

The characterisation of the Yellowwoods' leaf area index, within a southern African mistbelt forest, using Geographic Information Systems and Remote Sensing

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Abstract

Forests hold a plethora of ecological functions, that are critical in the maintenance of biodiversity. For instance, the mistbelt forests are small and fragmented forest ecosystems, which are dominated by South Africa's national tree - *Podocarpus latifolius* or the 'real' Yellowwood. The Yellowwood trees are regarded as a priority species, because they support large communities of plants, birds and mammals, attributing to the maintenance of biodiversity. They also store carbon and provide habitat as well as resources for pollinators. Meanwhile, they produce durable, high quality timber which is harvested for cultural, medicinal and commercial use. Subsequently, the podocarps have been listed as endangered species owing to extensive logging. Current forest species productivity information is urgently required in the characterisation of forest condition, especially that of disturbed habitats which support a variety of indigenous species and contribute immensely to ecosystem resilience. Leaf area index (LAI) is a widely applied measure of photosynthetic capacity and productivity, that may reveal this information. Meanwhile, local level floral biodiversity and productivity is driven by topographic heterogeneity. Micro landscape level processes associated with topography are important in the determination of leaf area index, that may be applied as proxy measures of productivity. However, this is not well understood, especially for unique forest types such as the Afromontane mistbelt forest. Recently, Geographic Information Systems and Remote Sensing, have progressed to assume a pivotal role in the monitoring of vegetation, offering increased spatial coverage and modern, automated processing techniques. The applicability of digital elevation models such as the Shuttle Radar Topographic Mission, facilitates the retrieval of objective topographic measurements, that can be used in the explanation of leaf area. Meanwhile, the onset of "new generation" sensors, such as Sentinel 2 Multispectral Instrument has provided opportunity for investigating leaf area index, which cannot be achieved using traditional field surveys. This progression is supplemented by the application of machine learning algorithms, in the modelling of ecological relationships. Applying these algorithms in this regard, has demonstrated strength in managing data of high dimensionality, with speed and accurate results. The study therefore set out to characterise the leaf area index of the Yellowwood within a southern African mistbelt forest, using Geographic Information Systems and Remote Sensing techniques. Specifically, the study evaluated the role of Shuttle Radar Topographic Mission digital elevation model derived topographic variables, in the explanation of LAI, using Principal Component Analysis (PCA) and regression analysis. It also assessed the utility of Sentinel 2 imagery, in the estimation LAI, using the Random Forest (RF) regression ensemble. The stepwise linear regression analysis showed that topographic indices accounted for approximately 85 % of leaf area index variance ($SEE = 35\text{m}^2/\text{m}^2$; $R^2 = 0.85$). Optimal topographic variables included the mass balance index and sky view factor. These can explain the micro landscape properties relating to ecosystem budgets and visible sky. Results also indicated that the backward elimination method optimally predicted the leaf area index of Yellowwood trees ($RMSE = 0.48$; $R^2 = 0.59$). Further, predictors derived from the Red Edge bands were the most influential variables in predicting leaf area index. The study demonstrated the applicability of remotely sensed data and Geographic Information Systems in the retrieval of forest productivity proxies, such as leaf area index.

Preface

The study was undertaken in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, from March 2018 to May 2020, under the supervision of Professor Onesimo Mutanga and Doctor Mbulisi Sibanda, to fulfil the requirements of a Master's of Science in Environmental Science.

I, Nokwanda Gumede, declare that the current work represents my own ideas and has never been submitted to any other academic institutions. Acknowledgement has been duly made for statements originating from other authors.

Nokwanda Gumede (Candidate)

Signed: N. Gumede Date: 5 May 2020

As the candidate's supervisors, we certify the aforementioned statement and have approved this thesis for submission.

Professor Onesimo Mutanga (Supervisor)

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Declaration

I, Nokwanda Gumede, declare that:

1. The research reported in this thesis, except where otherwise indicated is my original research.
2. This thesis has not been submitted for any degree or examination at any other institution.
3. This thesis does not contain other person's data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.
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Dedication

"To all those who let monotonous lives, in the hope that they may experience at second hand the delights and dangers of adventure." – Agatha Christie.

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I would like to thank God for His grace and mercy: *Qhubeka Nkosi usiphumelelise!*

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Chapter One

General introduction

1.1. Introduction

Forests hold the largest proportion of global biodiversity (FAO, 2015; Swingland, 2001; UNFCCC, 1997) and account for the largest share of terrestrial productivity per unit area (Beer et al., 2010). This productivity is concerned with critical ecological functions, including temperature regulation, nutrient cycling and carbon sequestration (Costanza et al., 1997; Gibbs et al., 2007; Oliver and Larson, 1996). Forests occupy an estimated 30 % of the total earth surface and are responsible for a functioning and healthy biosphere (UNFCCC, 1997). In southern Africa, there are two types of indigenous forests - lowland forests, near the eastern seaboard as well as the montane forests which are located in patches about 1 200 m above sea level (Mucina et al., 2006).

In South Africa, indigenous forests occupy an approximated 500 000 hectares, which is no more than 0.04 % of the country's land area (Lawes et al., 2004; Mucina and Rutherford, 2006). The evergreen forest patches associated with the Afromontane mistbelt forests, also known as the Yellowwood forests (Moll, 1972) cover less than 5 % of this area (Eeley et al., 1999; Eeley et al., 2001). These forests are home to the *Podocarpaceae*, which is the second largest conifer family and is recognised as one of the major genus's in biogeography studies (Quiroga et al., 2016). They are characterised by emergent trees, with large, wide spreading crowns. These trees function as keystone structures within the mistbelt forest ecosystem and they create microclimates through shade and provide understory layer growth (Lawes et al., 2004). The Yellowwood forests are home to the Red Listed, forest specialist – the Cape Parrot, which is estimated to have a population of less than 1000 in the wild. They further support other bird species, including the bush blackcap and woodpecker. These tree species are of national pride in South Africa. Specifically, *Podocarpus latifolius* is recognised as the National Tree and one of the Champion Trees of South Africa (Department of Agriculture, 2013). Subsequently, these tree species are protected under the National Forest Act of 1998. This call was made as Yellowwoods were once extensively logged for timber products (Hutchins, 1905; Moll, 1972) such that they were on the brink of extinction in certain areas (Adie et al., 2013; Eeley et al., 1999). Yellowwood timber products were commonly used for furniture and ornaments, which were displayed in many old buildings. Legally, acquiring Yellowwood timber is becoming increasingly costly and difficult to source. As a result, the illegal harvesting of timber is becoming more common (Lawes et al., 2004). Local communities also depend on the forest's resources, for firewood to sustain their livelihoods (Eeley et al., 1999; Rudel, 2013), which further threatens the already diminishing tree numbers (Lawes et al., 2004). There is, therefore, a pressing need to provide practical and effective mechanisms of assessing productivity of the Yellowwood forests in addition to the preservation of the tree species themselves.

Leaf area index (LAI) is a recognised vegetation parameter which can reveal information relating to primary production. LAI is a quantity of plant canopy, representing the total single sided surface area of the leaves within the canopy (Breda, 2003; Chen and Black, 1992). Processes such as light interception, photosynthesis and evapotranspiration are important input in the determination of primary productivity. Therefore, measuring the LAI of the Yellowwoods will provide the information necessary for understanding indigenous forest growth. Also important in this regard is the influence of local topographic variability. Topography assumes a pivotal role in forest condition, as it controls local hydrological and nutrient conditions, within ecosystems (Jucker et al., 2018). For instance, Alves et al. (2010) showed that more permanent topographic variables, such as aspect were more influential in regulating water availability to plants. Swetnam et al. (2017) evaluating the influence of topography on montane carbon, noted that average carbon loading increased with lower topographic positions and was higher on northern aspects. However, the integration of LAI and the landscape morphology has not been extensively explored in understanding species productivity. Limited literature merely demonstrates the importance of topography in correcting canopy LAI measurement errors (Jin et al., 2019). For example, Gonsamo and Pellikka (2008) applied different techniques for slope correction in the prediction of canopy LAI. However, there is still a need to assess the influence of topographic controls on the spatial variability of LAI, particularly that of keystone tree species, such as the Yellowwoods. This will in turn offer more accurate predictions of forest productivity, which is essential for deriving comprehensive monitoring and management strategies for conserving dwindling indigenous forests (Turner et al., 2003).

Previously, the retrieval of information relating to vegetation condition could only be achieved through tedious, labour intensive field surveys (Skole and Tucker, 1993). These surveys were unable to capture micro forest details and produced low accuracy maps. More recent advances in both the Remote Sensing (RS) and Geographic Information Systems (GIS) techniques have facilitated the investigation of biophysical forest attributes such as LAI at increased spatial and temporal resolutions (Adie et al., 2013; Aschbacher and Milagro-Pérez, 2012). Earth Observation (EO) systems have become predominant reservoirs of spatial data which is required in extensively investigating and understanding LAI as a proxy for vegetation productivity. This is because they provide near real time, continuous and synoptic datasets which avail information on forest condition. The applicability of digital elevation models (DEM's) facilitates the retrieval of objective landscape level topographic measurements that can be used in understanding specific ecosystem functioning proxies, such as leaf area index particularly in threatened forests (Coblentz and Riitters, 2004; Moore et al., 1991; Spadavecchia et al., 2008). DEM's are inexpensive data sources, when compared to field surveys and offer ease of use. Currently the longest running source of continuous elevation data can be obtained from the National Aeronautic Space Agency (NASA) Shuttle Radar Topographic Mission (SRTM). SRTM datasets are now freely available through the open access scheme, for all geographical regions with improved quality. DEM's are compatible with GIS, which provides a computing platform for the fast, automated processing of geospatial data. It is, therefore, perceived that SRTM derived topographic indices could be used in explaining the spatial variability exhibited by the productivity of Yellowwood tree species in the Afromontane forests.

