Field Spectroscopy of Plant Water Content in *Eucalyptus grandis* Forest Stands in KwaZulu-Natal, South Africa

By

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DECLARATION

This study was undertaken in fulfillment of a Geography Masters Degree and represents the original work of the author. Any work taken from other authors or organizations is duly acknowledged within the text and references chapter.

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ABSTRACT

The measurement of plant water content is essential to assess stress and disturbance in forest plantations. Traditional techniques to assess plant water content are costly, time consuming and spatially restrictive. Remote sensing techniques offer the alternative of a non destructive and instantaneous method of assessing plant water content over large spatial scales where ground measurements would be impossible on a regular basis. The aim of this research was to assess the relationship between plant water content and reflectance data in *Eucalyptus grandis* forest stands in KwaZulu-Natal, South Africa. Field reflectance and first derivative reflectance data were correlated with plant water content. The first derivative reflectance performed better than the field reflectance data in estimating plant water content with high correlations in the visible and mid-infrared portions of the electromagnetic spectrum. Several reflectance indices were also tested to evaluate their effectiveness in estimating plant water content and were compared to the red edge position. The red edge position calculated from the first derivative reflectance and from the linear four-point interpolation method performed better than all the water indices tested. It was therefore concluded that the red edge position can be used in association with other water indices as a stable spectral parameter to estimate plant water content on hyperspectral data. The South African satellite SumbandilaSat is due for launch in the near future and it is essential to test the utility of this satellite in estimating plant water content, a study which has not been done before. The field reflectance data from this study was resampled to the SumbandilaSat band settings and was put into a neural network to test its potential in estimating plant water content. The integrated approach involving neural networks and the resampled field spectral data successfully predicted plant water content with a correlation coefficient of 0.74 and a root mean square error (RMSE) of 1.41 on an independent test dataset outperforming the traditional multiple regression method of estimation. The potential of the SumbandilaSat wavebands to estimate plant water content was tested using a sensitivity analysis. The results from the sensitivity analysis indicated that the

xanthophyll, blue and near infrared wavebands are the three most important wavebands used by the neural network in estimating plant water content. It was therefore concluded that these three bands of the SumbandilaSat are essential for plant water estimation. In general this study showed the potential of up-scaling field spectral data to the SumbandilaSat, the second South African satellite scheduled for launch in the near future.

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Chapter One
1. Introduction

1.1. Background

There are approximately 1.5 million hectares of commercial forests in South Africa (Zwolinski *et al.*, 1998) with plantations taking up 1.1% of the country's land base (DWAF, 2005). *Pinus* and *Eucalyptus* species are planted extensively on selected areas in South Africa (Zwolinski *et al.*, 1998) with forest products contributing 1.2 % (approximately R 14 billion) to the country's gross domestic product (GDP) (Ismail *et al.*, 2008). *Eucalyptus grandis* which is the most dominant hardwood species accounts for 47.8 % of the total hardwood area in South Africa. South African hardwood species are mainly grown for pulpwood and mining timber, and is dominant in KwaZulu-Natal (DWAF, 2005). The success of commercial forest plantations in South Africa is highly dependent on accelerating forest productivity and tree growth through improved silvicultural and management techniques (Naidoo *et al.*, 2006).

Water and nutrient interactions have been widely recognized as key factors in determining forest productivity and tree growth (Campion *et al.*, 2005; Naidoo *et al.*, 2006). The growth rate and health of plantations is largely dependent on moisture availability which is often limited through high evaporation (Naidoo *et al.*, 2006). Water stress is one of the most common limitations of forest productivity, and is induced by the closure of the stomata which restricts transpiration (Ceccato *et al.*, 2001). Due to less water evaporating from the leaf surface, the temperature of the leaf increases putting the tree at stress and limiting productivity.

The detection of plant water content is important for monitoring the physiological status of plants and in the assessment of stress and disturbance in forest plantations (Ceccato *et al.*, 2001; Datt, 1999). According to Ripple (1986) traditional techniques for accurate ground based evaluation of plant water measurements are time consuming, costly and spatially restrictive. Although field based sampling of individual leaves and shoots provide the most accurate assessments of plant water status, such methods are not feasible when estimates are required over large areas of plantations. Remote sensing techniques offer the alternative of a non-destructive and instantaneous method of assessing water content over large spatial scales (Datt, 1999).

Remote sensing is the art and science of getting information about the earth's surface without really being in contact with it and this is done by earth observation technologies. Earth observation technologies such as satellites provide local to global coverage on remote areas where ground measurements are impossible on a regular basis. According to Ceccato *et al.*, (2001) different sensors are onboard earth observation satellites and may be used to monitor plant water content. However even with airborne multispectral scanners; remote sensing data collection is limited to a specified and finite number of spectral bands. Treitz *et al.*, (1999) states that satellite data have provided relatively poor spatial, spectral and temporal resolutions for measuring biophysical and physiological characteristics of forest health.

Remote sensing developments in hyperspectral technology provide the potential to monitor forest health. Hyperspectral refers to spectra consisting of a large number of very narrow contiguous bands in the electromagnetic spectrum and is also referred to as spectroscopy or spectrometry (Mutanga, 2004). Spectroscopy is the branch of physics concerned with the production, transmission and interpretation of electromagnetic energy. Spectrometers are used in laboratory, field, aircraft or satellite studies to measure the reflectance spectra of natural surfaces (Mutanga, 2004). Due to hyperspectral remote sensing having a variety of narrow spectral band features of less than 10 nanometers, changes in forest health can be detected. According to Schmidt (2003), the ability to assess plant water content using high spectral resolution data is a major goal for remote sensing research.

Eucalyptus grandis which is the most dominant hardwood species in South Africa is highly intolerant to adverse conditions and shows poor growth rate when there is a lack of moisture (Naidoo *et al.*, 2006). The growth rate and health of plantations which is largely dependent on moisture availability is often limited through high evaporation (Naidoo *et al.*, 2006). In the context of South African forest plantations where water content frequently limits growth and influences wood properties (Naidoo *et al.*, 2006), the measurement of water content is essential to detect stress and disturbance in plantations. Field spectroscopy together with suitable analysis techniques provides the potential to quantitatively measure water content in forest plantations.

A number of studies have measured water content in forest species using laboratory and field spectroscopy with the intention of up-scaling it to airborne and satellite remote sensing (Ceccato *et al.*, 2001; Datt, 1999; Liu *et al.*, 2004). The advances in laboratory and field spectroscopy allow for the measurement of forest condition from fine scale measurements such as leaves to coarser canopy scale studies (Milton *et al.*, 2007). Various water absorption bands and band indices have been developed to estimate water content (Gao, 1996; Hunt and Rock, 1989; Penuelas *et al.*, 1993). Water indices use reflectance measurements in the near-infrared and shortwave infrared regions to take advantage of known absorption bands to estimate water content. However, the remote sensing of plant water content is difficult because the absorption bands sensitive to water content are also affected by atmospheric vapour and they sometimes mask the absorption bands used for water estimation (Liu *et al.*, 2004). A method using non-water absorption bands but with minimum atmospheric interference such as the red edge position would be valuable in estimating plant water content. According to Liu *et al.*, (2004) the red edge can be used as a stable spectral parameter to estimate plant water content, but has not been utilized widely for plant water estimation. To the best of our knowledge, in South Africa the red edge position has not been tested for plant water estimation and has not been compared to the available water indices. The relationship between plant water content and the red edge position has therefore not been well established in South African forest plantations.

Internationally, the measurement of plant water content at field level has been carried out using very high resolution spectrometers such as the analytical spectral device (ASD) with spectral sampling intervals of less than 2nm (Liu *et al.*, 2004; Stimson *et al.*, 2005). However current operational airborne and spaceborne sensors have a much coarser resolution compared to that of field spectrometers. In view of the current availability of spaceborne sensors, it is of interest if these sensors can be related to plant water content, through resampling fine spectral resolution data from spectrometers to coarser spectral resolutions of the spaceborne sensors. If the results are positive, the measurement of plant water content in plantations could be operational on satellite platforms. Within the South African context, the SumbandilaSat is scheduled to be launched in the near future. The SumbandilaSat is the second satellite to be launched by South Africa after the launch of SunSat in 1999. The SumbandilaSat has 6 wavebands with a swath width of approximately 40 km and a ground sampling distance (resolution) of 6.5 metres (Scholes and Annamalai, 2006). It is imperative to test the utility of the SumbandilaSat bands in estimating plant water content in the *Eucalyptus grandis* forests stands of South Africa, an exercise that has not been carried out. This is critical for monitoring plantation health in South Africa using a cheaply available local sensor containing key vegetation wavelengths such as the red edge and the xanthophyll, which are not usually available on current operational multispectral satellite sensors but on hyperspectral sensors, which are expensive to acquire. In this regard, the development of techniques that can make use of the SumbandilaSat bands for plant water estimation are critical.

According to Mutanga and Kumar (2007) the successful extension of field spectroscopy to airborne and satellite remote sensing has been confounded by the use of linear models, such as stepwise regression, which does not take into account non-linearity in a data set. Neural networks are able to model non-linearity in a dataset and are a more powerful method of estimation compared to traditional linear models. By inputting water content in a neural network, Trombetti *et al.*, (2008) showed that MODIS satellite data can retrieve canopy water content in different vegetation types in the USA. The neural network approach outperformed the multiple linear regression approach which was also used to retrieve canopy water content. Similar results were reported by Mutanga and Skidmore (2004) who input the red-edge position and absorption features into a neural network and successfully mapped nitrogen concentration using an airborne hyperspectral image data. A neural network is capable of modeling various types of non-linear behaviour in a data set (Atkinson and Tatnall, 1997) which is expected in the forest plantations of KwaZulu-Natal, South Africa.

This study tests the potential of field spectroscopy to estimate plant water content in *Eucalyptus grandis* plantations in KwaZulu-Natal, South Africa. The study will compare the effectiveness of the red edge position and various indices in estimating plant water content. The field spectra will be resampled to the SumbandilaSat band settings and will be input into a neural network to test the potential for estimating plant water content using satellite remote sensing.

It is against this background that the study sets itself to the following aim and objectives:

1.2. Aim and objectives

The aim of this research is to assess the relationship between plant water content and reflectance data in *Eucalyptus grandis* forest stands in KwaZulu-Natal, South Africa. The main objectives of this thesis are:

- To test the relationship between plant water content from *Eucalyptus grandis* trees and reflectance data measured from a field spectrometer at each wavelength.

- To evaluate the effectiveness of several reflectance indices for estimating plant water content and compare them to the red edge position.
- To resample the field spectra to the SumbandilaSat band settings and assess its potential in estimating plant water content using an artificial neural network.
- To assess the relative importance of the individual SumbandilaSat wavebands in estimating plant water content using a sensitivity analysis.

1.3. The study area

The study area (30^0 29'S 29^0 82'E) is located in Richmond, KwaZulu-Natal, South Africa. The Richmond area falls in the Bioresource Group (BRG) 5 and is referred to as the *Moist Midlands Mistbelt*. Richmond is situated at an altitude range of 900 m – 1400 m above sea level and has a high percentage of arable land. The area receives an annual rainfall ranging from 800 mm to 1280 mm and has a mean annual temperature of 17^0 Celsius (Camp, 1997). The landuse potential of Richmond is good due to its favourable climate and high percentage of arable land. 37.7 % of the Bioresource Group has high potential soil and 47 % of the area is arable (Camp, 1997). Forestry is ecologically suitable and is the most widespread landuse. *Eucalyptus*, *Pinus* and *Acacia* species are grown on selected sites in the valleys on deep well drained soils. The study area was selected due to the wide variation in forest species and the fact that *Eucalyptus grandis* is the most dominant hardwood species in KwaZulu-Natal, South Africa (DWAF, 2005). Figure 1.1 shows the location of the study area in South Africa.

