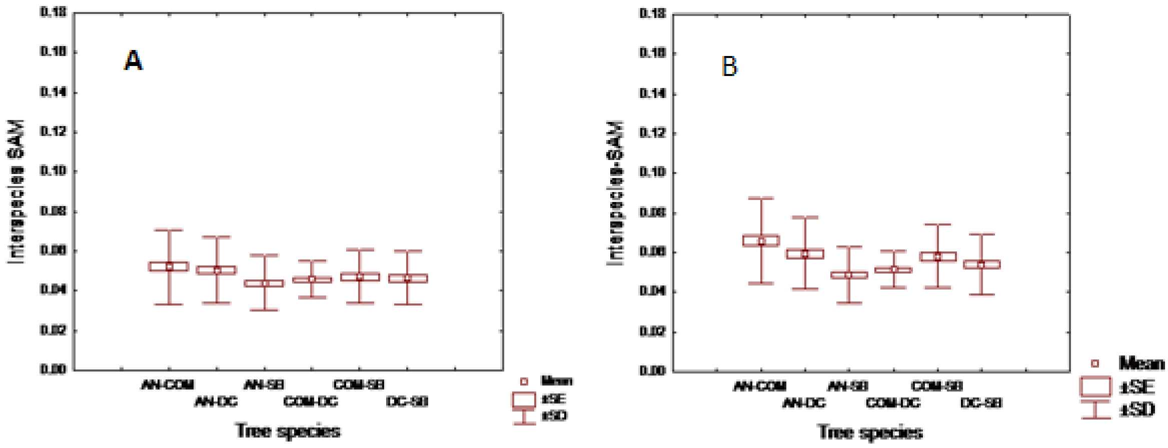




Appendix B.2 Spectral profile of the four tree species. AN= *Acacia nigrescens*; COM=*Combretum collinum*; DC=*Dichrostachys cinera*; SB=*Sclerocharya birea*. A1-A4 object-based spectra and B1-B4 pixel-based spectra



Appendix B.3 Intraspecies-SAM for four species; A=Object-based and B=Pixel-based.



Appendix B.4 Interspecies-SAM for four species; A=Object-based and B=Pixel-based.

Tree species classification

Appendix B.5 Confusion matrix from object-based classification using Random Forest on 8-bands of Worldview-2 image March date.

Classes	Com	AcNig	ScBi	DiCi	Total	Producer's accuracy	User's accuracy
Com	96	7	11	0	114	84.2%	84.2%
AcNig	6	69	7	15	97	58.4%	71.1%
ScBi	11	18	60	23	112	65.2%	53.5%
DiCi	1	24	14	70	109	64.8%	64.2%
Total	114	118	92	108	432		
Overall Accuracy	68.2%						
Overall Kappa	57.7%						

Appendix B.6 Confusion matrix from pixel-based classification using Random Forest on 8-bands of Worldview-2 image March date.

Classes	Com	AcNig	ScBi	DiCi	Total	Producer's accuracy	User's accuracy
Com	90	9	5	3	107	78.9%	84.1%
AcNig	3	81	14	4	102	68.6%	79.4%
ScBi	1	8	56	13	78	60.8%	71.7%
DiCi	20	20	17	88	145	81.4%	60.6%
Total	114	118	92	108	432		
Overall Accuracy	72.9%						
Overall Kappa	63.7%						

(Com= *Combretum spp.*, AN= *Acacia nigrescens*, SB= *Sclerocharya birrea* and DC= *Dichrostachys cinerea*)

Appendix B7 McNemar test for object-based versus pixel-based classification: March data

f_{11}	f_{12}	f_{21}	f_{22}	Z_{obt}	Z_{crit}	Df
105	32	12	283	2.864	3.841	1