Meanwhile, “new generation” sensors supplemented by field measurements have been proven to be important in understanding the LAI and productivity of changing forests to a higher degree of certainty (Ahmed et al., 2015; Goetz and Dubayah, 2011; Skole and Tucker, 1993). One such example, is the introduction of the Sentinel 2 Multispectral Instrument (S2 MSI) satellite series launched by the European Space Agency (ESA) (Aschbacher and Milagro-Pérez, 2012). The mission was launched to provide novel prospects for the scientific community, intended to complement the *Satellite Pour l’Observation de la Terre* (SPOT) in offering an advanced, improved resolution optical environmental observation system (Aschbacher and Milagro-Pérez, 2012; Drusch et al., 2012). The series is one of the more recent sensors to offer freely available, improved medium resolution products, that can be used in the retrieval of biophysical information (Masek et al., 2015). S2 MSI has additional Red Edge (RE) bands, specifically suited to retrieve information related to various biophysical vegetation productivity components such as chlorophyll content and LAI (Delegido et al., 2011; Drusch et al., 2012). It is, therefore, necessary to assess the utility of S2 MSI’s RE bands in estimating the LAI of Yellowwood tree species as a productivity proxy.

Applying GIS and RS in concert with simple but robust algorithms in the prediction and mapping of the drivers behind the spatial variability of LAI has presented itself as the most appropriate approach to forest productivity characterisation. The Principal Component Analysis (PCA) has been prominent in literature for its ability to reduce numerous explanatory variables into few manageable latent variables in vegetation mapping (Cushman et al., 2008; Jucker et al., 2018; Mertes, 2002). It is used in studies to reduce dimensionality and determine levels of relatedness among similar variables, and group these accordingly (Petrişor et al., 2012). PCA is particularly important in this study as topographic variables are correlated (Spadavecchia et al., 2008) and therefore variables can be summarised before relating them to LAI. Meanwhile the Random Forest (RF) regression ensemble has been extensively applied in the estimation of LAI owing to its accuracy and fast processing time (Belgiu and Drăguţ, 2016). Relatively few studies in the southern African context have sought to characterise emergent tree attributes such as the LAI, of the Yellowwoods using GIS and RS applications. It is in this regard that this study sought to predict the LAI of the Podocarps dominated indigenous forest using the PCA and RF regression ensemble, in conjunction with SRTM derived topographic indices as well as S2 MSI data.

1.2. Aim and Objectives

The aim of the study is, therefore, to characterise the LAI of the Yellowwood tree species in a southern African Afromontane mistbelt forest, using remotely sensed imagery; the SRTM DEM and the S2 MSI product. To achieve this the study

- 1.2.1. Evaluated the role of SRTM DEM derived topographic variables, in the explanation of LAI, using PCA and stepwise regression analysis.
- 1.2.2. Assessed the utility of S2 MSI imagery, in the estimation of LAI, using the RF regression ensemble.

1.3. Research Questions

- 1.3.1. Can the suite of topographic variables derived from the SRTM DEM, significantly explain LAI distribution?
- 1.3.2. Which of the topographic metrics selected in the stepwise linear regression, will have a greater role in LAI distribution?
- 1.3.3. Which of the model builder approaches, derived from the S2 MSI imagery will predict LAI to an acceptable level of accuracy?
- 1.3.4. To what extent do the RE bands and indices predict LAI?

1.4. Structure of the Thesis

The thesis presented contains four chapters, two of which may be regarded as standalone manuscripts. The two chapters contain similarities as they address the same overarching objective. The chapters are presented as follows:

Chapter One introduces the thesis, outlining the importance of, and contextualising the characterisation of LAI within an indigenous forest, using GIS and RS imagery. The aim, objectives, and research questions of the study, are included in this chapter.

Chapter Two presents the role of topographic variables, using PCA and stepwise linear regression models, in the explanation of LAI distribution in the forest.

Chapter Three evaluates the utility of a S2 MSI derived prediction model and compares different model builder approaches, using the RF regression ensemble in the prediction of LAI.

Chapter Four is a synthesis of **Chapters Two and Three**. The aim and objectives of the respective chapters are reviewed, together with conclusions. The chapter further discusses implications and recommendations for the study.

Chapter Two

The role of topographic variables in explaining leaf area index of the Yellowwood tree species in an Afromontane mistbelt forest of southern Africa

Abstract

Forming a holistic understanding of tropical indigenous forest vegetation dynamics is crucial for effective conservation monitoring and management strategies. Local surface topography assumes a pivotal role in the distribution and productivity of specialist forest species, such as the Yellowwood tree. Surface topography affects abiotic properties relating to soil, hydrology, drainage, and microclimate, that influences vegetation growth and contributes to environmental complexity. Meanwhile, the Yellowwoods contribute to the maintenance of biodiversity by providing a habitat to many forest species, such as the endangered Cape Parrot (*Poicephalus robustus*), that are heavily dependent on them. In this regard, understanding the influence of topography on the productivity and health condition of these trees will provide a framework required in drawing up effective conservation strategies for indigenous forest species. Tree properties such as leaf area index, are important indicators of plant condition and productivity, which are constrained by local topographic conditions. This study sought to assess the influence of topographic variables on the leaf area index of Yellowwood tree species. Principal component analysis and the stepwise linear regression were used to assess the influence of Shuttle Radar Topography Mission digital elevation model derived topographic variables, on leaf area index. Results of this study showed the catchment area, mass balance, sky view factor, convergence index, maximum curvature and aspect ($SEE = 35\text{m}^2/\text{m}^2$ and $R^2 = .85$), explained the spatial variation of the observed leaf area index of Yellowwood tree species in the Ingeli State Forest. The findings of this study are a fundamental step towards drawing up comprehensive frameworks for inventorying and monitoring indigenous forest species.

2.1. Introduction

Information on tree growth, particularly that of endangered species such as the Yellowwood's (*Podocarpae*) is pivotal to successful indigenous forest management. Topography is an abiotic factor that influences growing conditions for plants, which affects the composition and dynamics of ecological communities (Muscarella et al., 2020). Specifically, topography influences edaphic (Gessler et al., 2000), thermal and hydrological conditions of local landscapes (Moore et al., 1991; Turner, 1989). These factors assume a determinant role in tree growth characteristics such as biomass, foliage density and leaf area index (LAI) which maintain the structure and integrity of the forest community. Understanding the influence of local topography on tree growth characteristics of keystone species such as the indigenous Yellowwood tree species will be a step towards the conservation of many other indigenous forest species.

Specifically, the four species; *Podocarpus latifolius* (Real Yellowwood), *P. falcatus* (Outeniqua Yellowwood), *P. henkelii* (Henkel's Yellowwood) and *P. elongatus* (Breede River Yellowwood) play a critical environmental and ecological role in threatened indigenous forests (Moll, 1972). They provide a habitat and food to mammals and birds such as the rare colobus monkey (Hart et al., 2013; Negash and van Staden, 2003). Birds species, including the Narina Trogon, Bush Blackcap and the threatened forest specialist - Cape Parrot amongst others, rely on the trees for nesting sites (Wirminghaus et al., 2001). Furthermore, the *Podocarpus* trees also play an invaluable human and socioeconomic role. For instance, *P. falcatus* offers an odourless, resin-less and fine grained wood, regarded as a high quality timber for manufacturing various products such as cupboards (Negash and van Staden, 2003). In South Africa, the regulated harvesting of these *Podocarpus* spp., is permissible through the Department of Water Affairs and Forestry (DAFF) which supports smaller, domestic industry which assumes a considerable role in the local economy. The industry has an estimated annual worth of R16 million and has created over 500 job opportunities (Abdillahi et al., 2010; Merwe, 2002). The bark of the trees is used in traditional medicine, and the resin is an ingredient in domestic animal treatments (Dold and Cocks, 2001). It is because of their excellent multipurpose that the Yellowwoods have been categorised under the most heavily exploited trees (Adie et al., 2013), not only in South Africa, but across the entire African continent (Negash and van Staden, 2003). Subsequently, there is a need to develop comprehensive frameworks for inventorying, monitoring, and drawing up effective conservation strategies for critical indigenous forest species. For these frameworks to be effective, they require specific information on tree growth characteristics such as LAI as foundational steps.

The biophysical parameter, LAI is associated with the photosynthetic capacity of vegetation. Leaf area is the total one sided surface area per specified unit (Chen and Black, 1992). It serves a predictive proxy to infer carbon, energy and mass exchange (Jonckheere et al., 2004; Jordan, 1969). Forest growth and efficiency, vigor and biomass can also be inferred from the index (Waring, 1983) and this has been done in many studies, across varying biogeographical regions, and scales (Varvia et al., 2018; Xie et al., 2014). The spatial distribution of leaf area in a forest is the result of complex interrelationships between plant types and the environment (Cui et al., 2009; Lan et al., 2011). Thus, understanding

the relationship between topographic surface properties and LAI is a critical step towards understanding the plant physiological connections within the local environment. This in turn, will offer paramount information for deriving comprehensive monitoring and management strategies required in conserving the dwindling indigenous forests (Turner et al., 2003).