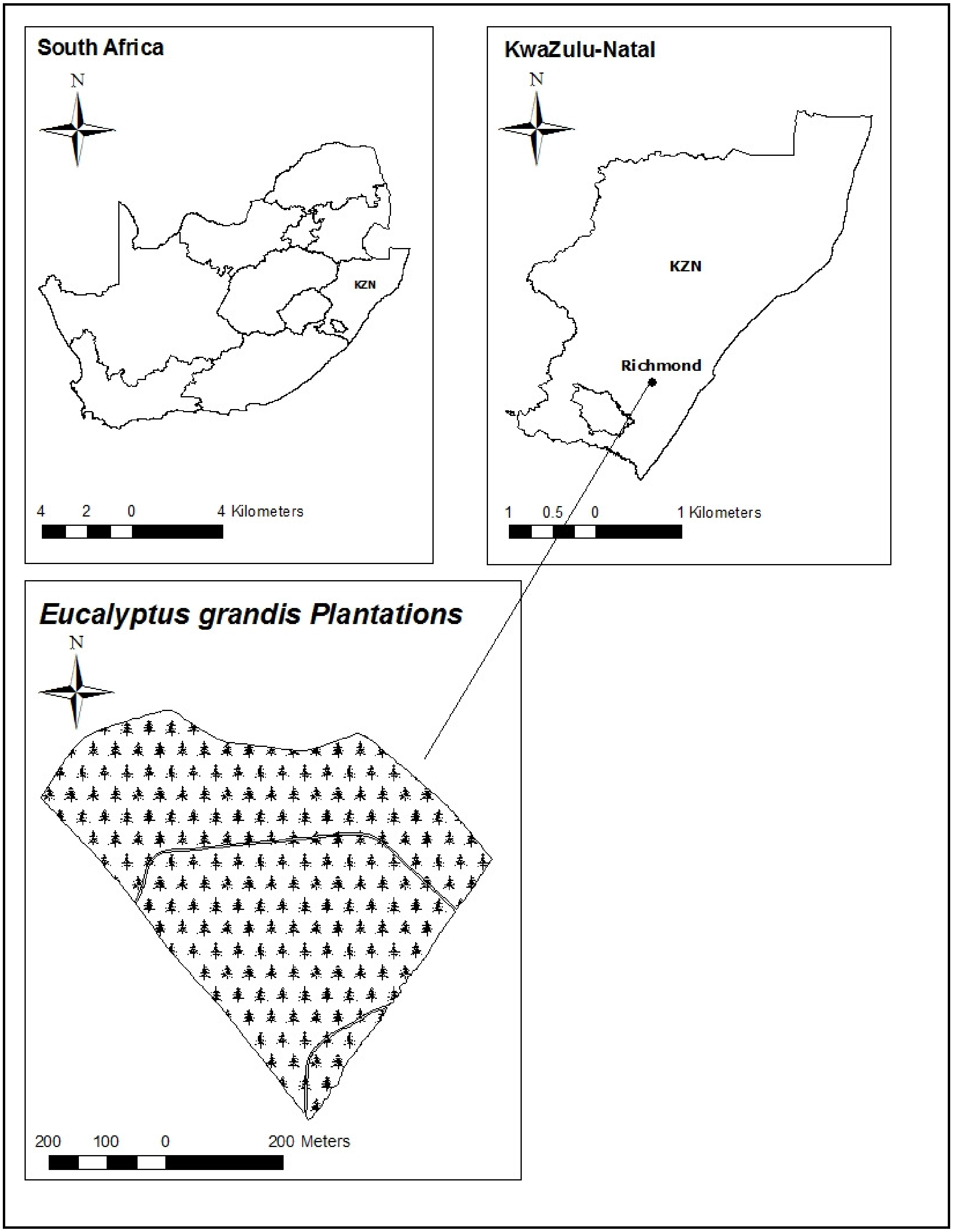


Figure 1.1. Location of the study area in South Africa. The study area is located in Richmond, KwaZulu-Natal. *Eucalyptus grandis* plantations were sampled.

1.4. Outline of thesis

Chapter 2 reviews the literature on remote sensing and plant water content. The use of spectral indices and the red edge region to assess plant water content is evaluated. Potential applications of the SumbandilaSat are summarized and the use of satellite remote sensing to estimate plant water content is discussed. The final section describes the theory behind neural networks and the integration with remote sensing data. Examples are given of how neural networks together with remote sensing data are used to estimate plant water content.

Chapter 3 reviews the methods used to carry out the research. The chapter outlines the field spectral measurements, the plant water samplings and the statistical techniques used to assess the relationship between plant water content and reflectance. The methods used to assess the relationship between plant water content, the water indices and the red edge position are described. The resampling of the field spectra to the SumbandilaSat wavebands and the neural network algorithm is discussed. The final section describes the sensitivity analysis carried out for the SumbandilaSat wavebands.

Chapter 4 outlines the results of the relationship between plant water content and field reflectance data and is reported in the form of a paper for publication therefore it has a separate results and discussion section. A comparison between the red edge position and the water indices in estimating plant water content is also discussed.

Chapter 5 outlines the results of integrating field spectroscopy with neural networks to estimate plant water content using spectra resampled to the SumbandilaSat wavebands and is also reported in the form of a paper for possible publication. The relative importance of the SumbandilaSat wavebands in estimating plant water content is also described using a sensitivity analysis.

Chapter 6 gives a conclusion to the study. The aim and objectives of the thesis are reviewed in order to ascertain how close the study came in order to achieve the goals set. Limitations of the study are evaluated and future recommendations are given.

Chapter Two

2. Literature Review

2.1. Introduction

Water availability is a critical factor for plant survival, development and distribution (Ripple, 1986). Water is one of the most valuable resources and the monitoring of water status has important ramifications for understanding plant stress, fire potential and ecosystem dynamics (Toomey and Vierling, 2005). The growth rate and health of plantations is largely dependent on moisture availability which is often limited through high evaporation (Naidoo *et al.*, 2006). When there is high evaporation, an imbalance occurs between water absorption by the roots and water loss by transpiration (Naidoo *et al.*, 2006) thereby causing disturbances in the organismic variables putting the tree at stress. *Eucalyptus grandis* is the most dominant hardwood species in South Africa and shows poor growth rate when there is a lack of moisture (Naidoo *et al.*, 2006). In the context of South African forest plantations where water content frequently limits growth and influences wood properties (Naidoo *et al.*, 2006), the measurement of water content is essential to detect stress and disturbance in forest plantations. Remote sensing techniques offer the potential to detect and monitor plant water content over large spatial scales. This chapter will review the techniques used in the remote sensing of plant water estimation.

2.2. Remote sensing and plant water content

According to Ripple (1986) traditional techniques for accurate ground based evaluation of plant water measurements are time consuming, costly and spatially restrictive. Ceccato *et al.*, (2001) states that the most practical and cost effective way to monitor vegetation from a local to global scale is to use earth observation technologies such as satellites. Satellites provide local to global coverage on a regular basis and also provide information on remote areas were ground measurements are impossible on a regular basis (Ceccato *et al.*, 2001). Different sensors are onboard earth observation satellites and may be used to monitor vegetation water content. However even with airborne multispectral scanners; remote sensing data collection is limited to a specified and finite number of spectral bands. Multi-spectral systems commonly collect data in three to six spectral bands from the visible and near infrared region of the electromagnetic spectrum (Govender *et al.*, 2007). Due to the restricted number of spectral bands, satellite data have provided relatively poor spatial, spectral and temporal resolutions for measuring physiological characteristics such as plant water content (Treitz and Howarth, 1999). However, over the past two decades, advances in sensor technology have overcome the limitations of multi-spectral systems, with the development of hyperspectral sensor technologies. Hyperspectral refers to spectra consisting of a large number of very narrow bands in the electromagnetic spectrum and is also referred to as spectroscopy or spectrometry (Mutanga, 2004). Spectrometers are the instruments used to measure reflectance of natural surfaces and are used in various remote sensing applications.

Hyperspectral data consists of many, very narrow contiguous spectral bands throughout the visible, near-infrared, mid-infrared and thermal infrared portions of the electromagnetic spectrum. These very narrow, contiguous spectral bands allow for in-depth examination of earth surface features which would be lost with other coarse multispectral scanners (Govender *et al.*, 2007). This development in spectroscopy provides the potential to detect manifestations in vegetation health such as stress and assess physiological characteristics including plant water content (Treitz and Howarth, 1999). Over the last twenty years spectroscopy has played a key role in understanding energy interactions from fine scale measurements such as leaves to coarser canopy based studies (Milton *et al.*, 2007). Internationally a number of studies have used laboratory and field spectroscopy to assess plant water content with the view of up-scaling it to airborne remote sensing (Datt, 1999; Liu *et al.*, 2004; Ripple, 1986). Various water absorption bands and water indices have been developed from the electromagnetic spectrum in order to estimate plant water content. The next section will describe the reflectance properties that occur within the electromagnetic spectrum and its associated relationship with plant water content.

2.3. Plant water content and reflectance properties

Water strongly absorbs radiant energy throughout the mid-infrared region (1300 - 2500 nm) of the electromagnetic spectrum with strong absorption bands centered on 1450, 1940 and 2500 nm; and weak absorption bands located in the near-infrared region (750-1300 nm) (Carter, 1991; Datt, 1999). Numerous correlations between spectral bands and bands related to water content have been developed to estimate plant water content. However in order to estimate plant water content using spectral reflectance data, there needs to be an understanding of how reflectance data is influenced by plant water content. According to Carter (1991) water has several primary and secondary effects which influence the spectral reflectance of leaves. The absorption of radiation by water within the 400-2500 nm causes leaf reflectance to decrease and this is an important primary effect that water has on reflectance. Other primary effects include multiple scattering by water molecules in leaves referred to as ray-leigh scattering or scattering of small particles (Carter, 1991; Gates *et al.*, 1965). Ray-leigh scattering of water molecules however does not have a significant effect on the spectral reflectance of leaves due to the short path-length within leaves (Carter, 1991). Secondary effects of water content on the spectral reflectance of leaves are influenced by the transmissive properties of water. This occurs when water is absorbed by other substances such as pigments and depends on leaf internal structure, cell size and cell shape. Together with this, wavelength independent processes such as multiple reflections occur within leaves and hence influence the spectral reflectance of leaves (Carter, 1991). As water is lost from leaves the intercellular air spaces begin to increase thereby increasing the intensity of multiple reflections within leaves. These wave-optical processes partially explain how water loss in leaves increases reflectance in the water absorption bands and throughout the 400-2500 nm spectrum (Carter, 1991). Using these water absorption bands and the reflectance properties of leaves, various techniques and indices have been developed to estimate plant water content (Hunt and Rock, 1989; Stimson *et al.*, 2005). The following section will describe the water indices used for plant water estimation.

2.4. Spectral indices and plant water estimation

Due to water absorbing radiant energy throughout the mid-infrared region (1300-2500 nm) of the electromagnetic spectrum, a number of indices have been developed for the estimation of water content. Water indices use reflectance measurements in the near-infrared and shortwave infrared regions to take advantage of known absorption features to estimate water content. Penuelas *et al.*, (1993) developed the water band index (WI) which is based on the ratio between the water band 970 nm and reflectance at 900 nm. The WI is a reflectance measurement that is sensitive to changes in canopy water status. The WI together with the first derivative minimum reflectance spectra in the 950-970 nm region was found to be strongly correlated with relative water content. Penuelas *et al.*, (1993) states that reflectance in the 950-970 nm region is an important indicator of plant water status at ground level.

Hunt and Rock (1989) developed the moisture stress index (MSI) which is the ratio of the Landsat Thematic Mapper (TM) satellite bands 5 to 4 (1550-1750 and 760-900 nm). The MSI is a reflectance measurement that is sensitive to changes in leaf water content. As leaf water content increases the absorption around 1599 nm increases and this is sensitive to changes in moisture stress (Hunt and Rock, 1989). Datt (1999) used the MSI to estimate plant water content in *Eucalyptus* leaves. The MSI was most sensitive to equivalent water thickness (EWT) compared to other water indices tested and yielded a significant correlation of $r = 0.67$. The EWT refers to the ratio between the quantity of water and the leaf area and is used for plant water estimation (Ceccato *et al.*, 2001).

Gao (1996) developed the normalized difference water index (NDWI). The NDWI is an index that is sensitive to changes in canopy water content and uses reflectance at 857 and 1241 nm. Reflectance at 857 and 1241 nm are similar but have slightly different liquid water absorption properties. Due to the scattering of light by vegetation the water absorption band at 1241 nm is enhanced and thus becomes useful for detecting changes in plant water status (Gao, 1996). The NDWI is used to predict water stress in canopies and assesses plant productivity (Gao, 1996).

Datt (1999) measured water content in several *Eucalyptus* species and developed two new semi-empirical indices for the estimation of plant water content. These new water indices are least sensitive to radiation scatter and possess advantages over other commonly used empirical indices such as simple ratios or normalized band ratios (Datt, 1999). The indices showed significantly stronger correlations with equivalent water thickness, compared to all other indices tested and yielded correlation coefficients of 0.78 and 0.76 respectively. Datt (1999) states that these indices are therefore proposed for the remote sensing of vegetation water content in all types of plants.

Vegetation indices play an important role in the estimation of plant water content and rely mainly on empirical methods (Colombo *et al.*, 2008). However, the remote sensing of plant water content is difficult because the absorption bands sensitive to water content are also affected by atmospheric vapour and they sometimes mask the absorption bands used for water estimation. A method using non-water absorption bands but with minimum atmospheric interference such as the red edge position would be valuable in estimating plant water content. The red edge which is a non-water absorption band has been proposed for plant water estimation (Liu *et al.*, 2004) but has not been used widely. The next section will discuss the red edge position and its relationship with plant water content.

2.5. Red edge and plant water estimation

According to Liu *et al.*, (2004) the red edge can be used as a stable spectral parameter to estimate plant water content, but has not been utilized widely for plant water estimation. The red edge position is the point of maximum slope in vegetation reflectance spectra that occurs between 690-720 nm (Filella and Penuelas, 1994; Horler *et al.*, 1983). It is characterized by low red chlorophyll reflectance to high reflectance around 800 nm associated with leaf internal structure and water content (Cho and Skidmore, 2006; Schmidt, 2003). Since the red edge is a wide feature of approximately 30 nm it is quantified by a single value known as the inflection point. The inflection point is the point of maximum slope on the infrared curve (Schmidt, 2003). For an accurate determination of the red edge inflection point a large number of very narrow bands are required. This is possible with hyperspectral data as the derivative spectra give an accurate position of the inflection point. A first derivative transformation of the reflectance spectrum calculates the slope values from the reflectance and can be derived from the following equation (Dawson and Curran, 1998):

$$FDS_{\lambda(i)} = (R_{\lambda(j+1)} - R_{\lambda(j)}) / \Delta\lambda \tag{2.1}$$

Where FDS is the first derivative reflectance at a wavelength *i* midpoint between wavebands j and j+1. $R_{\lambda(j)}$ is the reflectance at the j waveband, $R_{\lambda(j+1)}$ is the reflectance at the j+1 waveband and Δ_{λ} is the difference in wavelengths between j and j+1.

