

A quantitative assessment of the impacts of water status and chemical bioassays on structural attributes of *Eucalyptus* clones and plantation soil nitrogen using hyperspectral data

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## **Abstract**

A key aspect of commercial forest management is the continuous gathering of information on forest structural attributes. This information provides detailed inventory data for commercial forestry stands and is updated frequently for future monitoring purposes. Such datasets have previously been obtained using traditional methods such as field-based data collection campaigns. These campaigns have major implications for economic sustainability of future afforestation programmes, because they are regarded as labour-intensive, time consuming, and expensive. The introduction of remote sensing technologies has improved forest structural data collection over large areas due to its synoptic nature and relative cost-effectiveness. The advent of new sensors such as hyperspectral data also has enabled accurate estimations of forest foliar chemical bioassays, which are indicative of current forest biochemical and structural attribute states. This study advocates the quantitative assessments of the links between forest foliar characteristics and forest structural attributes. To date research has gone as far as estimating forest chemical attributes, but no research efforts have examined the interactions between forest foliar chemistry and forest structural attributes in South Africa. Forest foliar chemical composition provides information about the current status and productivity of forest plantations.

The forest stand structural attributes that are of significance to commercial timber resource assessments such as volume, basal area, and soil nitrogen under forest canopy, were surveyed in the field. Leaf and canopy spectral attributes were acquired coincident with the field inventories using both an analytical spectroradiometer (ASD) and airborne spectrometer for applications (AISA). A soil auger was used to gather soil samples diagonally (i.e. north, south, east and west) across centre tree at 0.3 - 0.7m depths. Various statistical analyses were performed to establish interactions between foliar chemistry and both forest structural attributes and soil nitrogen under the forest canopy. Finally, the study attempted to downscale from hyperspectral data to broadband sensor specifications to examine these interactions at a coarser, but more operational spectral resolution. The downscaling thus was an attempt to operationalise the main findings using cheaper and easily available broadband datasets.

The results suggested that the volume measurements and vegetation spectral indices relationships, derived from ASD spectral characteristics of *E. grandis* and *E. saligna* clones, yielded significant ( $p < 0.05$ ) correlations. The integration of all clones yielded stronger correlations than the relationships for *E. grandis*, but lower than that of *E. saligna*. Age, site quality, and the clone in question all had a significant ( $p < 0.05$ ) influence on the indices. Ancillary data, such as age and site index, also had a significant impact on the future volume models developed, e.g., adjusted  $R^2 = 0.78$ , RMSE =  $0.0176 \text{ m}^3/\text{ha}$ ,  $p < 0.0001$  compared to a low adjusted  $R^2$  of 0.47 and high RMSE ( $0.055 \text{ m}^3/\text{ha}$ ,  $p < 0.0001$ ). On further extending the analysis to airborne imagery, varied regression relationships between the indices and both volume and basal area were observed. These regression relationships had high adjusted  $R^2$  and low root mean square error (RMSE) values. The future models developed for volume and basal area estimations exhibited high adjusted  $R^2$  values ( $> 90\%$ ),  $p < 0.001$ , and low RMSE and PRESS statistics. These models approximated a 1:1 relationship, thereby suggesting that airborne remotely-sensed proxies of canopy chemical bioassays may generally be useful in the assessment of forest structural attributes.

Soil nitrogen was further estimated from leaf spectra, i.e., raw and continuum removed spectral transformation. Significant correlations ( $0.37 \geq r \geq 0.80$ ,  $p < 0.05$ ) were observed between leaf spectral indices and soil nitrogen. The significant spectral indices-site interactions were only observed between good-medium and good-poor sites and no differences were observed between medium and poor sites. Soil nitrogen model developed from continuum removed spectra returned a high adjusted  $R^2$  values ( $R^2 = 0.85$ ;  $p < 0.05$ ) and low PRESS statistic values (0.05) compared to approaches based on raw spectra ( $R^2 = 0.77$ ;  $p < 0.05$ ; PRESS = 0.07). Downscaling from hyperspectral data to Landsat TM spectral specifications showed that bands (i.e., TM2, TM3, TM4, TM5) yielding significant ( $p < 0.05$ ) correlations with volume and soil nitrogen, whilst basal area was significantly correlated ( $p < 0.05$ ) with all Landsat TM bands. Bands TM3 and TM5 exhibited much stronger correlations with volume, basal area, and soil nitrogen. A comparison between models developed from simulated Landsat TM bands and original Landsat TM bands indicate that simulated datasets performed better than the original Landsat TM dataset. The coefficient of determination for simulated volume, basal area and soil nitrogen models were 64 %, 64 %, and 64 % respectively.

77% and 91% compared to 13%, 47% and 50% returned by original Landsat TM datasets, respectively. The models developed from simulated datasets for future estimation of volume, basal area, and soil nitrogen showed that the soil nitrogen model had a superior goodness of fit statistic, followed by basal area model and lastly volume model, e.g., adjusted  $R^2 = 0.91$ , MAE = 0.030 % and 2.6;  $R^2 = 0.77$ , MAE = 0.047 m<sup>2</sup> and Mallow's Cp of 4.4;  $R^2 = 0.64$ , MAE = 0.594 m<sup>3</sup>/ha and Mallow's Cp of 1.5, respectively.

It was concluded that forest structural attributes and soil nitrogen under forest canopy can be estimated using foliar chemical proxies obtained from hyperspectral data and ancillary data, such as age and site index. Spectral resampling from hyperspectral to broadband data such as Landsat TM bands has the potential to estimate basal area and soil nitrogen with reasonable success. Resampling from hyper- to multispectral data properties for volume estimations was not as successful. The results of this study have important implications for future technology-based forest management and inventory updating approaches and monitoring and controlling of fertiliser applications on a regional basis.

## Preface

This work was undertaken at the University of KwaZulu-Natal and the Forestry and Forest Products Research Centre within the Council for Scientific and Industrial Research (CSIR) Natural Resources and the Environment Operating Unit. The financial support for this study was from a Studentship offered by the CSIR. This research was completed under the supervision of Professors F.B. Ahmed, Head of School of Environmental Sciences, University of KwaZulu-Natal, Durban and Jan van Aardt, Associate Professor, Rochester Institute of Technology, Centre for Imaging Science; Laboratory for Imaging Algorithms and Systems, Rochester, NY, USA.

I hereby declared that the contents of this work have not been submitted in any form to another University and, except where the work of others is acknowledged in the text, the results are the author's own investigation.

Thamsanqa Donges Mzinyane

28 February 2012

As the candidate's supervisors, we certify the above statement and have approved this thesis for submission. We certify that the above statement is correct:

- |                      |         |                        |
|----------------------|---------|------------------------|
| 1. Prof. Fethi Ahmed | Signed: | Date: 28 February 2012 |
| 2. Dr. Jan van Aardt | Signed: | Date: 28 February 2012 |

## **Declaration 1- Plagiarism**

I, Thamsanqa. D. Mzinyane declares that:

1. The research reported in this thesis, except where otherwise indicated, is my original research.
2. This thesis has not been submitted for any degree or examination at any other university.
3. This thesis does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.
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5. This thesis does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the thesis and in the References section.

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## Declaration 2 – Publications

1. Mzinyane, T, Ahmed, F and Van Aardt, J. 2011. Estimation of merchantable volume for *Eucalyptus* clones based on leaf-level hyperspectral data. *Forest Ecology and Management*. (Submitted)
2. Mzinyane, T, Ahmed, F and Van Aardt, J. 2011. Assessments of volume and basal area of *Eucalyptus grandis* using hyperspectral data (AISA). *International Journal of Remote Sensing*. (Submitted)
3. Mzinyane, T, Ahmed, F and Van Aardt, J. 2011. Predicting soil nitrogen content using narrow-band indices from *Eucalyptus grandis* canopies as proxy. *Forest Ecology and Management* (Submitted)
4. Mzinyane, T., Ahmed, F and Van Aardt, J. 2011. Modelling forest structural attributes and soil nitrogen using spectroradiometer data resampled to simulate Landsat TM data. *International Journal of Remote Sensing*. (Submitted)

Thamsanqa Mzinyane was responsible for the development, analysis, and writing of all the papers in this thesis. The contribution of the co-authors was providing comments during the development of the research questions and field data collection planning, analysis stage, as well as editing of the manuscripts.

Signed...

## **Dedication**

*I would like to dedicate this to my family, especially my late dad (gone too soon!)*

‘The fear of the Lord is the beginning of wisdom.’

‘For the Lord giveth wisdom: out of his mouth cometh knowledge and  
understanding.’ Proverb 2:6 & 9:10



## Acknowledgements

Firstly, I would like to acknowledge God for everything he has DONE for me and through HIM the word failure is non-existent. My sincere gratitude and many thanks to the supervising team, namely Professor Fethi Ahmed and Dr. Jan van Aardt. The support and encouragement, notwithstanding their thought provoking questions and assessments of the manuscripts throughout this study, is priceless! I had the most wonderful research experience under their tutelage.

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*God bless the supervising team (Professor Fethi Ahmed and Dr Jan van Aardt)*

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## Abbreviations

°C	Degrees Celsius
AISA	Airborne Imaging Spectrometer for Applications
ANOVA	Analysis of Variance
ASD	Analytical Spectral Devices
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVIRIS	Airborne Visible/Infrared Imaging Spectrometer
BA	Basal Area
BRG	Bioresource Group
C	Carbon
Chl	Chlorophyll
CI	Confidence Interval
CSIR	Council for Scientific and Industrial Research
DBH	Diameter at Breast Height
DGPS	Differential Global Positioning System
DW	Dry Weight
DWAF	Department of Water Affairs and Forestry
ENVI	Environment for Visualizing Images
FAO	Food and Agriculture Organisation of the United Nations
FDR	First Derivative Reflectance
FLAASH	Fast Line of Sight Atmospheric Analysis of Spectral Hypercubes
FW	Fresh Weight
FWHM	Full Width at Half Maximum
GCP	Ground Control Points
GDP	Gross Domestic Products
GENSTAT	Generalized Statistical Package
GIS	Geographical Information Systems
H	Height
HD	Dominant Height
ICFR	Institute for Commercial Forestry Research

LAI	Leaf Area Index
Landsat ETM+	Landsat Enhanced Thematic Mapper
Landsat TM	Landsat Thematic Mapper
LiDAR	Light Detection and Ranging
MAE	Mean Absolute Error
Max	Maximum
Min	Minimum
mNDVI	Modified Normalised Difference Vegetation Index
MRESRI	Modified Red Edge Simple Ratio Index
MSI	Moisture Stress Index
MTH	Mean Tree Height
MVA	Multivariate Analysis
N	Nitrogen
NDNI	Normalised Difference Nitrogen Index
NDRE	Normalised Difference Red Edge
NDVI	Normalised Difference Vegetation Index
NDVIg-b	Normalised Difference Vegetation Index green-blue
NDWI	Normalised Difference Water Index
NIR	Near Infrared
NRI	Nitrogen Reflectance Index
OSAVI	Optimized Soil-Adjusted Vegetation Index
P	Phosphorus
PCA	Principal Component Analysis
PLS	Partial Least Squares
PRESS	Prediction Residual Sum of Squares
<i>R</i>	Reflectance
RADAR	Radio Detection and Ranging
RE	Relative Error
$R_{re}$	Reflectance at the inflection point
RENDVI	Red Edge Normalized Difference Vegetation Index
REP	Red Edge Position
REPI	Red Edge Position Index
RMSE	Root Mean Square Error
RVI	Ratio Vegetation Index

SAM	Spectral Angle Mapper
SD	Standard Deviation
SEE	Standard Error of Estimation
SI	Site Index
SPAD	Soil Plant Analysis Development
SPHA	Stems per Hectare
SPOT	Systeme Probatoire d'Observation de la Terra
SPSS	Statistical Package for Social Sciences
SR	Simple Ratio
SWIR	Short Wave Infra Red
TAW	Total Available Water
TCARI	Transformed Chlorophyll Absorption Reflectance Index
V	Volume
$V_{i_{opt}}$	Optimal Vegetation Index
Vog1	Vogelmann Red Edge Index 1
WBI	Water Band Index
WBR	Water Band Ratio
WC	Water Content
WEDOC	Water Extractable Dissolved Organic Carbon
WEDON	Water Extractable Dissolved Organic Nitrogen
WGS	World Geodetic System
WI	Water Index



# CHAPTER 1: General Introduction

## 1.1. Introduction: Forest Growth and Yield

*Eucalyptus* species are highly commercialised hardwoods in South Africa and are mainly grown on short rotations for pulpwood, mining timber, and pole production (FSA, 2003, Majeke *et al.*, 2008). These species therefore are also important for growing the economy of South Africa. Forest growth and yield has become an essential component of the information needs required by forest managers for future planning. Forest growth is an indicator of growth potential of commercial forested areas. The forest growth and yields are calculated from a number of measured and derived structural attributes, such as diameter at breast height, height, basal area, merchantable volume, above ground biomass, and net primary productivity. The optimum growth and yields of commercial forestry ensure the significant contribution of this sector to employment, environmental, and economic fronts (DWAF, 1997, Tewari, 2001, Chamberlain *et al.*, 2005, Tewari, 2005). In South Africa, the commercial forestry sectors products and its related services was estimated to have created around 170 000 jobs in 2005, especially in areas where little or no alternative employment existed (Chamberlain *et al.*, 2005). Commercial forestry also provides an atmospheric filter of carbon dioxide and replaces it with oxygen, thus offsetting carbon emissions stored in deadwood, litter, and both above and below ground biomass (Beedlow *et al.*, 2004, Roberts *et al.*, 2008, FAO, 2010). Researchers have widely acknowledged the importance of including remotely sensed forest structural attributes in commercial forestry management and planning regimes (Jungho *et al.*, 2009). Such actions are likely to yield an important synoptic component for forest resource managers regarding status, trends, and structural characteristics of forest resources. This will empower them towards future forest planning and timeous forest operation interventions, whilst maintaining sustainability (Wulder, 1998, Boyd and Danson, 2005, FAO, 2005, Barth *et al.*, 2006)

Accurate information about the spatial distribution and status of forest structural attributes such as volume, basal area, diameter at breast height, height, and other

attributes is the cornerstone for proper management and planning. Manual or field-based methods are currently the preferred methods used to gather such information needs (Gebreslasie *et al.*, 2010). Even though the field-based procedures have been returning reasonably accurate data (Owen, 2000), they are known to be time consuming, expensive, and are often point-based, i.e., they are lacking in spatial extent or coverage (Lillesand *et al.* 2004 pp 615, Boyd and Danson 2005). According to Leckie (1990) and Smith *et al.* (2008), remote sensing techniques offer improved spatial coverage due to their synoptic nature over large areas, thereby reducing costs of field data collection and improve upon inventory estimates. Remote sensing though should not be seen as a substitute for field data collection, but the combination of the two methods (i.e. remotely sensed data and a small amount of field data collection) yield better results than each method alone (FAO, 2010). Studies such as Castro *et al.* (2003), Foody *et al.* (2003), Zheng *et al.* (2004), and Gebreslasie *et al.* (2008) bear testimony to the successful integration of remote sensing with minimum field data collection using statistical and empirical methods.

The utility of remote sensing to estimate various forest attributes for different forest species using different sensors have previously been explored, e.g., Eklundh *et al.* (2003), Hall *et al.* (2006), Gebreslasie *et al.* 2008, Roberts *et al.* 2008 , Tesfamichael *et al.* 2009, and Cho *et al.* (2010). These studies highlighted the distinct characteristics of remote sensing systems for specific applications, e.g., LiDAR sensors have high success rates in estimation of structural attributes when compared to multispectral data (Tesfamichael *et al.*, 2010), whilst hyperspectral data are more successful in foliar chemical estimations than multispectral data and LiDAR (Green *et al.*, 1998, Cho *et al.*, 2010). The success of recently developed hyperspectral sensors in foliar chemical estimations has increased the potential to resolve the spatial and spectral distributions of biophysiology-based information, thereby aiding forest classification, surveys, and management (Ismail *et al.*, 2008, Cho *et al.*, 2009, Oumar and Mutanga, 2010). The main focus of this study is imaging spectroscopy (hyperspectral sensing), which has thus been at the centre of estimating or derivation of biophysiology-based information of various plants.

## **1.2. Hyperspectral Remote Sensing**

Hyperspectral remote sensing, or imaging spectroscopy, acquires images in many narrow (< 10 nm) contiguous spectral bands throughout the visible to near infrared spectrum. Hyperspectral systems typically collect more than 200 bands of data, which enable the construction of a continuous reflectance spectrum curve for every pixel in the scene (Hansen and Schjoerring, 2003, Vaiphasa, 2006). These datasets are a three-dimensional pixel array, i.e. x-axis is the column indicator (x-coordinate), the y-axis is the row indicator (y-coordinate), and the z-axis is the band number, which is expressed as the wavelength of that band or channel (Galvao *et al.*, 2005). The continuous nature of the hyperspectral reflectance spectrum distinguishes imaging spectroscopy from the multispectral data. This has effectively provided new vegetation biophysical and chemical explorations because of the high data quantity and the high spectral resolutions. Amongst the first hyperspectral studies in forestry were estimations of foliar chemical contents (e.g., chlorophyll, nitrogen, lignin, cellulose, and water contents absorption features caused by chemicals present in plant foliage (Curran, 1989, Yoder and Pettigrew-Cosby, 1995, Plaza *et al.*, 2006, Abdel-Rahman *et al.*, 2008, Mokhele *et al.*, 2009). Plant foliage has been the focal point of these studies because of the important role played by foliage in forest ecosystem functioning, growth, and yield prediction (Peterson *et al.*, 1988). Foliage intercepts and absorbs the radiant energy which is later transformed to energy of organic substances through the complex process of photosynthesis (Coops, 1998, Gindaba *et al.*, 2005).

## **1.3. Remote Sensing of Forest Foliar Chemistry**

Global phenomena such as climate change bring about changes in ecosystems of the world (Chen *et al.*, 1999, De Boeck *et al.*, 2007). These changes are likely to be more pronounced on the plant foliage of various ecosystems because foliage is the proxy indicator of environmental variability (Curran, 1989). Remote sensing as a technology has evolved over time and has become one of the important techniques through which these changes can be tracked thereby providing valuable information on the vitality, state, and functioning of ecosystems over a wide range of scales from local to global (Majeke *et al.*, 2008). Recent studies of ecosystems have focused on forest foliar

chemistry as it provides information on present status of the plants at any given stage. These studies have used laboratory methods and to an extent multispectral data for monitoring of these leaf and canopy chemical attributes. Both these methods have shortfalls; laboratory methods are laborious, tedious, and time consuming (Wulder, 1998, Roberts *et al.*, 2011) while multispectral data have failed to provide consistent estimations of foliar chemistry, despite its dominance in remote sensing studies over the past decade (Stagakis *et al.*, 2010).

Multispectral data consist of few, wide spectral bands and have low spectral resolution and as a result lose vital information due to averaged information between these wide bands (Thenkabail *et al.*, 2000; Galvao *et al.*, 2005). These characteristics limit the capabilities of broad-band sensors in resolving details of vegetation canopy structure and chemistry. The breakthrough in foliar chemistry studies came with the advent of new sensors, such as imaging spectrometers. Amongst the leaf and canopy chemical components that have been retrieved using hyperspectral data are the pigments (chlorophyll a, chlorophyll b, and carotenoids), nutrients (nitrogen, carbon), structural molecules (cellulose, and lignin concentrations), and canopy water content (Filella *et al.*, 1995, Curran, 2001, Lamb *et al.*, 2002, Mokhele *et al.*, 2009, Abdel-Rahman *et al.*, 2008, Oumar and Mutanga, 2010). All these studies have proven the utility of imaging spectroscopy in estimating leaf and canopy chemical components and its use in forest applications in South Africa have received recent attention (Ismail *et al.*, 2008, Cho *et al.*, 2010, Oumar and Mutanga, 2011).

#### **1.4. Related Studies / Forestry Specific Studies**

Forest structural attributes provide an important indication of forest growth and form a large percentage of forest inventories. Assessing forest structural attributes is vital for practical and management purposes (Maselli *et al.* 2009). A number of studies have demonstrated the potential of imaging spectroscopy to detect important structural components with reasonable accuracy and precision, e.g., Smith *et al.* (2002) obtained a strong correlation ( $R^2 = 0.86$ ,  $SEE = 31.42\text{g.m}^{-2}.\text{y}^{-1}$ ) between foliar nitrogen and productivity using AVIRIS data. Gong *et al.* (2003) used Hyperion derived vegetation indices to estimate leaf area index (LAI). The authors found that vegetation indices derived from shortwave infrared (SWIR) region and the near-infrared (NIR) region produced higher correlation with LAI than vegetation indices

that used red and NIR bands. Lee *et al.* (2004) found that individual and narrow bands of AVIRIS data exhibited better relationships with LAI compared to broadband data for grassland and forest biomes. Schlerf *et al.* (2005) quantified forest LAI and volume using hyperspectral image and broad-band data. The authors found that hyperspectral datasets were more suitable to estimations of volume and LAI compared to broadband data, i.e., accuracy for hyperspectral data estimates was higher than that of broadband data.

Goodenough *et al.* (2008) compared AISA and AVIRIS datasets for mapping above ground forest carbon. A strong agreement ( $R^2 = 0.90$ ) between ground measured biomass and AVIRIS data was obtained, while AISA data resampled to AVIRIS spectral and spatial resolutions accounted for 89% classification accuracies in mapping above ground biomass of the forested portion of the site. Jusoff (2009) estimated Rubberwood standing volume using supervised classification technique based on spectral angle Mapper (SAM) and spectral matching techniques between image analysis of airborne hyperspectral and field work. The author managed to estimate volume of Rubberwood with an accuracy of 89%. All these studies highlight the relationships between canopy or leaf chemical attributes derived from hyperspectral data and forest structural attributes

### **1.5. Significance of the study**

Timely and accurate data on the nutrient status of the tree leaves and canopies in commercial forest are important for the industry from a management perspective. The nutrient status of tree leaves and canopies in commercial forest is indicative of growth status at any given stage (Gamon *et al.*, 1997). The advent of hyperspectral technologies and advances in hyperspectral data analysis, such as spectral resampling, have provided more potentially cost-effective means of obtaining foliage biochemical estimates over large areas. Remotely estimated pigment concentrations have the potential to improve our ability to provide more accurate estimates of forest structural attributes and productivity (Field and Mooney 1986, Reich *et al.*, 1999). Various methods have been used to estimate forest structural attributes, e.g., volume, basal area, stems per hectare, above ground biomass, and net primary productivity in South Africa (Dye *et al.*, 2002, Esprey, 2005, Tesfamichael *et al.*, 2009, Gebreslasie *et al.*,

2010, Roberts *et al.*, 2011), but little or no work has been done to examine and quantify the nature of the relationship between foliar chemistry as estimated using hyperspectral data and growth and yield of *Eucalyptus* species, hence the need for this research. The understanding of such relationships will be of operational value if it can be further extended over large areas using spectral resampling techniques to simulate much broader and cheaper sensors such as broad band multispectral sensors. This study therefore aims to assess and quantify the link between canopy chemical bioassays and forest structural attributes of even-aged *Eucalyptus* clones grown in South Africa.

### **1.6. Research questions**

This study seeks to answer the following questions:

- Is the spectral reflectance of cloned *Eucalyptus* forest canopies strongly related to growth and yield, as affected by water status, leaf chlorophyll, and nitrogen contents?
- Can leaf chlorophyll content of *Eucalyptus grandis* be used to infer soil nitrogen status?
- Can hyperspectral data be downscaled to simulate multi-spectral (broadband) data that can address the above-mentioned research questions?

### **1.7. Study Area**

The study was conducted in the Greenhill estates of Mondi Business Paper in the KwaZulu-Natal province of South Africa. The study sites are situated approximately 50km south of Pietermaritzburg around the town of Richmond (30° 29'S; 29° 82'E Figure 1.1). The study area falls within the summer rainfall region of South Africa and experiences cold, dry winters and warm, wet summers. Mean annual rainfall ranges from 746-1100mm, while the seasonal temperatures vary between a high of 25°C to a low of 10°C. The extreme temperature change is a function of altitude and proximity to the warm Indian Ocean, with higher altitudes experiencing much colder temperatures than lower lying areas. The gently undulating to highly dissected, strongly rolling, and hilly topography characterizes the terrain of the study area. Elevations range between 800m and 1400m above mean sea level. The geology

consists of sandstone and clay formations, which have resulted in sandy clay to sandy clay loam soils (Schulze, 1997). The primary land use in the Richmond area is agriculture, e.g., plantation forestry, sugar cane, and to a lesser extent, dairy farming.

Plantation forests are mostly stocked with exotic softwood (i.e., the genus *Pinus* with *P. patula*, *P. taeda* and *P. Elliottii*) and hardwood (species being either *Eucalyptus* (Gum) or *Acacia mearnsii* (Wattle)). Local small industries in the study area use these softwood and hardwood species mainly for timber i.e., furniture and construction purposes. The *Eucalyptus* species (subject of this study) consist of soft gums (sub-tropical) and hard gums (cold-tolerant). The soft gums are grown in the warmer areas whilst hard gums are found in colder areas. The wood density of soft gums is lower than hard gums. Soft gums include the *E. saligna* and *E. grandis* species, while hard gums include the *E. dunnii*, *E. nitens* and *E. smithii* variants. Recently the industry has been experimenting with clonal hybrids such as *E. grandis* x *E. nitens* (Norris-Rogers, 2006).

The sampling criteria adopted in this study was adopted from Gebreslasie *et al.*, (2008), Tesfamichael *et al.*, (2009) and Roberts *et al.*, (2011). The selection was based on spatial location, extent, age, felling dates, site index, and site productivity, i.e., an effort was made to select compartments on good, medium, and poor site productivity or qualities. The parameters of choice were diameter at breast height, height and in some cases soil samples.

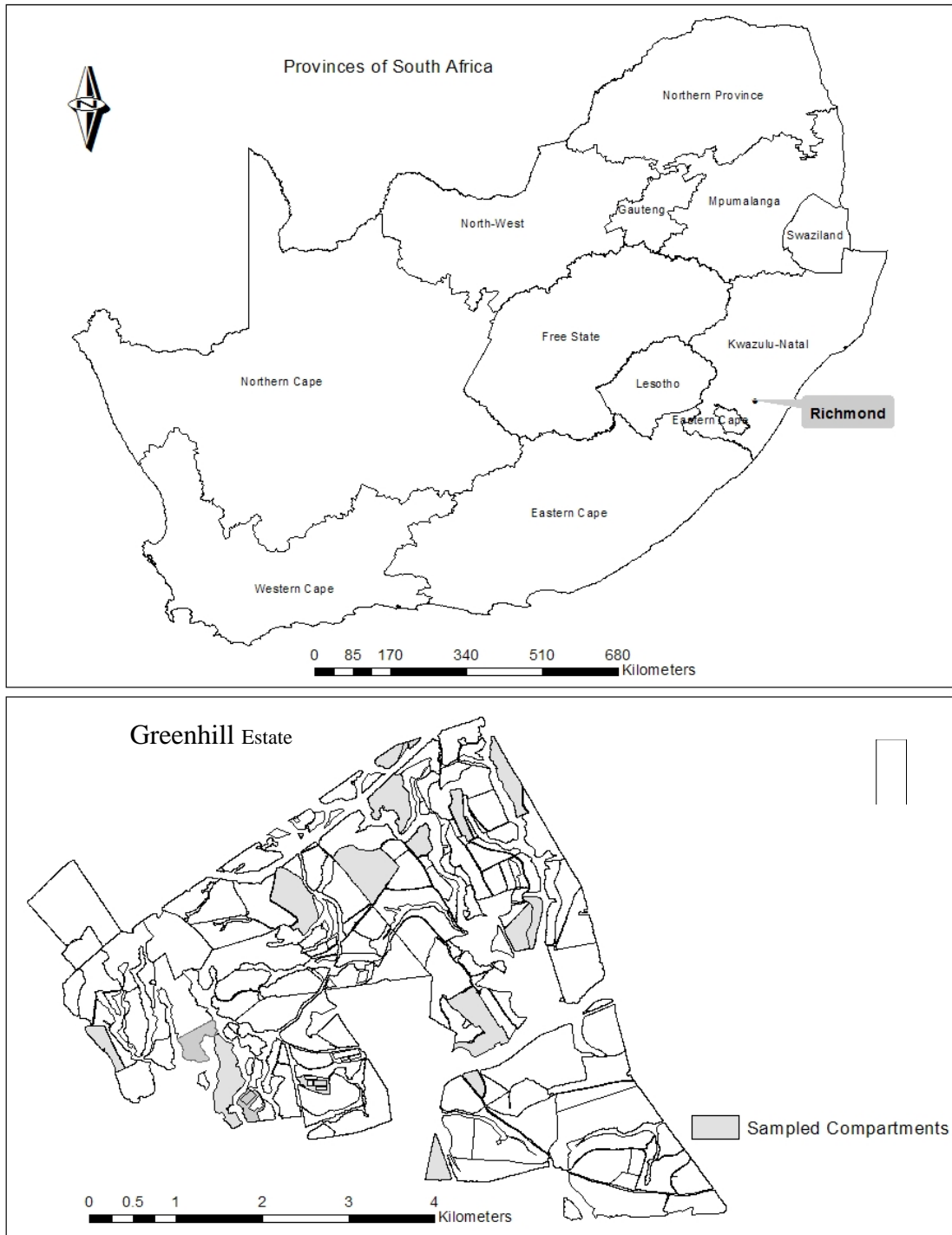


Figure 1.1. Map of the study area.



## 1.8. Outline of the thesis

The thesis consists of six chapters, four of which form stand-alone scientific papers as part of this thesis, contributing to the overall research objectives. These have already been submitted for publication in peer-reviewed journals. The general introduction was dealt with in the first chapter, i.e., Chapter 1, which covered the current research undertaken in forest foliar chemical analysis and its relationship to forest structural attributes, the research problem, and the objectives of the study. Also the description of the study area, i.e., the location, climate, geology, soil, topography, and the main land use practices were outlined.

Chapter 2 investigates the use of chlorophyll, nitrogen, and water related vegetation indices derived from spectroradiometric data in the estimation of volume in *Eucalyptus* clones in the Richmond area.

Chapter 3 focuses on an assessment of the utility of Airborne Imaging Spectrometer for Applications (AISA) for measurement of volume and basal area of *Eucalyptus grandis*.

Chapter 4 examines the potential of estimating soil nitrogen from raw and continuum-removed *Eucalyptus* leaf spectral measurements.

Chapter 5 consists of an evaluation of whether volume, basal area, and soil nitrogen can be estimated and modelled using the hyperspectral spectra, resampled and simulated to Landsat TM spectral configurations.

Finally, Chapter 6 brings all the research findings of the individual chapters into perspective as a synthesis.