Previously, conventional methods were used to understand the influence of situational factors and growth characteristics of tree species when drawing up conservation procedures for threatened species. These traditional methods include topographic characterisation techniques such as the physical recordings of Geographical Position Systems (GPS) locations, differential leveling, computation of locations and conversion into digital formats. However, these field surveys are complex and impractical when considering the temporal and spatial scales at which topographical and vegetation surveys are to be undertaken (Farr et al., 2007). Field techniques are unable to capture the three-dimensional nature of surfaces (Desmet and Govers, 1996; Hurst et al., 2012), rendering plot level measurements unrepresentative of the general landscape. In a similar manner, regional scale topographic maps are generally of poor quality, especially that of tropical regions (Farr et al., 2007). Therefore, there is a need for more accurate spatially, explicit, and versatile methods that could offer vegetation and topographic information at limited costs.

The scientific community has noted improvements in data acquisition techniques brought by the rapid advancement in earth observation technologies, making it easy to assess the relationship between topography and vegetation characteristics across various scales. Remote Sensing (RS) has enabled the digital quantification of not only the spatial variation of topographic features but also that of vegetation growth traits such as LAI. For instance, the Shuttle Radar Topography Mission (SRTM) from the National Aeronautics and Space Administration (NASA) produces the highest – rated digital elevation model (DEM) data with the oldest archives which are freely accessible with a near-global spatial coverage. This data has been widely used to characterise environmental factors such as elevation, drainage patterns and terrain morphology in concert with Geographic information systems (GIS) (Del-Toro-Guerrero et al., 2019; Emran et al., 2018; Gu and Wylie, 2016; Peng et al., 2020; Riihimäki et al., 2017). For example, Riihimäki et al. (2017) assessed the effect of topography on variations in Arctic - Alpine vegetation productivity in the Taihang Mountains of China. They noted that topo - climatic variables, specifically elevation and radiation, were the most influential variables in the explanation of vegetation productivity. Similarly, Gersie et al. (2019) used digital elevation model derivatives, namely the topographic wetness index (TWI) and topographic position classes (TPC's) to characterise the spatial distribution of productivity concerned with the shortgrass steppe in Colorado, United States of America (USA). Their model illustrated that TPC's effectively predicted grassland growth and grazing distribution when compared to TWI and this was attributed to the growing season, August – October, during which the vegetation grows more rapidly. All these works underscore the prospects of topographic variables derived from DEM's in characterising vegetation growth traits. However, most of these studies have used remotely sensed data derived topographic variables in characterising growth

traits of mixed vegetation species (Balzotti et al., 2017; Hwang et al., 2011; Yasuhiro et al., 2004). To the best of our knowledge, no study has attempted to assess the relationship between topographic variables and species - specific vegetation growth parameters, within an Afromontane mistbelt forest. Therefore, it is perceived that topographic variables could be applied, to accurately characterise the growth traits of threatened indigenous forest species, in this case, the Yellowwoods, *Podocarpus* spp.

This study, therefore, presents an investigation into the relative importance of topographic controls in estimating LAI, of the endangered Yellowwood species in an indigenous Afromontane mistbelt forest within southern Africa.

2.2. Materials and Methods

2.2.1. Study Area

The research was conducted in the Ingeli State Forest [3029DA WEZA], KwaZulu-Natal, South Africa (**Figure 2.1.**). The forest lies between Harding and Kokstad, on either side of the National Highway, nearing the border of the Eastern Cape, about the easternmost corner of the Muziwabantu Municipality. The forest represents one of the largest indigenous forest patches, which includes grassland and wetland habitats. The study site includes the largest forest patch, called Weza and smaller neighbouring forest fragments, surrounded by grassland and pine plantations. At an altitude averaging 1497 m, the forest occurs on dolerite soils, on south facing slopes. These forests are also known as Afromontane mistbelt forests, which experience rainfall > 1 000 mm per annum. The characteristically moist forest experiences summer mist and bouts of frost (Moll, 1972). The area is dominated by the Yellowwood's, red elder and sneezewood. The *Podocarpus* species which are dominant in the Ingeli forests are *P. henkelii* and *P. latifolius*. The forests are appreciated for avian diversity particularly the endangered Cape Parrot, ground thrush and bush blackcap.

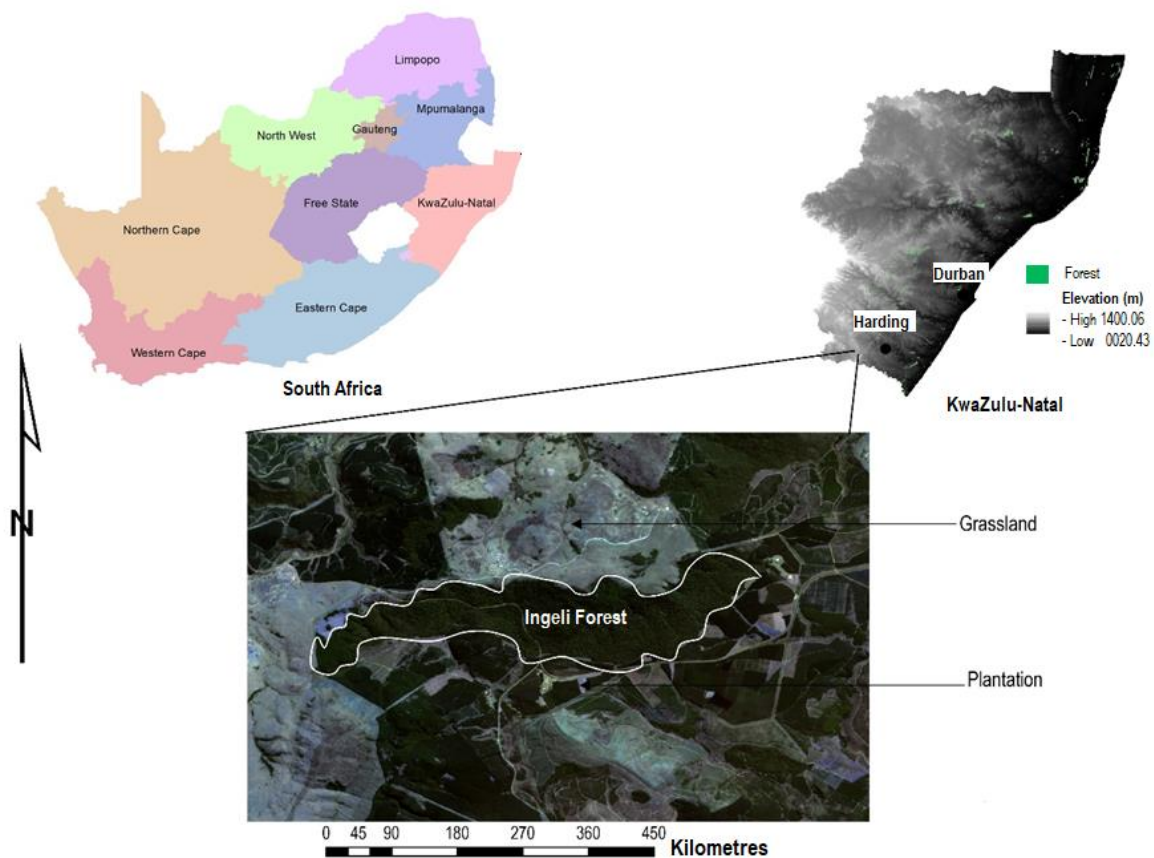


Figure 2.1. Study area within the Ingeli State Forest, in KwaZulu-Natal, South Africa.

The Yellowwood's serve as indicators of ecosystem condition, because of their longer-life span, which responds to the changing environment. This is especially important as the Ingeli forest represents a semi disturbed ecosystem in long standing recovery.

Henkel's Yellowwood is the most common tree which is widespread between Mt. Ayliff and Harding. This species is very tall and straight stemmed. The bark of this tree is of a grey – brown hue, with characteristically dark green pendulous leaves (**Figure 2.2 (b)**). The 'real' Yellowwood is common on the rocky, mountainous part of the mistbelt forest. Here it is more exposed, and it generally does not grow to be as large as henkel's Yellowwood. Leaves of this tree are narrower and grow longer, and seeds are a blue – grey in colour. While *P. falcatus*, termed the "big tree" of the Knysna forest, grows much faster to that of its counterparts. It can reach just over 40 m in height, with a wide spreading crown.