When hyperspectral data is unavailable the red edge position can be calculated using the linear four-point interpolation method developed by Guyot and Barett (1988). This method assumes that the reflectance curve at the red edge can be simplified into a straight line centered near the midpoint between the reflectance in the NIR at about 780 nm and the reflectance minimum of the chlorophyll absorption feature at about 670 nm (Cho and Skidmore, 2006). The linear four-point interpolation method uses four wavebands (670, 700, 740 and 780 nm), and the red edge position is determined using a two-step calculation procedure. The reflectance at the inflection point (R_{re}) is calculated by the following equation (Guyot and Barett, 1988):

$$(R_{re}) = (R_{670} + R_{780}) / 2 \qquad (2.2)$$

The red edge position is then calculated using the following equation:

$$\lambda_{re} = 700 + 40[R_{re} - R_{700}) / (R_{740} - R_{700})] \qquad (2.3)$$

700 and 40 are constants resulting from interpolation in the 700-740 nm intervals and R is the reflectance.

The first derivative reflectance and the linear four-point interpolation method are techniques developed to extract the red edge position from hyperspectral data. Liu *et al.*, (2004) correlated plant water content with the red edge in six different growth stages of wheat plants and got correlation coefficients between 0.62 to 0.72 at the 0.999 confidence level. The results were more reliable than the WI and the NDWI. Similar results were reported by Stimson *et al.*, (2005) who correlated foliar water content with the red edge position in *Pinus edulis* trees and got significant correlations of r^2 = 0.45 and r^2 = 0.65 respectively. In South Africa the red edge position has not been tested for plant water estimation and has not been compared to the available water indices to the best of the author's awareness. The red edge position has been used to estimate biochemical constituents such as foliar nitrogen concentration in the Kruger National Park (KNP), South Africa (Mutanga and Skidmore, 2007) however there is a lack of work on the relationship between plant water content and the red edge. The relationship between plant water content and the red edge position has thus not been well established in South African forest plantations under different environments and conditions. The next section will discuss the up-scaling of hyperspectral data to airborne and satellite remote sensing of plant water content.

2.6. Satellite remote sensing of plant water content

Internationally a number of studies have used laboratory and field spectroscopy to assess plant water content with the view of up-scaling it to airborne and satellite remote sensing (Datt, 1999; Liu *et al.*, 2004; Ripple, 1986). The measurement of plant water content at laboratory and field level has been carried out using very high resolution spectrometers such as the ASD spectrometer with spectral sampling intervals of less than 2 nm (Liu *et al.*, 2004; Stimson *et al.*, 2005). However current operational airborne and spaceborne sensors have a much coarser resolution compared to that of field spectrometers. If the currently available spaceborne sensors can be related to plant water content through resampling spectra from spectrometers, then the measurement of foliar moisture content in plantation forests could be operational on satellite platforms.

The up-scaling of field spectroscopy has played an important role for the calibration of aircraft and satellite sensors and provides users with greater confidence in measurements from earth orbiting sensors (Milton *et al.*, 2007). Internationally a number of studies have measured water content using satellite remote sensing (Jackson *et al.*, 2004; Toomey and Vierling, 2005; Yilmaz *et al.*, 2008). Toomey and Vierlang (2005) used Landsat TM and Advanced Spaceborne Thermal Emission and Reflectance Radiometer (ASTER) satellite data to quantify foliar moisture content in *Pinus* plantations. The Landsat satellite data demonstrated stronger correlations with foliar moisture content (r^2= 0.67) compared to the ASTER data. Similarly Yilmaz *et al.*, (2008) used ASTER and Landsat TM satellite data to assess the relationship between equivalent water thickness and the normalized difference infrared index (NDII). The NDII was significantly correlated with EWT and yielded an r^2= 0.85. Satellite remote sensing has therefore been applied internationally to quantify plant water content.

Within the South African context, the, SumbandilaSat is scheduled to be launched in the near future. The SumbandilaSat has 6 wavebands with a swath width of approximately 40 km and a ground sampling distance (resolution) of 6.5 metres (Scholes and Annamalai, 2006). The SumbandilaSat is a high resolution multi-spectral earth observation satellite with six spectral bands. The satellite has an off-nadir viewing capability with a viewing area of about 530 km in diameter (Figure 2.1). Using this off-nadir viewing capability, any point in South Africa can be revisited within 5 days. The principle will be to image during daytime passes and download during night time passes so data will be available within 12 hours at the download station (SunSpace, 2006).

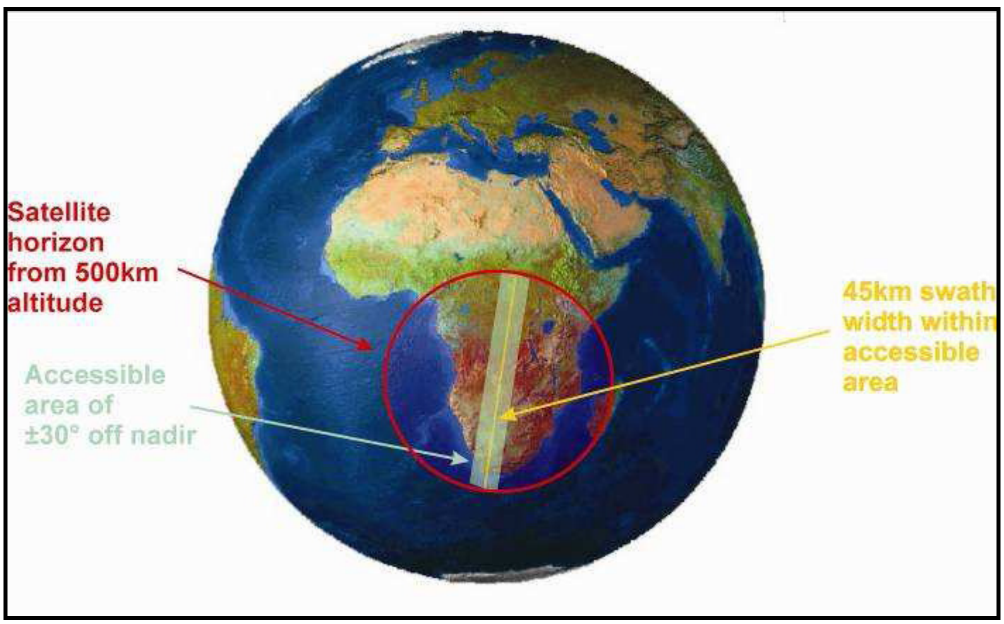


Figure 2.1. Example of SumbandilaSat coverage for image acquisition (SunSpace, 2006).

The SumbandilaSat is a high resolution multi-spectral earth observation satellite with six spectral bands. The spectral content of each band is explained in Table 2.1.

Table 2.1. SumbandilaSat wavebands and potential applications (van Aardt, 2007).

Wavelength Range	**Intended Application**
440-510 nm (blue)	Water bodies, soil/vegetation, deciduous/coniferous.
520-540 nm (xanthophyll)	Silt in water and deforested lands, urban areas.
520-590 nm (green)	Green reflectance peak for plant vigour.
620-680 nm (red)	Chlorophyll absorption, roads, bare soil.
690-730 nm (red-edge)	Plant Stress.
840-890 (near-infrared)	Plant-biomass estimates, water bodies, vegetation.

In South Africa, not much work has been done on the remote sensing of plant water content in forest plantations. There should be an increased interest in using high spectral resolution imagery for plant water estimation due to the future availability of hyperspectral sensors in South Africa. According to Scholes and Annamalai (2006) it is envisaged that after the launch of the SumbandilaSat, ZA Sat-003 which is yet to be named will be launched. ZA Sat-003 will carry a full multisensor microsatellite imager (MSMI) instrument as well as a hyperspectral sensor with a 14.9 km swath and 14.5 m ground sampling distance. This hyperspectral sensor will slice the spectrum between 400 nm and 2350 nm into 200 bands, each 10 nm wide. With the future availability of hyperspectral imagery in South Africa, the question that arises is whether there can be any successful estimate of plant water content.

Therefore the field reflectance data in this study will be resampled to the SumbandilaSat band settings to assess the potential of the SumbandilaSat wavebands in estimating plant water content, a study which has not been done before. However, according to Mutanga and Kumar (2007) the extension of field spectral data to airborne and satellite remote sensing has been constrained by the use of linear models, such as regression models, which ignores non-linearity in a dataset. Neural networks are used in conjunction with remote sensing data due to its ability to model non-linear behaviour in a dataset and its ability to reduce error. The next section will outline neural networks and its use in remote sensing studies.

2.7. Neural networks and remote sensing

Due to hyperspectral laboratory and field data having a large number of narrow bands, there is an increase in the size and amount of data. Whilst this data is essential for many environmental issues, they also pose challenges of data processing and interpretation (Atkinson and Tatnall, 1997). Furthermore, other traditional linear and non-linear techniques such as stepwise regression do not take into account non-linearity in a data set. Neural networks are a more powerful method of estimation compared to traditional linear and non-linear techniques (Jiang *et al.*, 2004). Neural networks employ a non-linear response function that iterates many times in a neural network structure to learn the complex relationship between input and output training data (Jiang *et al.*, 2004). In this context many researchers have applied neural networks to a variety of remote sensing applications (Mutanga and Skidmore, 2004; Trombetti *et al.*, 2008).

A neural network is defined as a mathematical model of brain activity and has been motivated by the realization that the human brain is very efficient in processing vast quantities of data from various sources (Atkinson and Tatnall, 1997; Sunar Erbek *et al.*, 2004). A neural network is composed of a large number of highly interconnected processing elements working in union to solve problems through a learning process (Sunar Erbek *et al.*, 2004). The use of neural networks in remote sensing is mainly due to their wide ability to incorporate different types of data from different sensors as well as ancillary data for analysis (Benediktsson and Sveinsson, 1997). Neural networks perform more accurately than other statistical classifiers and they perform better than other traditional multiple regression analysis (Mutanga and Skidmore, 2004).

One of the most common neural networks used in remote sensing is the multi-layer perceptron (MLP) which is a feedfoward neural network. Networks that have a single direction of information movement are known as feed-forward neural networks, and a neural network that has multiple directions of information flow are known as recurrent neural networks (Murphy *et al.*, 2003). In a MLP there are three types of layers which consist of nodes that are fully interconnected to each other. These layers are known as the input, hidden and output layers (Kavzoglu and Mather, 2003). A MLP (Figure 2.2) usually compromises one input layer, one or two hidden layers and an output layer.

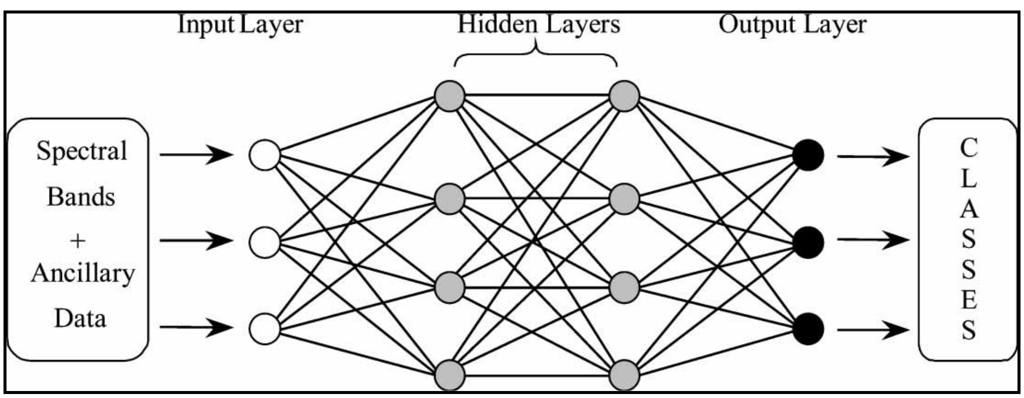


Figure 2.2. A four layer interconnected feed-forward neural network (Kavzoglu and Mather, 2003).

The input layer nodes corresponds to individual data sources such as bands of imagery, the hidden layers are used for computations, and the output layer includes a set of codes to represent the classes (Kavzoglu and Mather, 2003). A neural network also consists of a number of interconnected nodes which are equivalent to biological neurons. These nodes act as connectors and respond to weighted inputs they receive from other nodes within the network (Atkinson and Tatnall, 1997). Because information about the classes is known, the model is ‘taught’ to the network. One of the most common teaching methods is the ‘backpropagation learning algorithm’ (Kavzoglu and Mather, 2003). Backpropagation is a learning technique that aids in the accuracy of the model. According to Kavzoglu and Mather (2003) backpropagation works in two stages.

Stage 1: weights are randomly put through the network and are propagated forward to estimate the value for each training set (Kavzoglu and Mather, 2003).

Stage 2: the difference in error between the known and estimated output values are sent back through the network and the weights are changed to reduce error. The whole process is repeated and the weights are recalculated at every iteration until the error is minimal (Kavzoglu and Mather, 2003).