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## CHAPTER 2

### *Estimation of merchantable volume of Eucalyptus clones based on leaf-level hyperspectral data*

This chapter is based on: Mzinyane, T, Ahmed, F and Van Aardt, J. 2011. Estimation of merchantable volume of *Eucalyptus* clones based on leaf-level hyperspectral data. *Forest Ecology and Management*. (Submitted)

## Abstract

A growing demand for merchantable volume and forest products in South Africa's commercial forestry sector demands using technological advances which will ensure sustainable resource extraction. Such techniques arguably will facilitate management through improved silvicultural practices and proper planning for the future. This study assessed the suitability of chlorophyll, nitrogen, and water content, derived from leaf-level spectroradiometer data, for estimating volume of *Eucalyptus* clones in KwaZulu-Natal, South Africa. It was hypothesized that water status and chemical bioassays such as chlorophyll and nitrogen can contribute to estimation of merchantable volume. Volume was derived from field measurements of diameter at breast height (DBH) and tree height, while first derivative and continuum removed spectral transformations were applied to the spectral data. Chlorophyll, nitrogen, and water related indices were used to estimate merchantable volume of *Eucalyptus* clones. Pearson's correlations were used to assess the relationships between the indices and volume. Furthermore, ANOVA was used to assess whether significant differences could be detected amongst index values within the plots or compartments, based on different age groups, clones, and site qualities. Cross-validation and model selection based on adjusted  $R^2$  and low Mallows'  $C_p$  were utilised in the development of volume models. The volume and index relationships of *E. grandis* and *E. saligna* clones yielded significant ( $p < 0.05$ ) correlations. The strength of the correlations for all clones was found to be much higher than the relationships for *E. grandis*, but lower than that of *E. saligna*. ANOVA results show that the indices were significantly ( $p < 0.05$ ) influenced by age, site quality, and the clone in question. Models developed without ancillary data such as age and site index had low adjusted  $R^2$ , e.g., 0.47, and high RMSE (0.055 m<sup>3</sup>/ha,  $p < 0.0001$ ) values compared to models that included ancillary data ( $R^2 = 0.78$ , RMSE = 0.0176 m<sup>3</sup>/ha,  $p < 0.0001$ ). These results suggest that spectral measurements of chlorophyll, nitrogen, and water content have potential as independent variables for estimation of merchantable volume of *Eucalyptus* clones in KwaZulu-Natal when used in conjunction with ancillary data. This has important implications for extension of results to airborne data and regional assessments.

*Keywords: Spectral vegetation indices, forest merchantable volume, ASD, hyperspectral data*

## 2.1. Introduction

The improved silvicultural and management practices currently utilized by the South African commercial forestry industry enable sustainable growth of various commercial forestry species. These management practices require accurate but costly inventory data for management and planning purposes (Owen, 2000). According to Franklin (2001), inventory data should be spatially explicit, comprehensive, and geometrically accurate to ensure a sustainable commercial forestry sector. The management of this important resource therefore involves having up-to-date inventory data and the ability to objectively quantify biologically-significant attributes of forest stands by forest land managers (Latham *et al.*, 1998). Forest structural attributes, defined as the size, shape, and distribution of forest components in both the horizontal and vertical dimensions (Parker, 1995, Spies, 1998), form an integral part of forest inventories and management (Gebreslasie *et al.*, 2010). These forest structural attributes affect the ecosystem's composition, dynamics, and functioning and has been a central topic to forest ecology (Nadkarni *et al.*, 2008). The attributes are constantly measured and mapped within sustainable management protocols (Baskent and Keles 2005), using various techniques such as direct, sampling, and predictive methods (Avery and Burkhart, 2001, Rahman *et al.*, 2005). Although these techniques have been able to provide accurate data from which forest managers describe and deduce relationships for compartments, their drawback is that they are costly and time consuming, while the accuracy of forest structural attribute assessment is dependent on the skill level of the forester (von Gadow and Bredenkamp, 1992, Schreuder *et al.*, 1993, Trotter *et al.*, 1997, Avery and Burkhart, 2001). According to Esler (2004), the relative estimation error of forest structural attributes obtained from traditional field inventories at the stand-level typically varies between 10% and 15%.

Due to these reasons several researchers began to explore other avenues, such as remote sensing, for acquiring forests structural attributes at reasonable cost and accuracy (Lillesand *et al.*, 2004, Boyd and Danson, 2005, McRoberts and Tomppo, 2007). Remotely sensed data have been acknowledged and identified as an important tool for precision plant management because (i) it provides timely and georeferenced information on soil and plant condition (Moran *et al.*, 1997) and (ii) it has been used for identification of management zones, mapping of crop nutrient status and to detect pest infestations (Barnes *et al.*, 2000). In various cases, remotely sensed data, in

conjunction with field measured forests attributes, have been used to derive algorithms that explain the variance in field structural and chemical attributes and for extrapolation of such relationships over large areas in the form of thematic maps (Cohen *et al.*, 2003, Foody *et al.*, 2003, Zheng *et al.*, 2004). Such modelling has been done through various statistical techniques, i.e., forest characteristics are measured during field campaigns and empirically / statistically related to remotely sensed satellite data (Castro *et al.*, 2003, Lu 2005). Eklundh *et al.* (2001) obtained correlations ( $R^2$ ) above 0.7 between simple ratio (SR) and normalised difference vegetation index (NDVI) derived from Landsat ETM+ and leaf area index (LAI) of Norway spruce and Scots pines in Sweden. Gebreslasie *et al.* (2008), estimated plot-level forest structural attributes using high spectral resolution Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite data in even-aged *Eucalyptus* plantation, in KwaZulu-Natal, South Africa and their results indicated weak relationships (i.e., adjusted  $R^2 < 0.55$ ) between forest structural attributes studied ( i.e., stems per hectare (SPHA), diameter at breast height (DBH), mean tree height (MTH), basal area and volume and ASTER data. Most of the remote sensing applications in South African commercial forestry are recent and have explored the possibility of using remote sensing to estimate various forest attributes (such as leaf area index (LAI), lignin, forest health, height, diameter at breast height, and stems per hectare etc) of plantation forest species. These studies have used a variety of sensors, including multispectral (Gebreslasie *et al.*, 2008), imaging spectroscopy (Ahmed and Mthembu 2006, Ismail *et al.*, 2008, Cho *et al.*, 2010), fusion of RADAR and multi-spectral datasets (Roberts *et al.*, 2008), and LIDAR sensor types (Tesfamichael *et al.* (2009a, b).

Although results were encouraging, there seems to be a lack of species-specific extension of foliar chemical properties estimation for volume quantification. Foliar chemical composition is one of the most important forest characteristics, since it provides information about the ecosystem's processes, vegetation stress, and productivity (Curran, 1989, Haboudane *et al.*, 2002). These foliar chemical bioassays are known to have strong relationships with maximum photosynthetic capacity, ecosystem productivity, volume, and biomass (Field and Mooney 1986, Reich *et al.*, 1999). In South Africa, the utility of hyperspectral remote sensing in numerous

vegetation studies have been explored in the context of LAI and leaf and wood lignin estimations (Ahmed and Mthembu, 2006), identification of *Sirex noctilio* pest infestations (Ismail *et al.*, 2008), estimation of sugarcane leaf nitrogen concentration (Abdel-Rahman *et al.*, 2008), and detection of sugarcane African stalk borer (*Eldana saccharina* walker, *Lepidoptera pyralidae*) (Mokhele *et al.*, 2009). These studies have not attempted to establish relationships between foliar chemical bioassays and growth of various plantation forest species. This study was therefore designed to explore the relationship between leaf nitrogen, chlorophyll, and water content, as assessed using leaf- and canopy-level hyperspectral data, with volume of *Eucalyptus* clones in the Richmond area of KwaZulu-Natal, South Africa. The main question that we attempted to answer was: Is the spectral reflectance of South African forest canopy strongly related to volume, as affected by water status, leaf chlorophyll, and nitrogen content? It was hypothesized that water status and chemical bioassays, such as chlorophyll and nitrogen, have an impact on merchantable volume modelling without factoring in ancillary data such as stand age and site index.

## **2.2. Materials and methods**

### **2.2.1. Study area**

The study was conducted in the Greenhill estates of Mondi Business Paper in the KwaZulu-Natal province of South Africa. The study sites are situated around the town of Richmond (see figure 1.1.). The study area falls within the summer rainfall region of South Africa and experiences cold, dry winters and warm, wet summers. Mean annual rainfall ranges from 746-1100mm, while seasonal temperatures vary between a high of 20°C to below 10°C. The extreme temperature change is a function of altitude and proximity to the warm Indian Ocean, with higher altitudes experiencing much colder temperatures than lower lying areas. The terrain of the study area consists of flat gently undulating hilly topography and is classified as being low mountains (Schulze, 1997). Elevation ranges between 800m and 1400m above mean sea level. The primary land use in the Richmond area is agriculture, e.g., plantation forestry, sugar cane, and to a lesser extent, dairy farming. Plantation forestry is a major land use in the study area due to the suitable climate and soils. The geology consists of sandstone and clay formations, which have resulted in sandy clay to sandy clay loam soils (Schulze, 1997).

### **2.2.2. Field measurements**

Thirteen compartments<sup>1</sup> of *Eucalyptus* clones (i.e., 9 *Eucalyptus grandis*, 1 *Eucalyptus dunnii* and 2 *Eucalyptus saligna*) were selected from the Geographic Information Systems (GIS) database provided by Mondi-SA. The selection was based on spatial location, extent, age, felling dates, site index, and site productivity, i.e., an effort was made to select compartments on good, medium, and poor site productivity or qualities. The site quality classification is based on total available water in the soil profile, which is a function of effective rooting depth, soil type, rainfall, and temperature classes (Smith *et al.*, 2005). The field data collection was undertaken during spring (October) of 2009. The age of the *Eucalyptus grandis* trees at the time of the survey ranged from three to ten years, whilst *E. saligna* had ages of five to seven and only seven year old stands were available for *E. dunnii*. Spacing between and within rows of the stands were approximately 2.4m and 3m, respectively. In this study, a total of 48 square plots of 20x20m with homogeneous cover were enumerated in order to include an adequate number of trees per site quality and thereby strengthen the statistical reliability of the results. The distance from the centre tree to the nearest road was measured and geographical coordinates of that point on the road were recorded using a sub-metre differential global positioning system (DGPS). In each plot, only healthy trees with a diameter at breast height (DBH) greater than 5cm were considered for enumeration. This procedure is commensurate with the inventory protocol of the South Africa commercial forestry industry and has also been followed by other studies (e.g., Holmgren, 2004, Maltamo *et al.*, 2004, Gebreslasie *et al.*, 2008, Roberts *et al.*, 2008, Tesfamichael *et al.*, 2009a).

### **2.2.3. Merchantable volume measurement**

Trees across the range of the DBH greater than 5cm were selected for height measurement, thereby ensuring a representative sample across the entire DBH range. Tree heights of the selected trees were measured using a Vertex III hypsometer<sup>®</sup> (Haglöf, Sweden). Relationships between DBH and corresponding heights were

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<sup>1</sup> *Compartments* are blocks of trees where the trees of one compartment typically are all from the same species and age, and have all been planted at a fixed spacing

established at plot-level and based on site quality using regression analysis with  $R^2$ -values above 80% for the majority of plots. Heights of all trees within a plot were then estimated using the resultant regression equations of DBH-height relationships developed for each plot. The variability in tree merchantable volume is mostly explained by tree height and DBH as independent variables (Avery and Burkhart, 2001). Thus, when these attributes are known for individual trees, merchantable volume can be calculated for each tree (i.e., the total overbark merchantable limit was 5cm). The volume function based on Schumacher and Hall (1933) was used in this study (Equation 1).

$$\ln(V) = b_0 + b_1 \ln(DBH + f) + b_2 \ln(H), \quad 1$$

Where  $V$  is merchantable volume ( $m^3$ ),  $DBH$  is diameter at breast height (1.3m) (cm over bark),  $H$  is tree height (m), and  $f$  is a correction factor. Coefficients  $b_0$ ,  $b_1$ , and  $b_2$  used for this equation were those published in the South African Forestry Handbook (Bredenkamp, 2000). Plot-level volume was derived by adding volume of individual trees. The aggregate volume was then converted to a hectare scale based on the area of a plot. The descriptive statistics of the merchantable volume per compartment are shown in Table 2.1.

Table 2.1 A statistical summary of compartment-level volume ( $m^3$ ).

	<b>Max.</b>	<b>Mean</b>	<b>Min.</b>	<b>S.D.</b>	<b>n</b>
<i>E.grandis</i>	0.8896	0.1462	0.0083	0.0840	27
<i>E.dunnii</i>	0.8167	0.2665	0.0259	0.1543	3
<i>E.saligna</i>	0.9531	0.1712	0.0105	0.1159	6

#### 2.2.4. Site index

Site index describes the quality of a site and is also an indicator of the growth rate of trees within a compartment (Megown *et al.*, 1998). Site indices, using a base age of five years, were derived by calculating the mean height of 20% of the tallest trees in each stand and applying a modified Schumacher-difference form equation (Coetzee, 1994)

$$SI_5 = \beta_3 * HD_1 * \exp [\beta_1 (AGE_1 - AGE_2) + \beta_2 (1/AGE_1 - 1/AGE_2)] \quad 2$$

Where  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  = parameter estimates,  $AGE_1$  and  $AGE_2$  = compartment age at sampling and at base age five, respectively, and  $HD_1$  = average dominant height of the 20% tallest trees measured. This equation is the standard formulae used by commercial forest companies in South Africa.

### ***2.2.5 Leaf spectral measurements***

Leaf samples were collected from the sunlit branches within different site qualities, i.e., good, medium and poor. Leaves were then stacked 10 layers together and reflectance measurements taken using the leaf clip of the spectrometer. Leaf spectral measurements were taken using an ASD spectroradiometer (Fieldspec3 Pro), fitted with a 25° field of view bare fibre optic. The ASD field spectroradiometer senses in the spectral range of 350-2500 nm, with a bandwidth of 1nm (Analytical Spectral Devices, 2005). Radiance measurements were converted to target reflectance using a calibrated white spectralon panel on the leaf clip. Reflectance measurements were taken by averaging 40 scans with a dark current correction at every spectral measurement.

### ***2.2.6. Spectral transformation***

The spectral transformations applied in this study, apart from raw reflectance spectra, was continuum removal analysis to the selected or targeted absorption features (Table 2.2). The continuum is removed by dividing the original reflectance values in an absorption trough by corresponding values of the continuum line (Kokaly and Clark, 1999). Continuum removal normalizes reflectance spectra in order to allow for comparison of individual absorption features from a common baseline (Kokaly, 2001) and the resultant curves have values between 0 and 1, in which the absorption troughs are enhanced (Schmidt and Skidmore, 2001).



Table 2.2. Selected wavelength ranges and their associated absorption features for chlorophyll, nitrogen, and water content.

<b>Chlorophyll</b>	<b>Nitrogen</b>	<b>Water content</b>
440, 680, 720nm	420-490, 550-652 nm	900-1252nm
	680-790, 1611-2137nm	1442, 2252nm

### **2.2.7. Chemical analysis**

A Soil Plant Analysis Development (SPAD) chlorophyll meter (SPAD, 2009), was used to measure the leaf chlorophyll *in situ*, after which leaves were immediately stored in zip-lock bags. The SPAD chlorophyll meter allows for a non-destructive measurement of chlorophyll in plant leaves and is only useful if a proper statistical relationship with leaf chlorophyll has been established. The SPAD chlorophyll meter measures the “greenness” (amount of chlorophyll present) of the leave by measuring the absorbance of the leaf at two wavelength regions, namely blue (400-500nm) and red (600-700nm) (SPAD, 2009). The chlorophyll meter measures the absorption in the red and near infrared region of the spectrum and calculates a numerical SPAD value proportional to the amount of chlorophyll in the leaf. The leaves were separated into two sets, where the wet mass was measured for one set using a scale balance ( $\pm 0.01g$ ), followed by oven drying in the laboratory at 110 °C for 24 hours. Leaf water content was calculated following the procedure described by Liu *et al.* (2004) and Stimson *et al.* (2005):

$$WC (\%) = ((FW - DW) / FW) * 100 \quad 2$$

Where *FW* is the fresh weight of the sample and *DW* is the weight of the sample after oven drying. The other leaf set was used for nitrogen and chlorophyll analyses. The chlorophyll concentrations were determined spectrophotometrically against 80% acetone at 663, 646, and 470nm (Lichtenthaler, 1987) and nitrogen concentrations were determined using a modified Kjeldahl digestion method (Gupta, 1999).

### **2.3. Statistical data analysis**

A correlation analysis was conducted between chlorophyll and nitrogen contents extracted from SPAD measurements. The Pearson correlation coefficient,  $r$ , was calculated for all wavelengths in the 350-2500nm range for reflectance, continuum removed spectra, and first derivative reflectance in order to assess the relationship between chlorophyll, nitrogen, plant water content, and reflectance. The threshold for the Pearson correlation coefficient was set at  $\pm 0.65$  because lower values are generally regarded as unacceptable within South African industry. The wavelength regions of statistically significant correlation ( $p < 0.05$ ) were subsequently evaluated.

Partial least squares (PLS) regression was used to predict nutrient and water content concentrations from the reflectance and continuum removed spectra. Previous researchers have used PLS regression in order to deal with the problem of multicollinearity (Kooistra *et al.*, 2004, Feudale and Brown, 2005), which occurs when the number of samples is significantly smaller than the number of bands used in the analysis (Curran 1989, Nguyen and Lee, 2006). PLS is closely related to principal component analysis, but it does not decompose the spectra into a set of eigenvectors and scores. PLS regression uses the response variable information during the decomposition process (Geladi and Kowaski, 1986, Nguyen and Lee, 2006). PLS have been demonstrated as an alternative to conventional stepwise regression for estimating foliar nutrient content, such as nitrogen and chlorophyll (Hansen and Schjoerring, 2003). The centres of the chosen wavelengths are shown in Table 2.2. The spectral vegetation indices that are indicative of chlorophyll, nitrogen, and water content (Table 2.3) were computed using wavelengths near these centres.

### **2.4. Vegetation indices**

Vegetation indices are traditionally used to establish non-destructive linkages between physiological indicators, measured from the field and laboratory data, and vegetation reflectance (Elvidge and Chen, 1995, Thenkabail *et al.*, 2001). In this study, previously used narrow waveband spectral indices that are sensitive to leaf chlorophyll, nitrogen, and water content were computed and tested (see Table 2.3).

Table 2.3 Chlorophyll-, nitrogen-, and water-based narrow-band indices used in this study.

INDICES	FORMULA	REFERENCES
Red Edge	$700 + 40 * \frac{(R_e - R_{700})}{(R_{740} - R_{700})}$	Cho and Skidmore (2006)
Vogelmann Index	$\frac{R_{740}}{R_{720}}$	Vogelmann <i>et al.</i> (1993)
TCARI/OSAVI	$\frac{3*(R_{700} - R_{670}) - 0.2*(R_{700} - R_{670}) * \left(\frac{R_{700}}{R_{670}}\right)}{(1+0.16) * \frac{(R_{800} - R_{670})}{(R_{800} + R_{670} + 0.16)}}$	Albrechtová <i>et al.</i> (2008)
<b>Nitrogen indices</b>		
Normalised Difference Nitrogen Index (NDNI)	$\frac{(\text{Log}(1/R_{1510}) - \text{Log}(1/R_{1680}))}{(\text{Log}(1/R_{1510}) + \text{Log}(1/R_{1680}))}$	Serrano <i>et al.</i> (2002)
Normalized Difference Red Edge (NDRE)	$\frac{(R_{790} - R_{720})}{(R_{790} + R_{720})}$	Rodriguez <i>et al.</i> (2006)
Nitrogen Reflectance Index (NRI)	$\left(\frac{(R_{570} - R_{670})}{(R_{570} + R_{670})}\right)$	Zhao <i>et al.</i> (2005a & b)
<b>Water indices</b>		
Water Index (WI)	$\frac{(R_{900})}{(R_{970})}$	Peñuelas <i>et al.</i> (1997)
Moisture Stress Index (MSI)	$\left(\frac{R_{1600}}{R_{820}}\right)$	Hunt and Rock (1989)

Datt 1	$\frac{(R_{850} - R_{2218})}{(R_{850} - R_{1928})}$	Datt (1999)
Datt 2	$\frac{(R_{850} - R_{1788})}{(R_{850} - R_{1928})}$	Datt (1999)
Normalized Difference Water Index (NDWI)	$\frac{(R_{860} - R_{1240})}{(R_{860} + R_{1240})}$	Gao et al. (1996)

One-way ANOVA was used to assess whether significant differences could be detected amongst index values within the all plots based on different age groups, clones, and their interactions with site quality. *E.dunnii* was excluded in the subsequent analysis due to the sample size i.e. only 3 plot. A Pearson correlation matrix was constructed between the chlorophyll, nitrogen, and water content spectral indices. Goodness of fit was evaluated on the basis of correlation strength (r), adjusted coefficient of determination (adj. R<sup>2</sup>), significance of correlations (p<0.001), and the root mean square error (RMSE) of the prediction. Spectral indices which exhibited the highest significant correlations were further used to develop regression models for estimation of volume.

## ***2.6. Model development and validation***

The multivariate analysis (MVA) statistical method (Lu *et al.*, 2004, Sivanpillai *et al.*, 2006) was employed in this study for selection of the most useful indices for volume estimation. Multivariate models are known to offer robust and substantial improvement of models when compared to single variable approaches (Sivanpillai *et al.*, 2006). Finally, the selected indices were used for model development with and without ancillary data (age and site index) using stepwise backward regression. Backward stepwise regression first considers all the variables for the regression and proceeds by eliminating variables one at a time to produce the model that account for

the largest amount of explained variance with all the coefficients are significant (Sedano *et al.*, 2008). Incorporating ancillary data was shown to improve the model fit metrics in forest structural attributes studies (Gebreslasie *et al.*, 2010) and reduce the likelihood of over fitting a regression equation. These ancillary variables are especially useful since they generally are known entities in well-managed commercial even-aged plantation forestry.

Model validation is the most important step in the model development process if models are to be accepted for operational use and decision making. There are various established approaches to model validation, e.g., validation based on an independent test data set and cross-validation procedures, also called the leave-one-out methods. Ideally, validation based on independently gathered data is highly recommended, but is often expensive and time consuming (Tesfamichael *et al.*, 2009). In this study two techniques were tested, namely cross-validation (60% for model development and 40% validation) and model selection based on the highest adjusted  $R^2$  and lowest Mallows' Cp statistic. Mallows' Cp is a measure of the bias in a model, based on a comparison of total mean squared error to the true error variance. It thus follows that unbiased models have an expected value of approximately  $p$ , where  $p$  is the number of coefficients in the fitted model (including the constant). The ideal model should have Cp values close to  $p$  (Atkinson and Riani, 2008, Siniksaran, 2008). Lastly, a cross-validation procedure was adopted in this study and error of prediction reported. Cross-validation omits a subset of samples from the modelling effort and predicts the value(s) of the validation sample(s) (Yang *et al.*, 2004). According to Schlerf *et al.* (2005), cross-validation procedures are capable of providing nearly unbiased estimations of the prediction error. Figure 2.1 below presents a flow chart of tasks undertaken in this research

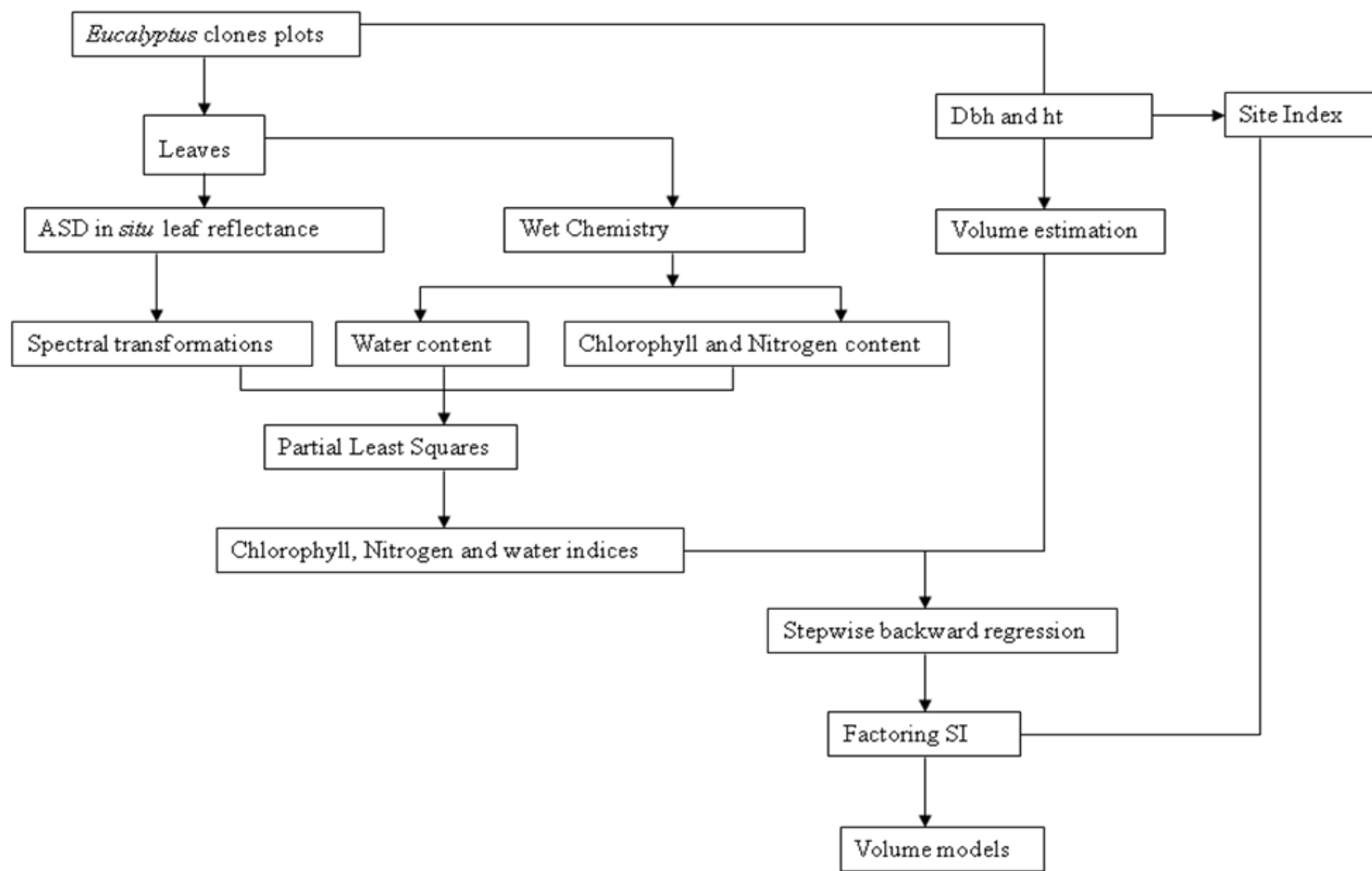


Figure 2.1. Flow chart of the tasks undertaken in this study

## 2.7. Results

### 2.7.1. Calibration of the SPAD chlorophyll meter

The SPAD chlorophyll meter was calibrated using chlorophyll and nitrogen data obtained from the laboratory analysis. The correlations between SPAD readings and extracted chlorophyll and nitrogen contents yielded equations 3 and 4, respectively. These equations were used to derive chlorophyll and nitrogen concentrations of all other samples. According to Peñuelas *et al.* (1994) and Hansen and Schjoerring (2003), nitrogen is strongly correlated with both chlorophyll *a* and *b* concentrations in plants and the metabolic functioning of the chlorophyll depends on nitrogen availability. A significantly strong linear correlation ( $r=0.95$ ,  $p<0.05$ ) with a high coefficient of determination ( $R^2= 0.89$ ) was observed between chlorophyll and nitrogen of *Eucalyptus* clones in this study.

$$\text{Chlorophyll} = 0.6126 * \text{SPAD} - 21.018 \quad (\text{Adjusted } R^2 = 0.71) \quad (3)$$

$$\text{Nitrogen} = 0.0011 * \text{SPAD} - 0.0375 \quad (\text{Adjusted } R^2 = 0.78) \quad (4)$$

### 2.7.2. Relationships between volume and indices

The correlations between volume and hyperspectral vegetation indices for each clone and a generalized *Eucalyptus* group are shown in Table 2.4. It is evident that for a vegetation index to be a good estimator of volume, it must exhibit a high correlation with volume. In this study, the correlations of volume with indices were examined for *E. grandis* and *E. saligna* separately, and for the combined clones' data set. The volume and index relationships of *E. grandis* and *E. saligna* clones yielded significant correlations ( $p<0.05$ ). No correlation analysis was performed for *E. dunnii* due to the limited sample size. High correlation values for *E. grandis* volume were evident in the cases of NRI, WI, Datt1, TCARI, and TCARI/OSAVI. When one compares correlation outcomes for *E. grandis* and *E. saligna*, the latter species exhibited distinctly stronger correlations close to 1 ( $r \geq 0.90$ ), whilst those of *E. grandis* were smaller than 0.70. From all the indices tested, chlorophyll-, nitrogen-, and water-based indices showed significant correlations in the case of both *E. grandis* and *E. saligna* volume, except for NDWI, which yielded non-significant correlations with volume for *E. saligna*. The strength of the correlations for the combined clone data set was found

to be higher ( $0.64 \leq r \leq 0.89$ ) than that of *E. grandis*, but lower than the correlations for *E. saligna*. The highest  $r$  values were observed for water indices (Datt 1 and 2) and nitrogen based indices (NRI).

Table 2.4. Correlations between volume and spectral vegetation indices for two Eucalyptus clones and a general species group

Index	<i>E. grandis</i>	<i>E. saligna</i>	All clones
Red edge	0.52*	0.91*	0.69*
Vogelmann	0.59*	0.95*	0.70*
Tcari /Osavi	0.67*	0.97*	0.82*
NDNI	0.66*	0.92*	0.80*
NDRE	0.57*	0.93*	0.69*
NRI	0.67*	0.95*	0.84*
WI	0.69*	0.93*	0.78*
MSI	0.62*	0.93*	0.77*
Datt 1	0.67*	0.94*	0.80*
Datt 2	0.62*	0.97*	0.88*
NDWI	0.49*	0.92*	0.64*

\*Significant at  $\alpha=0.05$

### 2.7.3. Assessing the effects of site quality, clone and age on the chlorophyll, nitrogen and water indices.

An ANOVA was also performed on indices to determine whether there were significant interaction effects due to factors such as age, clone, and site quality for *E. grandis*, due to variation in age groups. The general expected relationship is that volume is a function of both age and site quality, i.e., volume at an early age would be less than volume towards felling age and also volume at poor site qualities would be less than volume at either medium or good productivity sites. The ANOVA results showed that volume and chlorophyll, nitrogen, and water indices of *E. grandis* were significantly ( $p < 0.05$ ) influenced by age and site quality, thus corroborating the expected trend. The ANOVA analysis based on age groups seven (*E. grandis*, *E. saligna*, and *E. dunnii*) and five (*E. grandis* and *E. saligna*) furthermore detected the significant ( $p < 0.05$ ) influence that site quality and clones have on indices and volume. Surprisingly, most of the pronounced differences were detected between poor and good site qualities, while poor-medium and medium-good combinations showed no significant differences. This implies that differences of total available



water between medium and good or poor site qualities could be negligible or non-significant.