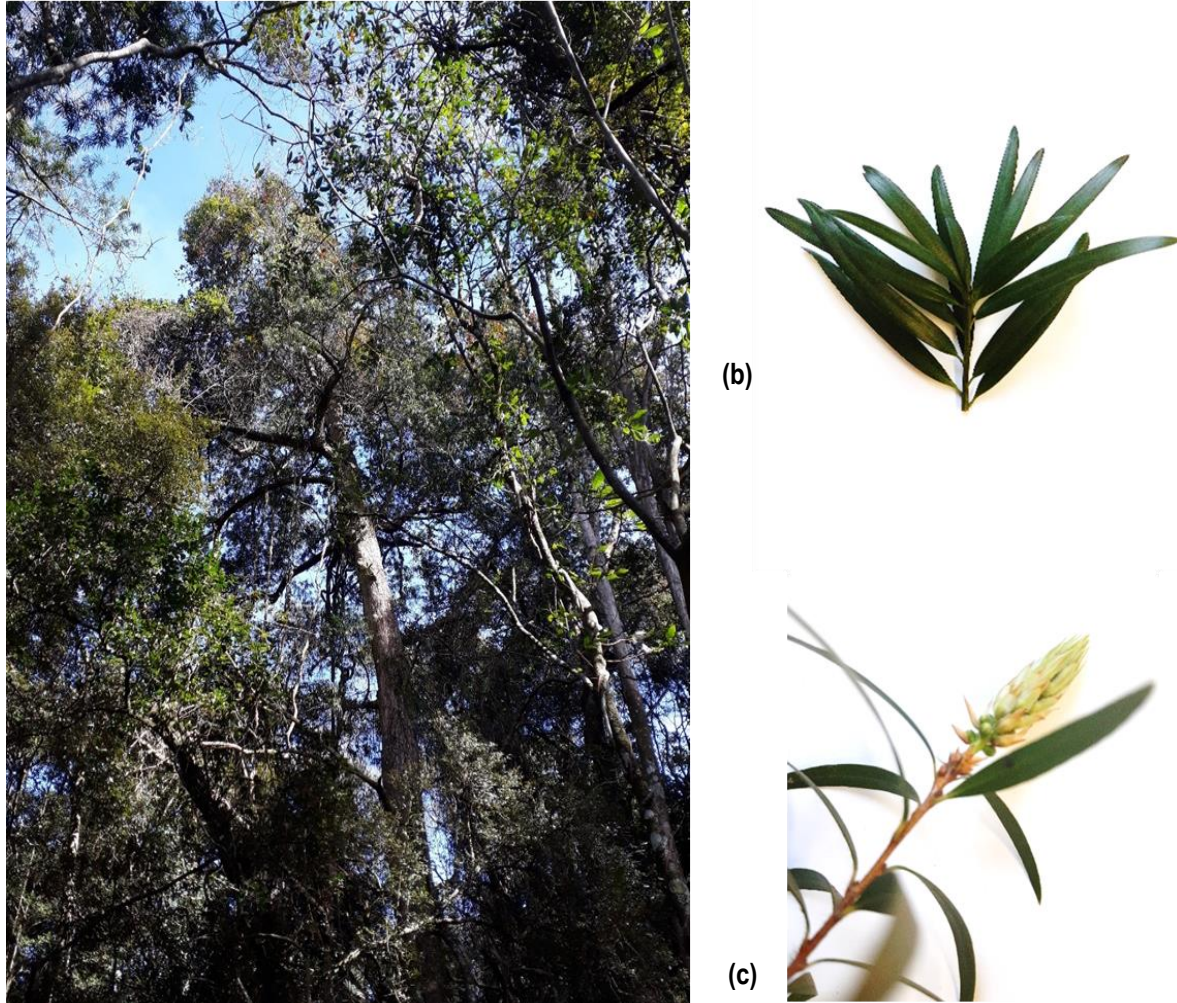


Figure 2.2. Yellowwood tree in the Ingeli State Forest **(a)**. Emergent *Podocarpus henkelii*, in the Ingeli Forest, **(b)** leaves and a young stem and **(c)** leaves and a flower.

2.2.2. Data preparation and collection

A field survey was conducted to measure Yellowwood tree attributes at the Ingeli State Forest from September 9 – 11 2018. Prior to the field work, random sampling locations which were > 20 m apart from each other were generated within Google Earth Pro Version 7.3. within the forest patches. These were imported into the handheld Geographic Positioning System (GPS) - Trimble XH and used to navigate to the sampling areas. Upon arrival at the sampling areas, a purposive sampling technique was employed to identify the Yellowwood trees (*Podocarpus latifolius* (Real Yellowwood), *P. falcatus* (Outeniqua Yellowwood) and *P. henkelii* (Henkel's Yellowwood)). Specifically, emergent trees, having larger canopy sizes (> 10 m) were considered in this study to avoid mixed pixels. This was also done to decrease the incidence of spatial autocorrelation. The location of each Yellowwood tree was recorded using the GPS.

LAI, tree height, crown size, as well as diameter at breast height (DBH) were also measured. LAI was measured using the LiCor LAI 2200 Plant Canopy Analyser. To estimate LAI, the analyser measures diffuse radiation, calculating the interception of blue light in 5 zenith angles, readings from above and below the canopy. The above and below measurements were compared by an inversion of the Poisson model equating the transmittances. From this, the portion of light absorbed by the canopies was assumed. A total of 60 averaged LAI samples were measured in the forest. GPS locations of sampling points were downloaded from the receiver and converted into points within the ArcMap Version 10.6 application.

Canopy height was measured using the hypsometer, Vertex III and Transponder T3. The Vertex is a device used in the measurement of heights, angle, inclination, distance, and air temperature (Haglöf Sweden AB 2005). Canopy size was estimated using user perspective and measurements of the widest and longest points of the canopy. DBH was measured using a tape measure, at average chest height – 1.30 m above ground level. For both canopy size and DBH, a tape measure was used.

2.2.3. DEM acquisition and generation of topographic variables

A DEM for the study area was acquired from NASA's SRTM datasets. The 30 m resolution DEM was subset to the study site and topographic metrics were generated using the System for Automated Geoscientific Analysis (SAGA) plugin, within QGIS Version 3.8.3. **Table 2.1.** lists in detail, all the topographic metrics computed and used in this study, using the slope, aspect, curvature module within SAGA. Topographic metrics were calculated about the landscape level. The generated point map of sampling locations was then used to extract the values of each topographic metric, from the DEM. These were then converted into Microsoft Excel format for statistical analysis.

Table 2.1. Mean and standard deviations of evaluated topographic variables.

Variable	Description	Function	Unit	Mean	Standard Deviation
Direct insolation	Incoming solar radiation	Air energy exchange, climate formation	Kw/m ²	7.14	0.51
Elevation	Height above sea level	Water, insolation, and soil properties	M	1300.48	101.34
Normalised height	Position between the channel and the valley, extension of catchment area	Water, insolation, and soil properties	m	.47	.22
Standardised height	Normalised height multiplied with absolute height, standardised for catchment	Water, insolation, and soil properties	M	624.64	343.60
Catchment area	Area of run off across land surface	Surface overland flow, runoff capacity, soil-water properties	M ²	5453.70	2046.05
Mass balance	Movement of materials/matter through environment	Material accumulation	M	105.34	0.23
General curvature	Plan and profile curvature	Slope of drainage basin to determine runoff capacity and volume	Degrees/m	500.01	0.01
Longitudinal curvature	Curvature relating to surface flow	Soil erosion, depositional processes	Degrees/m	-0.17	0.36
Maximum curvature	Curvature of the highest value of curvature at a specified point on earth's surface	Water flow capacity, soil erosion, deposition	Degrees/m	0.16	0.18
Wind effect	Above ground air flow	Soil moisture	m/s	0.86	0.12
Aspect	Slope direction	Solar radiation	-	3.93	1.34
Sky view factor	Unobstructed land surface	Incoming solar radiation	Radian	0.94	0.09
Convergence index	Positive surface curvature	Surface flow direction, relief structure	M	255.55	923.54
Topographic openness	Width a landscape can be viewed from any position	Indicates lowest and highest points of features	-	1.40	0.11

The topographic metrics used in the study represented the range of topographic metrics and micro topographic features. These can be grouped into three categories, namely local, nonlocal and collective topographic metrics (Florinsky, 2016; Li and McCarty, 2019). Local topographic metrics are specific to a point on the ground, while nonlocal topographic metrics are influenced by the relative positioning of specific point on the ground. Collective topographic metrics join both the local and nonlocal metrics, combining a specific and relational points on the ground surface

(Florinsky, 2016; Moore et al., 1991; Youfua et al., 2008). Examples of local metrics include slope, aspect and curvature related metrics. Catchment area and mass balance are examples of nonlocal metrics and collective metrics, respectively. Metrics can also be grouped into degrees of morphological function. For instance, first order topographic variables describe the aspect and slope metrics that are derived using only the initial partial derivation from the DEM, and second order variables are derived from second order derivatives (Shary, 1995; Youfua et al., 2008). The computation of these metrics differs in complexity and can serve as indicators of terrain complexity (Amatulli et al., 2018; Wilson and Gallant, 2000a). Specifically, normalised height values range from 0 to 1, representing lower to higher elevations. Standardised height, is the product of normalised height multiplied by absolute height. Catchment area, describes the surface flow contributing to upslope area (Wilson and Gallant, 2000b). Topographic openness indicates dominance (positive) or enclosure (negative) at a topographic point.

2.2.4. Data preparation and PCA model

The data, all calculated topographic variables, were then imported into SPSS statistical software package Version 25 for conducting the principal component analysis (PCA). The topographic variables were tested for auto correlation using the Durbin Watson Test prior to conducting the PCA analysis. The test statistic was 1.89, which fell within the acceptable range of - 1.5 to 2.5 for analysis. Since the data were acceptable for analysis, the PCA was used as a dimension reduction procedure. The topographic metrics were reduced and grouped into principal components of composite dimensions. This analysis was performed through a specified number of iterations from which similar variables were grouped. Using the dimension reduction factor task, the topographic variables were analysed. The steps undertaken in the PCA were as follows:

1. Computation of the correlation matrix.
2. Extraction of initial components from principal component loading matrix.
3. Determination of significant loadings, Eigen values > 1.

Influential components were denoted by their high Eigen values (> 1). Eigen values indicate how well suited the component (grouped topographic variables) are in the data from other topographical components. Significant loadings from each factor were identified based on their tabulated scores.

2.2.4. Stepwise linear regression analysis

A stepwise linear regression analysis was performed on extracted components, to determine which of the topographic variables were important in the explanation of LAI. A stepwise linear regression was conducted to assess the relationship between topographic variables and the variability of the Yellowwood species LAI. The model was run using the “exclude cases pairwise” option. This was done to further remove variables that may be used to explain the observed LAI to a level comparable to that of another variable. In the stepwise regression topographic variables were

removed if they did not contribute a statistically significant level to the model explanation. The stepwise regression method also helped to alleviate the issue of multi collinearity. Multi collinearity is problematic as interrelated variables – common in topographic features - decrease the level of model accuracy, as the coefficient of determination is then spread to describe non-significant variables. Here, the stepping method criteria was set to $F \leq .5$ for entry and $F \geq .10$ for removal. Topographic variables used in the stepwise regression, were user defined and from the regression inspection.