Many studies have used backpropagation neural networks in remote sensing to estimate vegetation biophysical characteristics (Mutanga and Kumar, 2007; Mutanga and Skidmore, 2004; Trombetti *et al.*, 2008). Mutanga and Skidmore (2004) integrated imaging spectrometry and neural networks to map nitrogen concentration in an African savanna rangeland. The integrated approach using neural networks and spectrometry explained 60% of variation in nitrogen concentration compared to 38% explained by a multiple linear regression. The study demonstrated the potential of spectrometry and neural networks to estimate physiological characteristics of vegetation. Trombetti *et al.*, (2008) applied a neural network to MODIS satellite data to retrieve vegetation canopy water content. The neural network algorithm showed good performance across different vegetation types with high correlation coefficients. The neural network approach outperformed a multiple linear regression approach which was applied to estimate canopy water content. The high correlations suggest that neural networks provide a basis for multi-temporal assessments of canopy water content (Trombetti *et al.*, 2008). Neural networks have been used concurrently with remote sensing data to estimate plant biophysical parameters including water content. In this study the field spectra will be resampled to the SumbandilaSat and will be input into a neural network to test the potential for estimating plant water content using satellite remote sensing.

2.8. Lessons learnt from the review

Water availability is essential for plant survival, development and distribution and the monitoring of plant water content has important ramifications for understanding plant stress and disturbance to forest plantations. Internationally, laboratory and field spectroscopy have measured water content using spectral indices. However within South Africa, the relationship between plant water content and field reflectance data is lacking. New techniques such as linking the red edge position to water content and comparing this to the available water indices has not been done in forest plantations. Furthermore with the launch of the SumbandilaSat in the near future, it is essential to test the potential of the SumbandilaSat in estimating plant water content by resampling the spectra to simulate the SumbandilaSat wavebands. However the successful extension of field spectral data to satellite remote sensing has been confounded by the use of linear models such as stepwise regression which does not take into account non-linearity in a dataset (Mutanga and Kumar, 2007). Neural networks have the ability to model non-linearity in a dataset and can incorporate data from different types of sensors. By inputting field spectral data into a neural network, non-linearity in a dataset is accounted for and neural networks are a more powerful method of estimation compared to the traditional linear techniques.

2.9. Conclusion

Plant water content is critical for plant survival, development and distribution (Ripple, 1986). The monitoring of plant water content is essential to assess stress and disturbance to forest plantations. With the advances in laboratory and field spectroscopy, plant water content can be quantitatively measured using suitable remote sensing techniques. The ability to assess plant water content using high spectral resolution data is a major goal for remote sensing research. In general this review has illustrated the ability of field spectroscopy, neural networks and satellite remote sensing in estimating plant water content in forest plantations.

Chapter Three

3. Methods

3.1. Introduction

This chapter will outline the methods and techniques used to assess the relationship between plant water content and field reflectance data in the *Eucalyptus grandis* forest stands of KwaZulu-Natal, South Africa.

3.2. Experimental setup

During July 2007, field reflectance measurements were taken at *Eucalyptus grandis* plantations (centroid 30^{0} 29’S 29^{0} 82’E) in Richmond, KwaZulu-Natal, South Africa. A total of 50 *Eucalyptus grandis* trees were selected for measurements. The sampling scheme was designed to cover a wide variation in leaf type and water content. Purposively selected sampling was done based on sunlit portions of the forests and on terrain that supported the cherry picker. Leaf samples were obtained using a cherry picker and leaves were picked from sunlit parts of the canopy (Figure 3.1). The leaves were stacked 5 layers together for reflectance measurements. After field reflectance measurements were taken, the leaf samples were stored over ice in a portable refrigeration unit to keep them fresh and were immediately taken to the laboratory for water content measurements.

Figure 3.1. Cherry picker used to access leaf samples.

3.3. Field reflectance measurements

Leaf spectral measurements were taken using an ASD spectrometer (Fieldspec3 Pro FR) fitted with a 25^0 field of view bare fibre optic. The ASD field spectrometer senses in the spectral range of 350-2500 nm at a sampling interval of 1.4-2.0 nm and has a resampled bandwidth of 1 nm (Analytical Spectral Devices, 2002). Radiance measurements were converted to target reflectance using a calibrated white spectralon panel on the leaf clip (Figure 3.2). Reflectance measurements were taken by averaging 10 scans with a dark current correction at every spectral measurement.

Figure 3.2. Leaf spectral measurement

3.4. Plant water content sampling

Plant water samplings were taken almost synchronously after spectral measurements. The leaf samples were stored over ice in a portable refrigeration unit and were immediately taken to the laboratory for water measurements. The leaf samples were weighed fresh (fresh weight, FW) and then dried in an oven for approximately 24 hours at 70^oC. The leaf samples were then weighed again after drying (dry weight, DW). Plant water content (PWC) was calculated after Liu *et al.*, (2004):

$$PWC = (FW - DW) / FW * 100\% \quad (3.1)$$

In the beginning of the study 25 samples were collected and were used for analysis with the reflectance data. In order to carry out the neural networks experiment 25 more samples were taken, increasing the sample size to 50 thereby making the neural network experiment more viable. The 50 plant water measurements were then used for analysis with the field reflectance data.

3.5. Relationship between plant water content and field reflectance

To assess the relationship between plant water content and reflectance the Pearson correlation coefficient r was calculated for all wavelengths in the range 350-2500 nm for the field reflectance and the first derivative reflectance. The first derivative reflectance was calculated after (Dawson and Curran, 1998):

$$FDS_{\lambda(i)} = (R_{\lambda(j+1)} - R_{\lambda(j)}) / \Delta\lambda \qquad (3.2)$$

Where FDS is the first derivative reflectance at a wavelength i midpoint between wavebands j and j+1. $R_{\lambda(j)}$ is the reflectance at the j waveband, $R_{\lambda(j+1)}$ is the reflectance at the j+1 waveband and Δ_λ is the difference in wavelengths between j and j+1.

The correlation coefficients for the field and first derivative reflectance were then plotted as correlograms. The wavelength regions of statistically significant correlation ($p < 0.05$), were then evaluated.

3.6. Estimating plant water content from reflectance indices

In order to ascertain the relationship between plant water content and reflectance indices, bootstrapping correlation was executed on 6 water indices. Bootstrapping is a general technique for estimating sampling distributions, standard errors and confidence intervals for any statistic and is the most common method for indicating statistical accuracy (Efron, 1982; 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 under study. On each replication a random sample size of N is selected with replacement from the available data (Efron, 1982; Mutanga and Skidmore, 2007). The statistic of interest which is the correlation coefficient is calculated on the bootstrapped sub-sample and recorded. The process is repeated several times in order to obtain the sampling distribution. According to Mutanga and Skidmore (2007) bootstrapping facilitates accuracy assessment using the same dataset. Six spectral indices were calculated from the field reflectance data and were correlated against the plant water content measurements. The six spectral indices are listed below:

Moisture Stress Index (MSI)

The MSI is a reflectance measurement that is sensitive to changes in leaf water content. The MSI was calculated according to Hunt and Rock (1989) using single wavelength reflectances in these 2 regions:

$$MSI = R1599 / R819 \tag{3.3}$$

Where, R represents the reflectance at the indicated wavelengths.

Water Index (WI)

Penuelas *et al.*, (1993) developed the water band index which is based on the ratio between the water band 970 nm and reflectance at 900 nm. The WI is a reflectance measurement that is sensitive to changes in canopy water status. The WI was calculated according to Penuelas *et al.*,(1993):

$$WI = R900 / R970 \tag{3.4}$$

Normalized Difference Water Index (NDWI)

The NDWI is used to predict water stress in canopies and assess plant productivity (Gao, 1996). The NDWI was calculated according to Gao (1996):

$$NDWI = (R860 - R1240)/(R860 + R1240) \tag{3.5}$$

Normalized Difference Vegetation Index (NDVI)

The NDVI was calculated according to Stimson *et al.*, (2005):

$$NDVI = (R860 - R690)/(R860 + R690) \tag{3.6}$$

Although the NDVI is not an index of plant water content, it is the most common vegetation index and was merely used for comparison with the other indices.

Datt (1999) developed 2 new indices for the estimation of plant water content. These indices in the thesis will be referred to as Reflectance I (RI) and Reflectance II (RII). These new water indices are least sensitive to radiation scatter and possess advantages over other commonly used empirical indices such as simple ratios or normalized band ratios (Datt, 1999).

Reflectance I (RI):

$$RI = (R850 - R2218)/(R850 - R1928) \tag{3.7}$$

Reflectance II (RII):

$$RII = (R850 - R1788)/(R850 - R1928) \tag{3.8}$$

Bootstrapping correlation was performed on the six water indices to assess their effectiveness in estimating plant water content.

3.7. Estimating plant water content from the red edge position

The red edge position was calculated using the first derivative spectra (FDS) (Dawson and Curran, 1998) and the linear four-point interpolation method developed by Guyot and Baret (1988). This was done to compare the two techniques used for extracting the red edge position and their associated relationship with plant water content.

The first derivative reflectance was calculated between wavelengths 690 – 720 nm. A first derivative transformation of the reflectance spectrum calculates the slope values from the reflectance and was calculated from equation 3.2 on page 27.

The linear four-point interpolation method was also used to calculate the red edge position (Guyot and Barett, 1988). The linear four-point interpolation method assumes that reflectance at the red edge can be simplified into a straight line centered on a midpoint between the reflectance in the NIR at 780 nm and reflectance at 670 nm (Mutanga and Skidmore, 2004). Reflectance measurements at 670 nm and 780 nm were used to estimate the inflection point reflectance (equation 3.9) and a linear interpolation procedure was applied between 700 nm and 740 nm to estimate the wavelength of the inflection point (equation 3.10).The reflectance value at the inflection point (R_{re}) was calculated as:

$$(R_{re}) = (R_{670} + R_{780}) / 2 \tag{3.9}$$

The red edge position was calculated as:

$$\lambda_{re} = 700 + 40[R_{re} - R_{700}) / (R_{740} - R_{700})] \tag{3.10}$$

Where R_{670}, R_{700}, R_{740} and R_{780} are the reflectance values at 670, 700, 740, and 780 nm respectively. The value 700 refers to the wavelength position belonging to R_{700}. The value 40 refers to the wavelength interval between 700 nm and 740 nm.

In order to ascertain the relationship between plant water content and the red edge positions bootstrapped correlations were performed on the 2 red edge techniques. The bootstrapping technique is designed to compute statistics so that an appropriate sample size can be established (Gomez-Buckley *et al.*, 1999). The strength of the bootstrapping technique is sampling with replacement from the available dataset. The bootstrapping technique enhances statistical significance testing to help determine the replicability of the results and facilitates accuracy assessment using the same dataset (Higgins, 2005; Mutanga and Skidmore, 2007).

3.8. Resampling the spectra to the SumbandilaSat

The field reflectance measurements were then resampled to the SumbandilaSat wavebands to simulate the reflectance and assess the potential of the satellite in estimating plant water content. This study was the first attempt to predict plant water content in *Eucalyptus grandis* forest stands using field spectra resampled to the SumbandilaSat band settings. The resampling of the field spectra was done using the ENVI (Environment for visualizing images, Research Systems, Inc.) software. The method uses a gaussian model with a full width at half maximum (FWHM) equal to the band spacings provided. The FWHM method is a simple and well defined number which is used to compare the quality of images under different resolutions. The technique uses the field spectral data from the ASD spectrometer and resamples it to the spectral width of the SumbandilaSat band settings. The 50 plant water measurements were then correlated with the resampled SumbandilaSat wavebands to assess the relationship with plant water content. Following this, the resampled SumbandilaSat wavebands were then input into a neural network algorithm to test its potential in estimating plant water content.

3.9. The neural network algorithm

An artificial neural network was used to estimate plant water content. A neural network is composed of a large number of highly interconnected processing elements working in union to solve problems through a learning process (Sunar Erbek *et al.*, 2004). Neural networks perform more accurately than other statistical classifiers and they perform better than other traditional multiple regression analysis (Mutanga and Skidmore, 2004). A multiple layer perceptron neural network was applied in this study as it has the ability to learn to weight significant variables and ignore less important ones.

A back-propagation algorithm was used in a three layer network which consists of an input, hidden and output layer (Figure 3.3). The algorithm was chosen due to its frequent use in remote sensing studies and the ability to minimize error. The back-propagation algorithm is designed to minimize the root mean square error (RMSE) between the actual output of a multiple layer perceptron and the desired output (Mutanga and Skidmore, 2004). Figure 3.3 shows the neural network structure that was used to predict plant water content (PWC) using the SumbandilaSat wavebands.