#### ***2.7.4. Model development for volume estimation through Chlorophyll, nitrogen, and water indices.***

The multiple regression approach using the stepwise backward method yielded a four variable model, namely datt1, MSI, NDWI, and Vog. These variables had significant ( $p < 0.05$ ) contributions in the model building, therefore there was no need to simplify the model further. This four variable model for volume estimation of *E. grandis* returned an adjusted  $R^2$  value of 0.72, significant at  $p < 0.01$ , with an RMSE of  $0.0218\text{m}^3/\text{ha}$  (Table 2.5). The aggregated clone model yielded an adjusted  $R^2$  value of 0.47 ( $p < 0.01$ ,  $\text{RMSE} = 0.0555\text{m}^3/\text{ha}$ ). Higher adjusted  $R^2$  values (0.88 and 0.81) were observed for *E. grandis* and an aggregated clone model, respectively, where inclusion of ancillary variables to model building is concerned. Factoring in ancillary data, i.e., age and site index, contributed to explaining more variability in volume for both the models and lower RMSE's when compared to other models. It was also observed that the *E. grandis* model only factored in age as an ancillary data, while the combined clone model included both ancillary data variables. Figure 2.2 shows the general volume model estimates which yielded a positive significant ( $p < 0.001$ ) linear relationship with an adjusted  $R^2$  value of 0.81 and comparably low RMSE of  $0.0176\text{m}^3/\text{ha}$ .

Table 2.5 Volume models developed with and without ancillary data variables age and site index

Clones	Models without Ancillary data	Adj. R <sup>2</sup>	RMSE (m <sup>3</sup> /ha)	Mallow's Cp	p-value
<i>E. grandis</i>	Vol=-1.88381+ 49.6856*Datt1-3.39352*MSI -90.0258*NDWI + 2.67079*Vog	0.72	0.0218	5	0.0001
All clones	Vol=0.507058+71.6366*Datt1+18.9024*Datt2-12.0988*Tcari/Osavi	0.47	0.0555	4	0.0001
	<b>Models with Ancillary data</b>				
<i>E. grandis</i>	Vol=0.0768542+0.0250322*Age-.228626*NDNI	0.88	0.0140	3	0.0001
All clones	Vol=-32.3131+0.0290976*Age-5.99652*TCARI/OSAVI +0.0157887*SI+32.6424*WI	0.81	0.0176	5	0.0001

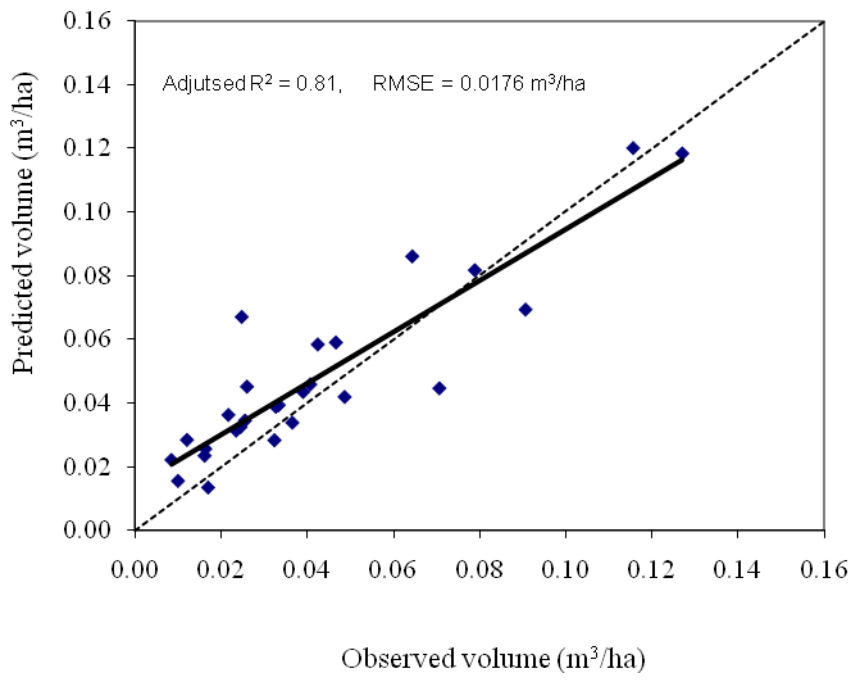


Figure 2.2. Observed vs. predicted volume of *Eucalyptus* clone model

## 2.8. Discussion

The aim of this study was to estimate the volume of *Eucalyptus* clones using foliar chemical and water content, derived from leaf-level hyperspectral data. Merchantable stem volume is an important attribute in the South African commercial forestry industry given its relation to standing stock. Modelling volume using remote sensing techniques therefore have been a focus of much research. The results obtained in this study highlight the importance and linkage of foliar chemical bioassays and water in growth and yield of *Eucalyptus* clones. These results will further enable the provision of vital information for monitoring tree growth towards improved forest management. This information includes accurate, non-destructive, and simple estimation of nitrogen, chlorophyll, and water content at both leaf- and canopy levels. The analysis in this study has shown significant ( $r > 0.80$ ,  $p < 0.05$ ) relationships between SPAD and both nitrogen and chlorophyll values, thereby emphasizing the viability of remote and non-destructive estimation of these variables across large hectares of forest land (Equations 3 and 4). Furthermore, chlorophyll content is known to be related to nitrogen content (Yoder and Pettigrew-Crosby, 1995) and this study found a significant linear relationship with a coefficient of determination ( $R^2$ ) of 0.89. These relationships were in agreement with results reported elsewhere, e.g., Jongschaap (1999) and Jongschaap and Booij (2004).

Leaf chlorophyll, nitrogen, water content, and other chemical constituents are important indicators of plant growth (Chapin *et al.*, 1990). As noted earlier, the importance of merchantable timber volume in commercial forestry has been intensively researched for future management applications using remote sensing (e.g., Tesfamichael *et al.*, 2010). A key aspect of commercial forestry production in South Africa is the management of silvicultural practices to enhance optimum growth. In most cases, the nutritional status of plants and their ability to respond to fertilizers, hence optimum growth returns are diagnosed using foliar analysis as a benchmark (Herbert and Schönau, 1989). The volume and indices related to chlorophyll, nitrogen, and water content and derived from hyperspectral data indicated significant correlations ( $p < 0.05$ ) as shown in Table 2.4. *Eucalypts* species are recognized as some of the fastest growing trees in a wide range of ecological conditions and site qualities and they are preferred because of high growth rate, short rotation length (8-10 years) and favourable pulpwood properties (FAO, 1988). In this study, *E. saligna* modelled

better than *E.grandis* as shown in Table 2. 4. This was due to the role played by the quality of the site where the compartments were located. The spatial database provided by Mondi-SA show that most of the *E.grandis* compartments were on medium and poor site qualities whilst *E.saligna* was planted on good site quality. Past studies have shown the capabilities of narrow band data in estimating foliar chemical attributes and improve the accuracy of modelling forest structural attributes compared to broadband e.g., Schlerf *et al.* (2005), Cho *et al.* (2009). In these studies narrow band data explained high variability's (60-85%) in forest structural attributes i.e., biomass, crown volume, and leaf area index (LAI).

The influence of site quality and age on the physiological indices was further evaluated. The respective site qualities are indicative of different total available water in the soil profile and hence their volume returns can be expected to be significantly different from one another. Site quality and age had a significant ( $p < 0.05$ ) influence on chlorophyll, nitrogen, and water content indices for all *E. grandis* age groups. Volume is a function of height and diameter at breast height and these variables increase with time and depend largely on site quality, i.e., volume at good productivity sites is expected to be much higher than volume at lower productivity sites. An ANOVA test of significance for age groups five and seven across clones showed that the indices were statistically ( $p < 0.05$ ) influenced by the clones and site quality, implying that a clone will exhibit variable volume growth, depending on the local site quality. Although there were significant effects from site and clone interactions, the more significant interaction was site quality, given that this variation in this factor far exceeds that from age groups and range (5-7). Future research should encompass and expand clone age to properly capture the associated variation, thus allowing interpolation rather than extrapolation for this factor. The significantly pronounced differences were found between good and poor sites and none between medium and both good and poor, which effectively implies that little or no differences exist in available soil water between medium and both good and poor site qualities.

Models were developed to estimate volume from the chlorophyll, nitrogen, and water content indices. The models developed in this study for *E. grandis* and for the combined clone model yielded lower than 0.65 adjusted  $R^2$  values (Table 2.5). The inclusion of ancillary data, i.e., age and site index, resulted in improved adjusted  $R^2$  values with low RMSE values when compared to models without ancillary data. Most

of the volume estimation models developed through methods other than remote sensing include ancillary data; these types of data furthermore are typically readily obtained. Site index also is a function of height-age and it was felt that a comparison needed to be made between models with and without such data. A previous study on the prediction of forest structural attributes using ASTER and ancillary data showed an increase in the adjusted  $R^2$  values when factoring in ancillary data (Gebreslasie *et al.*, 2010). The same increments to adjusted  $R^2$  and low returns of RMSE were observed in this study.

These combined remote sensing and ancillary data models had low Mallows  $C_p$  values, higher adjusted  $R^2$ , and low RMSE values (Table 2.5). The coefficient of determination for the modelled linear relationship between estimated and observed volume was 0.81 and exhibited a near 1:1 relationship and high correlation coefficient ( $r > 0.85$ ) (Figure 2.2). The results show a hint of an over-estimation of volume at older age groups and under-estimation at younger compartments. This was partly attributed to the fact that growth culminates at relatively young ages in these short rotation crops, resulting in overestimation of volume in the case of older compartment. To further understand these overestimations, measurements of leaf chlorophyll, nitrogen, and water content should be made at older aged compartments over time. This will give an indication of whether there is a change in these parameters once the growth culmination rotation age has been reached. This model fit was deemed satisfactory and hinted at an improved potential of estimating volume from hyperspectral data coupled with ancillary data, since adequate variation was explained in the volume enumerated data. The modelling approach is also suitable for estimation of volume under varying leaf area index (LAI) conditions, different soil backgrounds, and solar zenith angles, given the robust nature of independent variables such as TCARI/OSAVI. This index is known to be sensitive to chlorophyll content and insensitive to the mentioned variations (Haboudane *et al.* 2002, Albrechtová *et al.*, 2008). Overall, the assessment of leaf chlorophyll, nitrogen, and water content over large areas may assist with management of silvicultural regimes towards optimization of growth, since these metrics are indicators of plant status during the growing stages. The result of this study further affirms the reported strength of the relationships between growth and yield on the one hand and chemical bioassays and water on other (Brown *et al.*, 1997). These relationships have made it possible to provide an indication of processes that hinder growth over large areas.

## **2.9. Conclusion**

This study demonstrated the importance of integration of remote sensing and *in situ* data in modelling efforts to provide more accurate estimates of *Eucalyptus* clone volume in the commercial plantation forestry Greenhill estate in KwaZulu-Natal, South Africa. Foliar chemical bioassays and water content plays a crucial role in plant development over the growth period and hence provide valuable information on physiological condition and can identify areas where growth has been limited by a shortage of resources. These modelling efforts will in future contribute to improved management of forest resources by using airborne or spaceborne imaging spectroscopy at regional scales. The study has shown the potential for estimating chlorophyll and nitrogen non-destructively using a SPAD instrument and extending this to remote sensing data and scales. Stand volume was found to be influenced by chlorophyll, nitrogen, and water content as assessed at the leaf-level, as well as site quality and age as readily available ancillary variables. There is a need to upscale these results to airborne hyperspectral imagery in order to investigate the spatial patterns of volume based on chlorophyll, nitrogen, and water content. Such an approach will effectively allow forest managers to model, map, and manage forests at the appropriate scales and with a host of physiological and structural forest data at hand. The next chapter will upscale the leaf level results to airborne hyperspectral data using Airborne Imaging Spectroradiometer for Applications (AISA).

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## CHAPTER 3

*Assessments of volume and basal area of Eucalyptus grandis using hyperspectral data (AISA)*

This chapter is based on: Mzinyane, T, Ahmed, F and Van Aardt, J. 2011. Assessments of merchantable volume and basal area of *Eucalyptus grandis* using hyperspectral data (AISA). *International Journal of Remote Sensing*. (Submitted)

## **Abstract**

The success of commercial forestry depends on sound management and silvicultural practices adopted for optimum returns on a sustainable basis. Such management regimes theoretically manifest themselves in leaf biochemistry, which in turn is correlated to plantation growth and yield patterns. The study's objective is to assess the impacts of leaf water content, chlorophyll, and nitrogen on volume and basal area through simulated AISA hyperspectral data, acquired at the leaf level. Stand-level volume and basal area were modelled using independent variables associated with foliar biochemistry and extracted from hyperspectral data. Leaf-level spectroradiometer data and analysis were extended to the canopy level using airborne hyperspectral AISA imagery. Leaf chlorophyll, nitrogen, and water content were determined manually in the laboratory and related to canopy spectral properties. Volume and basal area were derived from field measurements of diameter at breast height (DBH) and tree height. Various chlorophyll, nitrogen, and water-based spectral indices were computed. These indices were used to explain the variance of merchantable volume and basal area of *Eucalyptus grandis* plantations. The correlations between measured values of chlorophyll, nitrogen, water content and airborne level spectral indices yielded strong ( $r > 0.70$ ) significant ( $p < 0.01$ ) Pearson's correlations with the airborne spectral indices of chlorophyll; nitrogen and water content, except for the correlation between water band index (WBI) and chlorophyll which exhibited a correlation of 0.60. The indices further explained above 65% of the variation in basal area and volume except for the water band (WBI) and Vogelmann (Vog1), which explained 63% and 44%, respectively. Bootstrapped histograms of the indices showed that they were more robust in their correlations with basal area and volume than simple Pearson's correlations. Regression relationships of the indices and both volume and basal area, varying from linear to exponential, yielded high adjusted  $R^2$  and low root mean square error (RMSE) values. Models developed for future estimation of volume and basal area had high adjusted  $R^2$  values ( $> 90\%$ ,  $p < 0.001$ ) and low RMSE ( $0.1613 \text{ m}^3/\text{ha}$  and  $0.0049 \text{ m}^2$ ), Cp Mallow (6 for volume and 5 for basal area), and PRESS statistic (0.004 for volume and 0.153 for basal area) values. The relationships between observed and predicted values for volume and basal area approximated a 1:1 relationship, thereby suggesting that airborne remotely-sensed proxies of canopy chemical bioassays may generally be

useful in the assessment of forest structural attributes. This has important implications for future technology-based forest management and inventory updating approaches.

*Keywords: Hyperspectral, forest volume, basal area, indices, bootstrap*

### **3.1. Introduction**

The increasing threat of the land reform process to South African commercial forestry sector could imply a reduction in forest coverage in South Africa in the near future (Dyer, 2007). The reduced area of forestry and the growing demand for forestry products would lead to demands for efficient and sustainable afforestation programmes to ensure optimum returns. These programmes will require accurate information about forest spatial distribution and status of forest structural attributes such as volume, basal area, diameter at breast height, height, and other system state attributes. Field surveys are typically employed to gather information on forest structural attributes (Gebreslasie *et al.*, 2010). These field-based surveys have been endured because they return reasonably accurate data (Owen, 2000), but they also have drawbacks. They are point-based (low spatial and temporal coverage), subject to the experience of the collector, and tedious and expensive, thus severely limiting decision making by forest resource managers (Lillesand *et al.*, 2000, Avery and Burkhart, 2001). Field surveys operate on a premise that homogeneous assemblages of plants typically occur, thus enabling extraction of average measurements or values for a given area. These average values are then extrapolated to a larger surrounding area under the same assumption that homogeneity is maintained and that the larger area can be considered as a unit or stand (Avery and Burkhart, 2001). However, this assumption does not always hold, since synoptic remote sensing studies on growth and yield, e.g., Coops *et al.* (1998), have shown that distinct within compartment variations exist.

Remote sensing offers an alternative way of monitoring these large tracts of commercial forestry in South Africa, given its ability to extend site-specific measurements to much broader scales and spatial extents (Smith *et al.*, 2008). This enables proper examination of key forest structural attributes over large tracts of land and assists with within compartments assessments and mapping of adverse disturbance and damage (Schreuder *et al.*, 1993, Avery and Burkhart, 2001).

However, it must be emphasized that remote sensing should not be regarded as a substitute for field data collection, but that the combination of the two approaches normally yields better results than either method separately (FAO, 2010). These spatially determined forest structural attributes are crucial for enhanced inventories and future planning of timber harvest rotations, thus saving both money and time (Lefsky *et al.*, 2001, Jusoff, 2008). Several authors have proven the capabilities of remote sensing as an alternative to field-based approaches for estimating forest structural attributes (e.g., Franklin *et al.*, 2000, Hall *et al.*, 2006, Breidenbach *et al.*, 2008, Tesfamichael *et al.*, 2009, Gebreslasie *et al.*, 2010). A synoptic approach becomes even more critical when within-stand variation of growth drivers, such as foliar biochemistry, is considered. The influence of silvicultural practices such as fertilization and interactions of water and nutrients on forest structural attributes and forest growth and yield potentials are well documented (Campion *et al.*, 2005, Naidoo *et al.*, 2006). Although these relationships are known, little work has been done towards integrating remote sensing capabilities and the influence of silvicultural practices on forest structural attributes, with a view to provide efficient management synergies for vast tracts of commercial forested land.

Recently developed remote sensing technologies, such as hyperspectral imaging, provide an enhanced capability for tracking leaf- and canopy-level silvicultural responses in vegetation studies. These sensors possess narrow spectral bands across a typically wide range of the electromagnetic spectrum (350-2500 nm), when compared to more traditional multispectral imagery (Zhao *et al.*, 2005a, Du *et al.*, 2006, Jain *et al.*, 2007, Majeke *et al.*, 2008). Multispectral imagery and its defining broad spectral bands, is known for often masking important spectral characteristics of plant biochemicals, thus resulting in the loss of vital information (Mokhele *et al.*, 2009). Unfortunately, this spectroscopic technology is a fairly new area of research in the South African context (Mutanga *et al.*, 2009) and has as a result recently attracted much interest from researchers, e.g., Ahmed and Mthembu (2006), Abdel-Rahman *et al.* (2008), Cho *et al.* (2010), and Oumar and Mutanga (2010). To the best of our knowledge, amongst these studies currently underway or completed, none has attempted to explore the relationship between forest leaf and canopy chemical bioassays (i.e., chlorophyll, nitrogen, water content) and forest structural attributes, such as volume and basal area of *Eucalyptus grandis*.

*Eucalypts grandis* timber forms an important source of fibre for the South African pulp and paper industry and is a highly commercialised species in the forestry industry, thus playing an important role in the country's economic growth (DWAF, 2005, Majeke *et al.*, 2008). As noted earlier and given that fertilization is an important component of growth and yield management in commercial forestry in South Africa, a need exists to characterize the spatial influence of vegetation biochemistry on forest structural attributes using remote sensing, especially hyperspectral sensing. The study's objective is to assess the impacts of leaf water content, chlorophyll, and nitrogen on volume and basal area through simulated AISA hyperspectral data, acquired at the leaf level. It is envisaged that such relationships would be able to explain variation in growth patterns, i.e., capture and detect scales of natural variation occurring within the compartments on the hyperspectral image.

## **3.2. Materials and Methods**

### **3.2.1 Study Area**

The study was conducted in Richmond (Bioresource Group (BRG) 5), in Kwazulu-Natal province of South Africa (Figure 3.1). Soils in the area are characterized by fine sandy clay and humic topsoils that are underlain by yellow or red apedal subsoils. The topography of the study area is flat with undulating hills and is classified by Schulze (1997) as being low mountains. Temperatures range from high 20°C values in summer to below 10°C in the winter. The area is regarded as a *Moist Midlands Mistbelt* and has favourable climate and high percentage of arable land. Altitude ranges from 300-2100m above sea level, with an average of approximately 850m. The area is prone to summer rainfall with cold, dry winters and warm, wet summers, with an annual rainfall ranging from 800-1280 mm and a mean annual temperature of 17°C (Camp, 1997, Schulze 1997). Forestry and sugar cane farming are the dominant land uses and both crops are grown on deep well drained soils.

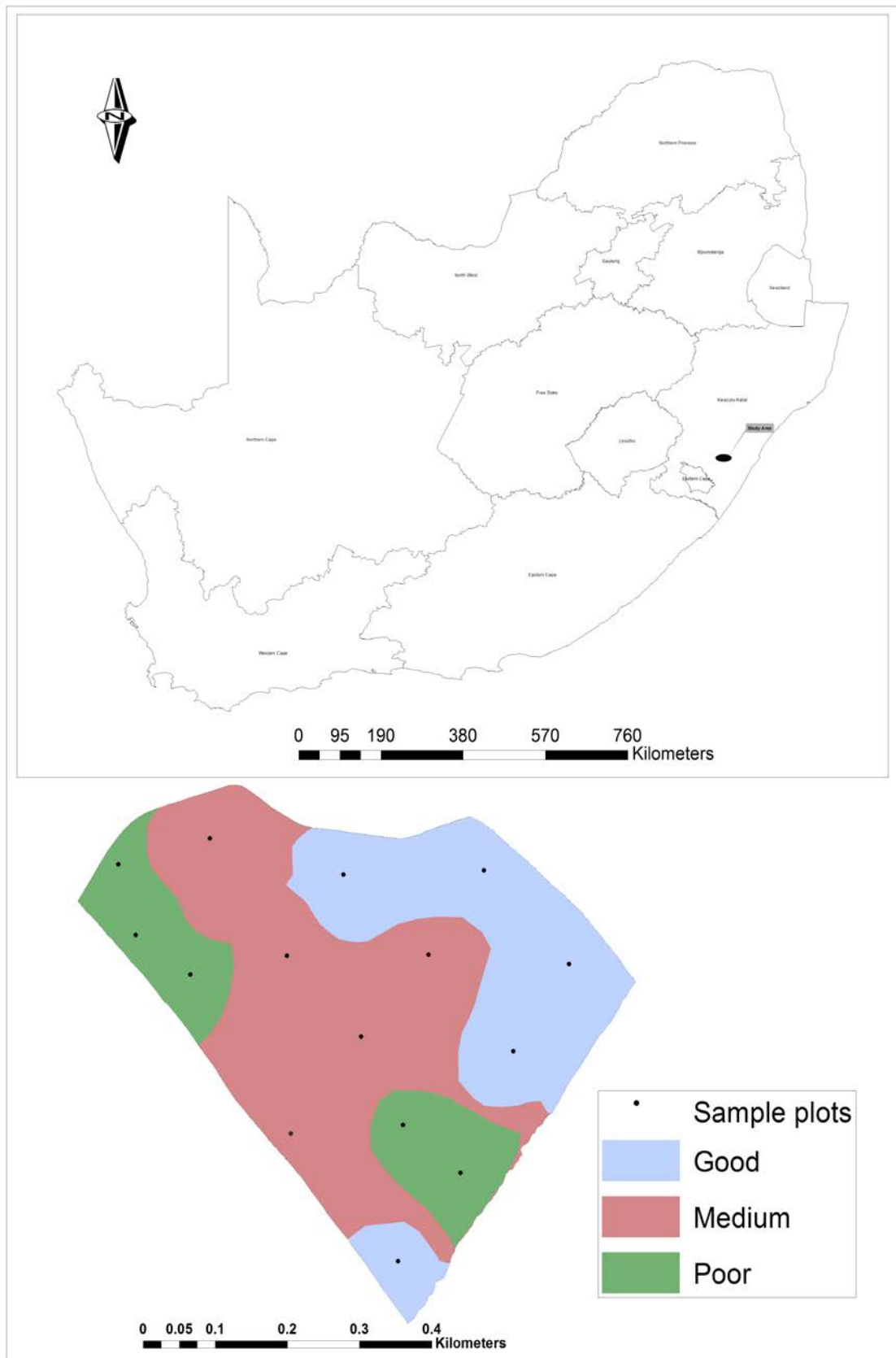


Figure 3.1, Map of the study area with sampling sites.

### 3.2.2. Field measurements

The Geographic Information System (GIS) database of forest compartments, provided by Mondi-SA, was consulted in order to select stands of interest. The field data collection coincided with the overpass of the airborne hyperspectral imager, i.e., AISA. Site selection was based on spatial location, extent, age, felling dates, site index, and site productivity; an effort was made to select forest compartments on good, medium, and poor site productivity or quality. 15 Plot locations i.e., 5 per site quality were located in the field using a hand held sub-meter differential Global Positioning System (DGPS). The number of plots per site quality within the compartment was determined based on the size of the compartment. 20m x 20m meter square plots were established and inventory measurements collected, namely diameter at breast height (*dbh*) and tree height (*tht*). All trees with a  $dbh \geq 5\text{cm}$  were measured within each plot, while heights were measured for only a sub-sample of trees based on *dbh* distribution within the plot.

### 3.2.3. Volume and Basal area measurement

Trees across the range of the *dbh* values were selected for height measurement, thereby ensuring a representative sample of the entire *dbh* range. Tree height was measured on a sample of trees using a Vertex III hypsometer<sup>®</sup> (Haglöf, Sweden). Relationships between *dbh* and corresponding heights were established at plot-level and based on site quality using regression analysis.  $R^2$  values above 80% were observed for the majority of plots. Heights of all trees within a plot were then estimated using the resultant *dbh*-height regression equations developed within each plot. The variability in tree volume is mostly explained by tree height and *dbh* forest attributes (Avery and Burkhart, 2001). Thus, when these attributes are known for individual trees, volume can be calculated for each tree. The volume function based on the Schumacher and Hall form (1933) was used in this study (Equation 1).

$$\ln(V) = b_0 + b_1 \ln(DBH + f) + b_2 \ln(H), \quad 1$$

Where  $V$  is utilisable volume ( $\text{m}^3$ ), *dbh* is diameter at breast height at 1.3m (cm over bark),  $H$  is tree height (m), and  $f$  is a correction factor. Coefficients  $b_0$ ,  $b_1$ , and  $b_2$  used for this equation were those published in the South African Forestry Handbook (Bredenkamp, 2000). Plot-level volume was derived by summing the volume of

individual trees. Basal area was derived using equation 2 below. These equations 1 and 2, are standard formulae used by commercial forest companies in South Africa.

$$BA = \frac{\pi}{4} \sum_{i=1}^n DBH^2 \quad 2$$

The aggregates of volume and basal area were then converted to a hectare scale based on the area of a plot. A statistical summary of the plot-level measured volume and basal area is shown in Table 3.1.

Table 3.1: Descriptive statistics for plot-level volume (m<sup>3</sup>) and basal area (m<sup>2</sup>)

Variable	Min	Max	Mean	Std. Dev	n
Volume	0.453	4.4096	1.738	1.2763	33
Basal Area	0.029	0.298	0.131	0.0586	33

### 3.2.3. Site index

Site index describes the quality of a site and also is an indicator of the growth rate of trees within a compartment (Megown *et al.*, 1998). Site index was calculated using the mean height of 20% of the tallest trees within each compartment for a base age of five years. A modified version of the Schumacher-difference equation was used to calculate the site index of each compartment (Coetzee, 1994).

$$SI_5 = \beta_3 * HD_1 * \exp [\beta_1 (AGE_1 - AGE_2) + \beta_2 (1/AGE_1 - 1/AGE_2)] \quad 3$$

Where  $\beta_1$ ,  $\beta_2$  and  $\beta_3$  are parameter estimates,  $AGE_1$  and  $AGE_2$  are compartment age at sampling and at base age five, respectively and  $HD_1$  is average dominant height of 20% tallest trees measured.

### 3.3. Remote sensing data

Tree climbers gathered leaf samples from the sunlit branches within the different site qualities, i.e., good, medium, and poor. Leaf spectra of *E.grandis* were acquired at geo-referenced points using an ASD spectrometer (Fieldspec3 Pro) fitted with a 25°



field of view bare fibre optic (Analytical Spectral Devices, Boulder, CO). The ASD field spectrometer sampling interval over the 350–1050 nm range is 1.4 nm with a spectral resolution (full bandwidth at half maximum) of 3 nm. Measurements were taken during cloud free periods, between 10h00 and 14h00 to minimise the change in illumination conditions. Radiance measurements were converted to target reflectance using a calibrated white spectralon panel on the leaf clip. Reflectance measurements were taken by averaging 40 scans with a dark current correction at every spectral measurement. Approximately 30-40 sunlit leaf samples were collected for leaf spectral and chlorophyll measurements.

### ***3.3.1. AISA imagery pre-processing***

The AISA data had a 2m spatial resolution and 272 wavebands in the 393-994nm spectral range. For calibration purposes, field spectra of spectrally invariant bodies such as tar roads, secondary roads, grass fields, water bodies (dark targets), and rock outcrops were collected during flight campaign using the ASD spectroradiometer. The imagery was atmospherically corrected using a vicarious calibration technique by the Ecosystems Earth Observation group at the Council for Scientific and Industrial Research (CSIR) in Pretoria, South Africa. The field spectra were spectrally resampled to the spectral configuration of the AISA sensor and used to convert the AISA radiance data to absolute reflectance using the empirical line correction tool in ENVI 4.7 software. A second-order Savitzky-Golay function was used to smooth the AISA image as it exhibited some spectral noise. A seven-band window size was used for the smoothing. In order to investigate the impact of leaf chlorophyll, nitrogen, and water content on forest structural attributes, vegetation indices (Table 3.2) that are indicative of these chemical bioassays were computed using ENVI software.

Table 3.2: Chlorophyll, nitrogen, and water content based indices used in this study

Index	Formula	Reference
Red Edge Normalized Difference Vegetation Index (RENDVI)	$NDVI_{705} = \frac{R_{750} - R_{705}}{R_{750} + R_{705}}$	Sims and Gamon, 2002
Modified Red Edge Simple Ratio MRESRI	$mRS_{705} = \frac{R_{750} - R_{445}}{R_{705} - R_{445}}$	Datt, 1999
Modified Red Edge Normalized Difference Vegetation Index (mNDVI <sub>705</sub> )	$mNDVI_{705} = \frac{R_{750} - R_{705}}{R_{750} + R_{705} - 2 * R_{445}}$	Datt, 1999
Vogelmann Red Edge Index 1 (VOG1)	$Vog1 = \frac{R_{740}}{R_{720}}$	Vogelmann <i>et al.</i> , 1993
Red Edge Position Index (REPI)	$REP = R_{700} + 40 * \frac{(Re - R_{700})}{(R_{740} - R_{700})}$	Curran <i>et al.</i> , 1995
Water Band Index (WBI)	$WBI = \frac{R_{900}}{R_{970}}$	Champagne, <i>et al.</i> , 2001
Water Band Ratio	Determined during this study	
R <sub>253</sub>	Determined during this study	
Optimal vegetation index	$VI_{(opt)} = \frac{(1 + 0.45)((R_{800})^2 + 1)}{(R_{670} + 0.45)}$	Reyniers <i>et al.</i> , 2006
Normalised Difference Vegetation Index green-blue	$NDVI_{g-b} = \frac{(R_{573} - R_{440})}{(R_{573} + R_{440})}$	Hansen and Schjoerring (2003)
Ratio Vegetation Index 1	$RVI_1 = \frac{R_{810}}{R_{660}}$	Zhu <i>et al.</i> , 2008
Ratio Vegetation Index 2	$RVI_2 = \frac{R_{810}}{R_{560}}$	Xue <i>et al.</i> , 2004
Nitrogen Reflectance Index	$NRI = \frac{(R_{570} - R_{670})}{(R_{570} + R_{670})}$	Zhao <i>et al.</i> (2005)

### 3.4. Chemical analysis

A Soil Plant Analysis Development (SPAD) chlorophyll meter was used to measure leaf chlorophyll *in situ*, after which the leaves were immediately stored in zip-lock bags and stored in a cooled container. The SPAD chlorophyll meter allows for non-destructive measurement of chlorophyll in plant leaves and is only useful if a proper statistical relationship with leaf chlorophyll has been established. The SPAD chlorophyll meter measures the “greenness” (amount of chlorophyll present) of the leaf by measuring the leaf absorption at two wavelength regions, namely blue (400-500nm) and red (600-700nm) (SPAD, 2009). The chlorophyll meter measures the absorption in the red and near infrared regions of the leaf and calculates a numerical SPAD value proportional to the amount of chlorophyll in the leaf (Perry and Davenport, 2007). The leaves were separated into two components: the wet mass of one batch (25 leaves samples) was measured using a scale balance ( $\pm 0.01\text{g}$ ), after which the leaves were oven dried in the laboratory at  $110^{\circ}\text{C}$  for 24 hours. The water content was calculated following the procedure described by Stimson *et al.* (2005),

$$WC (\%) = ((FW - DW) / FW) * 100 \quad 4$$

Where *FW* is the fresh weight of the sample and *DW* is the weight of the sample after oven drying. The second batch of leaves (20 leaves samples) was sent to the Institute for Commercial Forestry Research (ICFR) and Horticulture Department at the University of KwaZulu-Natal for nitrogen and chlorophyll analyses, respectively. The concentrations of chlorophyll were determined spectrophotometrically against 80% acetone at 663, 646 and 470nm (Lichtenthaler, 1987) and nitrogen concentrations were determined using a modified Kjeldahl digestion method (Gupta, 1999).