2.3. Results

2.3.1. LAI measurements descriptive statistics

Normality of LAI data, was tested using the Kolmogorov Smirnov test and it was noted that it did not significantly deviate from the normal distribution curve (p - value $< .005$), hence the observations were suitable for the PCA and stepwise linear regression analysis. LAI measurements ranged between 0.83 and 4.09 m^2/m^2 ($n = 60$, Mean = 2.24 m^2/m^2) (Figure 2.3).

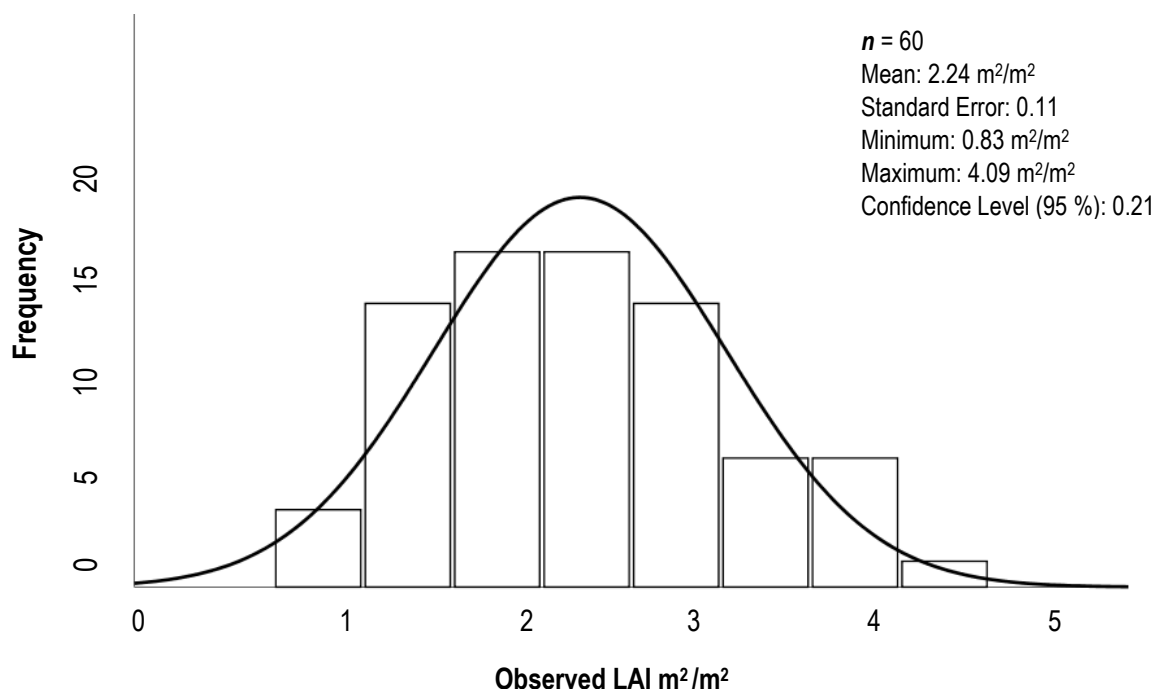


Figure 2.3. Descriptive statistics of observed LAI of the Yellowwoods.

2.3.2. PCA model

The PCA was conducted using the correlation matrix, with 14 topographic variables. The scree plot (**Figure 2.4**) shows the Eigenvalues and the components/topographic variables. Out of 14 components, 4 were above 1 in terms of their Eigen values hence they were considered in this study. Component 1 shows an initial value of 6.29, which then steadily declines to 3.75 at Component 2. The linear relationship is maintained, to return an Eigenvalue of 1.26 for Component 3. Component 4 yielded a value of 1.15. And remaining components taper off to return values < 1.

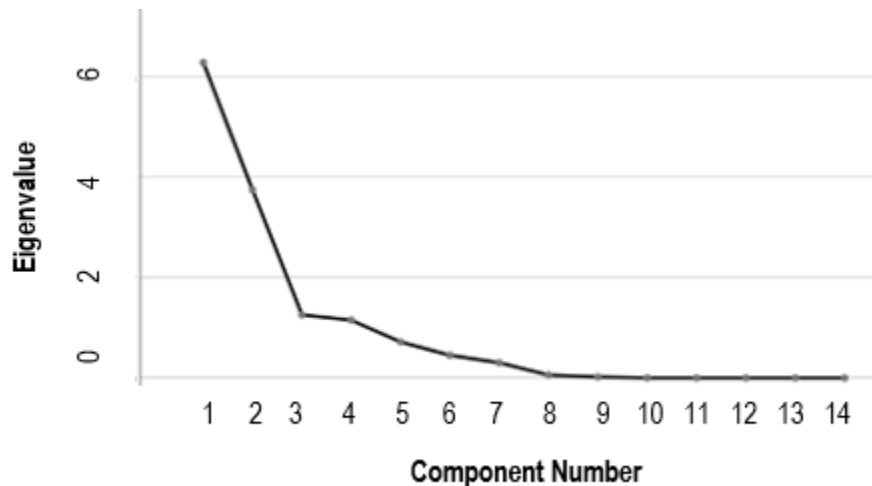


Figure 2.4. Scree plot for Eigenvalues associated with the component.

Table 2.2 shows the results from the PCA model. The highest acceptable percentage (%) of variance of 88.9 was explained by 4 significant components. However, the 100% cumulative variance was attained when 9 components were used. Five of these components (Component 5 to 9) least contributed in explaining the topographic variability.

Table 2.2. Total variance explained for topographic variables, using PCA.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.290	44.925	44.925	6.290	44.925	44.925
2	3.751	26.792	71.717	3.751	26.792	71.717
3	1.258	8.985	80.702	1.258	8.985	80.702
4	1.153	8.233	88.935	1.153	8.233	88.935
5	.718	5.132	94.067			
6	.452	3.230	97.298			
7	.303	2.161	99.459			
8	.058	.412	99.871			
9	.018	.129	100.000			

Table 2.3 shows the contribution of each topographic variable to each of the extracted 4 components considered in this study. Component 1 returned Catchment area and General curvature to see negative values, which is telling of a stronger inverse relationship to the topographic data. While the elevation variables; normalised and standardised height showed variance contributions above .9. General curvature showed the most significant contribution to Component 2, % variance = .924. Component 3 and 4, returned .838 and .555, for aspect and longitudinal curvature, respectively. From each of the extracted components only these topographic variables returned values, above .5. These two topographic variables were the only ones to report positive directional contributions to model variance, across the extracted components. Six topographical variables namely, Cross sectional curvature, direct insolation, general curvature, mass balance, normalised height, positive openness, profile curvature and standardised height were noted based on their contribution scores in **Table 2.3**, in explaining the topographical variation in the forest. Topographic variables were then used in a stepwise regression to establish a model for estimating the LAI of the Yellowwood tree species.

Table 2.3. Total variance explained for topographic variables, from the extracted 4 Components.

	1	2	3	4
Catchment area	-.684	-.250	.263	.239
Convergence index	.529	.401	-.265	-.265
Cross - sectional curvature	.757	-.396	-.220	.427
Elevation	.560	.421	-.397	-.259
Direct insolation	.523	-.824	.027	-.173
General curvature	-.300	.924	.156	.087
Longitudinal curvature	.699	.297	.016	.555
Maximal curvature	.528	.626	-.176	.494
Normalised height	.914	.283	.125	-.135
Positive openness	.804	-.562	.068	.121
Sky view Factor	.606	-.787	-.039	.041
Standardised height	.911	.320	.045	-.172
Wind effect	.825	.209	.361	-.341
Aspect	.405	.140	.838	.081

2.3.3. Stepwise linear regression model

The stepwise linear regression analysis results between topographic variables and the LAI of Yellowwood trees are displayed on **Table 2.4**. The 6th model exhibited an optimal relationship between species LAI and topographic variables. Specifically, Model 6 exhibited an R² of 0.85 the least standard error of estimate of 0.35 m²/m². The most optimal topographic variables that constituted this model were Catchment area, Mass Balance, Sky view Factor (SVF),

Convergence index, Maximum curvature and Aspect. It can also be observed that the model accuracy increased with an increase in the number of topographic variables selected and used in modelling LAI of Yellowwood trees.

Table 2.4. Stepwise regression model summary of selected topographic variables.

Model	R	R ²	Adjusted R ²	Std. Error of the Estimate (SEE)
1	.581a	.338	.318	.69
2	.777b	.604	.579	.54
3	.860c	.740	.715	.44
4	.887d	.786	.757	.41
5	.908e	.824	.794	.38
6	.922f	.850	.818	.35

1. Predictors: (Constant), Catchment area
2. Predictors: (Constant), Catchment area, Mass Balance
3. Predictors: (Constant), Catchment area, Mass Balance, Sky view Factor
4. Predictors: (Constant), Catchment area, Mass Balance, Sky view Factor, Convergence index
5. Predictors: (Constant), Catchment area, Mass Balance, Sky view Factor, Convergence index, Maximum curvature
6. Predictors: (Constant), Catchment area, Mass Balance, Sky view Factor, Convergence index, Maximum curvature, Aspect.

The summary of the model selected for explaining the variability of Yellowwood trees' leaf area is detailed in **Table 2.5**. Based on the t – value, an indicator of variable importance, mass balance, sky view factor and catchment area were the most optimal topographic variables that explained the variation of LAI in this study, in order of importance. Majority of the variables; Catchment area, Mass Balance, SVF and the Convergence index showed a positive relationship with LAI variability. That is with each unit increase in leaf area – a unit increase is observed for the topographic variables. Meanwhile, the inverse relationship was observed for maximal curvature and aspect which exhibited negative value coefficients.