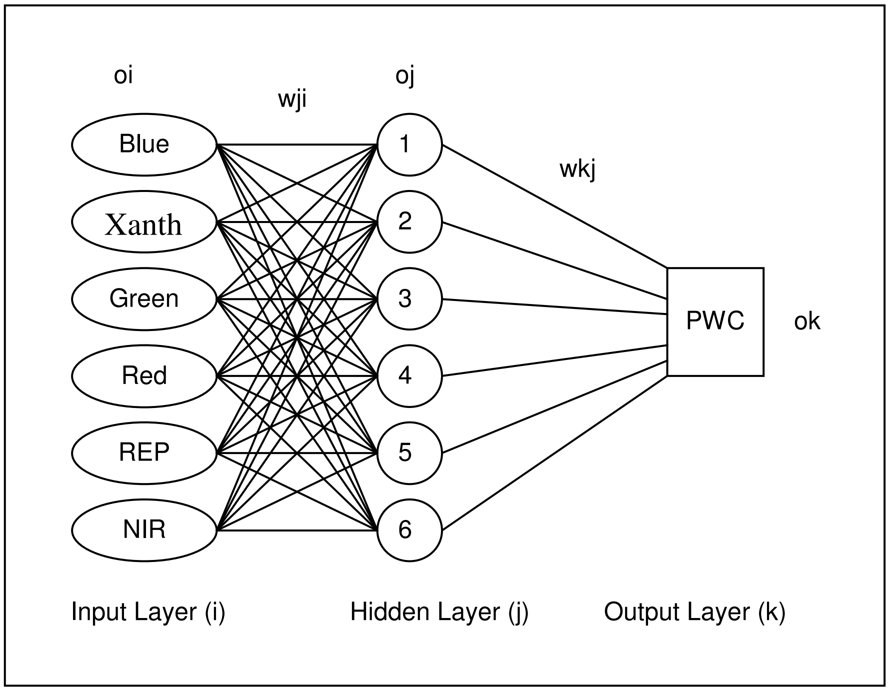


Figure 3.3. The neural network structure. The input layer (oi) consists of the SumbandilaSat wavebands. The inputs are connected to hidden nodes (oj), which are in turn connected to the output layer, which is the PWC (ok). Wji and Wkj refer to the weights between the input and hidden nodes, and between the hidden nodes and the output layer.

The back-propagation algorithm comprises a forward and a backward phase through the neural network. The forward phase occurs whereby the input values which are the SumbandilaSat bands (oi) are presented to a node and are multiplied by a weight factor (wji) (Skidmore *et al.*, 1997). The products are then summed at the hidden nodes (oj) to create a value z_j for the jth layer. The following description is after Skidmore *et al.*, (1997):

$$Zj = \sum_j Wji * Oi \tag{3.11}$$

For a three layer network with the layers i, j, k and k being the output layer z_k may be calculated as equation 3.11. Non-linearity is added to the network when the value z_j is passed through a sigmoidal activation function for each node. The output of this function is defined as:

$$O_j = \frac{1}{1+e^{-(z_j+\theta)^{\theta_0}}} \tag{3.12}$$

Where z_j is defined from equation (3.11), θ is a threshold or bias and θ_0 is a constant (Skidmore *et al.*, 1997).

The forward phase stops once the output values that is PWC (ok) is calculated for each output node. The second phase involves the back-propagation whereby the output node values are compared with the target values (measured PWC) and involves training of the network. The difference between the target (measured PWC) and calculated output values is referred to as error. This whole process whereby error is calculated represents one epoch of the back-propagation algorithm. Back-propagation of the error is achieved by changing the weights of each node during training. The whole process is repeated and the weights are recalculated at every iteration until the error is minimal.

The total dataset was randomly divided into two groups, one subset for training (38 samples) and the other subset for testing (12 samples). This was based on the ¾ training and ¼ testing sample criteria. This proportion is recommended in literature since it gives more weight to data for model building (Mutanga and Rugege, 2006). The training process was run 5 times with random initial weights (Zhang *et al.*, 2002). The performance of the network was tested by changing the number of hidden nodes in the neural network. The neural network that yielded the highest correlation coefficient as well as the lowest RMSE on the independent test data set was then selected. The RMSE was calculated according to Siska and Hung (2001):

$$RMSE = \sqrt{\frac{SSE^2}{n}} \tag{3.13}$$

Where SSE is the sum of errors (observed – predicted values) and n is the number of samples.

The utility of the neural network approach in predicting PWC was also compared with that of a stepwise multiple regression using the same training data (38 samples) and test data (12 samples). The performance of the stepwise multiple regression was assessed using the correlation coefficient as well as the RMSE.

3.10. Sensitivity analysis and the relative importance of the SumbandilaSat wavebands

A sensitivity analysis was carried out in order to assess the importance of the individual SumbandilaSat wavebands in estimating plant water content. A sensitivity analysis indicates which input variables (SumbandilaSat wavebands) of the neural network are most important and identifies wavebands that can be ignored for subsequent analysis. The results are explained in terms of ranked ratios with significant bands having higher ratios indicating the importance of that particular waveband in the neural network structure.

The results from this study will be described and discussed in the following chapters.

Chapter Four

4. Field spectroscopy of plant water content in *Eucalyptus grandis* plantations: A comparison between water indices and the red edge position

4.1. Overview

The measurement of plant water content is a major goal for ecological remote sensing applications (Ceccato *et al.*, 2001; Seelig *et al.*, 2008) and it is essential to detect stress and disturbance to forest plantations. Over the past few decades numerous studies have investigated water bands and water indices in order to estimate plant water content. However water indices rely mainly on empirical methods (Colombo *et al.*, 2008) and the remote sensing of water content becomes difficult because the bands that are used for water estimation are also affected by atmospheric vapour. According to Liu *et al.*, (2004) a method using non-water absorption bands but with minimum atmospheric interference such as the red edge position would be valuable in estimating plant water content. This paper evaluates the effectiveness of several water indices in estimating plant water content and compares them to the red edge position calculated from the first derivative reflectance and the linear four-point interpolation method. A comparison is also made between the field reflectance and the first derivative reflectance and their associated relationship with plant water content. This study was carried out in the *Eucalyptus grandis* forest stands of KwaZulu-Natal, South Africa and the results are described below.

Spectra of the mean reflectance and ± 95 confidence limits for the samples are shown in Figure 4.1. Like most green vegetation spectra, the average spectrum in Figure 4.1 shows high reflectance in the near infrared and low reflectance in the visible.

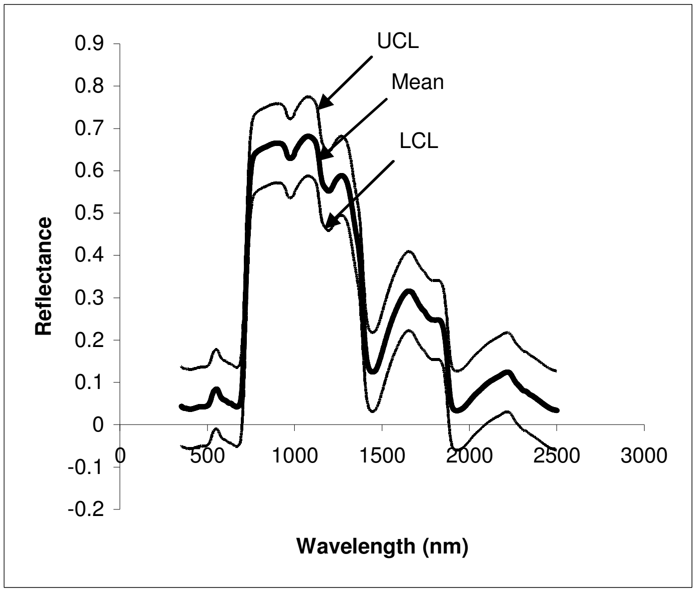
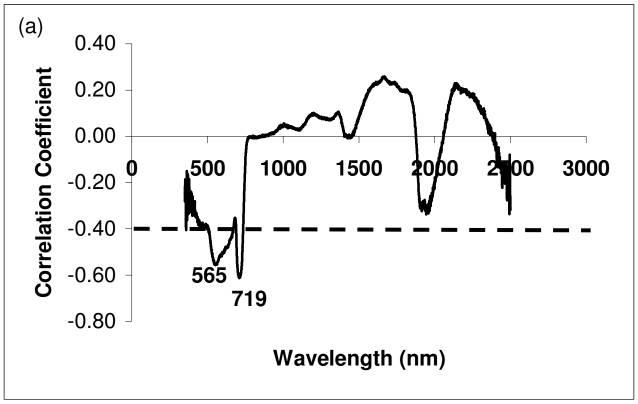


Figure 4.1. Reflectance spectra of *Eucalyptus grandis* leaves. The mean, upper 95 % confidence limit (UCL) and lower 95 % confidence limit (LCL) of the spectra are shown.

4. 2. Estimating plant water content from field and first derivative spectra

4.2.1. Relationship between plant water content and reflectance

To determine how the relationship between plant water content and reflectance changed with wavelength, the Pearson correlation coefficient, *r* was calculated for all wavelengths in the range 350-2500 nm for the field and first derivative spectra. The correlograms in Figure 4.2 show the wavelengths of statistically significant correlation ($p < 0.05$) and are indicated by wavelengths that are below the dashed line. For the field reflectance spectra, plant water content was significantly correlated with the visible portion of the spectrum with correlations ranging from -0.40 to -0.61. The first derivative spectra was significantly correlated with plant water content in the visible and mid-infrared regions with correlations ranging from -0.40 to -0.68.



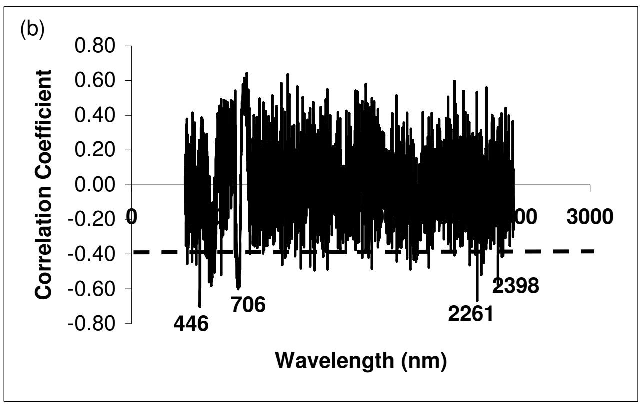


Figure 4.2. Relationship between plant water content and reflectance. (a) Field Reflectance (b) First derivative reflectance. Wavelengths of highly correlated peaks are shown.

4.3. Estimating plant water content from reflectance indices

4.3.1. Relationship between plant water content and reflectance indices

In order to ascertain the relationship between plant water content and reflectance indices, bootstrapping correlation was executed on 6 water indices. Table 4.1 shows the mean, standard errors and confidence intervals of the bootstrapped correlation coefficient between the 6 indices and plant water content.

Table 4.1. Bootstrapped correlation coefficients between plant water content and the six indices. A total of 200 iterations were executed for each pair.

Indices	**Mean**	**Standard Error**	**95% CL**
MSI	0.28**	0.0636	0.0088
WI	-0.15*	0.0788	0.0109
NDWI	-0.15*	0.0762	0.0106
NDVI	0.41**	0.0532	0.0074
RI	-0.34**	0.0603	0.0084
RII	-0.31**	0.0629	0.0087

**Significant: $p < 0.01$ *Significant: $p < 0.05$

The NDVI which was mainly used for comparison with the other water indices yielded the highest bootstrapped correlation coefficient with plant water content. The WI and the NDWI yielded the lowest negative correlation with plant water content. The MSI and the 2 semi-empirical indices developed by Datt (1999) performed well with significant correlations at $p < 0.01$. Figure 4.3 shows the bootstrapped correlations between the 6 indices and plant water content. The histograms show the normal distribution correlations produced by the bootstrapping methodology. The small 95 % confidence limits suggest that the bootstrapped correlation coefficients approach the population estimate with a high precision.

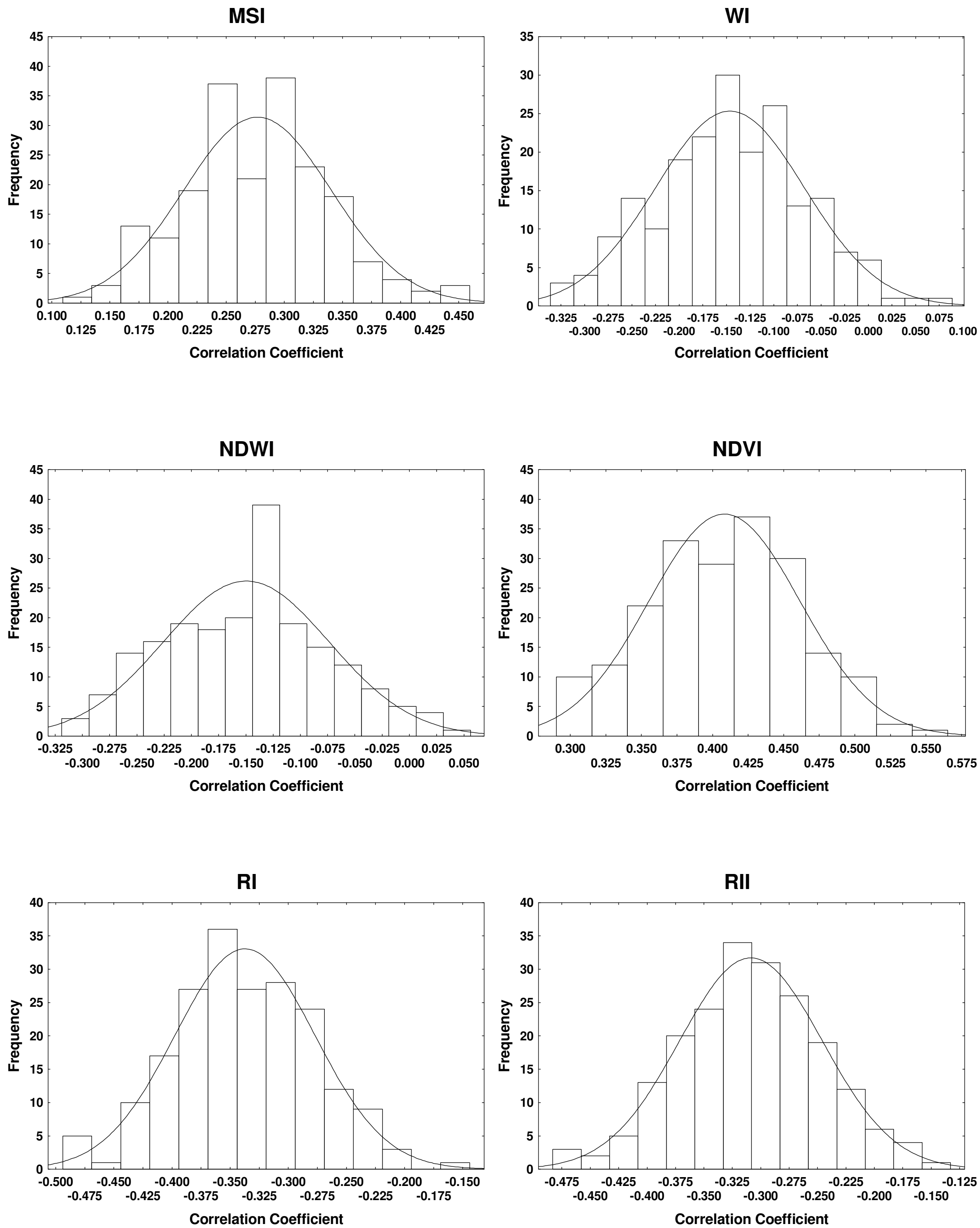


Figure 4.3. Bootstrapped correlation coefficients between plant water content and the six indices. A total of 200 simulations were run between plant water content and the six indices.