### 3.5. Statistical analysis

A correlation (*r*) analysis was undertaken to assess the correlation between actual leaf chlorophyll, nitrogen, and water content and reflectance at each measured wavelength, with the threshold for *r* set at  $\pm 0.70$ . A principal component analysis (PCA) approach was subsequently used to predict leaf chlorophyll, nitrogen, and water content concentrations from the resultant reflectance wavelengths. PCA was applied with the assumption that different measured values of leaf chlorophyll,

nitrogen and water content absorbs at different wavelength across the spectral range of AISA. PCA decomposes the nutrient data into a few uncorrelated or latent variables that best explain the nutrient data.

Stepwise backward regression was used to develop the best models explaining variance in volume and basal area from the indices derived from the resultant spectra. Backward stepwise regression first considers all the variables for the regression and proceeds by eliminating variables one at a time to produce the model that account for the largest amount of explained variance with all the coefficients are significant (Sedano *et al.*, 2008). The models' performances were evaluated through the coefficient of determination adjusted ( $R^2$ ), root mean square error (RMSE) (equation 3), and relative error (RE %) of the prediction relative to field measurements (Equation 4), Cp Mallow, and PRESS statistic. The stepwise statistical procedure selects independent variable(s) that provide the model with the best estimation accuracy. The model is said to have acceptable accuracy and precision if  $R^2$  is large and RMSE and RE% are small, respectively (Li *et al.*, 2010). An analysis of variance (ANOVA) was further used to test whether there were significant differences between observed and estimated means. For every model developed, its reliability must be tested using independent samples that were excluded from the model development phase (Kozak and Kozak, 2003).

In this study, the leave-one out cross-validation approach was adopted whereby each sample was removed iteratively and its value predicted using a model developed from the remaining samples. The error of prediction is then computed for the samples not used during model development until all samples are completed, with the sum of the errors of prediction commonly presented as the PRESS statistic (prediction residual sum of squares). In this study further tests of Cp Mallow statistic were included in the cross-validation procedure. Models with low Cp Mallow and PRESS statistics were selected as the best models for prediction of volume and basal area.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y})^2}$$

5

$$RE(\%) = \frac{RMSE}{\hat{y}} * 100$$

6

Where  $\hat{y}$ ,  $y_1$ ,  $y$  are the mean, measured, and predicted values, respectively.

The relationships between the indices and both volume and basal area were further tested for the robustness of their relationships using a bootstrapping method. A bootstrapping technique is a general technique for estimating sampling distributions, standard errors, and confidence intervals for any statistic and is the most commonly used method for assessing statistical accuracy (Efron, 1981; Mutanga and Skidmore, 2007). Bootstrapping simulates the sampling distribution of any statistic by treating the observed data as if it was the entire statistical population (Chernick, 1999). For each replication, a random sample size of  $N$  is selected with replacement from the available data (Efron, 1982; Mutanga and Skidmore, 2007). Bootstrapping facilitates accuracy assessment using the same dataset and is preferable in many cases to cross-validation (Souza *et al.*, 2010). In this study, the statistic of interest was the correlation coefficient ( $r$ ), which was bootstrapped a 1000 times using Simstat software.

### **3.6. Results**

#### ***3.6.1. Calibration of the SPAD chlorophyll meter using chlorophyll and nitrogen data obtained from the laboratory analysis***

The correlations between SPAD readings and extracted chlorophyll and nitrogen contents yielded significant ( $p < 0.05$ ) strong relationships ( $r > 0.80$  and adjusted  $R^2 > 70\%$ ). These relationships were then used to derive chlorophyll and nitrogen concentrations of all other samples. Foliar nitrogen content is known to be strongly correlated with both chlorophyll  $a$  and  $b$  concentrations in plants and as such the metabolic functioning of the chlorophyll depends on nitrogen availability (Hansen and Schjoerring 2003). In this study, a significantly strong linear correlation ( $r = 0.95$ ,  $p < 0.05$ ) with a high coefficient of determination (adjusted  $R^2 = 89\%$ ) was observed between chlorophyll and nitrogen of *Eucalyptus* clones in this study.

### ***3.6.2. Relationships between volume, basal area, and airborne level spectral indices***

Firstly we tested the correlations between measured values of chlorophyll, nitrogen, water content and airborne level spectral indices. All the measured values of chlorophyll, nitrogen and water content yielded strong ( $r > 0.70$ ) significant ( $p < 0.01$ ) Pearson's correlations with the airborne spectral indices of chlorophyll; nitrogen and water content (Table 3.3), except for the correlation between water band index (WBI) and chlorophyll which exhibited a correlation of 0.60. The correlations between merchantable volume, basal area, and hyperspectral vegetation indices for *Eucalyptus grandis* clone are shown in Table 3.4. The chlorophyll, nitrogen, and water content indices yielded significant ( $p < 0.01$ ) correlations with volume. The correlation relationships amongst the chlorophyll indices (i.e., RENDVI, MRESRI, MRENDVI, and REPI) exhibited strong relationships, i.e.,  $r > 0.70$ , except for Vogelmann red edge index 1, which had a correlation of  $r < 0.60$ . All the nitrogen indices exhibited highly significant correlations with volume ( $r > 0.85$ ,  $p < 0.01$ ). The water-related indices also yielded significant correlations ( $p < 0.01$ ), except for WBI, which returned a low, but significant relationship at  $r = 0.44$ . The correlations between basal area and all indices produced statistically significant relationships ( $p < 0.01$ ) with large  $r$  values ( $r > 0.70$ ). The regression relationships between indices and the other variables, i.e., basal area and volume also resulted in significant ( $p < 0.01$ ) coefficients of determination and varied from linear and power to exponential relationships. For clarity only a selection of regression relationships are depicted in Figures 3.2a and 3.2b below. The indices explained more than 70% of the variance in volume and basal area, thus signaling close relationships between chlorophyll, nitrogen, and water content with both volume and basal area.

### ***3.6.3. Bootstrapping statistics***

The relationships between the indices and both volume and basal area were further assessed for robustness using a bootstrapping method. Bootstrapping statistics (Table 3.5) and selected histograms (Figures 3.3a and 3.3b) confirmed the robustness of the relationships through mean  $r$  values above 0.60 for all the indices, except for Vogelmann red edge index 1. The indices returned high bootstrapped correlation coefficients for both volume and basal area, thus approaching the population estimate with high precision ( $p < 0.05$ ).

Table 3.3. Correlations between measured values of chlorophyll, nitrogen, water content and airborne level spectral indices

	R	WBI	R1	R2	NDVI	Vlopt	NRI	MRNDVI	MRESRI	RENDVI	REPI	VOG1
Chlorophyll	.963**	.795**	.981**	.963**	.972**	.985**	.981**	.892**	.984**	.964**	.913**	.903**
Nitrogen	.963**	.795**	.981**	.963**	.972**	.985**	.981**	.892**	.984**	.964**	.913**	.903**
Water content	.946**	.599**	.969**	.867**	.949**	.958**	.941**	.787**	.882**	.983**	.947**	.721**
**. Correlation is significant at the 0.01 level (2-tailed).												

Table 3.4. Correlations between volume, basal area, and spectral indices for *E.grandis*.

Variable / Indices	RENDVI	MRESRI	MRENDVI	REPI	Vog1	WBI	WBR	R	VI(opt)	NDVI	RV1	RV2	NRI
Volume (m3/ha)	0.79*	0.81*	0.71*	0.95*	0.58*	0.44*	0.95*	0.94*	0.93*	0.90*	0.93*	0.86*	0.91*
Basal Area (m2)	0.84*	0.86*	0.85*	0.91*	0.71*	0.63*	0.90*	0.97*	0.95*	0.97*	0.90*	0.94*	0.93*

\*p<0.05

Table 3.5. Bootstrapped correlation coefficients between volume, basal area, and all spectral indices. A total of 1000 iterations were executed for each pair.

BOOTSTRAP STATISTICS								
	Volume				Basal Area			
Index	Mean	CI	Std Error	Std Dev.	mean	CI	Std Error	Std Dev.
RENDVI	0.97*	0.94 - 0.98	0.0003	0.0101	0.90*	0.86 - 0.94	0.0006	0.0195
MRESRI	0.86*	0.79 - 0.92	0.0011	0.0333	0.95*	0.90 - 0.98	0.0006	0.0197
MRENDVI	0.74*	0.65 - 0.94	0.0026	0.0808	0.78*	0.62 - 0.89	0.0022	0.0686
VREI1	0.58*	0.46 - 0.77	0.0016	0.0516	0.90*	0.84 - 0.95	0.0008	0.0262
REPI	0.96*	0.93 - 0.98	0.0003	0.0103	0.94*	0.91 - 0.96	0.0004	0.0136
WBI	0.44*	0.33 - 0.60	0.0026	0.0826	0.71*	0.51 - 0.83	0.0025	0.0805
WBR	0.93*	0.88 - 0.97	0.0007	0.0236	0.90*	0.84 - 0.95	0.0009	0.0290
Vog1	0.58*	0.49 - 0.69	0.0016	0.0516	0.90*	0.81 - 0.95	0.0008	0.0262
R 253	0.92*	0.87-0.97	0.0007	0.0224	0.97*	0.94 - 0.98	0.0003	0.0102
VI(opt)	0.91*	0.86 - 0.95	0.0008	0.0255	0.95*	0.89 - 0.97	0.0006	0.0194
NDVI	0.89*	0.86 - 0.95	0.0007	0.0226	0.96*	0.94 - 0.99	0.0003	0.0099
RV11	0.90*	0.85 - 0.95	0.0007	0.0237	0.90*	0.84 - 0.94	0.0008	0.0255
RV12	0.86*	0.78 - 0.95	0.0013	0.0407	0.94*	0.88 - 0.98	0.0008	0.2520
NRI	0.89*	0.82 - 0.95	0.001	0.0320	0.93*	0.89 - 0.96	0.0006	0.0189
* p<0.01	CI= confidence interval							



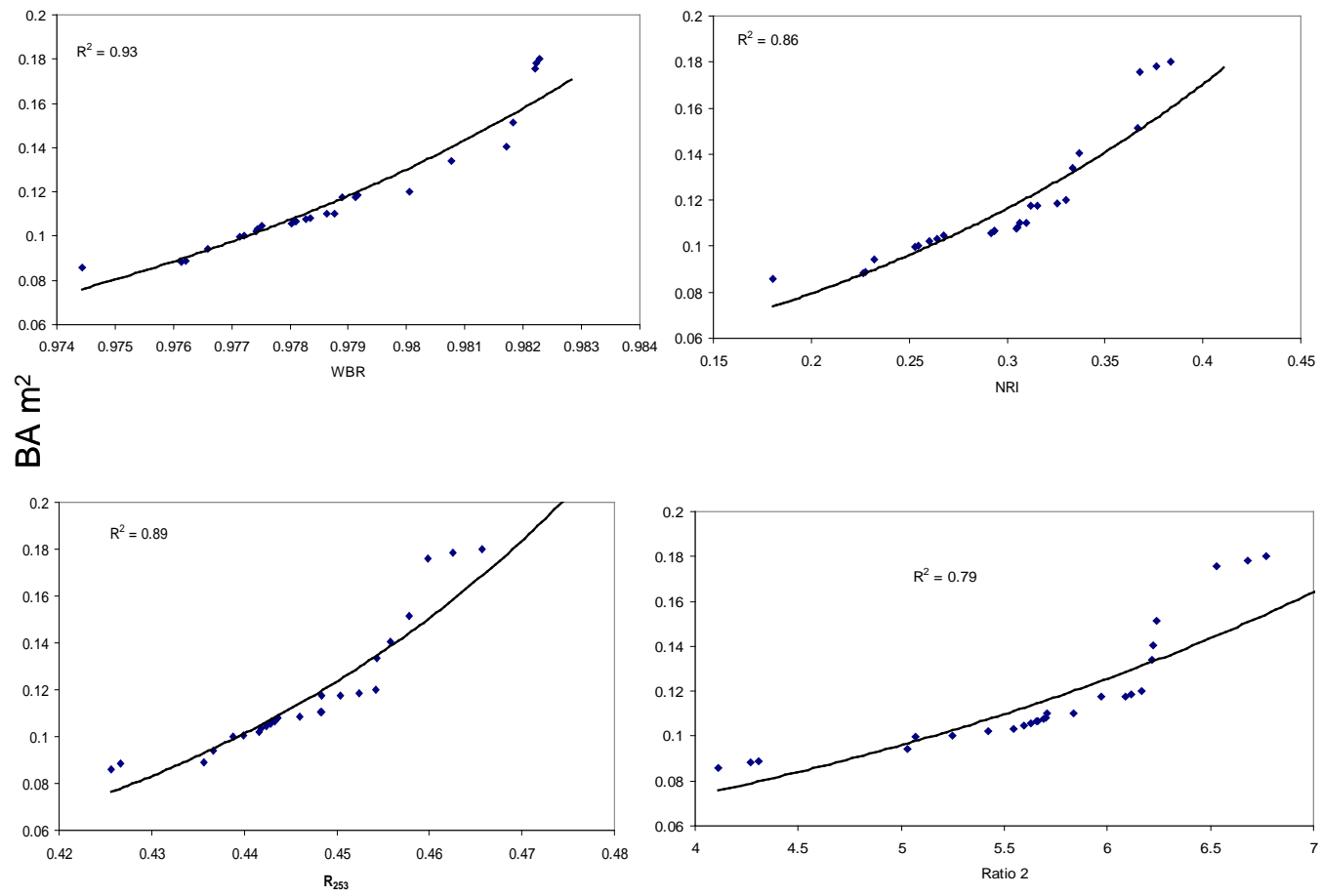


Figure 3.2a A graphical depiction of the relationships between basal area and selected indices

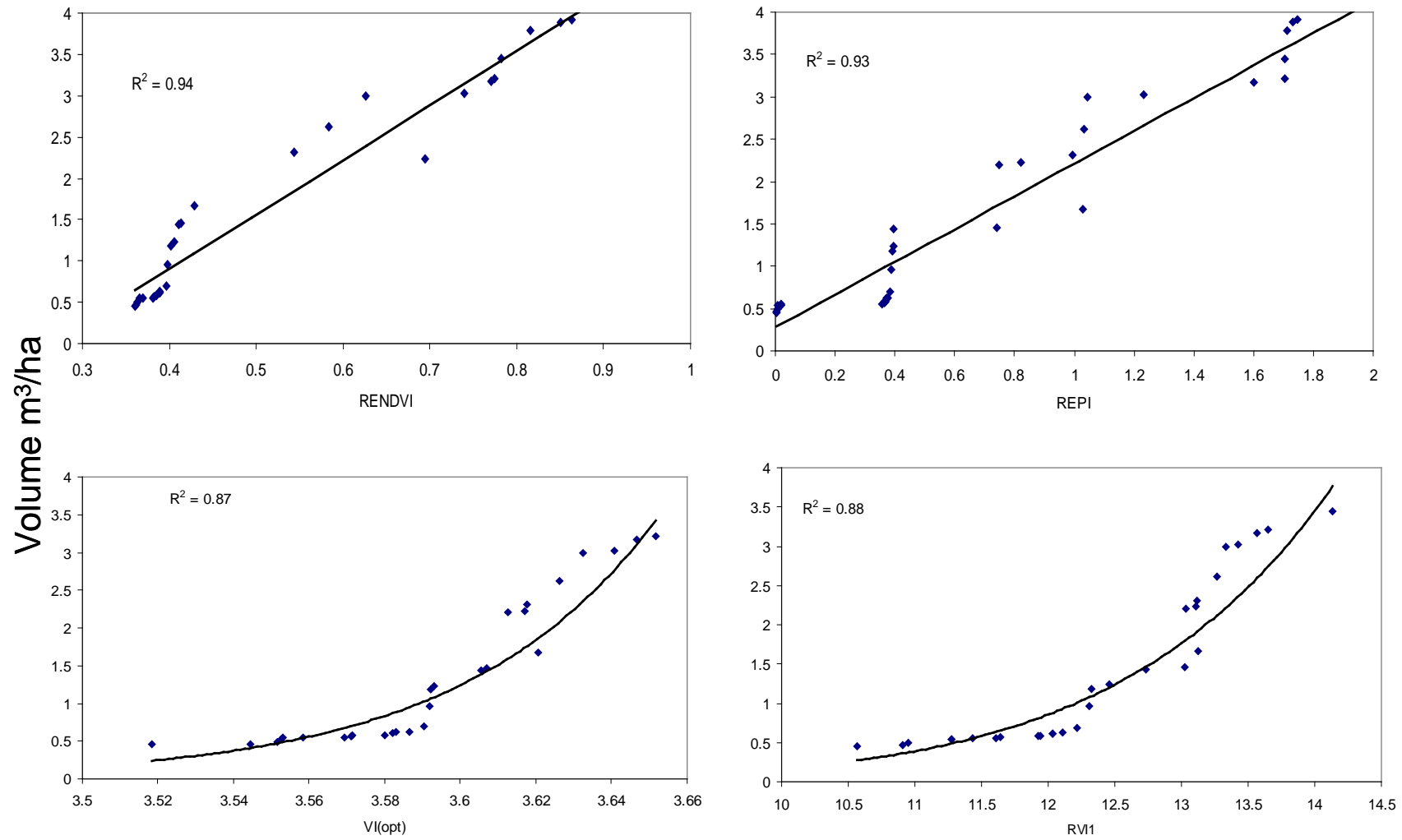


Figure 3.2b A graphical depiction of the relationships between volume and selected indices

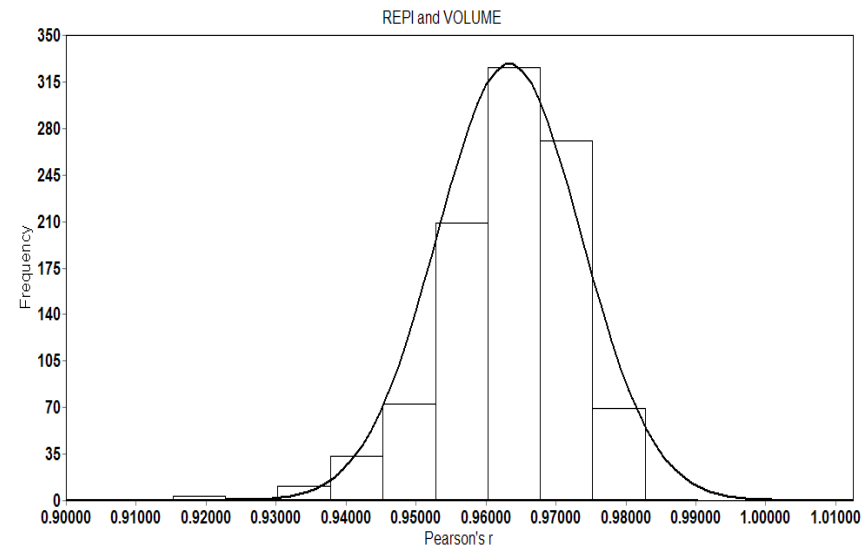
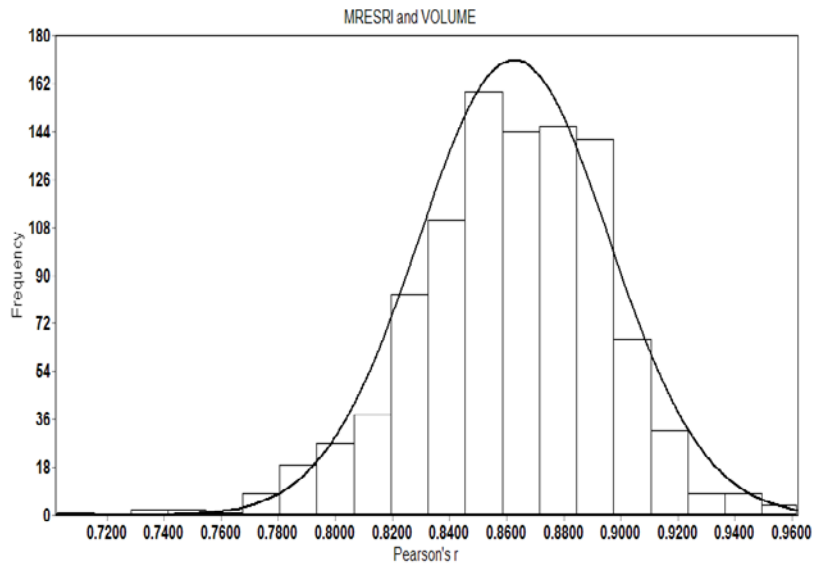
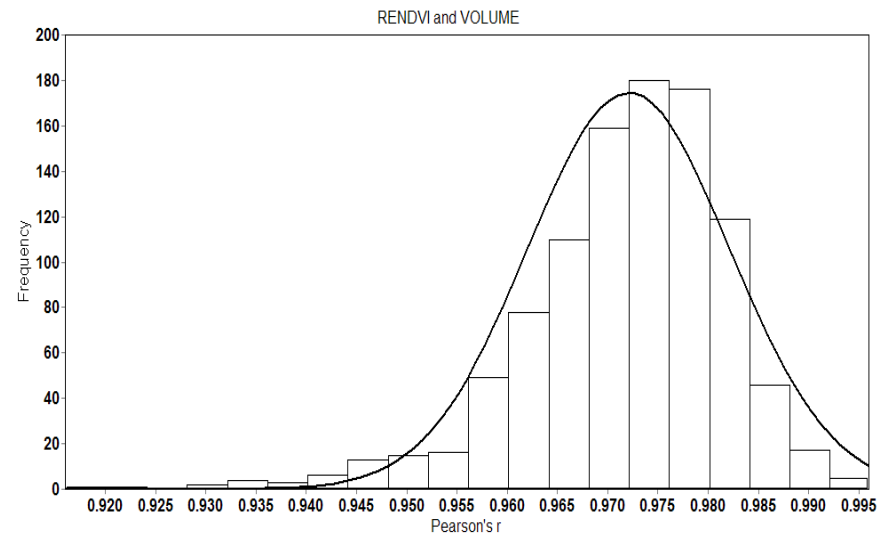
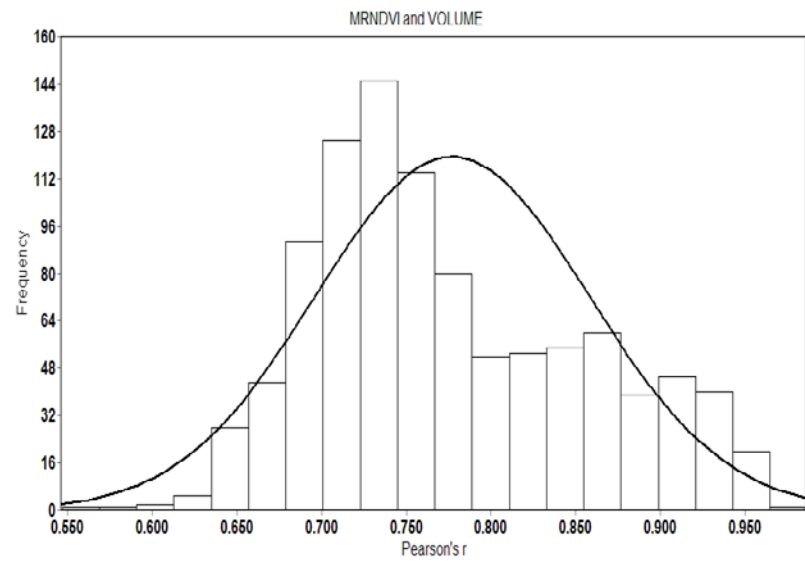


Figure 3.3a. Bootstrapped correlation coefficients between volume and a selection of spectral indices. A total of 1000 iterations were executed for each pair

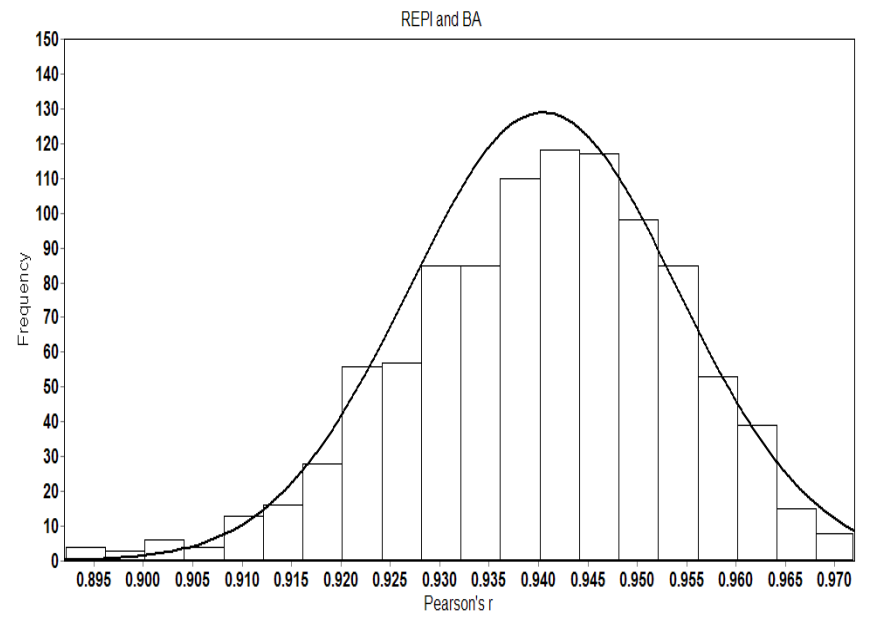
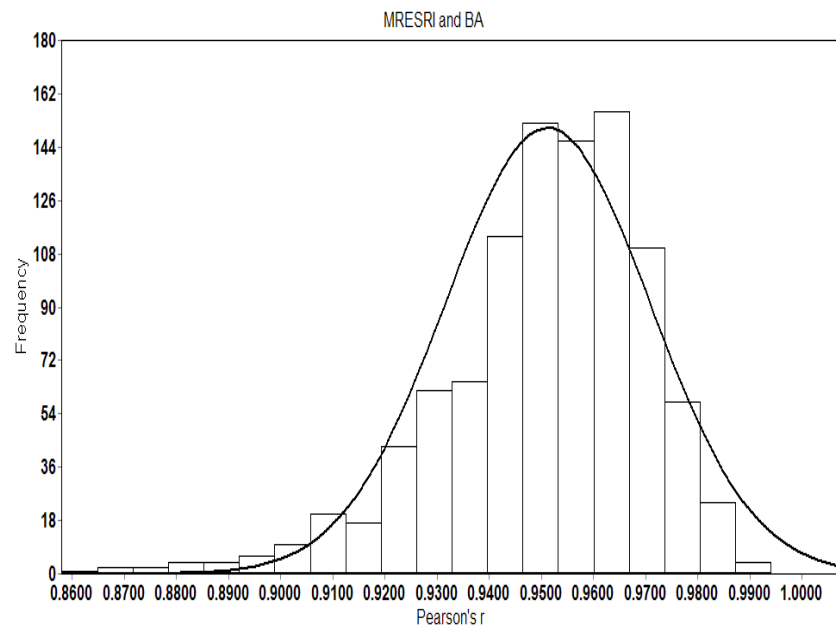
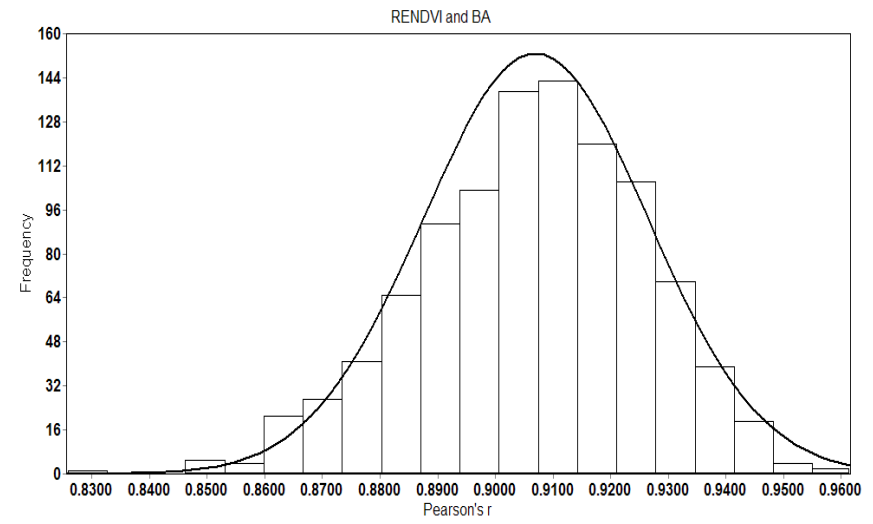
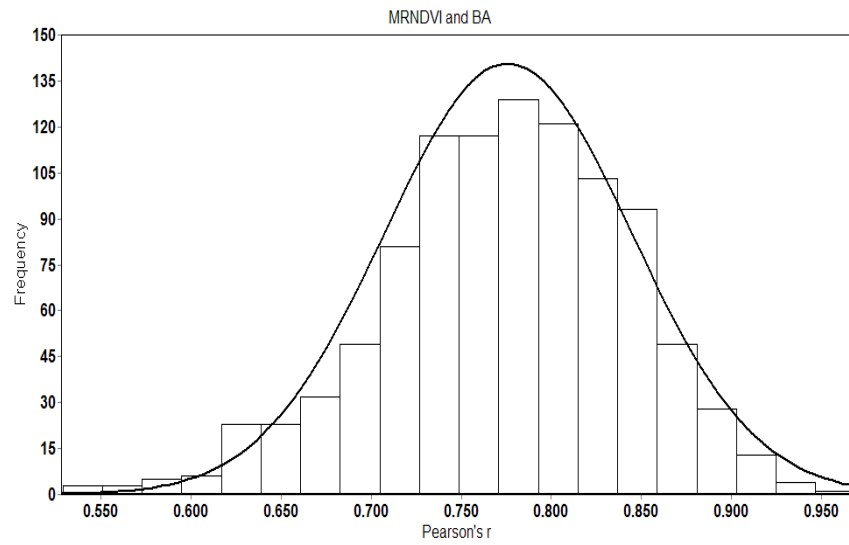


Figure 3.3b. Bootstrapped correlation coefficients between basal area and selected indices. A total of 1000 iterations were executed for each pair.