Table. 2.5. Model coefficients of selected topographic variables.

	Unstandardised Coefficients	Standardised Coefficients		t	Sig.
	B	Std. Error	Beta		
(Constant)	-3.031	0.925		-3.277	0.003
Catchment area	0	0	0.401	4.067	0
Mass Balance	1.612	0.234	0.592	6.893	0
Sky view Factor	4.941	0.985	0.412	5.018	0
Convergence index	0.029	0.009	0.322	3.357	0.002
Maximal curvature	-100.433	45.134	-0.227	-2.225	0.034
Aspect	-0.102	0.047	-0.167	-2.177	.038

Therefore, the following model was used to explain the topographic variability of LAI in the study area:

Observed LAI = -3.031 + 0*Catchment area+ 1.612*Mass Balance + 4.941*SVF + 0.029*Convergence index - 100.433*Maximal curvature - 0.102*Aspect

2.4. Discussion

The aim of this study was to evaluate the role of topographic variables in observed LAI within the Ingeli State Forest.

2.4.1. Influential topographic variables

Results of this study showed that the spatial variability of Yellowwood tree species LAI in the Ingeli Afromontane mistbelt forest could be optimally ($SEE = 35\text{m}^2/\text{m}^2$ and $R^2 = 0.85$) explained by the catchment area, mass balance, SVF as topographic variables, in order of importance. Catchment area, which is the area of water flow, supported by a single drainage system, was the third influential variable that optimally explained the LAI variability of Yellowwood tree species. The optimal influence of the catchment area of the Ingeli forest on the spatial distribution of Yellowwood tree species could be attributed to the fact that the catchment area is dominated by large, emergent, indigenous forest trees which tend to encourage high infiltration and percolation of precipitation Balzotti et al. (2017). This results in high soil moisture content which further facilitates high vegetation species productivity (Pilgrim et al., 1982) and hence high foliage densities and LAI.

Mass balance refers to the movement of material, either transformed or untransformed within the environment. Balances such as concentrations of atmospheric constituents, biomass, nutrients accumulation and leaf fall are associated with the variation in topography (Weiss, 2001). Topographically, low lying sections of the study area facilitate higher concentrations and accumulations of moisture as well as soil nutrients which are washed away from sections characterised by high altitude and steep slopes. Subsequently, lower lying areas become more conducive for vegetation productivity exhibiting healthier trees, characterised by high foliage densities in relation to steep areas which drive the movement of ecosystem resources (Liu et al., 2014). Therefore, due to mass balance, some sections of the

Ingeli forest are characterised by high deposition of transformed material such as top soil, soil nutrients and moisture facilitating high productivity of the Yellowwood trees with foliage density which varies from sections that are associated with the transportation of materials in steep slopes and highly elevated landscapes. Meanwhile, sections characterised by high transportation of materials tend to have trees that are relatively limited in terms of productivity, due to the reduced nutrient availability and moisture conditions.

Sky view factor (SVF), represents the proportion of radiation that reaches the ground, slanted at an random angle (Watson and Johnson, 1987), was the second influential topographic variable explaining the variability of Yellowwood trees species LAI. The factor is a proxy for relief illumination, that is the sky visibility at the relief horizon (Zakšek et al., 2011). SVF, similarly to aspect, is associated with the amount of radiation that is available for facilitating the vegetation photosynthesis related processes. Aspect is comparable to SVF in that these two variables are important in the explanation of more localised factors such as air temperature and moisture availability (Gosz and Sharpe, 1989). However, results showed that a stronger direction of variation is exhibited for SVF when compared to aspect. And a positive relational change is associated with SVF, while a negative variation exists for aspect in relation to LAI (Table 2.5.). Aspect assumes a downslope direction at a maximum rate of change in value from one point to another, and the effect of aspect becomes more pronounced in mountainous areas (Emran et al., 2018; Lakshmi and Yarrakula, 2019) as is exhibited in the Ingeli forest. Noting that mean aspect measured for the sampled locations recorded 3.93 radians or 225.1724° (Table 2.1.), which is indicative of southwest facing slopes. Southwestern slopes are characteristically cooler and are also slower to warm, retaining heat longer (Måren et al., 2015) in the southern hemisphere. The more mesic conditions of southwest facing slopes are in line with the Afromontane mistbelt forest type - underpinning the moisture component for the environment. In this regard, steady leaf growth, is observed, which is also supportive of findings made in a study by Badano et al. (2005). The authors found that aspect was most influential in creating a meso climate, in the Mediterranean-type matorral in middle eastern Chile. Further, evergreen vegetation was found to be more dominant in shaded parts of the matorral. Therefore, given that the study area is a mistbelt forest type and with the knowledge that *Podocarpus spp.* are characteristically evergreen, the leaf growth concerned with a cooler, moisture rich environment creates favourable conditions for leaf growth – as is observed for the LAI observations made in this study.

Areas characterised by high SVF tend to facilitate high vegetation productivity whereas areas with low visibility tend to have reduced rates of photosynthetic activities. This is because high SVF is associated with high exposure to incident radiation whereas the less SVF values are associated with less exposure to radiation required for photosynthetic activities. In this regard, it is not surprising that SVF is one of the factors that explain the LAI variability of Yellowwoods tree species in this study. The areas with high visibility will tend to facilitate higher levels of tree productivity, yielding high foliage density whereas the less visible areas will have reduced photosynthesis rates resulting in less foliage densities due to the regulated photosynthesis rates (Jucker et al., 2018).

The regression model further identified the lesser topographic variables, that is maximal curvature. Curvature, similarly, to the convergence index is identified as an important input variable in erosion and hydrological models as it is more representative of micro surface features (Amatulli et al. 2018). More convex areas are characterised by higher erosion and transportation of soil material, which tends to limit productivity of tree species when compared to concave areas. Similarly, more moisture accumulates in concave areas facilitating high productivity of vegetation species associated with them (Hurst et al., 2012). Deng et al. (2007) considered the relationship between vegetation and topographic features in the Santa Monica mountains. Similar to this study, work by Deng et al. (2007) indicated significant correlations with profile and plan curvature. This illustrated the importance of curvature in mountains or elevated areas, as curvature dictates erosional rates. This is unsurprising as the curvature metrics are dominant in explaining environmental factors in areas of high relief (Emran et al., 2018; Kang et al., 2004), as observed for in the forest. The Ingeli Forest experiences moderate to steep slopes i.e. from the sampled locations, average elevation was recorded at 1300 m (See Table 2.1.).

It is critical to note that most studies explained variability in forest structure using landscape metrics for large areas, which are more generalised and therefore do not capture local variability. By using high resolution topographic DEM's derived from remotely sensed data, this study evaluated micro variability in LAI at finer scales, a process that is critical for local scale forest management operations. The results of the study have demonstrated the applicability of GIS, and DEM's in the explanation of the observed LAI distribution of the Ingeli forest Yellowwood trees. The SRTM DEM's exploratory power for emergent tree properties such as, leaf area combined with variable selection techniques are therefore appropriate in assessing vegetation condition.

2.5. Conclusion

Based on the findings of this study it can be concluded that the topographic metrics particularly, catchment area, mass balance and SVF optimally explain the spatial variability of Yellowwood tree species LAI. The results of the study have demonstrated the applicability of GIS, and DEM's in the explanation of observed LAI distribution of the Ingeli forest Yellowwood trees. The SRTM DEM's exploratory power for emergent tree properties such as, leaf area combined with variable selection techniques are appropriate in studying vegetation condition. Findings could have applications in explaining landscape patterns of LAI in forested environments, in South Africa. The analysis of landscape level topography is important in understanding forest structure determinants, for conservation and forest management.

Chapter Three

Estimating leaf area index of the Yellowwood tree in an indigenous southern African forest, using Sentinel 2 Multispectral Instrument imagery and the Random Forest regression ensemble

Abstract

Podocarpus (spp.) holds the esteemed biodiversity status, as key forest species in the mistbelt Afromontane forest of southern Africa. The podocarps are listed as endangered species owing to extensive logging. The forest species support large communities of plants and birds, attributing to the maintenance of biodiversity. Therefore, there is need to understand the condition of such keystone species if effective and comprehensive biodiversity conservation measures are to be drawn for these dwindling forests. Leaf area index is a crucial eco-physiological parameter applied in the evaluation of the growth and productivity of forest trees. The index serves as an indicator of canopy condition and photosynthetic capacity; hence it is a suitable proxy for understanding the condition of Yellowwood trees. This study therefore sought to estimate the leaf area index of the Yellowwood spp. using Sentinel 2 Multispectral data in concert with the Random Forest regression ensemble. Specifically, individual wavebands and vegetation indices were used in developing leaf area index prediction models based on two approaches. The multistage approach, categorised the predictors according to the generalised order of progression, from standard spectral bands to Red Edge wavebands and indices. The second approach involved using a pooled set of predictors, with the backward elimination of poorly performing wavebands and vegetation indices. Results showed that the backward elimination method produced a better model ($R^2 = 0.59$; RMSE = 0.48) when compared to the multistage approach ($R^2 = .50$; RMSE = .48). Furthermore, the most influential predictor variables in both models were Band 5 and NDVI Red Edge 2, both characterised by the Red Edge region of the electromagnetic spectrum. Results of this study underscore the prospects of Sentinel 2 data i.e. Red Edge wavebands and indices, in characterising the productivity of critical forest species such as the Yellowwoods of the Afromontane forest in southern Africa. The findings of this study are a fundamental step towards understanding forest health and productivity, required in deriving comprehensive monitoring and management strategies in biodiversity conservation.