4.4. Estimating plant water content from the red edge position

4.4.1. Calculating the red edge position from derivative spectra

The red edge position was calculated using the first derivative reflectance and the linear four-point interpolation method developed by Guyot and Baret (1988). Figure 4.4 shows the first derivative reflectance and the peaks that are found at the respective wavelengths. Previous studies have also found double peaks in the first derivative spectra (Boochs *et al.*, 1990; Cho and Skidmore, 2006; Smith *et al.*, 2004) and this is merely a function of natural florescence emission that occurs at 690 and 730 nm (Cho and Skidmore, 2006). The red edge positions at the peaks were correlated with plant water content. The positions that yielded the highest Pearson correlation coefficient were then selected for the subsequent bootstrapping analysis. Figure 4.4 shows the derivative spectra of the samples within the red edge region indicating the peaks and Figure 4.5 shows the mean derivative spectra within the red edge region.

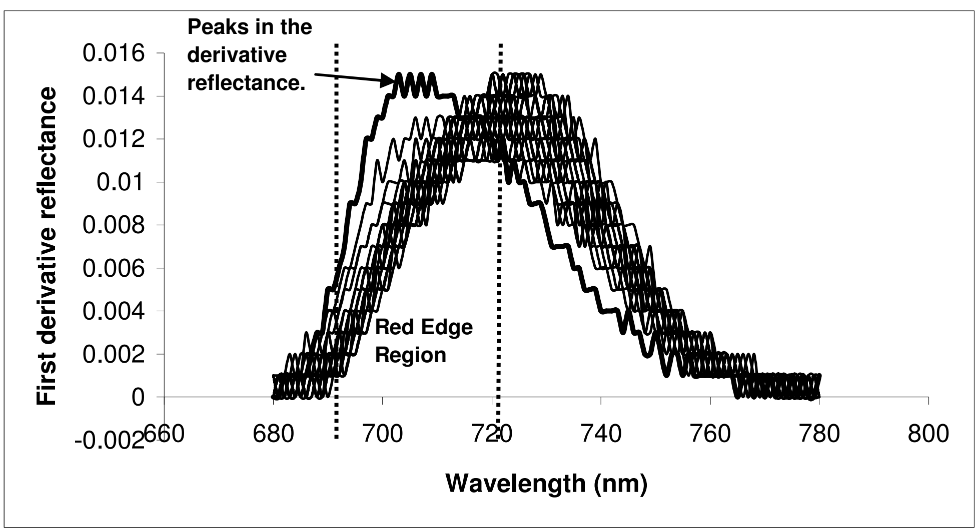


Figure 4.4. First derivative spectra and the double peaks within the red edge region.

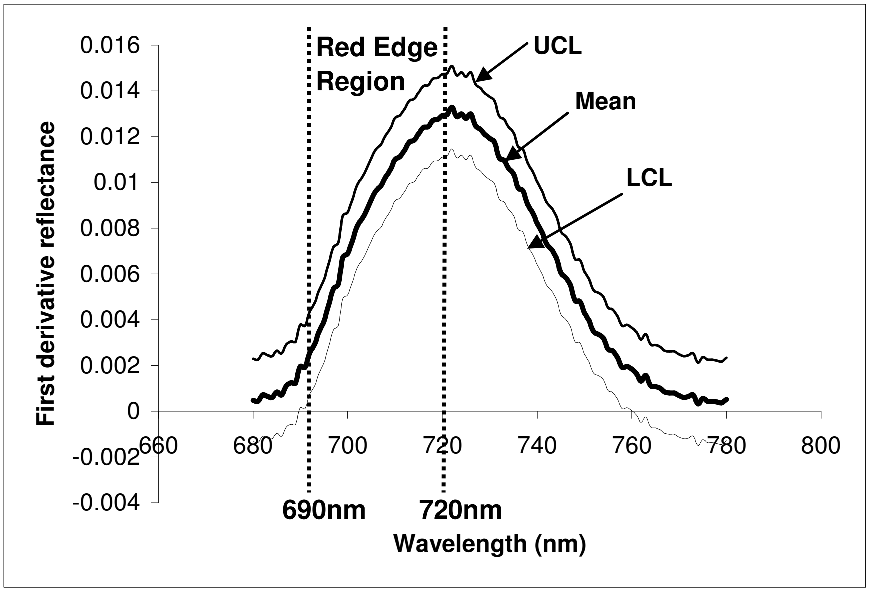


Figure 4.5. Mean first derivative spectra of *Eucalyptus grandis* leaves. The mean, upper 95 % confidence limit (UCL) and lower 95 % confidence limit (LCL) of the spectra are shown.

4.4.2. Relationship between plant water content and the red edge positions

In order to ascertain the relationship between plant water content and the red edge positions, bootstrapped correlations were performed on the two red edge techniques. Table 4.2 shows the mean, standard errors and confidence intervals of the bootstrapped correlation coefficient between the two red edge positions and plant water content.

Table 4.2 Bootstrapped correlation coefficients between plant water content and the two red edge positions. A total of 200 iterations were executed for each pair.

Indices	**Mean**	**Standard Error**	**95% CL**
Red Edge (FDR)	0.65**	0.0280	0.0039
Red Edge (Interpolation)	0.56**	0.0421	0.0058

**Significant: $p < 0.01$

The red edge positions were significantly correlated with plant water content yielding correlations of 0.65 and 0.56 respectively. Figure 4.6 (a) and (b) shows the bootstrapped correlations between the two red edge positions and plant water content. The histograms show the normal distribution correlations produced by the bootstrapping methodology.

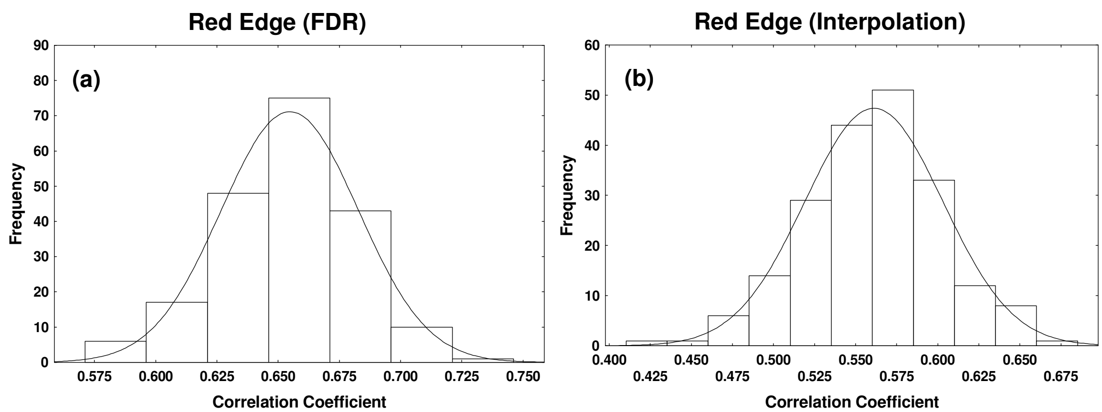


Figure 4.6. (a) Bootstrapped correlation coefficients between plant water content and the red edge position: first derivative reflectance (FDR). (b) Bootstrapped correlation coefficients between plant water content and the red edge position (Linear four-point Interpolation).

4.5. Discussion

Two main aspects are discussed in this section, (1) the relationship between plant water content and field reflectance, and (2) the relationship between water indices as compared to the red edge position in estimating plant water content.

4.5.1. Relationship between plant water content and reflectance

One of the major problems in relating plant water content to spectral reflectance is the variation in leaf internal structure (Datt, 1999). According to Datt (1999) differences in leaf internal structure and thickness cause changes in the scattering properties of leaves thereby producing reflectance differences that are unrelated to water content. A method that suppresses the effects of differences in leaf internal structure and overlapping spectral features such as derivative spectroscopy has more potential in relating leaf reflectance to water content (Danson *et al.*, 1992). From the results above plant water content was significantly correlated with field reflectance in the visible portion of the spectrum with highly correlated peaks at 565 nm (r = -0.55) and 719 nm (r = -0.61). For the first derivative reflectance, plant water content was significantly correlated with reflectance in the visible and mid-infrared portions of the spectrum with peaks at 446 nm (r = -0.68), 706 nm (r = -0.59), 2261 nm (r = -0.67) and 2398 nm (r = -0.57). Similar results were reported by Danson *et al.*, (1992) on the derivative reflectance with strong correlations in the mid-infrared regions. Danson *et al.*, (1992) states that the first derivative of leaf reflectance is better at predicting leaf water status than the original reflectance spectrum when there is a variation in leaf internal structure. The visible and mid-infrared portions of the spectrum are therefore proposed as suitable regions for plant water estimation as they were significantly correlated with plant water content.

4.5.2. Comparison between water indices and the red edge in estimating water content

Water indices use reflectance measurements in the near-infrared and short wave infrared regions of the electromagnetic spectrum to estimate water content. Of all the indices tested NDVI yielded the highest bootstrapped correlation coefficient of (r = 0.41). Similar results were reported by Stimson *et al.*, (2005) whereby the NDVI yielded the highest correlation of r^2 = 0.71 compared to the other water indices tested on *Pinus edulis* trees. The relationships with water content for the other indices were: MSI (r = 0.28); WI (r = -0.15,); and NDWI (r = -0.15). Datt (1999) reported poor correlations with the indices tested above except for the MSI that yielded a significant correlation of (r = 0.67). The two new semi-empirical indices developed by Datt (1999) for water estimation performed better than the other water indices tested and yielded bootstrapped correlation coefficients of:

RI (r = -0.34) and RII (r = -0.31). The red edge which is a non-water absorption band has been proposed for plant water estimation (Liu *et al.*, 2004) but has not been used widely. The bootstrapped correlation coefficients for the red edge positions yielded higher correlations (r = 0.65) and (r = 0.56) at the 0.999 confidence level compared to all the water indices tested. This confirms the capability of the red edge position in estimating plant water content. The first derivative reflectance technique performed better than the linear four-point interpolation method in estimating plant water content. This is expected in spectroscopy as the first derivative reflectance gives a more accurate determination of the red edge inflection point due to the large number of narrow bands found in hyperspectral data (Schmidt, 2003). The linear four-point interpolation method developed by Guyot and Barett (1988) is used when a large number of bands are not available in the red edge region and hence is calculated by an equation. Liu *et al.*, (2004) reported similar results whereby the red edge yielded high correlations at the 0.999 confidence level and performed better than the WI and the NDWI. The red edge region which is less subject to background effects and has minimum atmospheric interference has thus been proposed for plant water estimation on hyperspectral data. The results from this study indicate that the red edge position can be used for plant water estimation as it performed better than the traditional indices used for water estimation.

4.6. Conclusion

This study had two main objectives: 1) to assess the relationship between plant water content and leaf reflectance and 2) to compare the effectiveness of the red edge position compared to the other water indices tested in estimating plant water content. The following conclusions can be drawn:

1: the visible and mid-infrared regions of the electromagnetic spectrum were significantly correlated with plant water content using the first derivative reflectance.

2: the red edge position can be used as a stable spectral parameter to estimate plant water content as it performed better than the traditional indices used for water estimation.

Overall the potential of spectroscopy and the red edge position in estimating plant water content has been confirmed by this study. Future research should investigate other water parameters such as relative water content, water potential and equivalent water thickness with the red edge region. Due to time constraints within this study these water parameters could not be tested.

This paper assessed the relationship between plant water content and reflectance data using univariate correlations. However it is important to predict plant water content on unsampled sites using predictive models. The next chapter will therefore develop models based on artificial neural networks and data resampled to the SumbandilaSat band settings for the possible purpose of mapping water content in plantation forests.