#### ***3.6.4. Model development for volume and basal area estimation through Chlorophyll, Nitrogen, and water indices.***

Multiple regression analysis using the stepwise backward method show that volume variability was best explained by five independent variables or indices, namely MNDVI, RVI<sub>1</sub>, Vog 1, WBI, and WBR, while basal area variation was explained by four variables, namely MRNDVI, R<sub>253</sub>, RVI<sub>1</sub>, and RENDVI. These variables exhibited significant contributions ( $p < 0.05$ ) in the model building, which negated the need to simplify the models further, i.e., predefined statistical criteria were fulfilled. Both volume and basal area models returned high adjusted  $R^2$ -values ( $R^2 > 0.90$ ,  $p < 0.001$ ) and low Mallow Cp values, as shown in Table 3.6. Error estimates for the respective models are represented by the RMSE values. The RMSE of the volume model was 0.1283 m<sup>3</sup>/ha and that of the basal area model 0.0038 m<sup>2</sup>, or 7% and 2%, respectively, relative to the mean of each estimate.

Scatter plots that show the field-measured vs. model predicted values for volume and basal area are shown in Figures 3.4 and 3.5, respectively. These figures show no evidence of over- or underestimation in either case, indicative of a random error distribution without any discernable patterns. Means of the estimated values for volume and basal area were compared with the observed mean for each variable and the results showed that there were no significant differences between the predicted-observed pairs. Finally, assessment of the model performance for future predictive purposes, based on a leave-one-out cross-validation approach, was performed using the PRESS statistic (Table 3.7). The PRESS statistics for volume and basal area models were 0.153 and 0.004, respectively. The predictive maps of basal area and volume are depicted in figures 3.6 and 3.7, respectively. Basal area ranged from 0 to 0.5 m<sup>2</sup>, whilst volume ranged from 0 to 0.47 m<sup>3</sup>/ha. These maps show within compartment variations of the forest structures i.e., distribution of both volume and basal area within the compartment was not uniform.

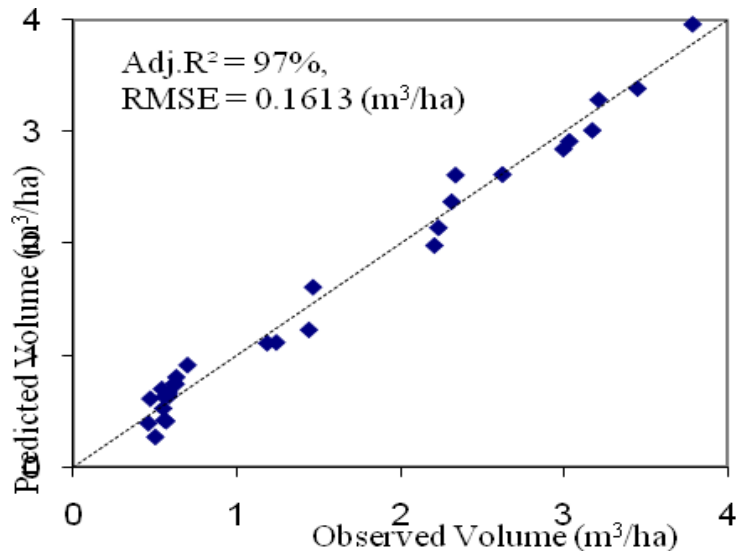


Figure 3.4 Observed vs. predicted volume of *Eucalyptus grandis*

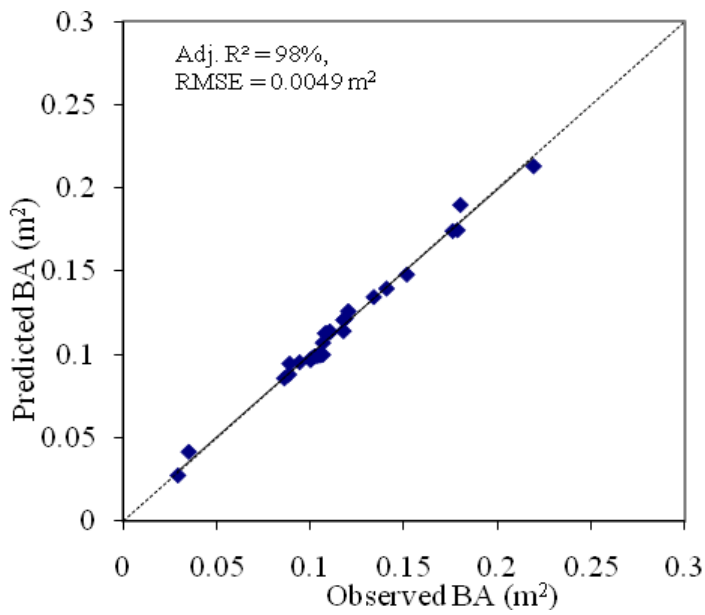


Figure 3.5 Observed vs. predicted basal area of *Eucalyptus grandis*

Table 3.6. Spectral index-based volume and basal area models for *E. grandis*

Variable	Models	Adj.R <sup>2</sup>	RMSE	%RMSE	Cp Mallow	p-value
Volume	Vol= -241.75 - 26.4842*MRNDVI + 1.33718*Ratio 1 - 6.52123*VOG1 + 3.36104*WBI + 242.818*WBR	0.97	0.1613 m <sup>3</sup> /ha	7	6	0.0001
BA	BA= -1.57007 + 0.813811*MRNDVI + 3.78568*R - 0.0281675*Ratio 1 + 0.0523769*RENDVI	0.98	0.0049 (m <sup>2</sup> )	2	5	0.0001

Table 3.7. Predicted and observed volume and basal area models

	Model	Adj. R2	RMSE	PRESS
Basal Area (m <sup>2</sup> )	Predicted BA = 0.9871*Observed BA + 0.0015	0.98	0.004	0.004
Volume (m <sup>3</sup> /ha)	Predicted Volume = 0.9831*Observed Volume + 0.0259	0.98	0.147	0.153

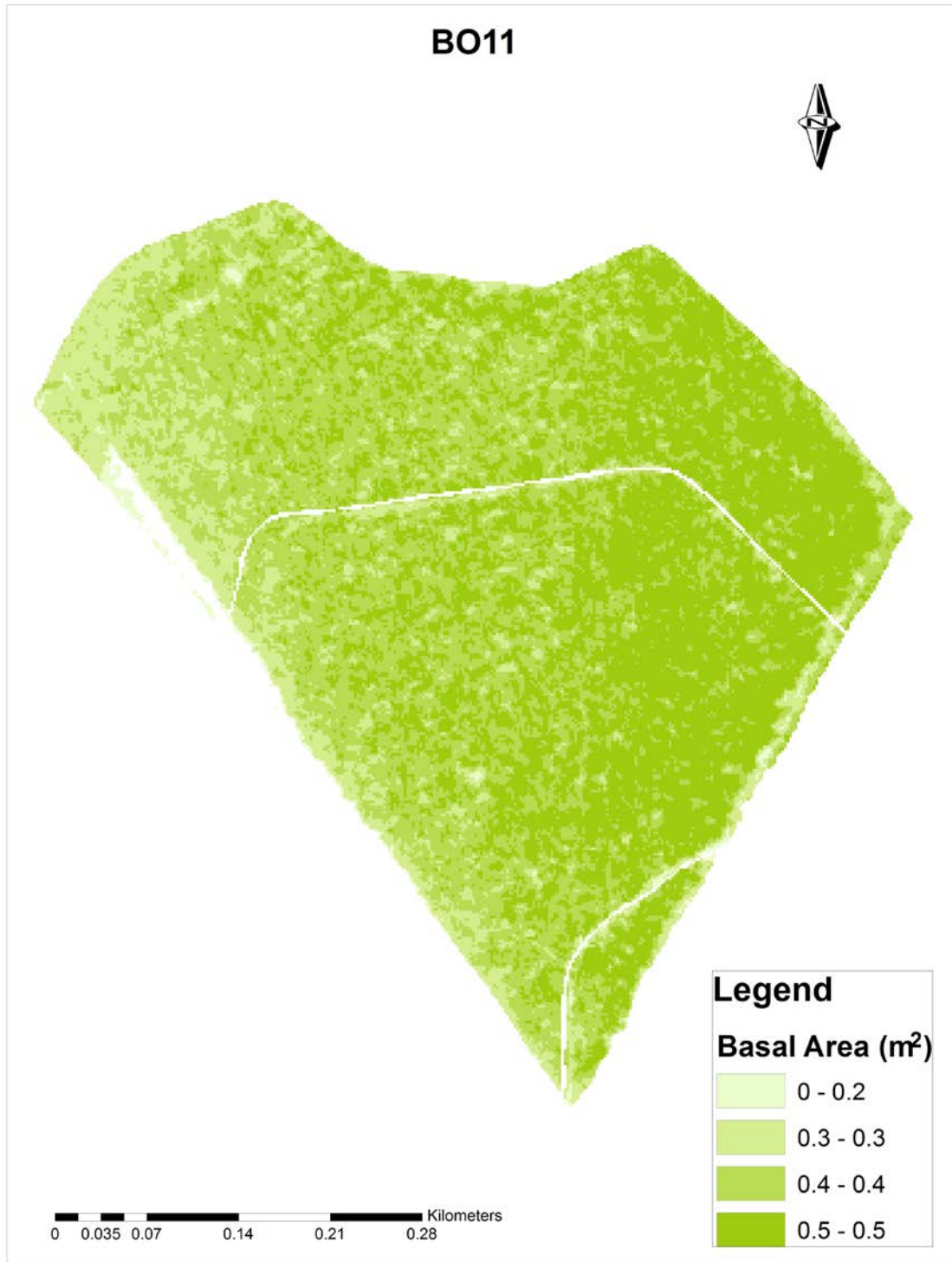


Figure 3.6 Map of the distribution of basal area (m<sup>2</sup>) within compartment BO11



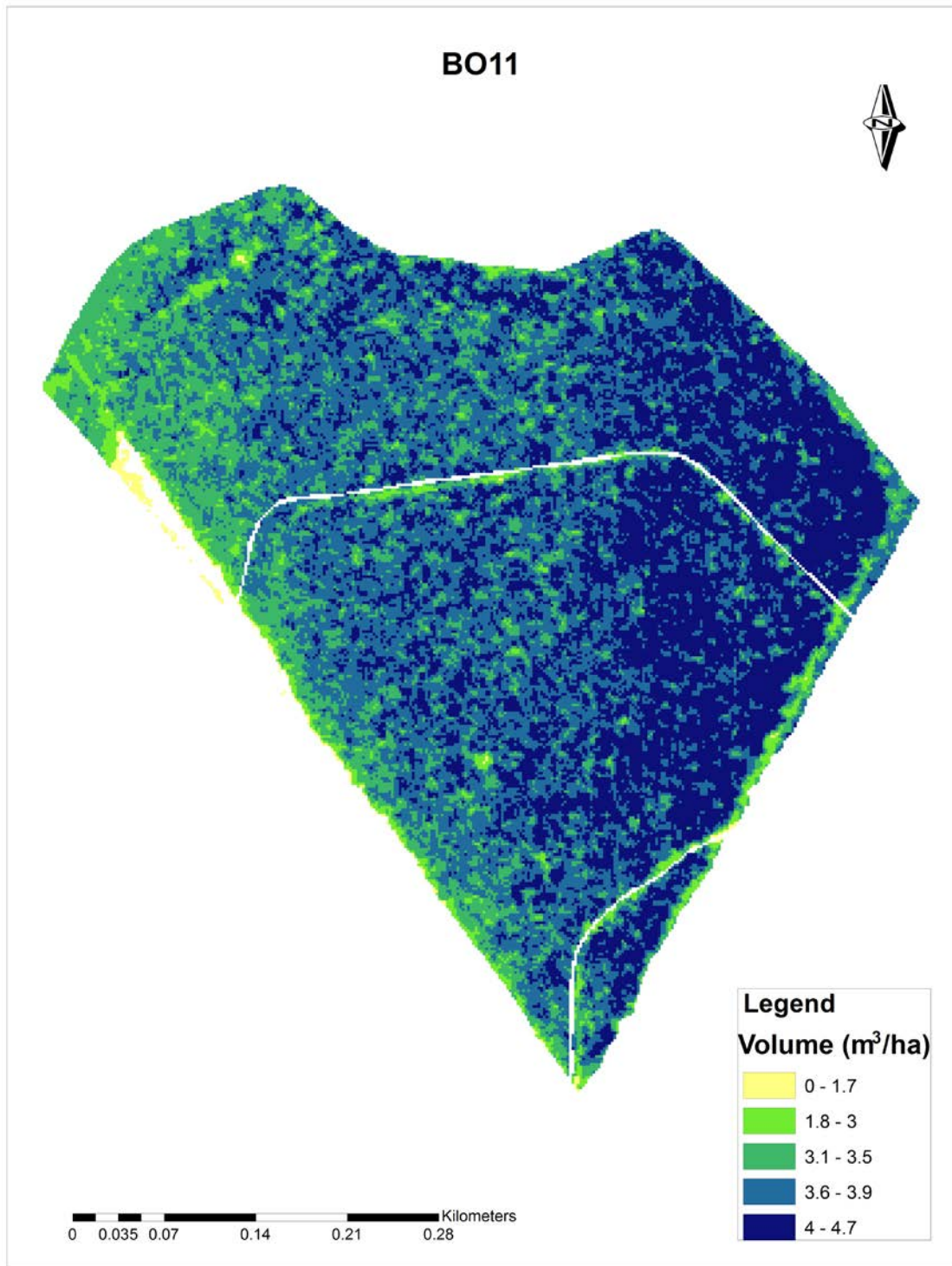


Figure 3.7 Map of the distribution of volume (m<sup>3</sup>/ha) within compartment BO11

### 3.7. Discussion

The effective management of commercial forestry demands better understanding of the interactive processes taking place between chemical and structural components of the forest. Such an understanding is important and can be obtained in a spatially explicit manner at high temporal frequency through remote sensing techniques for commercial plantation forestry. The objective of this study was to examine the impacts of calculated chlorophyll, nitrogen, and water content indices on volume and basal area simulated through AISA hyperspectral data, acquired at leaf level. Pearson's  $r$  and bootstrapping methods were used to assess the relationships and robustness of these relationships.

#### 3.7.1. Assessing relationships between indices, volume and basal area

Plant foliage plays a crucial role in the forest ecosystem monitoring and acts as an indicator of a plant's productivity (Peterson *et al.*, 1988). Consequently, healthy forest plantations exhibit associated performance in terms of structural attributes. Related studies on forest structural estimations using hyperspectral data have shown that narrow band indices have higher correlations with forest structural parameters than standard vegetation indices, derived from broad band multispectral data e.g., Lefsky *et al.* (2001), Jusoff, (2008), Cho *et al.* (2009), Souza *et al.* (2010), Stagakis *et al.* (2010). These studies extracted empirical relationships between field-measured plant variables and vegetation indices from the reflectance data (Stagakis *et al.*, 2010). In this study the relationships between field-measured variables, namely volume and basal area, and chlorophyll, nitrogen and water content indices, derived from AISA hyperspectral reflectance imagery, were assessed. High correlations ( $r > 0.65$ ,  $p < 0.01$ ) were obtained for relationships between volume and basal area and chlorophyll, nitrogen, water-based indices, with the exception of Vogelmann red edge index 1 and water band index ( $r < 0.60$ ,  $p < 0.01$ ) (Table 3.4). These results emphasized the strong influence that the foliar nutrient content, i.e., leaf chlorophyll, nitrogen, and water content have on the structural attributes such as volume and basal area of *E. grandis*.

The robustness of these relationships for all the indices, with the exception of WBI, was further confirmed by bootstrapping histograms that presented mean  $r$  values of

+0.60 and +0.70 for volume and basal area, respectively (Table 3.5). This was hardly surprising given that the success of commercial forest plantations is heavily dependent on improved silvicultural and management techniques to accelerate forest productivity and tree growth (Tilman, 1997, Naidoo *et al.*, 2006). Similar results were observed elsewhere (Souza *et al.*, 2010), where narrow band indices derived from Hyperion imagery returned above 90% correlation coefficients with basal area and canopy cover in a Brazilian savannah environment. Bootstrap statistics yielded robust *r* values, ranging from 0.9 to 0.97 for both variables (basal area and canopy cover), for the current study. Relationships between volume, basal area, and foliar nutrients, as represented by chlorophyll, nitrogen, and water based indices, exhibited high coefficients of determination (adjusted  $R^2 > 70\%$ ). These relationships varied from linear to power and exponential relationships, thus reflecting the predictive capabilities of the indices when assessing relevant structural parameters (see Figures 3.2a and 3.2b). The predictive ability of models should exceed a predetermined value in order for relationship to assist in future predictions of forest structural attributes i.e.,  $R^2$  values above 65% are treated as useful in South Africa scenarios (Naidoo *pers.comm*). For example, regression relationships that explained greater than 70% of the variance in the volume and basal area dependent variables were obtained. This variance explained in this study is in agreement with other studies elsewhere e.g., Sivanpillai *et al.* (2006), were able to predict stand age and tree density of commercially managed loblolly pine (*Pinus teada L.* with adjusted  $R^2=78\%$  and  $R^2=60\%$ , respectively using Landsat ETM+ reflectance values. Also Hall *et al.* (2006) obtained satisfactory adjusted  $R^2$  values (adjusted  $R^2 > 70\%$ ) for volume and aboveground biomass.

### **3.7.2. Model development and validation**

Leaf and canopy pigments, especially chlorophyll, nitrogen, and water content, are useful for distinguishing between healthy or stressed forest plantations (Sampson *et al.*, 2002). A "healthy" condition in forest stands represents close to optimum forest productivity, while stress leads to strained productivity and forest decline. An attempt to estimate such pigments visually would not be enough to track the changes in productivity or continuous stand condition, as opposed to using remote sensing techniques. An ideal situation would be to monitor forest structural attributes, such as

volume and basal area, over large areas with a minimum amount of required field work. Field plots can be established merely to calibrate already developed models. Several studies have shown that it is possible to develop remote sensing models which explain a significant amount of variation (i.e., greater than 80% variation) in structural attributes over large tracts of forest land with reasonable or acceptable accuracies (Jusoff, 2008, Woulter *et al.*, 2009, Pasher and King, 2010). The models developed explained a significant amount of variation in volume and basal area, i.e., above 95% with low RMSE and Mallows Cp values (see Table 3.6). Similar low errors (5 -10%) were reported elsewhere e.g., Lefsky *et al.* (2005), Woulter *et al.* (2009) and Tesfamichael *et al.* (2009). Furthermore, the  $R^2$  values obtained for both the volume and basal area models indicate that narrow band indices can overcome the observed problem of saturation at full canopy closure, as experienced by broadband indices (Cho *et al.*, 2009). The models developed in this study for both volume and basal area, based on canopy chlorophyll, nitrogen, and water content indices, attest to the usefulness of such a large area approach to forest structural and condition assessment.

Scatter-plots obtained during cross-validation of the models using the leave-one-out approach corroborated the initial fit statistics in terms of high adjusted  $R^2$  values that were significant at  $p < 0.0001$ . These models returned low RMSE and low PRESS statistics, where the PRESS statistic is regarded as indicative of the predictive power of the model, as shown in Table 3.7. The models furthermore exhibited a near 1:1 relationship between observed and predicted values ( $r > 0.90$ ) (Figures 3.4 and 3.5). The results of this study further affirm the reported strength of the relationships between growth and yield and silvicultural practices, such as fertilization and thinning. These practices respectively bolster leaf health/growth and reduce competition for natural resources, such as water and nutrients (Aussenac, 2000). Additional research might be required in order to operationalise the proposed approach. For example, the outcomes from this study could be downscaled to multispectral imagery in order to cut the cost of future volume and basal area predictions, since multispectral data are now freely available for large areas. Overall, the assessment of leaf chlorophyll, nitrogen, and water content over large areas may assist in the design of silvicultural and management regimes to ensure optimum growth, since these variables are indicators of the status of a plant during the growing stages.

### **3.8. Conclusions**

The analyses of this study highlight the potential of hyperspectral data in indirect monitoring forest structural attributes through sensing of leaf chemical constituents. The objective of this study was to assess the relationships between foliar leaf chlorophyll, nitrogen, and water content and volume and basal area. This study have demonstrated that remotely sensing chlorophyll-, nitrogen-, and water-based narrow band indices are directly correlated to forest growth status in terms of standing volume and basal area. The indices exhibited high correlations with both volume and basal area in that a significant amount of variation in volume and basal area could be explained. The results in this study is a first attempt in even-aged *Eucalyptus grandis* forest environments and there is potential to extend the approach to other forest species and also downscale results to significantly cheaper and readily available broad-band multispectral sensors for management purposes. The next chapter investigates the feasibility of narrow band indices derived from leaf spectra of *Eucalyptus grandis* in predicting soil nitrogen content.

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## CHAPTER 4

*Predicting soil nitrogen content using narrow-band indices from Eucalyptus grandis canopies as proxy*

This chapter is based on: Mzinyane, T, Ahmed, F and Van Aardt, J. 2011. Predicting soil nitrogen content using narrow-band indices from *Eucalyptus grandis* canopies as proxy. *Forest Ecology and Management* (Submitted)

## Abstract

A key component to successful commercial forestry production in South Africa is the application of silvicultural practices to optimize soil fertility, given its crucial role in tree growth. The success of applicable silvicultural practices is often reflected in plant foliage pigmentation, because leaf pigmentation provides information on the current status of the plants and may reflect the amount of nutrients available in the soil. This study aims to estimate soil nitrogen content using narrow-band leaf spectral indices derived from hyperspectral data, captured with a hand-held 350-2500nm spectroradiometer. It has been hypothesized that there is a significant link between the amount of soil nitrogen and the spectral behaviour of such leaf spectral indices of *Eucalyptus grandis* across different site qualities, i.e., good, medium and poor. Leaf-level spectral data were collected and subjected to continuum removal spectral transformations, in addition to using raw reflectance spectra. These leaf spectral indices were used to explain the variance of soil nitrogen status in the forest soils of compartments under *Eucalyptus grandis* canopies. Soil samples were collected at depths of 0.3- 0.7m and analyzed for nitrogen. Results indicated variable but significant correlations ( $0.37 \geq r \geq 0.80$ ,  $p < 0.05$ ) between leaf spectral indices and soil nitrogen. The ANOVA results for spectral indices-site interactions showed that differences between site qualities can be assessed using specific indices. Significant differences were only observed between good-medium and good-poor sites. No significant differences were observed between medium and poor sites. A comparison between models developed from raw and continuum removed spectral indices for future estimation of soil nitrogen showed that continuum removed spectra had high adjusted  $R^2$  values ( $R^2 = 0.85$ ;  $p < 0.05$ ) and low PRESS statistic values (0.05) when compared to approaches based on raw spectra ( $R^2 = 0.77$ ;  $p < 0.05$ ; PRESS = 0.07). The results obtained show the potential that forest managers may be able to monitor the status of soil nitrogen in commercial forestry compartments and determine how much fertilizer is required to optimize tree growth.

*Key words: leaf spectral indices, soil nitrogen, spectroradiometer hyperspectral data.*

#### 4.1. Introduction

Commercial forestry plays an important role in South Africa's economy through job creation and boasts a 1.8% contribution to the country's gross domestic product (GDP) (Chamberlain *et al.*, 2005; Tewari, 2005). However, the long term sustainability of this resource will depend on proper planning, monitoring, and management regimes implemented by the commercial forestry sector. The success of these management regimes involves to a large extent the ability to assess growth rates and the health of forests and application of best silvicultural practices. Soil fertility is one property which is heavily influenced by silvicultural practices (Ranger and Turpault, 1999), and is geared to promote long term sustainable growth of commercial forestry in South Africa. Specific challenges that face managers in the commercial forestry sector are twofold, namely (i) optimizing fertiliser applications in order to sustain stand productivity and establishment whilst protecting the environment (Wilson *et al.*, 2005) and (ii) addressing the question of how to balance the costs of fertilizer and environmental concerns over vast tracts of land? Growth rates of forest trees in many parts of the world are limited by the supply of soil N and P, either singly or in combination (Khanna, 1994, Lee *et al.*, 1999, Niinemets and Kull 2005). A deficiency in soil nitrogen does not only cause a reduction in growth, but also induces leaf chlorosis as nitrogen is relocated from old leaves to new growth (Jifon *et al.*, 2005).

Some of the methods that have been used to estimate soil nitrogen status of forest sites include soil nitrogen index, direct measurement of N mineralization in the field, and model simulations of mineralization (Paul *et al.*, 2002). Although these methods are effective, they are also site-specific, expensive, time-consuming, and can only be extended over large areas with great difficulty. A rapid and efficient method for estimating soil nitrogen status, which can be applied over large areas, is therefore necessary. Remote sensing technologies can provide an alternative way of minimizing the effects of excessive fertilization by enabling farmers to manage nutrient applications more efficiently while sustaining environmental resources. Nutritional status of the plants and their ability to respond to fertilizers are commonly examined via plant foliage, given that foliage represents a major locus for energy capture and water exchange in forest and other ecosystems (Field and Mooney, 1986, Schönau

and Herbert, 1989, Curran, 1989, Coops, 1999). Imaging spectroscopy datasets have been used to measure a multitude of individual absorption features for plant foliage, such as pigment composition and content (Lichtenthaler *et al.*, 1996, Gitelson and Merzlyak 1997), canopy water content (Peñuelas *et al.*, 1994), and canopy dry plant litter or wood (Asner *et al.*, 1998). Such approaches have also been used to quantify vegetation health, physiological status, and productivity of various ecosystems, e.g., forestry and agriculture (Haboudane *et al.*, 2002, Chen *et al.*, 2007, Abdel-Rahman *et al.*, 2008, Barry *et al.*, 2008, Ismail *et al.*, 2008, Mokhele *et al.*, 2009, Cho *et al.*, 2010). Although these studies have reported varying success, conclusive attempts to relate forest foliar chemistry to forest floor mineral soil characteristics are still lacking. Imaging spectroscopy of soil nutrients, texture, organic matter, and spectral variability have received some attention (Ben-Dor *et al.*, 2002; Udelhoven *et al.*, 2003). Aitkenhead-Peterson *et al.* (2006) and Albrechtová *et al.* (2008) went a step further in their research by linking foliar chemistry and forest floor solid, organic phase carbon and nitrogen and reported encouraging results ( $R^2 > 75\%$ ,  $p < 0.01$ ). It is worth noting that in South Africa, spectroscopy studies relating foliar chemistry to soil nutrients in short-rotation, highly productive sites are severely lacking. This study therefore seeks to utilize spectroscopy for detailed examination of soil nitrogen using narrow-band spectral indices obtained from hand held spectroradiometer at leaf-level and thereby extend results from previous studies in other locations (Thomasson *et al.*, 2001, Ben-Dor *et al.*, 2002, Udelhoven *et al.*, 2003, Aitkenhead-Peterson *et al.* (2006) and Albrechtová *et al.*, 2008).

## **4.2. Materials and methods**

### **4.2.1. Study area**

The study was conducted in the Greenhill estates in KwaZulu-Natal province of South Africa. The study sites are situated approximately 50 km south of Pietermaritzburg around the town of Richmond (Figure 4.1). The study area falls within the summer rainfall region of South Africa and experiences cold dry winters and warm wet summers. Mean annual rainfall ranges from 746-1100 mm while temperatures vary between a high of 25°C to below 10°C (Schulze, 1997). The extreme temperature change is a function of elevation and proximity to the warm Indian Ocean with higher lying areas experiencing much colder temperatures than low lying areas. Dominant



soil forms are Inanda and Mogwa, with Hutton being the subdominant soil form. Huttons are characterized by a topsoil (0.4-0.5 m) on a red, apedal, clay loam subsoil (>1 m). A large number of *Eucalyptus grandis* plantations in the area are located on this Hutton soil form. The topography of the Richmond area is flat with undulating hills and is classified as being low mountains. Altitude ranges from 362 meters to over 1500 meters above sea level with an average of around 874 m (Schulze, 1997).

#### **4.2.2. Leaf spectral measurements**

The field data collection was undertaken at the beginning of winter 2009 during clear sky days. The *Eucalyptus grandis* plots were located across different site qualities, namely good, medium and poor. The site quality classification is based on total available water (TAW) in the soil profile, which is a function of effective rooting depth, soil type, rainfall, and temperature classes (Smith *et al.*, 2005). Homogeneous cover square plots of 20m by 20m were enumerated in order to include up to 45 trees per site quality and thereby strengthen the statistical reliability of the results. Leaf samples were gathered from the sunlit branches within different site quality classes using tree climbers. Leaves were then stacked 10 layers together and reflectance measurements taken using the leaf clip of the spectrometer. The ASD field spectroradiometer sampling interval over the 350–1050 nm range is 1.4 nm with a spectral resolution (full bandwidth at half maximum) of 3 nm. Over the 1050–2500 nm range, the sampling interval is 2 nm and the spectral resolution is between 10 nm and 12 nm (Analytical Spectral Devices, 2002). Radiance measurements were converted to target reflectance using a calibrated panel on the leaf clip. Reflectance measurements were taken by averaging 40 scans with a dark current correction at every spectral measurement. Continuum removal transformations were applied to the resulting spectra (Kokaly and Clark, 1999). Continuum removal normalizes reflectance spectra in order to allow for comparison of individual absorption features from a common baseline (Kokaly, 2001) and the resultant curves have values between 0 and 1, in which the absorption troughs are enhanced (Schmidt and Skidmore, 2001). A total of 55 leaves samples were then immediately stored in zip-lock bags and a cooled container for chemical laboratory analyses.