3.1. Introduction

Fromontane forests, characterised by Yellowwood tree species, are widespread across the African highlands (Yirdaw et al., 2015). They are renowned for their distinctive fauna and flora, substantial carbon stocks among a range of invaluable socioeconomic and ecological functions. The Yellowwoods are important habitats for nesting species, such as the endangered Cape Parrot. The decrease in the population sizes of the podocarps stalls the reproductive capacity of these habitat specialists and threatens their population (Hart et al., 2013). However, these *Podocarpus* forests are vulnerable to a host of factors, including habitat destruction mainly due to the fact that they are concentrated around areas of high population density, where there is a high prevalence of fire events, crop-farming and plantations (Moll, 1972). The Yellowwoods have been selectively and extensively logged for fuelwood, construction planks, furniture and, in some instances they have been cleared for grazing lands (Abiem et al., 2020; King, 1941; Moll, 1972). This habitat destruction has compromised the health and productivity of southern Africa's *Podocarpus* forests. Subsequently, the longer term monitoring of these forests is crucial and urgently required to devise effective management strategies at local and regional scales, as well as in fostering the continuity of the services and bio products they provide (Abiem et al., 2020).

Forest canopies serve as the most apparent indicators of their ecosystem health condition (Jennings et al., 1999), which is required in understanding tree to stand level dynamics (Nakamura et al., 2017). Forest canopies are effectively the initial point of interface between vegetation and the atmosphere (Ozanne et al., 2003) and are the most apparent evidence of stand productivity (Sampson et al., 1998). Therefore, insights into leaf – level biophysical properties will further supplement biophysical knowledge, that can be applied to biodiversity conservation measures. Leaves inherently hold information about biological processes, such as photosynthesis and energy exchange which influence the entire canopy, to provide a more holistic understanding into tree physiology (Ozanne et al., 2003). Canopies are inextricably linked to leaf area index (LAI) (Jennings et al., 1999), which is defined as the total of one-sided area of green leaf tissue per unit area (Jordan, 1969). Leaf area is an important eco physiological measure of vegetation cover which serves as a proxy for foliage cover and may therefore be used in the monitoring of forest growth and productivity (Chen et al., 1997; Jordan, 1969). LAI is a widely applied measure in understanding canopy microclimates, water and gaseous exchange (Breda 2003) and is included in the 50 essential climate variables (ECV's) in the Global Climate Observing System (GCOS) (GCOS, 2016; Pereira et al., 2013). It further serves as a critical indicator of species morphological features. Therefore, investigating the LAI of indigenous, keystone forest species such as the Yellowwood could be a step towards the establishment of a comprehensive management and conservation measures.

Quantifying LAI involves both direct and indirect methods. Direct methods involve in-situ observations of vegetation (Chen et al., 1997), and indirect techniques are reliant on distant or remote measurement techniques (Jonckheere et al., 2004). Recently, the development of electronic measurement instruments, such as the Plant Canopy Analyser has allowed for more accurate and temporally considerate LAI estimates. Despite the high accuracy associated with direct

measurement methods, they tend to be labour intensive and often destructive in some instances (Breda, 2003; Liu et al., 2015). Physical sampling techniques further hold the risk of being subjective due to the user's influence, which then compromises the data quality. However, Remote Sensing (RS) technologies have advanced to assume an integral part of species attribute measurements in biodiversity monitoring studies (Melesse et al., 2007; Wang et al., 2010), across a range of spatial and temporal scales (Sabins, 2007; Turner et al., 2003). RS data is objective, affordable and synoptic in nature when compared to other datasets (Mutanga et al., 2016). It assumes that species specific spectral signatures are linked to the physiochemical properties of vegetation (Sabins, 2007), thus effective in the retrieval of LAI using satellite sensors (Curran, 1985; Rees, 2013). In this regard, a relationship could be established between tree species attributes as those of the *Podocarpus* spp. and earth observation data (Jonckheere et al., 2004; Melesse et al., 2007; Turner et al., 2003).

The RS community has seen numerous advancements in earth observation sensor technologies, which have led to the launching of "new generation" sensors such as Sentinel series. The series form part of the European Space Agency (ESA) programme known as the Global Monitoring for Environment and Security (GMES). Sentinel - 2 Multispectral Instrument (S2 MSI) is a small and low-cost mission, acquiring observations over terrestrial and coastal regions, through two instruments, with a revisit period of 5 days. This satellite has on board the MSI, with a corresponding 13 band spectral resolution. Bands have a spatial resolution of 10m, 20m and 60m, across the visible to shortwave infrared regions (ESA, 2018), which are suitable for characterising vegetation attributes such as LAI. The S2 MSI is most notable for its incorporation of three Red Edge (RE) wavebands, at 705, 740 and 783 nm (Drusch et al., 2012; Zarco-Tejada et al., 2018) which are specifically suited for mapping vegetation. Towards understanding forested ecosystems, the S2 MSI mission further offers a finer spectral resolution which may be suited to stand - level tree studies when compared to its predecessors, such as Landsat 7 (Korhonen et al. (2017).

Spectral responses of plant attributes form the underlying basis for vegetation monitoring. Literature shows that the relationship between vegetation attributes such as LAI and spectral responses is best understood through the band combinations of multispectral remotely sensed data (Turner et al., 2003). Vegetation attributes such as LAI tend to be better characterised using vegetation indices (VI's) because they are insensitive to soil background effects (Schumacher et al., 2016). The most used vegetation index is the Normalised Difference Vegetation Index (NDVI) developed by Rouse Jr et al. (1974) (Bannari et al., 1995). NDVI combines the red near infrared (NIR) regions of the electromagnetic spectrum (EM) and has been shown to be effective in the retrieval of LAI (Croft et al., 2014; Nguy-Robertson et al., 2012; Xie et al., 2018). Yet, the index has been noted to saturate for LAI measurements > 3 (Korhonen et al., 2017; Mao et al., 2019). The advancement of sensor technologies to "new generation" sensors, such as S2 MSI with RE wavebands brought forth narrow band VI's which are less sensitive to high chlorophyll content and LAI measurements (Laurin et al., 2016). These RE VI's, also known as 'novel' VI's are increasingly being incorporated into forest mapping and monitoring studies (Forkuor et al., 2018; Frampton et al., 2013; Verrelst et al., 2015; Xie et al.,

2014). It is understood that these VI's could accurately and effectively be applied in predicting and mapping the spatial distribution of the *Podocarpus* species LAI as a step towards developing conservation strategies.

Accurately modeling the relationship between field measured LAI estimates and satellite derived data is facilitated by a range of machine learning algorithms (Lary et al., 2016). In this regard, the most notable algorithm is the Random Forest (RF) regression ensemble, which offers flexibility, and performance abilities with limited training data (Karlson et al., 2015; Pal, 2005; Zhu et al., 2017). The RF is non – parametric ensemble which is computationally 'light' and offers ease of access and use, especially for vegetation modelling applications based on RS data (Pal, 2005). It is for this reason that the ensemble often outperforms other machine learning models such as artificial neural networks (ANN) (Belgiu and Drăguț, 2016; Karlson et al., 2015; Srinet et al., 2019; Zhu et al., 2017). To achieve the optimal prediction model, numerous approaches to data management are applied. For example, the grouping of predictor variables according to generalised rules or categories has been noted to exhibit a robust predictive capability in RS studies (Lyon et al., 1998; Mac Nally, 2000; Mróz and Sobieraj, 2004). Similarly, the removal of poorly performing model predictors through a backward elimination approach (Dube et al., 2017; Lawrence and Ripple, 1998; Mao et al., 2019; Sutter and Kalivas, 1993) has been noted to be another plausible data management approach (Dube et al., 2019). In this regard, there is need to evaluate the performance of generalised rules and categorisation of predictor variables to accurately model the LAI of the endangered *Podocarpus* forest species for monitoring and management purposes.

The study, therefore, sought to assess the utility of S2 MSI remotely sensed data in estimating LAI of the *Podocarpus* tree species within an indigenous Afromontane forest. Specifically, this study assessed the effect of the RE derived spectral predictors as well as the data management approaches in predicting and mapping LAI of *Podocarpus* tree species.

3.2. Materials and Methods

3.2.1. Study Area

The research was conducted in the Ingeli State Forest [3029DA WEZA], KwaZulu-Natal, South Africa (**Figure 3.1**). The forest lies between the towns of Harding and Kokstad, on either side of the N2 highway, nearing the border of the Eastern Cape province in South Africa. It represents one of the largest indigenous forest patches in the country. The study site includes the large Weza forest patch and smaller neighbouring forest fragments. At an altitude averaging 1497 m, the forest occurs on dolerite soils on south facing slopes. The forest experiences rainfall > 1 000 mm per annum as well as summer mist and bouts of frost (Moll, 1972). The area is dominated by the Yellowwood tree species, specifically, *Podocarpus latifolius* (Real Yellowwood) and *P. henkelii* (Henkels Yellowwood), alongside the timbers, red elder and sneezewood. The forests are appreciated for avian diversity, noting the endangered Cape Parrot, ground thrush and bush blackcap.