Chapter Five

5. Integrating field spectroscopy and neural networks to estimate plant water content using spectra resampled to the Sumbandila Satellite

5.1. Overview

The monitoring of plant water content has important ramifications for understanding plant stress, fire potential and ecosystem dynamics (Toomey and Vierling, 2005). According to Ceccato *et al.*, (2001) the most practical and cost effective way to monitor plant water content from a local to global scale is to use earth observation technologies such as satellites. Satellites provide local to global coverage on a regular basis and also provide information on remote areas where ground measurements are impossible on a regular basis. In the context of South Africa, studies focusing on the estimation of plant water content using hyperspectral data have been limited due to the cost and availability of imagery. However it is envisaged that the South African satellite, Sumbandila (ZASat-002) is due for launch in the near future from a Russian submarine (Scholes and Annamalai, 2006). With the future availability of satellite imagery available in South Africa, the question then arises: is there the potential to successfully estimate plant water content? This study resamples field spectral data from *Eucalyptus grandis* stands in KwaZulu-Natal, South Africa to the band settings of the SumbandilaSat in order to test its potential in estimating plant water content using an artificial neural network, a study which has not been done before. The potential of the individual SumbandilaSat bands in estimating plant water content will be assessed using a sensitivity analysis. The next section will describe the results.

Table 5.1. Variation in plant water content

Variable	Samples	Mean (%)	Minimum (%)	Maximum (%)	Standard Deviation
Water Content	50	52.03	44.72	73.19	6.55

Plant water content measurements (Table 5.1) varied from 44.72 % to 73.19 % with an average of 52.03 %. Similar water content measurements were reported by Ceccato *et al.*, (2001) at leaf level that ranged from 58.07 % to 61.31 % on four species in a temperate forest. The differences in the plant water measurements can be explained by the wide variation in leaf type and cover of *Eucalyptus grandis* leaves. Spectra of the mean reflectance and ± 95 confidence limits for the samples are shown in Figure 5.1.

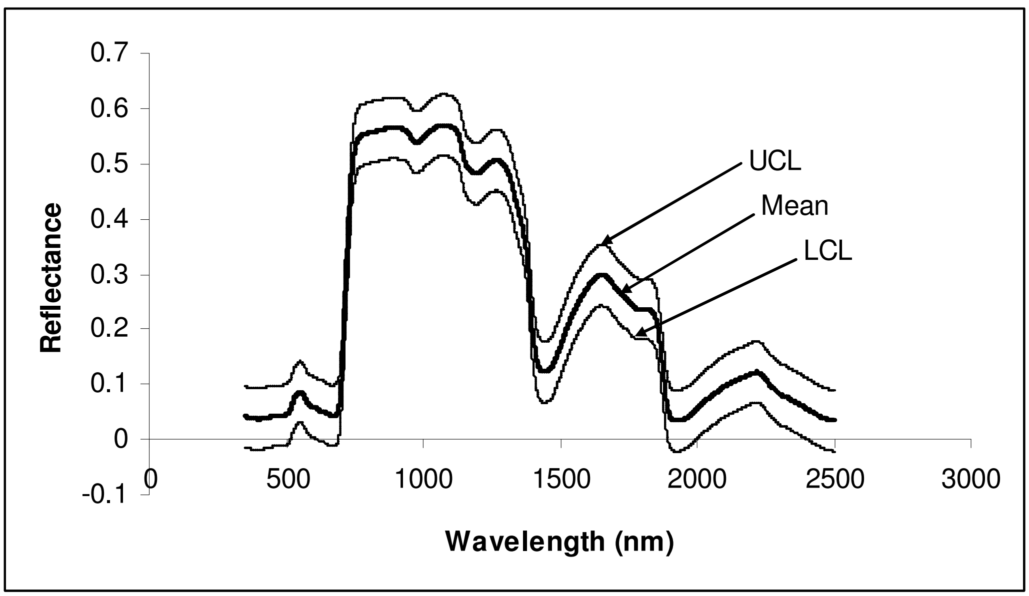


Figure 5.1. Reflectance spectra of *Eucalyptus grandis* leaves (n = 50). The mean, upper 95 % confidence limit (UCL) and lower 95 % confidence limit (LCL) of the spectra are shown.

5.2. Resampling field spectra to the SumbandilaSat wavebands

The field spectra were resampled to simulate the SumbandilaSat wavebands using ENVI (Environment for visualizing images, Research Systems, Inc) software. The method uses a gaussian model with a full width at half maximum (FWHM) equal to the bands spacings provided. The FWHM method is a simple and well defined number which is used to compare the quality of images under different resolutions. The technique uses the field spectral data from the ASD spectrometer and resamples it to the spectral band width of the SumbandilaSat band settings. Figure 5.2 shows the mean resampled spectra of the SumbandilaSat wavebands.

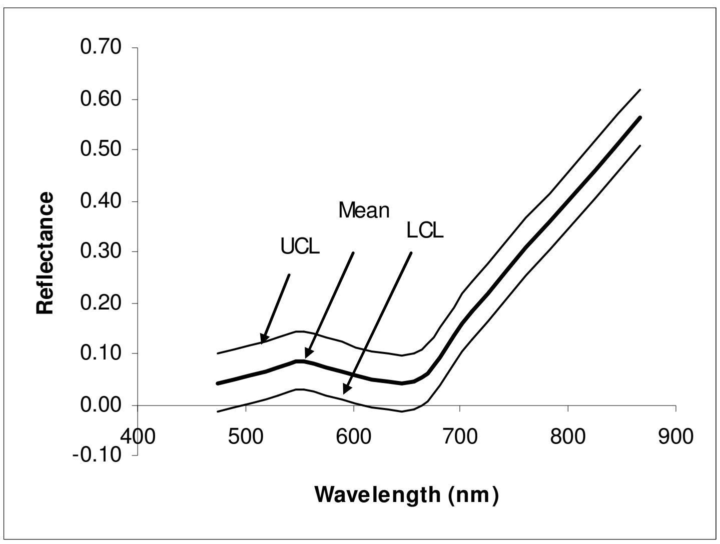


Figure 5.2. Mean resampled spectra of the SumbandilaSat wavebands. The mean, upper 95 % confidence limit (UCL) and lower 95 % confidence limit (LCL) of the spectra are shown.

5.3. Relationship between SumbandilaSat wavebands and plant water content

The 50 plant water measurements were correlated with the resampled SumbandilaSat wavebands. Table 5.2 shows the correlation coefficients of the SumbandilaSat wavebands with plant water content. None of the SumbandilaSat wavebands were significantly correlated with the plant water content measurements. The xanthophyll waveband yielded the highest correlation of 0.24 and the red edge yielded the lowest correlation of 0.03.

Table 5.2. SumbandilaSat relationship with plant water content

SumbandilaSat Wavebands	**Correlation Coefficient (r)**
Blue	0.15
Xanthophyll	0.24
Green	0.21
Red	0.16
Red Edge	0.03
Near-infrared	-0.22

Due to the limited number of wavebands on the SumbandilaSat, water indices could not be calculated as the bands used for water estimation are unavailable. The NDVI which is mainly used to assess vegetation cover was calculated and yielded a Pearson correlation coefficient of -0.31. In comparison with the hyperspectral data the NDVI yielded a significant correlation of 0.41 at the 0.999 confidence interval. The resampled SumbandilaSat wavebands were then put into a neural network to test its potential in estimating plant water content.

5.4. Parameters of the neural network

The six SumbandilaSat wavebands were input into a neural network to test its potential in estimating plant water content. The total dataset was randomly divided into two groups, one subset for training (38 samples) and the other subset for testing (12 samples). The effect of increasing the number of nodes on the performance of the neural network was tested. According to Atkinson and Tatnall (1997) the larger the number of nodes in the hidden layer, the better the neural network's ability to represent the training data, however at the expense of the ability to generalize. Figure 5.3 shows that as the number of nodes increase the correlation coefficient increases for both the training and test dataset. However once the number of hidden nodes reached six the correlation coefficient for both the training and test dataset began to decline.

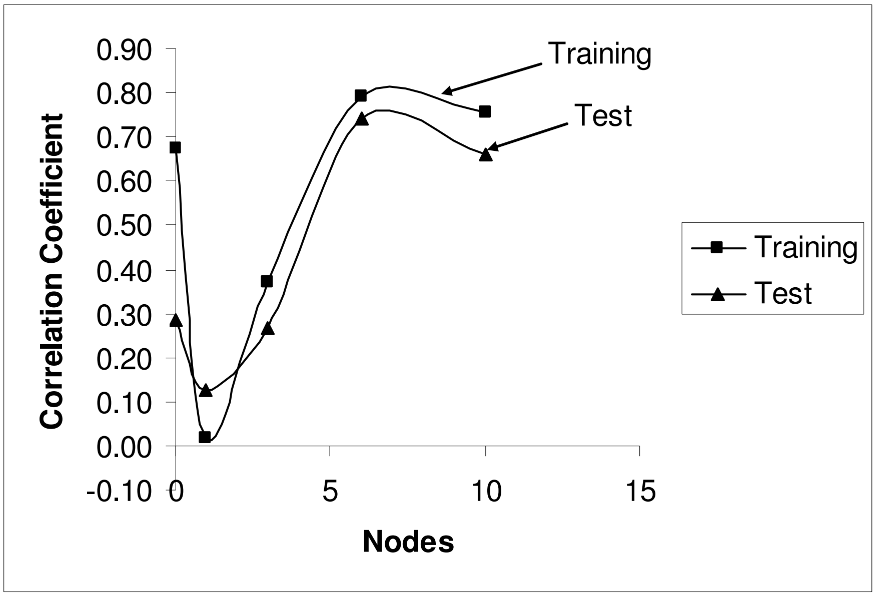


Figure 5.3. Number of nodes versus correlation coefficients for the training and test data sets.

Following a series of experiments to obtain the optimum neural network settings (changing the number of nodes versus the correlation coefficient) Table 5.3 shows the neural network parameters for the trained neural network that was used to estimate plant water content.

Table 5.3. Parameters for the trained neural network used for predicting plant water content.

Parameter	**Value**
Number of inputs	6
Number of outputs	1
Number of layers	3
Number of hidden nodes	6
Neural Network	Multiple layer perceptron

5.5. Applying the neural network to estimate plant water content

The neural network parameters presented in Table 5.3 were used in training the neural network. The training process was run 5 times with random initial weights (Zhang *et al.*, 2002). The prediction capability of the neural network was assessed using the correlation coefficient and the root mean square error (RMSE). The neural network that yielded the highest correlation coefficient as well as the lowest RMSE was then selected. Figure 5.4 shows a scatter plot of the predicted and measured plant water content using the best-trained neural network. Table 5.4 shows the results from the other neural network experiments.

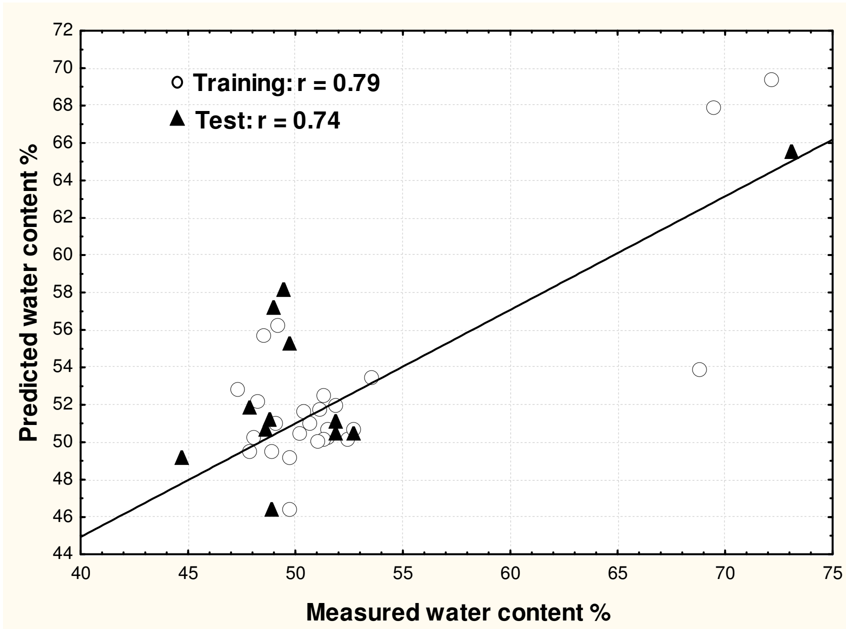


Figure 5.4. Scatterplot obtained from the best trained neural network that was selected.

Table 5.4. Results from the Neural Network Experiments

Neural Network	Training (r)	Test (r)
1	0.67	0.28
2	0.02	0.13
3	0.37	0.27
4*	0.79	0.74
5	0.75	0.66

*Best trained neural network.

5.6. Comparison between neural networks and multiple regression

The performance of the neural network in estimating plant water content was compared to that of a stepwise multiple regression. The same training dataset for the neural network algorithm was put into a forward stepwise multiple regression model. The regression model yielded a correlation coefficient of 0.51 with the xanthophyll, green and red wavebands showing significance at $p < 0.04$. These wave bands were then used in predicting plant water content on the test dataset. The performance of the multiple regression was assessed using the correlation coefficient as well as the RMSE. Table 5.5 shows the comparison between the multiple regression and the neural network experiments.