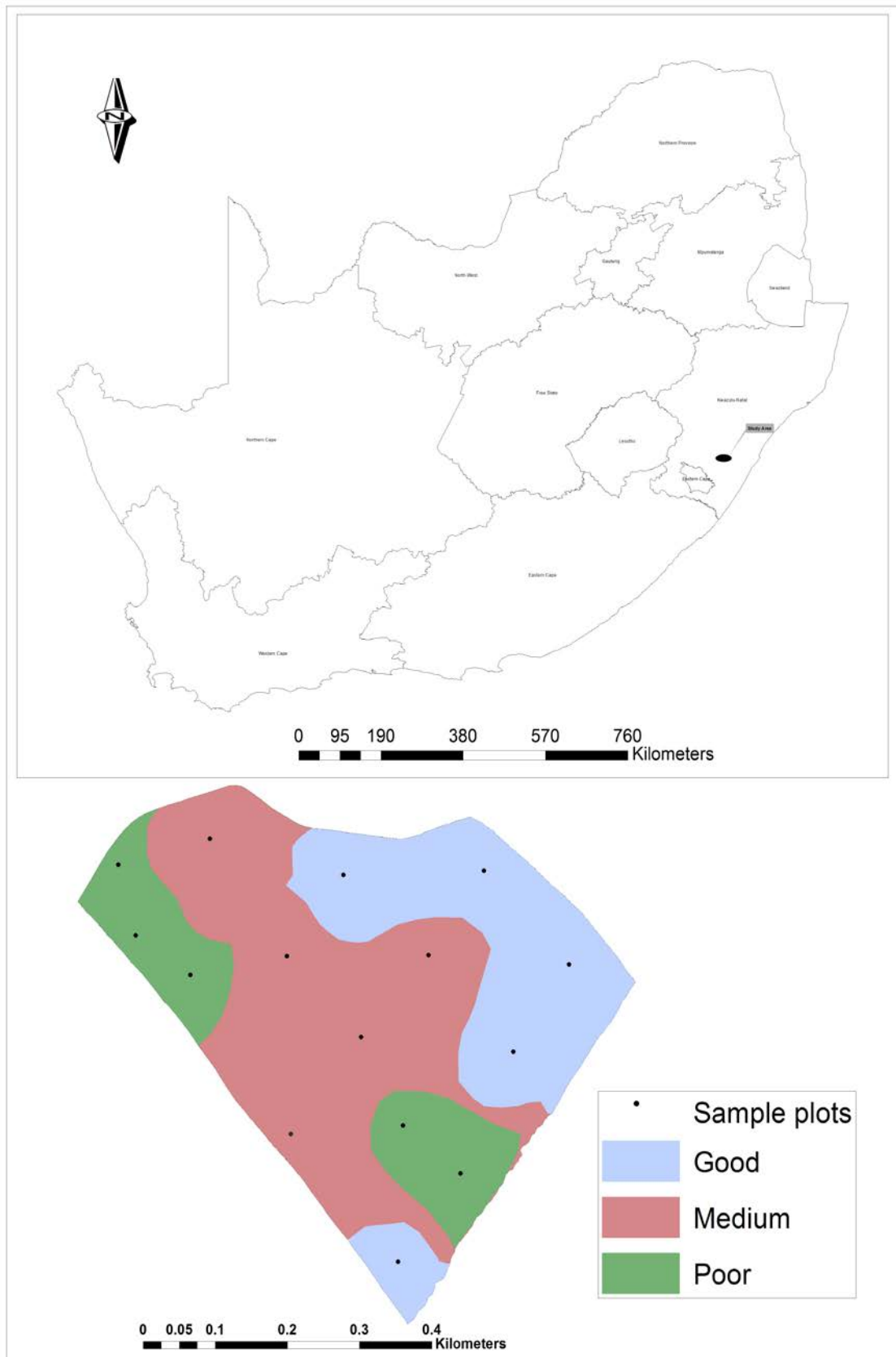


Figure 4.1. Map of study area

#### ***4.2.3. Soil measurements and chemical analysis***

Soil samples were taken at depths of 0.3-0.7 m using a soil auger for the three different site qualities. These depths were selected because the study area contains shallow soils and the age of the trees was at 6 years. The soil samples were taken at opposite directions from the centre tree in a 20 by 20m plot, approximately 1.5 meters away from the base of the centre tree and diagonally (i.e. North, South, East and West) across centre tree. The values were averaged for each plot to serve as an overall description of the compartments. A total of 57 soil samples were collected and transported back to the laboratory for nitrogen determination. The Kjeldahl method was used for soil nitrogen determination (Bremner and Mulvaney, 1982).

#### ***4.2.4. Leaf chemical analysis***

*In situ* leaf chlorophyll firstly was assessed using a Soil Plant Analysis Development (SPAD) chlorophyll meter. The SPAD chlorophyll meter measures the “greenness” (amount of chlorophyll present) of the leaf by measuring the absorption of the leaf at two wavelength regions, i.e. blue (400-500nm) and red (600-700nm) (SPAD, 2009). This is followed by calculation of a numerical SPAD value which is proportional to the amount of chlorophyll in the leaf (Perry and Davenport, 2007). Leaves were then transported to the laboratory for chlorophyll analysis in zip-locked bags, stored in cooled containers. The concentration of total chlorophyll was determined spectrophotometrically against 80% acetone at 663nm, 646nm, and 470nm. The concentrations of chlorophylls and pigments were determined according to the methods established by Lichtenthaler (1987).

#### ***4.3. Statistical data analysis***

The data analysis followed in this study was adopted from Lee *et al.* (1999) and was conducted using SPSS ver. 18 statistical package. The first step was to conduct a correlation analysis between actual leaf chlorophyll content and SPAD measurements to validate the latter. This was followed by correlation analysis between soil nitrogen and leaf spectra to determine which wavelengths would return significant correlations

with soil nitrogen. Since the initial aim of this study was to infer soil nitrogen from both leaf spectra and leaf chlorophyll, a correlation analysis was undertaken to assess the correlation between actual leaf chlorophyll content and reflectance at each wavelength, with the threshold for  $r$  set at  $\pm 0.65$ . Well established chlorophyll spectral indices were then computed using Microsoft office excel, as well as other two-wavelength vegetation indices such as simple ratio SR-based and normalised difference vegetation index NDVI-based indices. These latter indices were based on wavelengths for which strong positive or negative relationships ( $r = \pm 0.60$ ) were found. Pearson bivariate correlations then were extended to soil nitrogen and both chlorophyll indices and leaf spectral indices to test the strength and significance of correlations i.e. ( $r$  values are reported as a measure of relationship strength between soil nitrogen and leaf spectral indices). Analysis of variance (ANOVA) was used to assess the impact of site quality on chlorophyll and leaf spectral indices. Although model development was not the aim of this study, models were developed for both raw and continuum removed spectral indices. Stepwise regression was used to identify models that best explained variance in soil nitrogen from the indices derived from raw and continuum removed spectra. The models validation approach adopted in this study was a leave-one-out cross-validation method (Efron, 1981), whereby each sample was iteratively removed and its value predicted using a model developed from the remaining samples. The error of prediction is computed for the sample not used in developing the model. This process continues until all samples are predicted in a similar manner and the sum of the prediction errors is presented as the PRESS statistic (prediction residual sum of squares) (Allen, 1974). We compared PRESS values of the models developed using spectral indices from raw and continuum removed spectra. A model with the smallest PRESS value was deemed the most reliable.

#### ***4.4. Vegetation indices***

Spectral vegetation indices (VIs) are mathematical transformations of vegetation reflectance that have been developed to reduce high dimensional datasets to a single number (Nilsson, 1995). Researchers have used spectral vegetation indices to assess various plant characteristics such as green biomass, leaf area index (LAI), leaf gap fraction, N, chlorophyll, and plant stress (Pinter *et al.*, 2003, Cho, 2007, Wu *et al.*, 2008). Detailed reviews of spectral indices that have been applied to vegetation

spectra are provided in Gamon and Surfus (1999), Thenkabail *et al.* (2000, 2004), Tilling *et al.* (2007), Albrechtová *et al.* (2008), and Meyer and Neto (2008). According to Thenkabail *et al.* (2004), there is no single best approach for determining the optimum number and combination of narrow wavebands for estimating agricultural crop characteristics. As a result, spectral vegetation indices consist of combinations of several values that are either multiplied, subtracted, added, or divided in such a way that they yield a single value that serve as a significant indicator of vegetation status within a pixel (Campbell, 2002). A number of examples are presented below.

- *Chlorophyll normalized difference vegetation index (NDVI)*

NDVI is a widely used index for monitoring vegetation condition and is correlated and sensitive to a wide range of chlorophyll concentrations (Gitelson and Merzlyak, 1994). This index is based on the high reflectance of living vegetation in the near infrared region of the electromagnetic spectrum and low reflectance (high absorption) in the red spectral region (Gamon and Surfus, 1999, Gitelson, 2004):

$$NDVI = \frac{(R_{750} - R_{705})}{(R_{750} + R_{705})} \quad (1)$$

- *TCARI / OSAVI*

The ratio of transformed chlorophyll absorption in reflectance index / optimized soil-adjusted vegetation index (TCARI/ OSAVI) is strongly sensitive to chlorophyll content and insensitive to the influence of variations in LAI, the effects underlying the soil background (Haboudane *et al.*, 2002), and solar zenith angle at the canopy level (Albrechtová *et al.*, 2008):

$$TCARI / OSAVI = \frac{3 * (R_{700} - R_{670}) - 0.2 * (R_{700} - R_{670}) * \frac{(R_{700})}{(R_{670})}}{(1 + 0.16) * (R_{800} - R_{670}) / (R_{800} + R_{670} + 0.16)} \quad (2)$$

- *Red edge*

The red-edge is the name given to the abrupt reflectance change in the 680-740nm region of vegetation spectra that is caused by the combined effects of strong chlorophyll absorption (red region) and leaf internal scattering (near-infrared region) (Filella and Peñuelas, 1994). Although the red edge was initially thought to be exclusively sensitive to chlorophyll, Curran *et al.* (1991) and Cho *et al.* (2007) have shown the sensitivity of the red edge to foliar mass, leaf area index (LAI), and water content. The red edge position was located using (i) the linear four point interpolation technique and (ii) the linear extrapolation technique (Cho and Skidmore, 2006).

(i) Linear four-point interpolation technique

The linear four-point interpolation method assumes that the reflectance curve at the red edge can be simplified to a straight line centred near the midpoint between the reflectance in the near infra-red (NIR) at approximately 780 nm and the reflectance minimum of the chlorophyll absorption feature at approximately 670 nm. This technique uses four wavebands (670nm, 700nm, 740nm, and 780 nm) and the red edge position (REP) is determined by using a two-step calculation procedure:

a) Calculation of the reflectance at the inflection point

$$R_{re} = \frac{(R_{670} + R_{780})}{2} \quad (3)$$

Where,  $R$  is reflectance.

b) Calculation of the red edge wavelength or red edge position is

$$REP = 700 + 40 \frac{(R_{re} - R_{700})}{(R_{740} - R_{700})} \quad (4)$$

Where, 700 and 40 are constants resulting from interpolation in the 700-740 nm intervals.

(ii) Linear extrapolation technique

This technique is based on linear extrapolation of two straight lines (Equation. 3 and 4) through two points on the far-red (680-700 nm) and two points on the NIR (725-760 nm) flanks of the first derivative reflectance spectrum (FDR) of the red edge region (Cho and Skidmore, 2006). The REP is then defined by the wavelength value at the intersection of the straight lines (Equations. 5 and 6):

$$\text{Far-red line: } \text{FDR} = m_1 \lambda + c_1 \quad (5)$$

$$\text{NIR line: } \text{FDR} = m_2 \lambda + c_2 \quad (6)$$

Where,  $m$  and  $c$  represent the slope and intercept of the straight lines. At the intersection, the two lines have equal  $\lambda$  (wavelength) and FDR values. The REP, or the wavelength the intersection is therefore given by equation 7:

$$\text{REP} = \frac{-(c_1 - c_2)}{(m_1 - m_2)} \quad (7)$$

The REP by linear extrapolation method requires four coordinate points (or wavebands), e.g., two bands near 680 nm and 700 nm to calculate  $m_1$  and  $c_1$  for the far-red line and two bands near 725 nm and 760 nm to calculate  $m_2$  and  $c_2$  for the NIR line. Other spectral and chlorophyll indices used in the study are shown in Table 4.1.

Table 4.1. Spectral and chlorophyll-based vegetation indices applied in this study

Index	Formula	References
NDVI	$\frac{(R_{750} - R_{705})}{(R_{750} + R_{705})}$	Gitelson and Merzlyak, (1994)
TCARI / OSAVI	$\frac{3*(R_{700} - R_{670}) - 0.2*(R_{700} - R_{670})}{(1 + 0.16)*\frac{(R_{800} - R_{670})}{(R_{800} + R_{670})}}$	Haboudane <i>et al.</i> (2002)
Red Edge Index	$\frac{(R_{740})}{(R_{720})}$	Vogelmann <i>et al.</i> (1993)
Lichtenthaler Index 2 LIC 2	$\frac{(R_{440})}{(R_{690})}$	Lichtenthaler <i>et al.</i> (1996)



Normalized total Pigment Chlorophyll a ratio Index (NPCI)	$\frac{(R_{680} - R_{430})}{(R_{680} + R_{430})}$	Peñuelas <i>et al.</i> (1994)
NDVI <sub>(380, 440)</sub>	$\frac{(R_{380} - R_{420})}{(R_{380} + R_{420})}$	Determined during this study
SR <sub>(600, 790)</sub>	$\frac{(R_{600})}{(R_{790})}$	Determined during this study
NDVI <sub>(1891, 1991)</sub>	$\frac{(R_{1891} - R_{1991})}{(R_{1891} + R_{1991})}$	Determined during this study
SR <sub>(2440, 2490)</sub>	$\frac{(R_{2440})}{(R_{2490})}$	Determined during this study
R <sub>(2393)</sub>	$R_{2383}$	Determined during this study
R <sub>(499<sup>-1</sup>)</sub>	$\frac{1}{(R_{499})}$	Determined during this study

### 4.3. Results

#### 4.3.1. Calibration of the SPAD meter

The SPAD chlorophyll meter data were calibrated using the chlorophyll data obtained from the laboratory. The chlorophyll concentration of all samples was obtained using the calibration equation (Equation. 8) between SPAD data and laboratory data:

$$\text{Chlorophyll} = 0.199 e^{(0.054 \times \text{SPAD})} \quad \text{Adjusted } R^2 = 0.92\%, \text{ SEE} = 1.99, p < 0.001 \quad (8)$$

#### 4.3.2. Relationship between spectral indices and soil nitrogen

The correlation analysis between soil nitrogen and leaf spectra, undertaken to determine which wavelengths would return significant correlations with soil nitrogen, showed that bands 350-521 nm, 588-800 nm, 1889-1998 nm, and 2391-2500 nm were significantly correlated with soil nitrogen. The correlations between spectral indices derived from these significant bands and soil nitrogen are shown in Table 4.2. These results show that, amongst the spectral indices derived from raw spectra, red edge and Vogelmann (Vogelmann *et al.*, 1993) or red edge index returned the strongest correlations with soil nitrogen ( $r > 0.70$ ,  $p < 0.05$ ). The other indices yielded significant ( $p < 0.05$ ), but much weaker correlations ( $r < 0.65$ ) with soil nitrogen when compared to the red edge and Vogelmann approaches. Amongst the continuum removed spectral indices, NDVI<sub>(1891, 1991)</sub> and R<sub>(2393)</sub> yielded much stronger significant correlations (0.63 and 0.68, respectively) when compared to other indices such as NDVI<sub>(380, 440)</sub>, SR<sub>(600, 790)</sub>, SR<sub>(2440, 2490)</sub>, and R<sub>(499<sup>-1</sup>)</sub>. These latter correlations were significant ( $p < 0.05$ ) but weaker (0.37-0.48). Laboratory measured leaf chlorophyll exhibited the highest significant correlation ( $r = 0.95$ ,  $p < 0.05$ ) with soil nitrogen.

Table 4.2. Correlations of spectral indices with soil nitrogen

Raw Spectra	Vegetation index	r
	Red edge	0.85*
	Vogelmann	0.85*
	NDVI	-0.64*
	LIC2	0.62*
	NPCI	-0.49*
	TCARI / OSAVI	0.40*
	Chlorophyll	0.95*
Continuum Removed	NDVI <sub>(380, 440)</sub>	0.37*
	SR <sub>(600, 790)</sub>	0.47*
	NDVI <sub>(1891, 1991)</sub>	0.68*
	SR <sub>(2440, 2490)</sub>	0.48*
	R <sub>(2393)</sub>	0.63*
	R <sub>(499<sup>-1</sup>)</sub>	0.37*

\*Significant at  $p < 0.05$ .

#### 4.3.3. Assessing spectral index interactions with site quality

The spectral indices were further investigated to determine if different site qualities could be detected. The ANOVA results of interactions between site quality and spectral indices showed that only four indices, namely NDVI, Lichtenthaler, Normalized total Pigment Chlorophyll a ratio Index (NPCI), and TCARI/OSAVI were able to detect subtle site quality differences. It was noticed that differences between good-medium and good-poor sites were observed based on NDVI, NPCI, and TCARI/OSAVI, while no differences were detected between medium-poor sites. The Lichtenthaler index showed differences between good-poor site qualities only. All the other indices and the actual leaf chlorophyll content did not yield any significant differences amongst the site qualities.

#### 4.3.4. Models development and validation

Models were developed using indices derived from raw spectra and continuum removed spectra. From the indices derived from raw spectra, multiple regression

analysis using the stepwise backward approach, indicated that TCARI/OSAVI and REP explained 77.25% of the variability in soil nitrogen, while 85% of the variability in soil nitrogen was explained by continuum removed spectra for four independent variables, namely  $SR_{(600, 790)}$ ,  $NDVI_{(1891, 1991)}$ ,  $R_{(2393)}$ , and  $R_{(499^{-1})}$ . These variables exhibited significant contributions ( $p < 0.05$ ) in the model building, which negated the need to simplify the models further, i.e., predefined statistical criteria for model fitting were fulfilled. Scatter plots that show the field-measured vs. model-predicted values for soil nitrogen for both scenarios are shown in Figures 4.2 and 4.3, respectively. An assessment of the model performance for future predictive purposes, based on a leave-one-out cross-validation approach, was performed using the PRESS statistic. It was concluded, based on adjusted  $R^2$  and PRESS values for models derived from raw spectral indices and continuum removed spectral indices, that the best predictive capability was generated from continuum removed spectral indices (Figure 4.3, adjusted  $R^2 = 85\%$ , PRESS = 0.05) compared to raw spectral indices (Figure 4.2, adjusted  $R^2 = 77\%$ , PRESS = 0.07). Furthermore, ANOVA results for the estimated and observed values for soil nitrogen showed that there were no significant differences between the predicted-observed pairs.

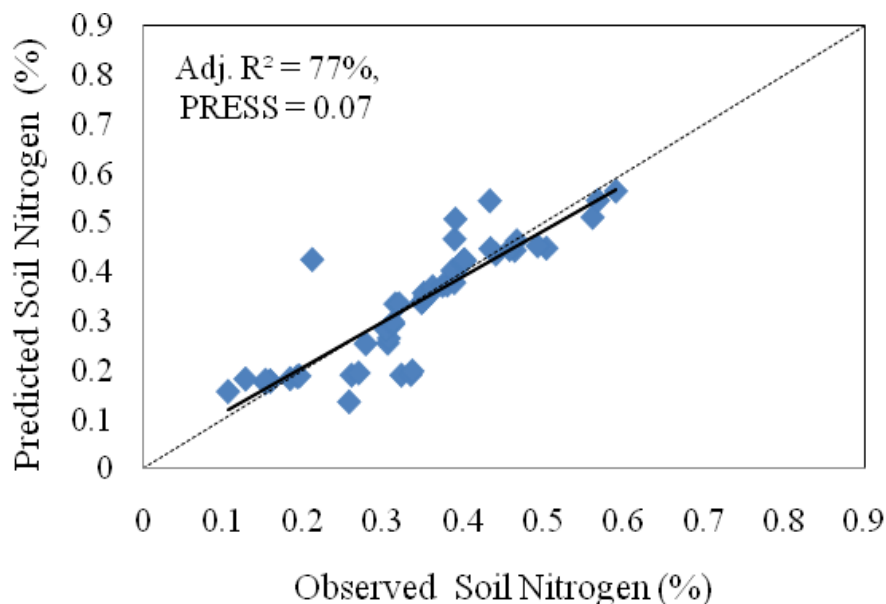


Figure 4.2. Observed and predicted soil nitrogen model based on raw spectral indices

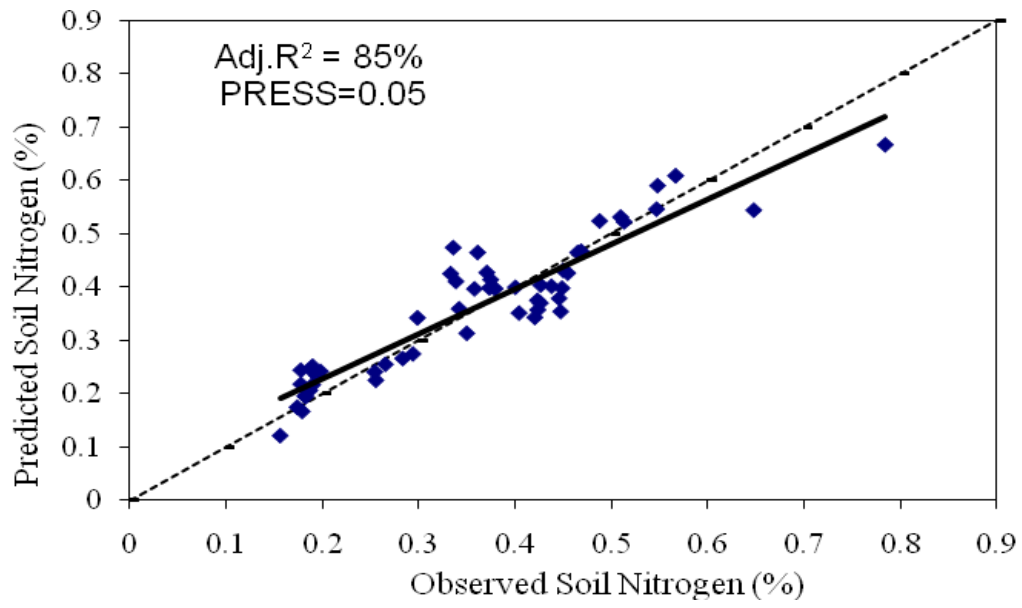


Figure 4.3. Observed and predicted soil nitrogen model based on continuum removed spectral indices

#### 4.4. Discussion

Adequate soil nitrogen is essential throughout the life of a crop towards optimized growth, yield, and economic return. A fine balancing act is required to minimize risk to the environment due to nutrient mobility and leaching, while ensuring that there are enough nutrients at the beginning of the growing season to sustain crop development. Given the continued decrease of commercial forested area due to environmental concerns and political factors in South Africa (Dovey, 2009), accurate information pertaining to silvicultural regimes, such as fertilization over large areas, is necessary and will enhance management strategies. The results of the present study suggest that vital information, such as soil nitrogen content of the forest floor, can be assessed using spectroscopy data. It is widely known that leaf spectral characteristics and pigmentation can often serve as a measure of the crop response to nitrogen application, i.e. tracking short or medium term changes in the nutrient status of the soil (Stovall *et al.*, 2011). This study has shown that visible, red edge, and middle infrared regions of the electromagnetic spectrum are the most important spectral regions for assessment of soil nitrogen. Chlorophyll pigments are known to absorb in the visible and red edge portions of the spectrum (Sims and Gamon, 2002, Kumar *et al.*, 2003) and is central to the understanding of the functioning of agro-ecosystems and modeling of crop growth development processes (Jarmer *et al.*, 2008, Wu *et al.*, 2008). As such one would expect that farmers, foresters, and agronomists could benefit from operational assessment of crop canopy health status, abundance, and vigor using leaf pigmentation (chlorophyll assessment) as proxy. What is needed is a reduction of over-sampled, high dimensional spectral to multispectral and arguably more operational solutions.

Our results have shown strong relationships between soil nitrogen and leaf spectral indices across different site qualities (Table 4.2). Although the strength of correlations between leaf spectral indices and soil nitrogen content varied ( $0.37 \geq r \geq 0.85$ ), there seems to be an unequivocal link between forest foliage properties and the forest floor soil nutrients. These results were not wholly surprising, since Filella and Peñuelas (1994) showed that optimum leaf pigment content depends largely on the amount of nitrogen in the soil. Our results are also comparable to those from a study conducted by Albrechtová *et al.* (2008), where the authors examined the potential links between

spectral foliar data and the organic C and N of forest soils. Strong significant correlations ( $r > 0.65$ ,  $0.05 \leq p \leq 0.001$ ) between foliage chlorophyll content and forest floor dissolved organic carbon were obtained, with higher foliage chlorophyll content corresponding to lower forest floor dissolved organic carbon. Furthermore, variations within conifer sites between total chlorophyll content and forest floor water extractable dissolved organic carbon (WEDOC) and water extractable dissolved organic nitrogen (WEDON) were explained using strong and negative relationships ( $r = 0.42-0.99$ ). Aitkenhead-Peterson *et al.* (2006) also reported strong and negative correlations ( $r = 0.91$  and  $r = 0.72$ ;  $p < 0.05$ .) between foliar nitrogen and WEDOC and C: N ratio, respectively. In our study, the results further confirm that an increase in soil nutrient supply to plants results in an increase in essential foliar pigments and chemical constituents such as chlorophyll, nitrogen, etc. (Peñuelas *et al.*, 1994, Yoder and Pettigrew-Crosby, 1995, Kokaly, 2001), while a deficiency in soil nutrient content leads to a decrease in vital leaf pigments such as chlorophyll (Zhao *et al.*, 2005). Determination of soil nitrogen from leaf pigments will enable sound silvicultural decisions in terms of fertilizer application given the risk of over-fertilization and costs. These relationships can therefore be used to detect early nutrient deficiency before permanent growth-limiting physiological processes are visible to the naked eye. Given the significant nature of the relationships, the narrow band indices derived from hyperspectral remote sensing would thus enable timely interventions to combat nutrient stress in commercial forestry. This is underscored by the fact that we have reduced a high dimensional dataset to only a few spectral bands, thus enabling a more operational implementation.

As mentioned earlier, the site quality classification is based on total available water (TAW) in the soil profile which is a factor of effective rooting depth, soil type, rainfall, and temperature classes (Smith *et al.*, 2005). The ANOVA results suggested that there could be a miss-classification between medium-poor site qualities, since these classes went largely undetected when using the spectral indices. This implies that medium-poor site quality TAW could be similar or very close to one another and might require a re-evaluation of the site quality classification scheme. The model generated from spectral indices derived from continuum removed spectra (Figure 4.3) showed better results compared to the one developed from raw spectral reflectance

(Figure 2). The continuum removal model yielded a higher adjusted  $R^2$  value with a low PRESS static ( $R^2 = 85\%$ , PRESS =0.05) compared to raw spectral model ( $R^2 = 77\%$ , PRESS =0.07). These results from continuum removed model could be attributed to the ability of continuum removal to enhance and transform differences in shape of absorption features of interest (Kokaly and Clark, 1999, Mutanga *et al.*, 2004). Finally, the results of this study attest to the importance of hyperspectral remote sensing, specifically narrow-band sensing, in providing more rapid, scalable, and more affordable assessments of soil nutrient status than is possible with laboratory analysis. The potential for synoptic visualization of soil nitrogen status over large areas is evident when these results are extended to airborne sensors or much cheaper satellite imagery. This will contribute to (i) a better understanding of how different management operations over compartments alter soil nutrient status over time and (ii) quantification of site nutrient supply and demand. Further research is needed to study the temporal stability of the approach the impact of the soil nitrogen-leaf chlorophyll relationship on commercial forestry growth and yield, i.e. is growth of commercial forestry species dependent on this relationship? It should be noted that since the forest canopies varies with time, continuous monitoring of soil nitrogen over the entire growth period is required. This could be achieved by simulating the results of this study to much cheaper broad-band sensors (next chapter). The broad-band sensor's offers continuous simulated data which can be used to monitor soil nitrogen over the full rotation length of forest plantations.

#### **4.5. Conclusions**

Monitoring the biogeochemical status of forest ecosystems is a key component of assessing forest productivity and limiting management impacts on the surrounding environment in South Africa. This study has contributed to a better understanding regarding the health status of trees and the associated soil nitrogen content. It has been shown that there is a close relationship between leaf chlorophyll content, leaf spectral indices, and soil nitrogen in the visible region of the electromagnetic spectrum. Leaf chlorophyll, an indicator of photosynthesis activity, is of particular significance to precision agriculture and is a key component of forest productivity, health, and producing a sustainable yield. Hyperspectral remote sensing, specifically narrow-band remote sensing, has the potential to help address a key forest management challenge,



namely the determination of optimum fertilizer use without negative impacts on the surrounding environment. The dynamics of foliar-soil nutrients concentrations effectively can be assessed using a narrow-and multispectral approach and resultant outputs can feed into the management of plant-environment interactions. However, the extension of the approach through time and the impact of such leaf-soil relationships on commercial forestry health and sustainable growth and yield in South Africa require further research. It is only when we fully understand such interactions, their assessment, and can extend such assessments to synoptic platforms, that we will be able to operationally monitor forest management requirements and impacts at regional scales. The next chapter will investigate the feasibility of modelling forest structural attributes and soil nitrogen using spectroradiometric data resampled to simulate Landsat TM data. This is done based on the cheapness, free availability and capture frequency of broad-band sensors over the landscape.

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## CHAPTER 5

*Modelling forest structural attributes and soil nitrogen using spectroradiometric data resampled to simulate Landsat TM data*

This chapter is based on Mzinyane, T., Ahmed, F and Van Aardt, J. 2011. Modelling forest structural attributes and soil nitrogen using spectroradiometer data resampled to simulate Landsat TM data. *International Journal of Remote Sensing*. (Submitted)

## Abstract

Forest structural attributes and soil nutrients modelling over large tracts of commercial forestry is important for management and monitoring purposes. These attributes are closely linked to forest foliar chemical content. Estimations of forest foliar chemical contents over large areas would be expensive and cumbersome, given the costs of hyperspectral data and smaller swath widths of such datasets. This study attempted to resample hyperspectral data to broadband data and estimate forest structural and soil nitrogen under forest canopy. Volume and basal area were derived from field measurements of diameter at breast height (DBH) and tree height whilst soil nitrogen was obtained from laboratory analyses of soil samples collected at depths of 0.3-0.7m. Canopy spectral data were collected during the summer and fall of 2009 and were resampled to simulate the Landsat TM spectral characteristics. Pearson's correlations were used to assess the relationships between individual Landsat TM bands and volume, basal area and soil nitrogen. The models for estimations of volume, basal area and soil nitrogen were developed using only Landsat TM bands which exhibited significant correlations with volume, basal area and soil nitrogen. Cross-validation and model selection was based on adjusted  $R^2$  and low mean absolute error (MAE) and low Mallows Cp. Landsat TM bands (i.e., TM2, TM3, TM4, TM5) yielded significant ( $p < 0.05$ ) correlations with volume and soil nitrogen whilst basal area was significantly correlated ( $p < 0.05$ ) with all Landsat TM bands. The strength of the correlations TM3 and TM5 were found to be much higher than the relationships for other Landsat TM bands. A comparison between models developed from Landsat TM bands for future estimation of volume, basal area and soil nitrogen showed that soil nitrogen model had a superior goodness of fit statistic followed by basal area model and lastly volume model i.e., adjusted  $R^2 = 0.91$ , MAE = 0.030 % and 2.6.; adjusted  $R^2 = 0.77$ , MAE = 0.047 m<sup>2</sup> and Mallow's Cp of 4.4; adjusted  $R^2 = 0.645$ , MAE = 0.594 m<sup>3</sup>/ha and Mallow's Cp of 1.5 respectively. These results indicate that Landsat TM bands have the potential to estimate basal area and soil nitrogen with reasonable success and are not convincing for volume estimations. This has important implications for monitoring and controlling of fertiliser applications and basal area regional assessments.

Keywords: *Hyperspectral, Landsat TM, volume, basal area and soil nitrogen*

## 5.1. Introduction

Commercial forestry is important for economic purposes and social development in South Africa (DWAF, 2005). The economic return of commercial forestry is normally measured in terms of structural attributes such as merchantable volume, above ground biomass and stand density. These aspects of forest structure are important for characterization of ecosystem productivity and development (Smith *et al.*, 2008). An attempt to assess these forest structural attributes over vast tracts of forested lands would be virtually impossible and costly using manual or field-based methods (Jusoff and Malek, 2008, Roberts *et al.*, 2011). These assessment tasks and mapping of commercial forestry are further made difficult by the wide distribution and highly fragmented nature of forestry (Geldenhuys and Mucina, 2006). Although the field-based methods return acceptable accurate measurements (Owen, 2000), they are also known to lack continuous data obtained at a synoptic scale over large areas (Scurlock and Prince, 1993, Gower *et al.*, 1999, Jongschaap and Booij, 2004) i.e., they give point based measurements, are cumbersome, and may be costly in time and resources over large areas (von Gadow and Bredenkamp, 1992, Schreuder *et al.*, 1993, Avery and Burkhart, 2001).

An alternative to field-based methods would be remote sensing technologies which offer a more practical approach in forest conditions monitoring across different scales i.e., local, regional and global scales including places that are inaccessible during field campaigns (Norris-Rogers *et al.*, 2006, Tesfamichael *et al.*, 2008, Roberts *et al.*, 2008, Gebreslasie *et al.*, 2008). According to Jusoff and Malek, (2008), FAO, (2010), Pasher and King, (2010), neither of the methods can yield satisfactory results alone but a combination of remote sensing and limited field sampling can produce an excellent framework for field inventories and save on cost. Numerous studies have showcased the interaction of the two methods using either statistical methods or empirical algorithms (e.g., Castro *et al.*, 2003, Lu 2005, Hall *et al.*, 2006, Chubey *et al.*, 2006, Ozdemir, 2008). Detailed information extraction about forest structural attributes could only be obtained through suitable spectral and spatial resolutions of remote sensing sensors (Boyd and Danson, 2005). Recent advances in remote sensing technologies and sensors have enabled varying capabilities in vegetation studies thus facilitating rigorous advances in understanding overall ecosystem functioning, forest

survey, inventory and mapping (Rosenqvist *et al.*, 2003, Wang *et al.*, 2004, Chubey *et al.*, 2006, Pandey *et al.*, 2010). Some of the sensors e.g., Light Detection and Ranging (LIDAR), Radio Detection and Ranging (RADAR) exhibit higher success rate in structural attributes estimations (Tesfamichael *et al.*, 2009) whilst hyperspectral sensors are more capable for leaf and canopy biochemical assays studies (Mutanga and Skidmore, 2007, Abdel-Rahman *et al.*, 2008, Cho *et al.*, 2010, Mokhele *et al.*, 2010). The information about these biochemical assays is located in the plant foliage (Gindaba *et al.*, 2005). These biochemical assays are indicative of vegetation health, productivity and sustainable yields (Ismail *et al.*, 2008). A healthy commercial forest is indicative of well-maintained stands and compartments due to adequate silvicultural regimes applied throughout the plants' entire life (Chatziphilippidis and Spyroglou, 2004). Tracking contributions of foliage chemical bioassays to growth and yield of various vegetation types can now be quantified given the capabilities of sensors such as hyperspectral datasets. A review on hyperspectral sensors and their successful applications in foliar chemistry is well documented e.g., Majeke *et al.* (2008).

Although these sensors are valuable, they are also expensive considering the vast areas of commercial forestry in South Africa and in other countries. The costs and coverage of these sensors are envisaged to detract forest companies from investing in further research involving them, given that South Africa is a developing country. Innovative ways to operationalise and or apply the findings of research outputs using hyperspectral data in forestry are needed. One such way is to extend findings to large areas using other sensors with wider swath widths. Several techniques developed such as spectral resampling and statistics have shown reasonable success in vegetation studies. The premise, on which this resampling technique is based, is that field based hyperspectral data such as spectrometric data is resampled to match spectral characteristics of easily accessible or freely available sensors with large swath widths, such as Landsat TM, SPOT. Schlerf *et al.* (2005) resampled HyMap reflectance to Landsat TM channels in order to compare the estimates of forest stand variables i.e., leaf area index (LAI) and volume from both narrow band and broadband vegetation indices. Their main finding was that broadband multispectral data exhibited lower accuracy compared to hyperspectral data. Duan *et al.* (2007) assessed chlorophyll-a concentration for Lake Chagan using field spectral data resampled to Landsat TM channels and they obtained  $R^2 = 0.67$  using Landsat TM band ratio TM4/TM3. This

study aimed to investigate if hyperspectral data can be resampled to Landsat TM to (1) estimate forest structural attributes (2) infer soil nitrogen of the forest floor. In order to achieve these objectives, AISA spectral attributes were resampled to match spectral characteristics of Landsat TM.

## **5.2. Materials and methods**

### ***5.2.1. Study area***

The study was conducted in Richmond in the municipality of Sisonke in the Kwazulu-Natal province of South Africa (Figure 5.1). Soils in the area are characterized by fine sandy clay and humic topsoils that are underlain by yellow or red apedal subsoils. The topography of the study area is flat with undulating hills and is classified by Schulze (1997) as being low mountains. Temperatures range from high 20°C values in summer to below 10°C in the winter. The area is regarded as a *Moist Midlands Mistbelt* and has favourable climate and high percentage of arable land. Altitude ranges from 300-2100m above sea level, with an average of approximately 850m. The area is prone to summer rainfall with cold, dry winters and warm, wet summers, with an annual rainfall ranging from 800-1280mm and a mean annual temperature of 17°C (Camp, 1997, Schulze 1997). Plantation forestry dominates the land use in the area, with species from the *Eucalyptus* and *Pinus* genera primarily grown.

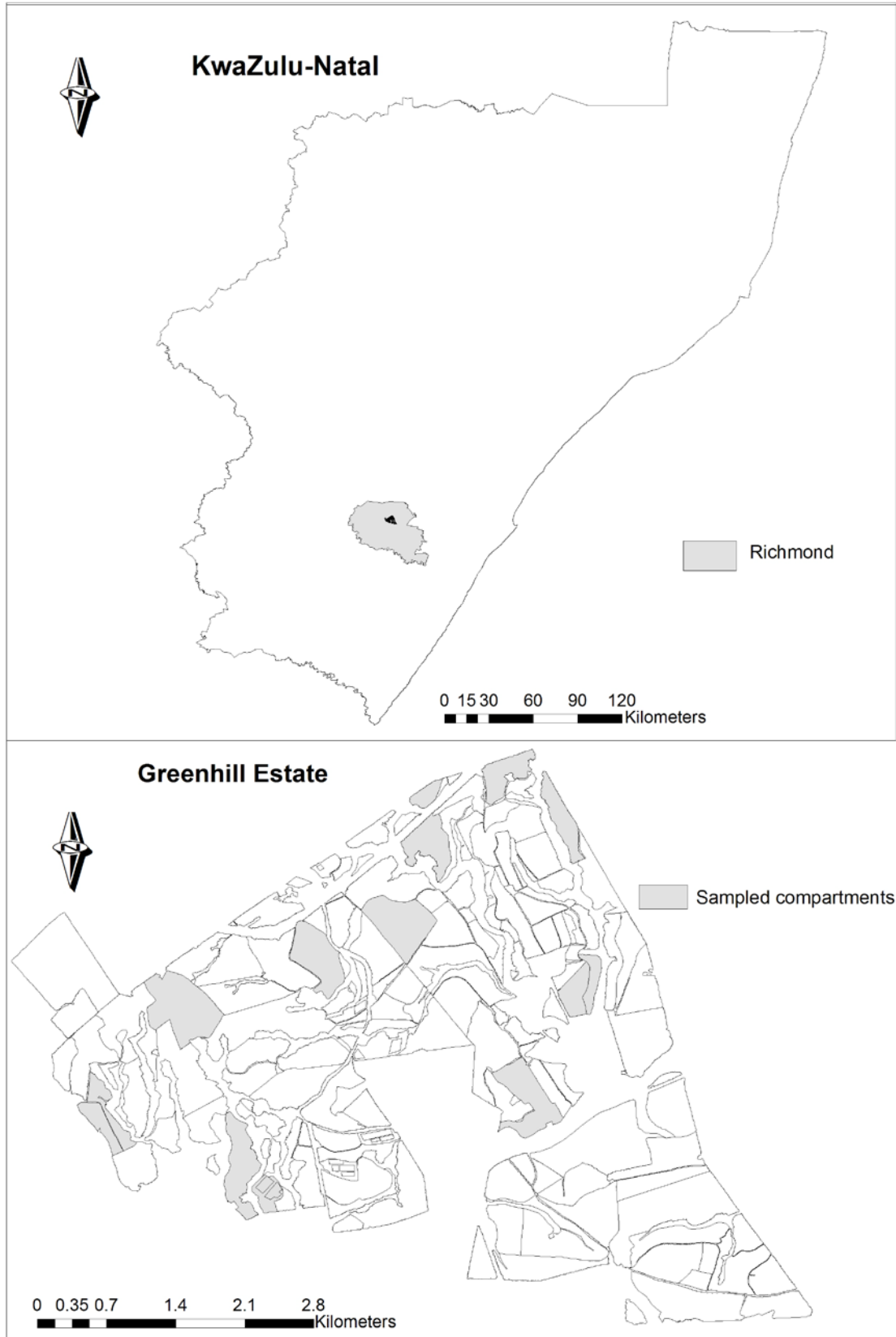


Figure 5.1: Map of the study area

### 5.2.2. Field measurements

The Geographic Information System (GIS) database of forest compartments, provided by Mondi-SA, was consulted in order to select stands of interest. The field data collection coincided with the overpass of Landsat TM. Site selection was based on spatial location, extent, age, felling dates, site index, and site productivity; an effort was made to select forest compartments on good, medium, and poor site productivity or quality. Plot locations were located in the field using a hand held sub-meter differential Global Positioning System (GPS). The number of plots per site quality within the compartment was determined based on the size of the compartment. 20m by 20m square plots were established and inventory measurements collected, namely diameter at breast height (*dbh*) and tree height (*tht*). All trees with a *dbh*  $\geq$  5cm were measured within each plot, while heights were measured for only a sub-sample of trees based on the *dbh* distribution of trees within the plot. Trees that appeared to be damaged, dead, or dying were excluded from the enumeration process, given that the commercial forest industry rarely includes such trees in their accounting scheme.

### 5.2.3. Volume and Basal area measurement

Trees across the range of the *dbh* values were selected for height measurement, thereby ensuring a representative sample of the entire *dbh* range. Tree height was measured on a sample of trees using a Vertex III hypsometer<sup>®</sup> (Haglöf, Sweden). Relationships between *dbh* and corresponding heights were established at plot-level and based on site quality using regression analysis.  $R^2$  values above 80% were observed for the majority of plots. Heights of all trees within a plot were then estimated using the resultant *dbh* -height regression equations developed within each plot. The variability in tree volume is mostly explained by tree height and *dbh* forest attributes (Avery and Burkhart, 2001). Thus, when these attributes are known for individual trees, volume can be calculated for each tree. The volume function based on the Schumacher and Hall form (1933) was used in this study (Equation 1).

$$\ln(V) = b_0 + b_1 \ln(DBH + f) + b_2 \ln(H), \quad 1$$

Where  $V$  is utilisable volume ( $m^3$ ), *dbh* is diameter at breast height at 1.3m (cm over bark),  $H$  is tree height (m), and  $f$  is a correction factor. Coefficients  $b_0$ ,  $b_1$ , and  $b_2$

used for this equation were those published in the South African Forestry Handbook (Bredenkamp, 2000). Plot-level volume was derived by summing the volume of individual trees. Basal area was derived using equation 2 below. These equations are standard formulae used by commercial forest companies in South Africa.

$$BA = \frac{\pi}{4} \sum_{i=1}^n DBH^2 \quad 2$$

The aggregates of volume and basal area were then converted to a hectare scale based on the area of a plot. A statistical summary of the measured volume and basal area is shown in Table 5.1.

Table 5.1. Descriptive statistics for plot-level volume (m<sup>3</sup>) and basal area (m<sup>2</sup>)

Variable	Minimum	Maximum	Mean	Std. Dev	N
Volume	0.453	4.096	1.738	1.2763	33
Basal Area	0.029	0.298	0.131	0.0586	33

#### **5.2.4. Soil measurements and chemical analysis**

Soil samples were taken at depths of 0.3-0.7 m using a soil auger for the three different quality sites. These depths were selected because the study area contains shallow soils. The soil samples were taken at opposite directions from the centre tree in a 20 by 20m plot, approximately 1.5 meters away from the base of the centre tree and diagonally (i.e. North, South, East and West) across centre tree. The values were averaged for each compartment to serve as an overall description of the compartments. A total of 57 soil samples were collected and transported back to the laboratory for nitrogen determination. The Kjeldahl method was used for soil nitrogen determination (Bremner and Mulvaney, 1982).

#### **5.3. Remote sensing data**

Tree climbers gathered leaf samples from the sunlit branches within the different site qualities, i.e., good, medium, and poor. Leaf spectra of *E.grandis* were acquired at geo-referenced points using an ASD spectrometer (Fieldspec3 Pro) fitted with a 25° field of view bare fibre optic (Analytical Spectral Devices, Boulder, CO). The sampling interval over the 350–1050 nm range is 1.4 nm with a spectral resolution



(full bandwidth at half maximum) of 3 nm. Over the 1050–2500 nm range, the sampling interval is 2 nm and the spectral resolution is between 10 nm and 12 nm (Analytical Spectral Devices, 2002). Measurements were taken during cloud free periods, between 10h00 and 14h00 to minimise the change in illumination conditions. Radiance measurements were converted to target reflectance using a calibrated white spectralon panel on the leaf clip. Reflectance measurements were taken by averaging 40 scans with a dark current correction at every spectral measurement. Approximately 30-40 sunlit leaf samples were collected for leaf spectral and chlorophyll measurements.

### ***5.3.1. Landsat TM imagery pre-processing***

The Landsat TM imagery acquired on March 2009 consisted of seven bands ranging in wavelength from 0.45 micrometer ( $\mu$ ) to 2.35  $\mu$  with four of the bands falling in the infrared part of the spectrum. The imagery was already referenced and in the correct coordinates system i.e., (WGS 84 with Gauss Conform projection at longitude of 31°E), but further geometric corrections were still needed. The imagery was georeferenced using a 10 m spatial resolution digital terrain model and ground control points (GCPs) of water bodies, rocky outcrops, tar roads and road intersections digitized from a 1:50 000 topographical map. A nearest neighbour resampling technique was used and an overall total root mean square error (RMSE) of 1.74 was obtained.

Atmospheric correction was undertaken using the Fast Line of Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) algorithm (Mezned *et al.*, 2010) using a standard mid-latitude summer atmospheric model in conjunction with a rural aerosol model. The ASD field spectra were spectrally simulated to the spectral configuration of the Landsat TM sensor using the ENVI (Environment for visualizing images, Research Systems, Inc.) software, assuming no atmospheric effects in the Landsat TM. The method uses a Gaussian model with a full width at half maximum (FWHM) equal to the band spacing's provided. This method is well defined number which is used to compare the quality of images under different resolutions. The main aim of simulation was to produce lower-spatial-resolution images from high-spatial-resolution hyperspectral images that are comparable spectrally to the original images.

The spectral response functions of Landsat TM were used in the simulation in ENVI software.

### **5.3.2. Statistical analysis**

The data analysis was conducted using two statistical packages, *viz.* SPSS version 18 and Statistica version 6. The analysis was undertaken using both the original Landsat TM datasets and the simulated datasets. The aim of this study was to estimate forest structural attributes and soil nitrogen under forest canopy from Landsat TM simulated datasets and compare the models developed to original Landsat TM bands. A correlation analysis was undertaken to assess the correlation strengths and significance between volume, basal area, soil nitrogen and both original Landsat TM bands and Landsat TM simulated bands *i.e.*, (Pearson's correlation coefficient  $r$  values are reported as a measure of relationship strength between the variables). The Landsat TM bands which exhibited significant correlations with volume, basal area and soil nitrogen were further used to in stepwise-backward regression approach to identify models that best explained variance in volume, basal area and soil nitrogen. In this study two techniques were tested, namely cross-validation (Efron, 1982) and model selection based on the highest adjusted  $R^2$  and lowest Mallows' Cp statistic. Mallows' Cp is a measure of the bias in a model, based on a comparison of total mean squared error to the true error variance. We report on the mean absolute error (MAE) of the models instead of root mean square error (RMSE). According to Willmott and Matsuura, (2005) MAE is a natural measure of error compared to RMSE.

### **5.3.3. Comparison of the model developed from Landsat TM and simulated Landsat TM bands**

The models developed from the original Landsat TM bands were compared to the models developed from the simulated data. This was done to test if the atmospheric obscurities had an impact on the models developed from both datasets *i.e.*, original Landsat TM data and simulated data. The models comparisons was based on the adjusted  $R^2$  values

### 5.3. Results

#### *5.3.1. Relationships between volume, basal area, soil nitrogen, Landsat TM bands and simulated Landsat TM bands*

The correlations between simulated Landsat TM bands and volume, basal area and soil nitrogen were all positive and as shown in Table 5.2. From the table, it can be seen that simulated Landsat TM bands except for band 7 yielded significant correlations ( $p < 0.05$ ) with volume. For the original Landsat TM bands, only TM4 correlated significantly ( $p < 0.05$ ) with volume (Table 5.3). The strength of correlations for the simulated Landsat TM bands varies between 0.38 and 0.59 i.e.,  $0.38 \leq r \leq 0.59$ , whilst original TM4 band returned a negative correlation i.e.,  $r = -0.37$ . On comparison amongst the simulated Landsat bands, band 5 performed the strongest ( $r = 0.59$ ) than other bands followed by band 3 ( $r = 0.52$ ), band 4 ( $r = 0.41$ ) and band 2 ( $r = 0.38$ ).

The comparison of the strength of basal area correlations with simulated Landsat TM bands and original Landsat TM bands indicates that simulated bands exhibited higher strength of correlations compared to original Landsat bands i.e.,  $0.37 \leq r \leq 0.80$ , compared to  $-0.29 \leq r \leq 0.36$ . The strength of performance for basal area- simulated Landsat TM bands correlation was observed to be much higher than that of volume with the same bands. All simulated Landsat TM bands correlated significantly ( $p < 0.05$ ) with basal area and Band 5 exhibited a stronger correlation strength  $r > 0.70$  with basal area. Other bands (2, 3, 4) yielded moderate correlation strengths ( $r = 0.55, 0.60, 0.68$ , respectively) whilst band 7 showed weaker significant correlation strength  $r = 0.37$  with basal area. Landsat TM band 5 from original dataset exhibited a much stronger correlation  $r = 0.36$  compared to TM1 ( $r = 0.22$ ) and TM 4 ( $r = -0.29$ )

Soil nitrogen correlated significantly ( $p < 0.05$ ) with simulated Landsat TM bands 2, 3, 4 and 5 but Band 7, which yielded non-significant correlation with soil nitrogen. Bands 1, 4 and 4 from the original dataset correlated significantly ( $p < 0.05$ ) with correlation strength ranging between 0.30 to 0.42). The strength of correlation between soil nitrogen and simulated Landsat bands ranged from moderate to high

strength i.e.,  $0.55 \leq r \leq 0.85$ , with band 5 the highest followed by band 3, band 4 and lastly band 2. The correlation strengths of soil nitrogen- simulated Landsat TM bands and basal area-Landsat TM bands were almost in the same low range but differ on the high range. Examining individual simulated bands performance with forest variables i.e., volume, basal area and soil nitrogen, TM2 had higher significant ( $p < 0.05$ ) correlations with basal area and soil nitrogen ( $r > 0.50$ ) than with volume ( $r = 0.38$ ). From the original Landsat TM datasets, TM4 had higher significant ( $p < 0.05$ ) correlations with volume ( $r = 0.42$ ) than with basal area and soil nitrogen ( $-0.37 \leq r \leq -0.29$ ). The correlations strength trends for TM3 and TM5 show that soil nitrogen correlates significantly better than basal area and volume, respectively. TM4 yielded stronger significant correlations with basal area, soil nitrogen and volume in that hierarchical order. TM7 had non-significant correlations with both volume and soil nitrogen and weak significant correlation with basal area.

Table 5. 2. Correlations between Landsat TM simulated bands and volume, basal area and soil nitrogen

<b>Variables/Landsat TM Bands</b>	<b>TM2</b>	<b>TM3</b>	<b>TM4</b>	<b>TM5</b>	<b>TM7</b>
Volume	0.38*	0.52*	0.41*	0.59*	ns
Basal Area	0.55*	0.60*	0.68*	0.80*	0.37*
Soil Nitrogen	0.55*	0.75*	0.58*	0.85*	ns

$\alpha < 0.05$

Table 5. 3. Correlations between Landsat TM and volume, basal area and soil nitrogen

<b>Variables / Landsat TM bands</b>	<b>TM1</b>	<b>TM2</b>	<b>TM3</b>	<b>TM4</b>	<b>TM5</b>	<b>TM7</b>
Volume	ns	ns	ns	-0.37*	ns	ns
Basal Area	0.22*	ns	ns	-0.29*	0.36*	ns
Soil Nitrogen	0.30*	ns	ns	0.42*	0.38*	ns

$\alpha < 0.05$

**5.3.2. Developing predictive models for volume, basal area and soil nitrogen estimations through simulated Landsat TM bands and original Landsat TM bands.**

- Simulated Landsat bands

The results of multiple regression approach using the stepwise backward method are shown in Table 5.4. The selection procedure was based on the Landsat TM bands which gave the best regression results in terms of adjusted  $R^2$  and mean absolute error and Mallows Cp (table 5.4). The variability in volume and soil nitrogen was explained by two Landsat TM bands i.e., TM 4 and TM5 whilst four Landsat TM bands i.e., TM 3, TM4, TM5 and TM7 explained variability in basal area. These Landsat TM bands had significant ( $p < 0.05$ ) contributions in the building of models therefore there was no need to simplify the models further. The predicted vs. observed plots for volume, basal area and soil nitrogen; yielded positive significant ( $p < 0.01$ ) linear relationships, as shown in figures 5.2, 5.3 and 5.4. Volume model exhibited adjusted  $R^2$  value of 64% with a mean absolute error of 0.594  $m^3/ha$  and Cp Mallow of 1.5, whilst basal area model had an adjusted  $R^2$  value of 77%, mean absolute error of 0.047  $m^2$  and Cp Mallow of 4.4 and soil nitrogen model had a superior goodness of fit statistic i.e., adjusted  $R^2 = 0.91$ , with a mean absolute error of 0.030 % and Cp Mallow of 2.6.

Table 5.4 Mean absolute error, adjusted  $R^2$  and Mallows Cp computed for all Landsat TM band combinations in estimation volume, basal area and soil nitrogen

<b>Variable</b>	<b>MAE</b>	<b>Adj.R2</b>	<b>Cp</b>	<b>Landsat Bands</b>
Volume ( $m^3/ha$ )	0.594	64%	1.5	TM4 and TM5
Basal area ( $m^2$ )	0.047	77%	4.4	TM3, TM4, TM5 and TM7
Soil nitrogen (%)	0.03	91%	2.6	TM4 and TM5

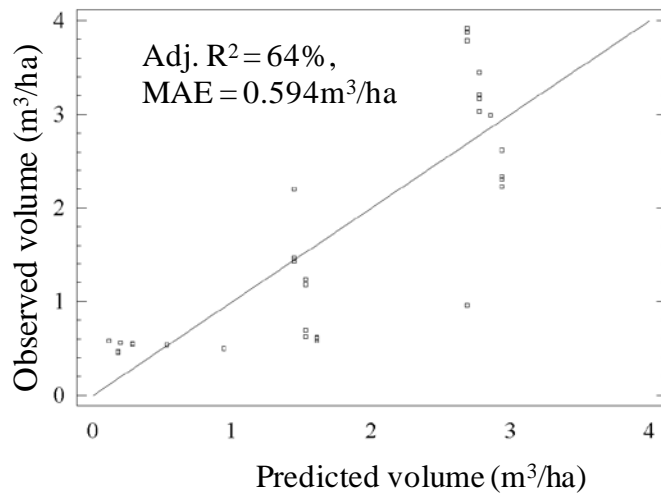


Figure 5.2. Observed and predicted volume model based on Landsat TM

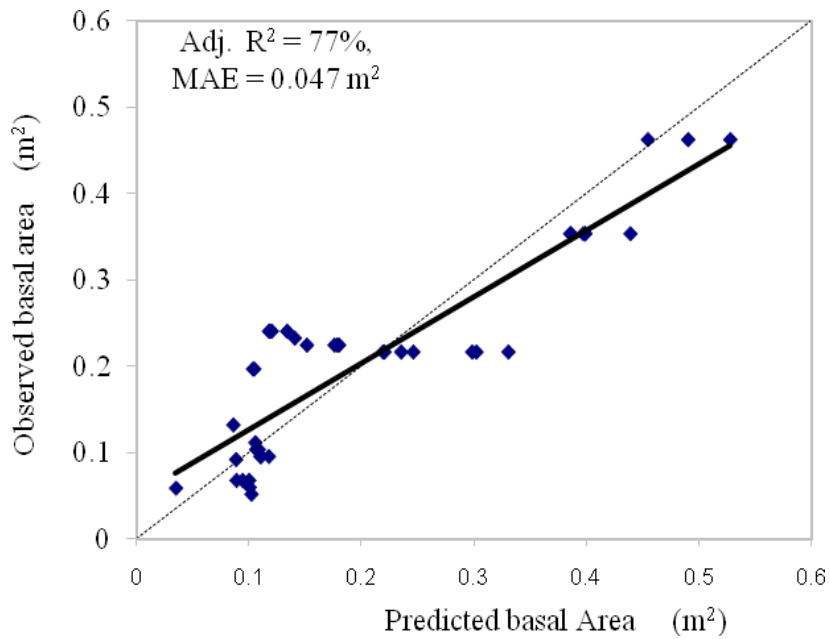


Figure 5.3. Observed and predicted basal area model based on Landsat TM

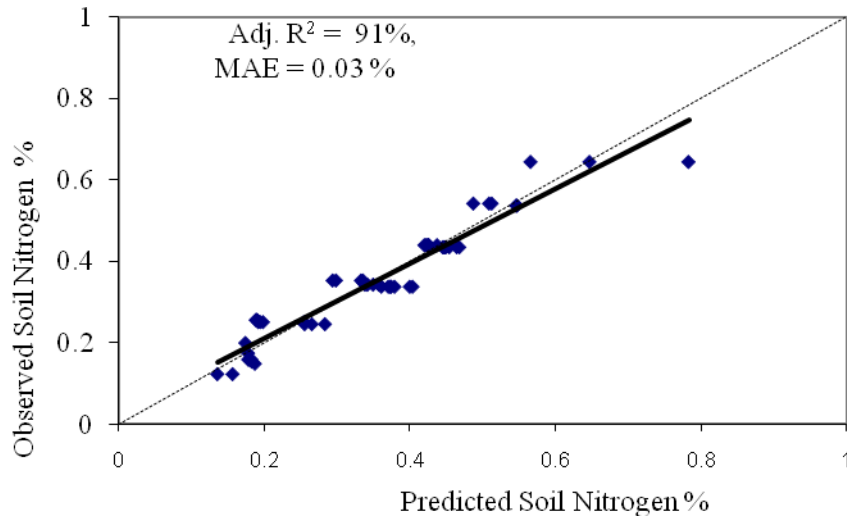


Figure 5.4. Observed and predicted soil nitrogen model based on Landsat TM

- Original Landsat TM bands

Table 5.5. shows the results of multiple regression approach using the stepwise backward method. The best regression results in terms of adjusted R<sup>2</sup> and mean absolute error and Mallows Cp are reported (table 5.5). The variability in volume was explained by Landsat TM band 4, whilst three Landsat TM bands i.e., TM 1, TM4 and TM5 explained variability in basal area and soil nitrogen. The predicted vs. observed plots for volume, basal area and soil nitrogen; yielded positive significant ( $p < 0.01$ ) linear relationships, as shown in figures 5.5, 5.6 and 5.7. Volume model exhibited a low adjusted R<sup>2</sup> value of 13% with a mean absolute error of 0.0246 m<sup>3</sup>/ha and Cp Mallow of 2.3, whilst basal area model had an adjusted R<sup>2</sup> value of 47%, mean absolute error of 0.0325 m<sup>2</sup> and Cp Mallow of 2 and soil nitrogen model returned an adjusted R<sup>2</sup> = 0.50, with a mean absolute error of 0.047 and Cp Mallow of 3.2.