Table 5.5. Comparison between multiple regression and neural networks

	Multiple Regression		**Neural Network**	
Plant Water Content	Training	Test	Training	Test
Correlation coefficient	0.51	0.70	0.79	0.74
RMSE	0.80	2.83	0.78	1.41

The neural network yielded a higher correlation coefficient (r = 0.74) compared to the multiple regression (r = 0.70) on an independent test data set. The prediction capability of the regression model and the neural network was also measured using the RMSE. The neural network yielded a lower RMSE (1.41) compared to the multiple regression RMSE (2.83) on an independent test data set.

5.7. Sensitivity analysis and the relative importance of the SumbandilaSat wavebands

The relative importance of the SumbandilaSat wavebands in predicting plant water content was tested using a sensitivity analysis. A sensitivity analysis indicates which input variables of the neural network are most important. For each variable (SumbandilaSat wavebands), the network is executed as if that variable is unavailable in the model. The error obtained when that variable is unavailable is then divided by the error obtained when the variable is available. Important variables have a high ratio, indicating that the performance of the network will deteriorate if that variable is no longer available to the model. Table 5.6 shows the relative importance of the SumbandilaSat wavebands in estimating plant water content.

Table 5.6. Sensitivity analysis of the SumbandilaSat bands used in the neural network

Rank	**Variable**	**Ratio**
1	Xanthophyll	2.04
2	Blue	1.46
3	Near-Infrared	1.43
4	Red Edge	1.09
5	Red	1.07
6	Green	1.06

The sensitivity analysis indicates the relative importance of the xanthophyll band which was ranked 1 and the blue and near-infrared bands which were ranked 2 and 3 in estimating plant water content. These bands are therefore essential in estimating plant water content from the SumbandilaSat.

5.8. Discussion

This section will discuss the potential of field spectroscopy and neural networks in estimating plant water content using the resampled spectra, and assess the importance of resampling the spectra to simulate the SumbandilaSat wavebands.

5.8.1. Integrating neural networks and spectroscopy to estimate plant water content

This study has demonstrated the potential of integrating field spectroscopy and neural networks to estimate plant water content. The resampled field spectra that was put into a neural network yielded a correlation coefficient of, r = 0.74 with a RMSE of 1.41 between the predicted and measured plant water content measurements on an independent test data set. The neural network approach outperformed the conventional multiple regression method used for prediction. The ability of a neural network to model complex behavior and non-linearity within a dataset through its weighting function therefore confirms that it is better at predictive modeling compared to a multiple regression approach. The results from this study are comparable with that of Mutanga and Skidmore (2004) who integrated imaging spectrometry and neural networks to predict nitrogen concentration in an African savanna. The neural network approach explained 60% of variation in nitrogen concentration compared to 38% explained by a multiple regression. Similarly Trombetti *et al.*, (2008) applied a neural network to MODIS satellite data to retrieve vegetation canopy water content. The neural network algorithm showed good performance across different vegetation types and yielded high correlation coefficients. This study therefore confirms previous studies that have successfully applied neural networks and remote sensing data to estimate biochemical constituents such as water content.

5.8.2. Resampling to the SumbandilaSat wavebands

The resampling of the field spectra to simulate the SumbandilaSat wavebands is of great importance due to the launch of the satellite in the near future and to assess the potential of the satellite in determining vegetation vigour and health. This study was the first attempt to predict plant water content in *Eucalyptus grandis* forest stands using the resampled field spectra of the Sumbandila satellite. There were no significant correlations between the 50 plant water measurements and the resampled bands. However, the xanthophyll waveband yielded the highest correlation of 0.24 and was ranked the most important waveband used by the neural network in estimating plant water content using a sensitivity analysis. The sensitivity analysis gives important insights into the usefulness of individual wavebands and identifies wavebands that can be ignored for subsequent analysis. The xanthophyll, blue and near infrared wavebands were ranked the three most important wavebands used by the neural network in estimating plant water content as they yielded the highest ratios. If these bands were removed the performance of the neural network in predicting plant water content will deteriorate. In general this study demonstrated the importance of resampling the field spectra to simulate the performance of the SumbandilaSat wavebands in estimating plant water content.

5.9. Conclusion

The main objective of this paper was to assess the potential of integrating field spectroscopy and neural networks to estimate plant water content using spectra resampled to the SumbandilaSat band settings. The following conclusions can be drawn:

1: the integrated approach involving resampled field spectra and neural networks successfully predicted plant water content with a correlation coefficient of 0.74 and a RMSE of 1.41 between the predicted and measured data on an independent test dataset. The result indicates the potential of the SumbandilaSat, the South African satellite which is proposed for launch in the near future.

2: the neural network approach performed better than the traditional multiple regression method for estimating plant water content.

3: the xanthophyll, blue and near-infrared bands of the SumbandilaSat are proposed for plant water estimation.

Overall the potential of integrating field spectroscopy and neural networks to estimate plant water content has been confirmed by this study. With the launch of the SumbandilaSat evident in the near future, this was the first attempt to predict plant water content in *Eucalyptus grandis* forest stands using spectra resampled to the SumbandilaSat band settings and this has yielded positive results.

Chapter Six

6. Conclusion

6.1. Introduction

This study aimed to assess the relationship between plant water content and reflectance data in *Eucalyptus grandis* forest stands in KwaZulu-Natal, South Africa. This chapter will review the aim and objectives of this study and examine how close the study came in order to achieve the goals set. Limitations of the study will be evaluated and future recommendations in the field of spectroscopy and plant water content will be made.

6.2. Aim and objectives reviewed

The aim of this research was to assess the relationship between plant water content and field reflectance data in *Eucalyptus grandis* forest stands in KwaZulu-Natal, South Africa. In order to achieve this aim the following objectives were carried out:

- To test the relationship between plant water content from *Eucalyptus grandis* trees and reflectance data measured from a field spectrometer at each wavelength.

This was achieved by correlating the field reflectance and the first derivative reflectance with plant water content at each wavelength in the electromagnetic spectrum. The results show that the first derivative reflectance performed better than the original reflectance in estimating plant water content with significantly high correlations in the visible and mid-infrared portions of the electromagnetic spectrum. Similar results were reported by Danson *et al.*, (1992) on the derivative reflectance with strong correlations in the mid-infrared regions. It was therefore concluded that the visible and mid-infrared portions of the electromagnetic spectrum are suitable for plant water estimation. It was also concluded that the first derivative reflectance is better at predicting plant water content when there is a variation in leaf internal structure which was present in the *Eucalyptus grandis* forest stands of KwaZulu-Natal, South Africa.

- To evaluate the effectiveness of several reflectance indices for estimating plant water content and compare them to the red edge position.

This was done by performing bootstrapping correlations on six water indices and on the two red edge positions. From the reflectance indices, NDVI yielded the highest bootstrapped correlation coefficient followed by the two new semi-empirical indices developed for plant water estimation by Datt (1999). The bootstrapped correlation coefficients for the red edge positions yielded higher correlations $r = 0.65$ and $r = 0.56$ at the 0.999 confidence level compared to all the water indices tested. Liu *et al.*, (2004) reported similar results whereby the red edge yielded high correlations at the 0.999 confidence level and performed better than the WI and the NDWI. It was therefore concluded that the red edge position can be used for plant water estimation on hyperspectral data as it performed better than the traditional indices used for water estimation.

- To resample the field spectra to the SumbandilaSat and assess its potential in estimating plant water content using an artificial neural network.

To achieve this objective the field reflectance data was resampled to simulate the SumbandilaSat wavebands and was input into a neural network to assess its potential in estimating plant water content. Following a series of experiments to obtain the optimum neural network settings by changing the number of hidden nodes, the neural network that yielded the highest correlation coefficient as well as the lowest RMSE was then selected to predict plant water content. The neural network approach performed better than the traditional multiple regression approach for estimating plant water content and yielded a correlation coefficient of

0.74 and a RMSE of 1.41 between the predicted and measured data on an independent test dataset. It was therefore concluded that neural networks can be successfully integrated with remote sensing data to estimate plant water content.

- To assess the relative importance of the individual SumbandilaSat wavebands in estimating plant water content using a sensitivity analysis.

The potential of the SumbandilaSat wavebands in estimating plant water content was assessed using a sensitivity analysis. A sensitivity analysis indicates which input variables of the neural network are most important and identifies wavebands that can be ignored for subsequent analysis. The xanthophyll, blue and near infrared wavebands were ranked the three most important wavebands used by the neural network in estimating plant water content as they yielded the highest ratios indicating their importance in estimating plant water content. It was therefore concluded that the xanthophyll, blue and near-infrared bands of the SumbandilaSat are essential for plant water estimation.

6.3. A synthesis

This study has showed the potential of field spectroscopy in estimating plant water content in the *Eucalyptus grandis* forest stands of KwaZulu-Natal, South Africa. From this study it is evident that the visible and mid-infrared portions of the electromagnetic spectrum are suitable for plant water estimation as they were strongly correlated with plant water content using the first derivative spectra. The study evaluated the effectiveness of several water indices in estimating plant water content and compared them to the red edge position. The red edge position outperformed all the traditional indices used for plant water estimation and yielded significantly high correlations at the 0.999 confidence interval. However when the spectra was resampled to the SumbandilaSat band settings, the xanthophyll, blue and near-infrared bands were ranked more important than the red edge. This is possible because the derivative spectra give a more accurate determination of the red edge position compared to a multi-spectral satellite such as the SumbandilaSat which has a limited number of wavebands. The SumbandilaSat wavebands are made up of the red edge reflectance and not the red edge position. Due to the restricted number of bands available on the SumbandilaSat the resampling technique could not accurately determine the red edge position whereas with the hyperspectral data, the red edge position can be accurately calculated due to the large number of bands available. It was therefore possible that the red edge was thus not picked up as the most significant band for plant water estimation and was thus ranked fourth in importance, compared to the other wavebands. However, the SumbandilaSat wavebands successfully predicted plant water content with a correlation coefficient of 0.74 and a RMSE of 1.41 between the predicted and measured data on an independent test dataset using an artificial neural network. The sensitivity analysis also indicated the importance of the xanthophyll, blue and near-infrared bands in estimating plant water content. This study has indicated the potential of estimating plant water content using field spectroscopy. Furthermore the study has demonstrated the potential of up-scaling field hyperspectral data to satellite remote sensing using the South African satellite SumbandilaSat, which is scheduled for launch in the near future.

6.4. Limitations of the Study

One of the limitations of this study was sampling on the edge of the forestry compartments referred to as the 'edge effect' in forestry. Sampling was done on trees that grew on the edge of the *Eucalyptus grandis* compartments as the cherry picker could not be taken inside the forest stands. Future research on plant water content in forest stands should allow for the branches to be shot down or the trees should be climbed and branches should be cut in order to obtain samples. This will compensate for the edge effect in forest stands and reduce bias sampling.

6.5. Future recommendations and Conclusion

Future research in plant water content and spectroscopy should investigate other water parameters such as relative water content, water potential and equivalent water thickness with the red edge region as the results from this study show that the red edge performs better than the conventional indices used for water estimation on hyperspectral data. This was the first attempt to predict plant water content in *Eucalyptus grandis* forest stands using spectra resampled to the SumbandilaSat band settings. When the SumbandilaSat becomes operational, research should also incorporate neural networks with imagery in estimating plant water content in South African plantations. Traditional techniques to assess plant water measurements and forest stress are time consuming, costly and spatially restrictive. The ultimate goal will involve developing reliable and stable methods to estimate plant water content using airborne satellite remote sensing. Satellite remote sensing provides local to global coverage on remote areas where ground measurements are impossible on a regular basis and enables effective management of forest health.

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Appendix
Plant Water Content

Samples	Fresh Weight (g)	Dry Weight (g)	% Moisture
1	4.192	2.077	50.451
2	4.612	2.276	50.660
3	5.631	2.799	50.287
4	4.408	2.156	51.089
5	5.342	2.538	52.495
6	4.548	2.263	50.234
7	4.741	2.380	49.810
8	4.900	2.354	51.951
9	5.351	2.732	48.934
10	3.847	1.989	48.285
11	4.380	2.228	49.136
12	6.253	3.154	49.566
13	4.565	2.330	48.967
14	4.990	2.378	52.344
15	4.937	2.627	46.779
16	4.358	2.024	53.570
17	6.636	3.240	51.172
18	5.884	2.850	51.558
19	6.601	3.121	52.724
20	4.025	1.936	51.887
21	6.149	3.042	50.533
22	4.301	2.082	51.588
23	7.226	3.670	49.214
24	5.868	2.824	51.877
25	4.398	2.282	48.114
26	7.091	1.901	73.186
27	9.081	2.744	69.788
28	8.324	2.317	72.166
29	8.506	2.590	69.551
30	8.626	2.686	68.864
31	6.989	3.864	44.716
32	8.197	4.212	48.617
33	6.144	3.120	49.225
34	6.491	3.378	47.954
35	4.893	2.494	49.034
36	6.166	2.999	51.357
37	5.250	2.733	47.949
38	5.845	3.101	46.946

Samples	Fresh Weight (g)	Dry Weight (g)	% Moisture
39	3.161	1.625	48.587
40	7.007	3.688	47.365
41	9.495	4.767	49.797
42	4.038	2.066	48.829
43	5.521	2.688	51.320
44	4.765	2.485	47.858
45	5.120	2.505	51.072
46	5.301	2.628	50.425
47	5.844	2.950	49.523
48	5.228	2.468	52.788
49	5.702	2.747	51.817
50	4.986	2.505	49.760