Table 5.5 Mean absolute error, adjusted R<sup>2</sup> and Mallows Cp computed for all Landsat TM band combinations in estimation volume, basal area and soil nitrogen

Variable	MAE	Adj.R2	Cp	Landsat Bands
Volume (m <sup>3</sup> /ha)	0.0246	13%	2.3	TM4
Basal area (m <sup>2</sup> )	0.0325	47%	2	TM1, TM4 and TM5
Soil nitrogen (%)	0.0470	50%	3.2	TM1, TM4 and TM5

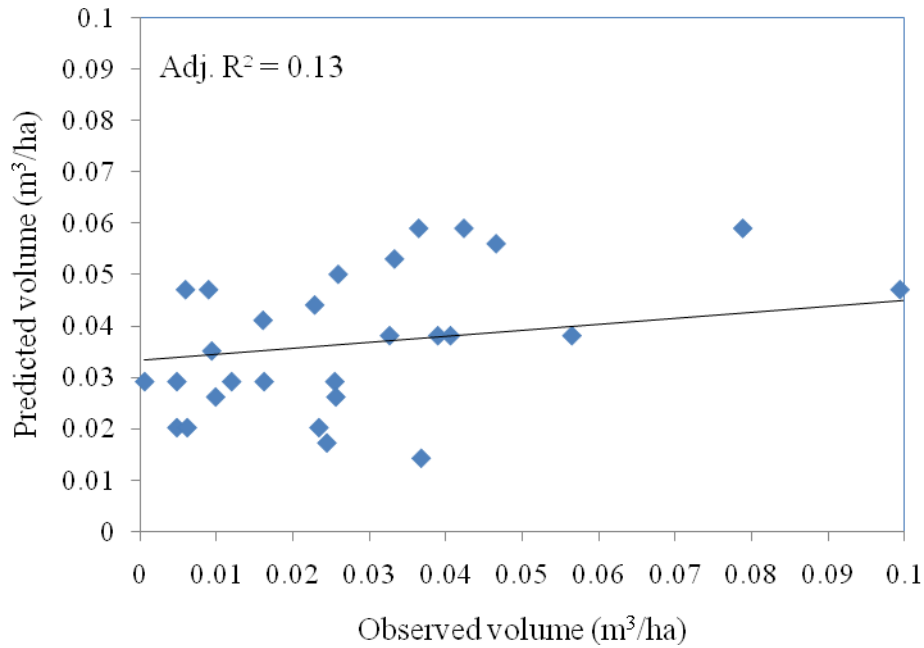


Figure 5.5. Observed and predicted volume model based on Landsat TM

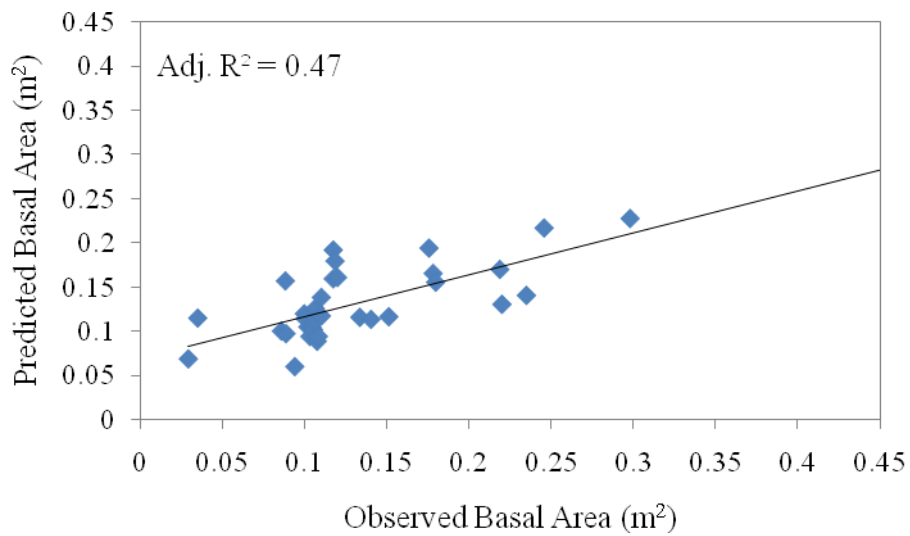


Figure 5.6. Observed and predicted basal area model based on Landsat TM



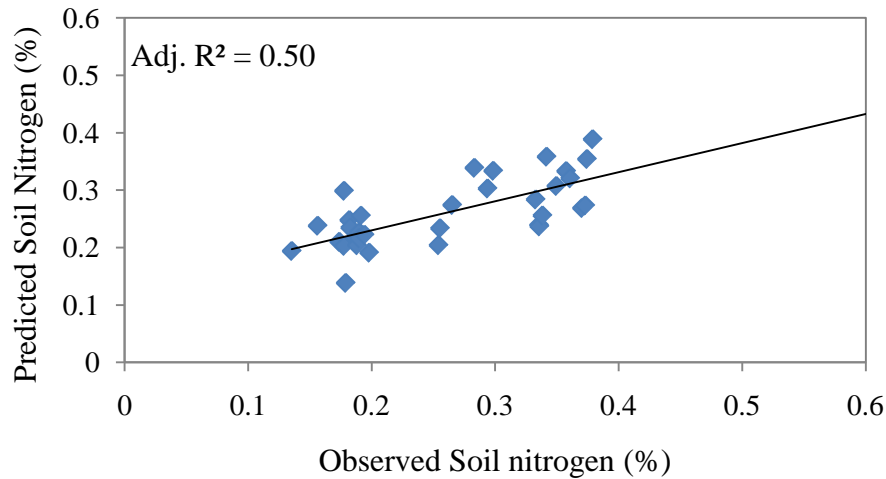


Figure 5.7: Observed and predicted soil nitrogen model based on Landsat TM

#### 5.4. Discussion

The possibility of obtaining much quicker estimates of forest structural attributes and soil chemistry using remote sensing techniques is attractive for scientific and practical purposes. This is especially true for commercial forest plantations given the vast hectares they occupy and in areas that are not easily accessible (Maselli and Chiesi, 2006, Tesfamichael *et al.*, 2009). More specifically, their ability to provide techniques such as spectral resampling helps downscale from higher spectral resolutions datasets to lower spectral resolutions datasets. The purpose would be to cover larger areas since it is widely acknowledged that different sensors have different swath widths and capabilities. This study aimed to investigate if the ASD data resampled to simulate Landsat TM can be able to (1) estimate forest structural attributes (2) can be used to infer soil nitrogen of the forest floor. The objective was to determine if the simulated Landsat TM bands can produce models with acceptable accuracy compared to raw Landsat TM bands.

The correlation analyses undertaken using simulated datasets and original Landsat datasets provided descriptive information on the strength of each band in relation to volume, basal area and soil nitrogen as shown in table 5.2 and 5.3. The relationships derived from simulated datasets, are such that among Landsat spectral values, mid-

infrared spectral range (TM5) consistently returned stronger (positive) correlation compared to green (TM2), red (TM3) and near-infrared (TM4) spectral regions. This was surprising because TM5 is known to be more suitable for vegetation moisture content determination (Hunt and Rock, 1989). Similar results were reported elsewhere e.g., Ingram *et al.* (2005) found basal area to be negatively correlated with spectral reflectance (i.e.,  $r = -0.77$ ,  $p < 0.01$ : middle-infrared band) and stand density returned a weak relationship density ( $r = -0.21$ ,  $p < 0.01$ ) with spectral response of the red band. Schlerf *et al.* (2005) obtained strong negative and positive correlations between TM4 and forest variables such as leaf area index, stem density, canopy closure, perimeter at breast height, stem biomass and stand height. Landsat TM5 band from original dataset exhibited higher correlations (positive and negative) compared TM4, TM3 and TM2.

The lack of strong correlations i.e.,  $r > 0.80$  of green, red and infra-red spectral bands with forest attributes was a cause for concern given that these bands are considered optimal for vegetation analysis. The plausible explanations that could be advanced is that the compartments had reached full canopy at the time of field data collection meaning that leaf area index was a high leaf area index causing these bands to saturate (Mutanga and Skidmore, 2004). Also the timing of field data collection (summer) could have affected the amount of leaf water content at the time of field data collection. Despite the weaker correlations exhibited by green, red and infra-red spectral bands, it was encouraging to note that these bands managed to detect the amount of nitrogen in the soil under forest canopy. These regions are known to represent vegetation greenness which in turn would be indicative of a plant response to silvicultural practices such as fertiliser and normally such responses manifest on the plant foliage (Jokela *et al.*, 1988).

The performance of regression models (i.e., from simulated datasets) based on the cross-validation procedure used to assess the prediction power of regression models, indicate that whilst there appears to be some reasonable potential for mapping basal area and soil nitrogen ( $R^2 = 91\%$  and  $77\%$ , respectively), an uncertainty exists for future volume predictions due to lower coefficient of determination ( $R^2 = 64\%$ ) and higher mean absolute error (MAE = 0.594). This uncertainty is actually consistent with Landsat TM saturation characteristic and has been reported elsewhere (Steininger, 2000). The simulated models performed better than the original Landsat

TM dataset. The coefficient of determination for simulated volume, basal area and soil nitrogen models were 64 %, 77% and 91% compared to 13%, 47% and 50% returned by original Landsat TM datasets, respectively. This is consistent with other results reported elsewhere e.g., Schlerf *et al.* (2005) and Duan *et al.* (2007). Since this is the first resampling attempt in South Africa, a conclusion that can be drawn from these results is that Landsat TM datasets are not suitable for forest structural attributes estimations due to problems of saturation at certain biomass levels. Only simulated results are report henceforth.

Linear combinations of simulated Landsat TM bands 4 and 5 explained more variance in volume and soil nitrogen than other combinations of simulated bands, whilst bands 3,4,5 and 7 explained more variance in basal area. The significant relationship at the 95% probability level, adjusted  $R^2$ , MAE and Mallow's Cp all demonstrate the relative applicability of the method to estimate volume, basal area and soil nitrogen using hyperspectral data resampled to Landsat TM spectral configurations in the study area.  $R^2$  values obtained for volume and basal area in this study were higher than the ones reported elsewhere e.g., Maselli *et al.* (2005) ( $R^2 = 59\%$  for Basal area), Trotter *et al.*, 1997 and Hall *et al.*, 2006 ( $R^2 = 30\%$  in both cases). Unfortunately, soil nitrogen  $R^2$  values could not be comparable to other study because there is little done on soil nitrogen using Landsat TM. Other studies have reported promising coefficients of determinations using Landsat TM e.g., Lu, (2005) obtained an  $R^2$  value of 76% for above ground biomass for tropical forest in Brazilian Amazon area, whilst Jensen and Binford, (2004) used multiple regression to estimate LAI from Landsat ETM+ with an  $R^2$  of 0.83%. These studies highlight the differences in geographic settings of various study sites and level of management on forest sites and that will have a major impact on the relationships between forest structural attributes and remote sensing data. Overall, Landsat Thematic Mapper (TM) have been shown to yield stronger predictions of certain forest structural features comparable to other sensors (Lefsky *et al.*, 2001, Ingram *et al.*, 2005).

## **5.5. Conclusions**

Timely information on forest structural and soil nutrient characteristics is a premium requirement for optimally managing South African commercial forestry resources. In

this study, we assessed the relationship between resampled hyperspectral data to reflectance data contained in the Landsat TM bands and forest stand structural and soil nitrogen characteristics through multivariate regression analyses. Statistically significant relationships were obtained between volume, basal area and soil nitrogen and corresponding reflectance values recorded by the Landsat TM sensor. The models generated for volume, basal area and soil nitrogen estimations can be applied to the study area and there is a need for testing these model coefficients to larger areas using tiled scenes. We conclude that hyperspectral data simulated to Landsat TM data provide useful platform to estimate forest volume, basal area and soil nitrogen. The next chapter provides a synthesis of the whole study i.e., the research findings of the individual chapters will be brought into perspective as a synthesis.

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## CHAPTER 6

A quantitative assessment of the impacts of leaf water content and chemical bioassays on structural attributes of *Eucalyptus* clones and plantation soil nitrogen using hyperspectral data: A Synthesis.

## 6.1 Introduction

Forests are globally important for human survival and enterprise and South Africa is no exception. However, many of these forests are under threats which could lead to degradation or extinction in extreme cases in the near future. Factors such as climate change will have reductive effects on yields and growths of these forest resources. Given the changes that would be brought about by these factors, forest inventory data will need to be updated periodically to track such changes and hence manage forest resources sustainably and consistently. In South Africa, prediction of growth and yield of commercial forestry have relied on the use of empirical models derived from field enumerated variables, such as DBH and height. Although these empirical models are known for their ability to result in accurate predictions with good precision, such assessments typically occur under static climatic conditions. They therefore lack flexibility in predicting growth under fluctuating weather conditions and are insensitive to major influential factors which influence growth rates, such as management strategies and environmental factors (e.g., rainfall) (Esprey, 2005).

Traditional field-based methods would be virtually impossible to undertake if the changes to growth and yields due to natural phenomena are to be quantified. This is further compounded by the vast areas of forested lands, some of which is impossible to access. Current and/or future anticipated remote sensing techniques offer a feasible solution to tracking such changes due to synoptic, timely, and repeated data collection capabilities (Jensen *et al.*, 1989). It must however be noted that the combination of remote sensing with minimal field data collection is the preferred manner to track such changes (FAO, 2010). Various factors such as economic, spectral, spatial, and radiometric resolution mostly affect the selection of remotely sensed data to be used. Despite these challenges, the success stories of remote sensing applications in forest and vegetation related studies are well documented worldwide, e.g., Mutanga and Skidmore, (2004), Ingram *et al.* (2005), Zarco-Tejada and Sepulcre-Cantó, 2007, Cho *et al.* (2009), and many more. These and other studies provide an indication of the capabilities of different sensors in various forest environments. The continual development of hyperspectral sensors has enabled leaf and canopy chemical attributes estimations (see Majeke *et al.*, 2008 for a review of hyperspectral studies). Such

information is important in many ways, e.g., it could provide vital information about the current status of the plant (in this case, forestry) and provide indicators of any disturbance which might hinder growth before being visible to the naked eye. This information could then be used to monitor the effects of global warming and climate change and associated changes in growths and yields. According to Louw (2003), an efficient prediction of growth and yields information underpins sustainable management of forest resources and decision making processes

Although a plethora of studies have attempted to estimate leaf chlorophyll, nitrogen, lignin, cellulose, and other leaf chemical constituents from the leaf spectral response using hyperspectral data, little or no work has been done to establish the extent of the relationship between leaf chemical attributes as estimated through hyperspectral data and forest growth or structural attributes. These attributes include volume and basal area and soil nutrients in South Africa. The leaf spectral response of a forest is known to be indirectly affected by the forest structural attributes such as diameter at breast height, height, and biomass (Lefsky *et al.*, 1999), while growth is an indirect indicator of a plant response to fertilizer (Stovall *et al.*, 2011). The aim in this study was to assess the impacts of water content and chemical bioassays such as chlorophyll and nitrogen on growth of *Eucalyptus* clones using hyperspectral remote sensing. The pertinent questions that this study attempted to answer were:

- Is the spectral reflectance of forest canopy strongly related to growth and yield, as affected by water status, leaf chlorophyll and nitrogen contents?
- Can leaf chlorophyll content be used to infer soil nitrogen status?
- Can hyperspectral data be downscaled to multispectral data to address the above pertinent questions?

### **6.1.1 Is the spectral reflectance of forest canopy strongly related to growth and yield, as affected by leaf water content, leaf chlorophyll and nitrogen contents?**

The plant foliar chemical composition is one of the most important forest characteristics, because it captures most of the radiant energy needed for photosynthesis (Danson and Steven, 1992). Most of the information about the ecosystem would therefore be correlated to the status of plant leaves. Prior to

advances in science, most inspection of current plant condition were through visual inspection techniques. There would always be drawbacks to visual inspection, since it is dependent on the interpreter skill and the degree of damage on the leaves. The progression of remote sensing science through the years saw the emergence of techniques such as hyperspectral remote sensing or imaging spectroscopy, which have vastly improved the assessments of the immediate status of the plants. The immediate status of a plant can be monitored using leaf spectral properties related to physiological estimates of chlorophyll, water, dry matter, and nitrogen (Zarco-Tejada and Sepulcre-Cantó, 2007). The results obtained in this study further add to the body of knowledge, since very little has been done in linking leaf chemical bioassays to growth, even though it is a “known” fact that leaf chemistry is linked to plant growth. Significant correlations ( $p < 0.05$ ) were obtained between volume and leaf chlorophyll, nitrogen, and water content indices (Table 6.1). These indices were also significantly influenced by age, site quality, and clone type, thus indicating that leaf spectral characteristics of *Eucalyptus* clones differ by age and site quality, i.e., good, medium, and poor site qualifications.

Table 6.1. Summary of correlations results between volume and spectral vegetation indices for two *Eucalyptus* clones and a general species group

<b>Index</b>	<b><i>E. grandis</i></b>	<b><i>E. saligna</i></b>	<b>All clones</b>
Red edge	0.52*	0.91*	0.69*
Vogelmann	0.59*	0.95*	0.70*
Tcari /Osavi	0.67*	0.97*	0.82*
NDNI	0.66*	0.92*	0.80*
NDRE	0.57*	0.93*	0.69*
NRI	0.67*	0.95*	0.84*
WI	0.69*	0.93*	0.78*
MSI	0.62*	0.93*	0.77*
Datt 1	0.67*	0.94*	0.80*
Datt 2	0.62*	0.97*	0.88*
NDWI	0.49*	0.92*	0.64*

Based on these significant correlations between the spectral indices and volume, models were developed for *Eucalyptus grandis* volume estimation. It was observed that volume models, without factoring ancillary data such as age and site index, yielded low adjusted  $R^2$  values with high root mean square errors (RMSE), e.g.,  $R^2 =$

0.47 and RMSE of 0.055 m<sup>3</sup>/ha, p<0.0001. This R<sup>2</sup> value was deemed as weak and it could not be used operationally to estimate volume in Richmond, KwaZulu-Natal. Readily available ancillary data were then factored in the model to evaluate if there could be an improvement. This was done because a study in the same area using ASTER data to estimate forest structural attributes came to a conclusion that the models were improved when factoring in the ancillary data (Gebreslasie *et al.*, 2010). The model did exhibit a much improved R<sup>2</sup> value with a low RMSE i.e., R<sup>2</sup> = 0.78 and RMSE =0.0176 m<sup>3</sup>/ha (p<0.0001) after incorporating ancillary data. The general model that was developed to estimate volume yielded a positive significant (p<0.001) linear relationship with an adjusted R<sup>2</sup> value of 0.81 and comparably low RMSE of 0.0176m<sup>3</sup>/ha (Figure 6.1)

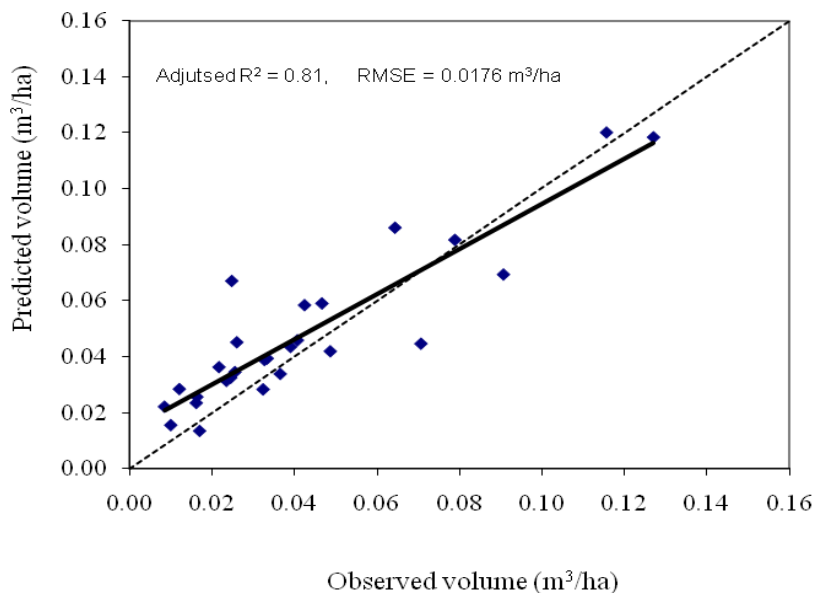


Figure 6.1 Observed vs. predicted volume of from the general *Eucalyptus* clone model

On the basis of these results, we concluded that significant potential exists to use leaf spectral measurements of chlorophyll, nitrogen, and water content as independent variables for estimation of merchantable volume of *Eucalyptus* clones in KwaZulu-Natal, when used in conjunction with ancillary data, and that such an approach potentially could be extended to airborne data and regional assessments.

Leaf-level spectral measurements were subsequently expanded to include canopy-level measurements using the Airborne Imaging Spectrometer for Applications (AISA). A decision was taken to include another forest structural attribute in the analysis, namely basal area. It was in this study that chlorophyll, nitrogen, and water content indices explained above 65% of the variance in volume, while these variables also explained more than 60% of the variance in basal area, except for the water band index and Vogelmann red edge index. The accuracy of correlations between the forest structural attributes and indices was tested using bootstrapping techniques. Low confidence limits and high precisions ( $p < 0.05$ ) of estimates were observed between chlorophyll, nitrogen, and water content indices and forest structural attributes. The models developed for future estimation of volume and basal area based on these indices exhibited high adjusted  $R^2$  values,  $p < 0.001$ , and low RMSE, and PRESS statistic values (e.g.,  $R^2 > 0.95$ , RMSE = 0.1613  $m^3/ha$  and 0.0049  $m^2$ , PRESS= 0.153 and 0.004 for volume and basal area, respectively). The scatterplots of observed and predicted volume and basal area did not show any signs of overestimation or overestimation of these variables, i.e., the points fell within the confidence limit ( $p < 0.001$ ) (figure 6.2.). We concluded that silvicultural and management regimes currently employed by the commercial forestry sector in South Africa are adequate and has important implications for future technology-based forest management and inventory updating.

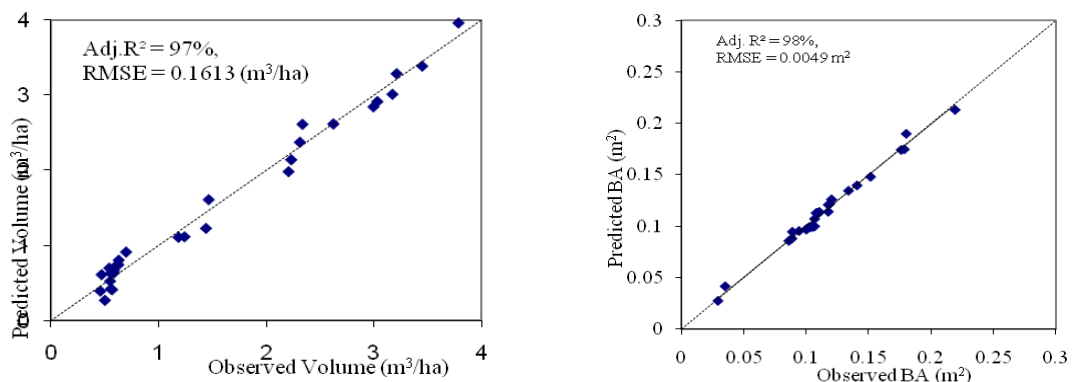


Figure 6.2 Observed vs. predicted volume and basal area of *Eucalyptus grandis*



### 6.1.2. Can leaf chlorophyll content be used to infer soil nitrogen status?

This research question was developed because we saw a necessity to develop ways to help forest managers in general to improve the quality of their soils, determine areas that need fertiliser as opposed to blanket fertilizer application to the whole area, and to exercise greater control over tedious, costly, and time-consuming forestry management operations. There exist serious concerns about the environmental impacts of over-fertilization, e.g., leaching of fertilizer to groundwater and water bodies has serious impacts for aquatic life (Wilson *et al.*, 2005). It is widely accepted that fertiliser enhances growth in any vegetation, forestry included (O'Connell and Rance, 1999) and the success of fertiliser application normally manifest in the plant foliage pigmentation, increased leaf area, and stem mass (Samuelson *et al.*, 2004). It then follows that leaf pigmentation, such as chlorophyll and nitrogen, would be able to reflect the amount of nutrients available in the soil.

The results obtained in this study showed that a link exists between soil nitrogen and leaf chlorophyll indices across different site qualities, namely good, medium, and poor. The strength of correlations between leaf spectral indices and soil nitrogen content varied between  $r = 0.37$  to  $0.85$ . Our results are in line with other studies published elsewhere, e.g., Albrechtová *et al.* (2008), and confirm the dependency of soil nitrogen and optimum leaf pigment content (Filella and Peñuelas, 1994). ANOVA results suggested that significant differences in site qualities could only be explained between good-medium and good-poor sites, whilst no differences were detected between medium-poor sites. We further tested which model would be best suited to estimate soil nitrogen with the highest precision, considering models based on raw spectra and continuum removed spectra. Although both models explained above 70% variation in soil nitrogen, the continuum removed spectral model yielded a distinctly higher adjusted  $R^2$  value with low PRESS static than the raw spectral model (figure 6.3)

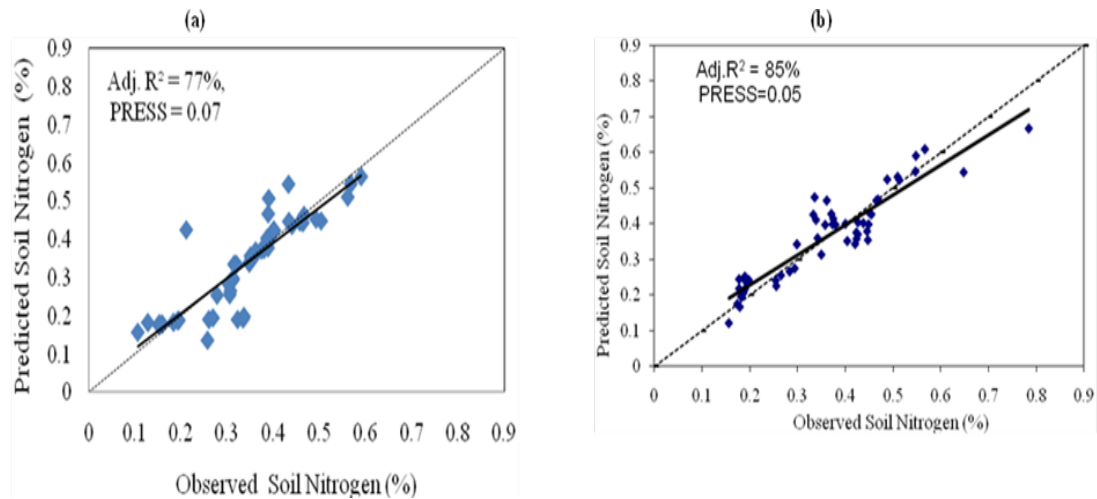


Figure 6.3 Observed and predicted soil nitrogen models (a: raw spectra and b: continuum removed spectra)

In conclusion, these results have added to a body of scientific evidence that leaf chemical attributes, such as chlorophyll, can be used to monitor soil nitrogen content. This is envisaged to have a significant impact in commercial forest management practices in South Africa by mapping soil nutrients from leaf spectra using much cheaper and easily available imagery, i.e., by resampling ASD data or any hyperspectral data to multispectral data to cover a much larger area.

### 6.1. 3 Can hyperspectral data be downsampled to simulate multispectral data to address the above pertinent questions?

The question of downscaling from hyperspectral data to multispectral data was born out of the need to operationalise this study's research findings in a cost-efficient manner. That is only possible if easily available imagery, such as multispectral datasets, can be utilised. The rationale behind downsampling to multispectral datasets, besides being cost-effective and readily available can be traced to the fact that multispectral data typically has a wider swath width compared to hyperspectral data. This translates into a much wider area under commercial forestry being covered. Several authors have used resampling techniques, i.e., from hyperspectral to multispectral data, and the results were encouraging (e.g., Schlerf *et al.*, 2005). Given the cost of hyperspectral data and the fact that South Africa is a developing country,

Landsat TM was deemed suitable for this study; we therefore downsampled from hyperspectral to Landsat multispectral data.

Our main objective was to develop models for estimation of volume, basal area, and soil nitrogen using resampled spectra and compared it to original Landsat TM datasets. The simulated models performed better than the original Landsat TM dataset i.e., their adjusted  $R^2$  values were much higher than original datasets (volume 64% to 13%, basal area 64 % to 47% and soil nitrogen 91% compared 50%). Since our main focus was to report on best results between the two datasets, the following section only relates to simulated data. The variance explained by the models for volume, basal area, and soil nitrogen varied in their effectiveness. The soil nitrogen model variance was explained by two simulated Landsat TM bands (TM4 and TM5) and exhibited the highest strength of association between observed and predicted values, namely  $R^2 = 0.92$  or 92%. Basal area variance was explained by four Landsat TM bands, namely TM3, TM4, TM5, and TM7 and an  $R^2$  of 0.77 was observed between predicted and observed values. The performance of the volume model was not satisfactory, given that an  $R^2 > 0.70$  is regarded as an acceptable criterion for a model. Volume model variance was explained by Landsat TM bands TM4 and TM5 ( $R^2 = 0.64$ ).

The performance of individual bands with volume, basal area, and soil nitrogen is shown in table 6.2 below. TM2 performed weaker among the variables, i.e.,  $r < 0.60$ ,  $p < 0.05$ . TM3, TM4, and TM5 were better correlated with basal area and soil nitrogen ( $0.58 \leq r \leq 0.85$ ,  $p < 0.05$ ) and lesser with volume ( $0.38 \leq r \leq 0.59$ ,  $p < 0.05$ ). Landsat band TM7 was weakly correlated with basal area only ( $r = 0.37$ ,  $p < 0.05$ ). The performance of Landsat TM bands green (TM2), red (TM3), and near-infrared (TM4) spectral regions was not surprising, given that these bands are known to be suitable for vegetation analysis. We concluded that the leaves had high moisture content during sampling (sampling took place in summer) and that manifested itself in the mid-infrared spectral range (TM5) by consistently exhibiting stronger correlations with volume, basal area, and soil nitrogen. A similar trend was reported in other studies, e.g., Ingram *et al.* (2005). In conclusion, spectral resampling from hyperspectral data to Landsat TM data was suitable for estimation of basal area and soil nitrogen, but not for volume.

Table 6.2. Correlations between Landsat TM bands with volume, basal area and soil nitrogen

<b>Variables/Landsat TM Bands</b>	<b>TM2</b>	<b>TM3</b>	<b>TM4</b>	<b>TM5</b>	<b>TM7</b>
Volume	0.38*	0.52*	0.41*	0.59*	ns
Basal Area	0.55*	0.60*	0.68*	0.80*	0.37*
Soil Nitrogen	0.55*	0.75*	0.58*	0.85*	ns

## 6.2 Conclusions

This study makes a contribution in the domain of hyperspectral remote sensing of forest structural attributes through sensing of leaf chemical constituents. Numerous studies have extracted information relating to leaf and canopy chemical content; however, this study has gone a step further and assessed the impacts of forest foliage chemical bioassays on forest structural attributes and soil nitrogen under *Eucalyptus* forest canopies. The major contributions of this study were the resampling of hyperspectral data to simulate Landsat TM to attempt to address matters that concern the commercial forestry sector, i.e., creating a framework from which forest structural attributes and soil nitrogen under forest canopy could be mapped over large areas. These have major implications in the day-to-day management and planning of commercial forestry in South Africa.

The study has proven the potential for estimating chlorophyll and nitrogen non-destructively using a SPAD instrument and extending this to remote sensing data and scales. We also highlighted the importance of incorporating ancillary data with remote sensing and *in situ* data in modelling efforts to provide more accurate estimates of *Eucalyptus* clone volume in the commercial plantation forestry Greenhill estate in KwaZulu Natal, South Africa. These modelling efforts will enable forest managers to model, map, and manage forests effectively over large areas with a host of physiological and structural forest data at hand.

In line with other studies, e.g., Aitkenhead-Peterson *et al.* (2006) and Albrechtová *et al.* (2008), this study has contributed to a better understanding of the health status of trees and the associated soil nitrogen content. A close relationship exists between leaf chlorophyll content, leaf spectral indices, and soil nitrogen in the visible region of the electromagnetic spectrum. This hints at the potential of hyperspectral data to feed into the management of plant-environment interactions and could in the process help to address a key forest management challenge, namely the determination of optimum fertilizer use without negative impacts on the surrounding environment.

This study is a first attempt to downscale results from hyperspectral data to significantly cheaper and readily available broad-band multispectral sensors for management purposes in South Africa's *Eucalyptus* plantations. A possibility exists to estimate basal area and soil nitrogen with acceptable precision, while the volume model could only be used to describe plantation volume variation in the Greenhill area. A combination of Landsat TM bands TM4 and TM5 produced more accurate estimates of soil nitrogen, while TM3, TM4, TM5, and TM7 yielded an acceptable precision for basal area estimations. These results show the importance of developing reliable and stable techniques, such as spectral resampling, to estimate volume, basal area, and soil nitrogen under forest canopies using multi-spectral data.

### **The Future**

The future for the commercial forestry sector in South Africa relies on new technologies underpinned by scientific research approaches. These scientific approaches should add to and improve the body of existing scientific knowledge related to forest structural attributes and soil chemistry. The findings of this thesis and spatial understanding of spatial forest attributes and soil chemical constituents will improve inventory data, management, and planning. The recent development of low-cost SumbandilaSat-type sensors is arguably crucial in the future assessments of forest structural interactions with foliage chemical bioassays and soil chemistry. These interactions and responses can be used to assess climate or land use change at the regional to global scales.

The research undertaken in this study should be extended to other forest types and vegetation studies in general. The ultimate aim would be to develop maps as GIS

layers, which could be linked to strategies aimed at offsetting challenges faced by forestry, e.g., pest and diseases assessment, fire management, and many more. Importantly, synoptic mapping of forest structural attributes at local, regional, and national scales will contribute to effective quantification of short and long-term carbon stock changes brought about by climate change.

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