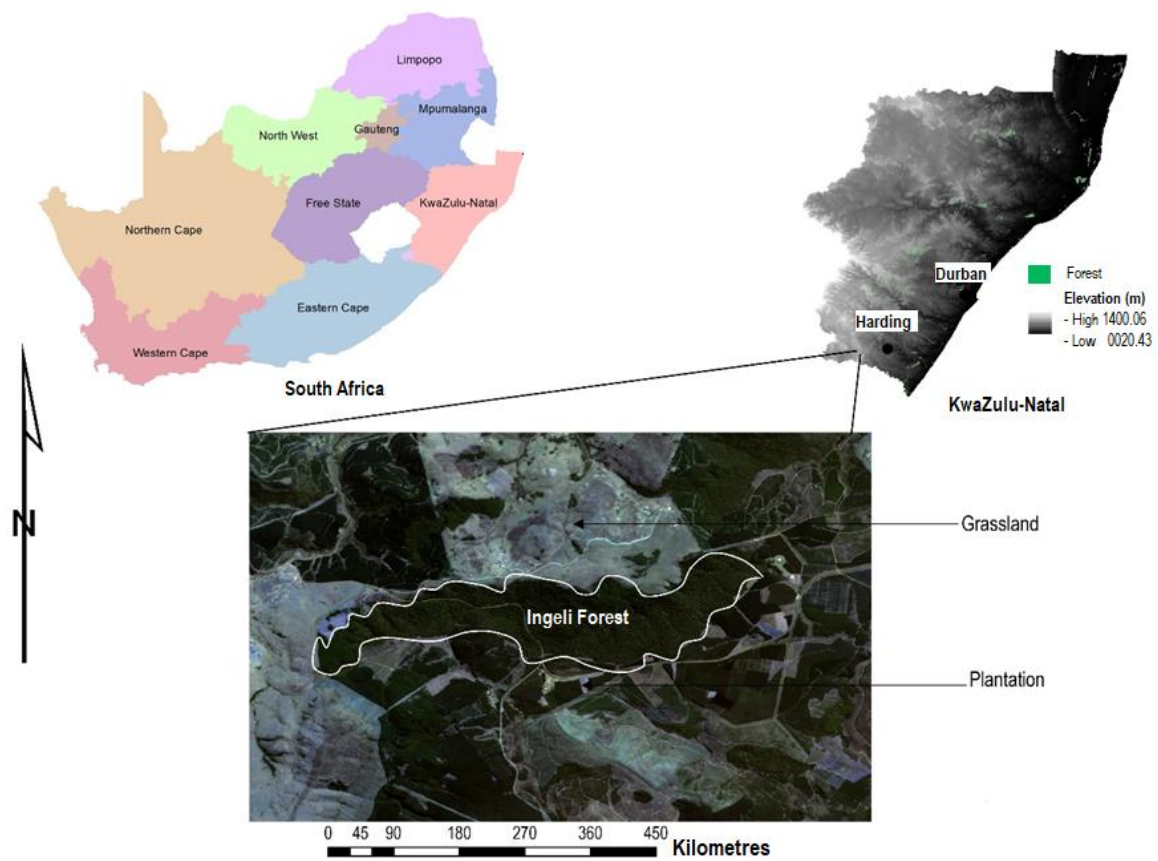


Figure 3.1. Study area within the Ingeli State Forest, in KwaZulu-Natal, South Africa.



Figure 3.2. Yellowwood tree in the Ingeli State Forest (a). Emergent *Podocarpus henkelii*, in the Ingeli Forest, Kokstad, (b) leaves and a young stem and (c) leaves and a flower.

3.2.2. Data preparation and field data collection

A field survey was conducted to measure Yellowwood tree attributes in the Ingeli forests from September 9 – 11, 2018. Prior to the field work, forest fragments shape files were generated using Google Earth Pro Version 7.3. and used in a GIS platform to compute random sampling locations, which were > 20 m apart from each other. These were then imported into the handheld Trimble XH GPS receiver and used to navigate to the sampling areas. Upon arrival at the sampling areas, a purposive sampling technique was employed in the identification of the Yellowwood trees (*Podocarpus latifolius* (Real Yellowwood), *P. falcatus* (Outeniqua Yellowwood) and *P. henkelii* (Henkel's Yellowwood)). Specifically, trees that exhibited larger canopy sizes were considered in this study to avoid mixed pixels. The location of each Yellowwood tree was recorded using the GPS receiver, in addition to LAI, tree height, crown size, as well as diameter at breast height (DBH) were measured. LAI was measured using the LiCor LAI 2200 Plant Canopy Analyser.

All canopy measurements were determined under standard clear sky conditions (Varvia et al., 2018). The plant canopy analyser measures diffuse radiation, calculating the interception of blue light in 5 zenith angles, from readings from above and below the canopy. The above and below measurements were compared by an inversion of the Poisson model and transmittances. From this, the portion of absorbed light by the canopies was assumed. DBH and crown size were measured using a tape measure. A total of 60 averaged sampling locations were recorded in the Ingeli forest. Emergent trees, with large spreading crowns (> 10 m) were identified. This is consistent with the spatial resolution of the S2 image, for tree crowns are identifiable. This was also done to decrease the incidence of spatial autocorrelation. The GPS locations of sampling points were downloaded from the receiver and converted into points with the ArcMap Version 10.6 application.

3.2.3. S2 MSI data acquisition and pre processing

The S2 MSI product was acquired for September 9, 2018 from the European Space Agency's (ESA's) Sentinel Scientific Hub. The product was a Level 1C product, consisting of geo-coded top of atmosphere (TOA) reflectance. An atmospheric correction was applied, using the Sen2cor module version 2.2.1, within the Sentinel 2 Toolbox (S2TBX), Sentinel Application Platform (SNAP), Version 4.0.2. The S2 MSI product was first subset to the extent of the study area to reduce the image size and processing time. The image was then converted into a bottom of the atmosphere (BOA) Level 2A image. The image was further projected into a Universal Transverse Mercator (UTM) Zone 36S, WGS 84, in ArcMap Version 10.6. The point data of Yellowwood trees was then overlaid with the pre-processed image to extract the spectral signatures. The spectral signatures were then exported into Microsoft Excel files.

Table 3.1. Spectral specifications of the S2 MSI product.

Band Number	Function	Central Wavelength (nm)	Band Width (nm)
1	Coastal aerosol	443	27
2	Blue	490	98
3	Green	560	45
4	Red	665	19
5	Vegetation Red Edge	705	18
6	Vegetation Red Edge	740	28
7	Vegetation Red Edge	783	145
8	Near Infrared	842	115
8a	Vegetation Red Edge	865	33
9	Water vapour	945	26
10	Shortwave infrared– cirrus	1380	75
11	Shortwave infrared– cirrus	1610	143
12	Shortwave infrared– cirrus	2190	242

3.2.4. Satellite derived predictor variables and modelling

The spectral signatures derived from the preprocessed image were used to compute VI's in Microsoft Excel. A total of 50 predictor variables were computed, which were used to estimate the LAI of Yellowwood tree species in this study (**Table 3.2**). VI's used in the study were selected based on their performance in literature.

Two data management approaches were used in predicting LAI, that is the four - tiered categorisation for the multistage approach and the pooling of all spectral variables for the backward elimination approach. The four - tiered categories of predictor variables were namely: Standard Bands, Traditional Vegetation Indices, Modified Vegetation Indices and RE bands and indices. Standard bands represent the spectral information that is generally covered by all sensors which is in the visible and near infrared sections of the EM, except for the vegetation RE Bands 5, 6, 7 and 8a. Bands 1, 9, and 10 were not utilised in this study since they are not suitable for vegetation mapping. Traditional VI's are

derived from the red and near infrared regions of the EM and modified VI's are generally improved computations of traditional VI's. RE or novel bands/indices are those computed inclusive of Bands 5, 6, 7 and 8a (**Table 3.2**).

Table 3.2. Evaluated bands and VI's, in grouped predictor variable categories.

Traditional Vegetation Indices			
Normalised Difference Vegetation Index	NDVI	$(R842 - R665) / (R842 + R665)$	Rouse Jr et al. (1974)
Normalised Pigment Chlorophyll Index	NPCI	$(R665 - R430)/(R665+R430)$	Penuelas et al. (1995)
Green Normalised Vegetation Difference	gNDVI	$(R780 - R560) / (R780+R560)$	Gitelson and Merzlyak (1996)
Greenness Index	G	$R554/R677$	Zarco-Tejada et al. (2018)
Gitelson Ratio Green	GRg	$(R842/R560) - 1$	Gitelson et al. (2003)
Difference Vegetation Index	DVI	$(R842 - R665)$	Jordan (1969)
Enhanced Vegetation Index	EVI	$2.5[(R864 - R665) / ((R864) + (6 * R665) - (7.5 * R560) + 1))]$	Huete et al. (1994)
Enhanced Vegetation Index 2	EVI2	$(2.5 * (R842 - R665)) / (R842 + 2.4 * R665 + 1)$	Jiang et al. (2008)
Soil Adjusted Vegetation Index	SAVI	$((R842 - R665) / (R842 + R665 + 0.25)) * (1 + 0.25)$	
Simple Ratio	SR	$R842/R665$	Jordan (1969)
Pigment Specific Simple Ratio chlorophyll a	PSSRa	$(R864/R665)$	Blackburn (1998)
Pigment Specific Simple Ratio chlorophyll b	PSSRab	$(R842/R665)$	Blackburn (1998)
Green Chlorophyll Index	CI Green	$R842/R560 - 1$	
Tassled Cap Vegetation	GVI	$(R443 : R520) - (R520 : R600) - (R630 : R690) + (R760 : R900) + (R1560 : R1740) - (R2080 : R2350)$	Bauer et al. (1994)
Photosynthetic Vigour Ratio	PVR	$(R560 - R665) / (R560 + R665)$	Metternicht (2003)
Triangular Vegetation Index	TVI	$0.5 * (120 * (R740 - R560) - 200 * (R665 - R560))$	
Modified Vegetation Indices			
Modified Normalised Vegetation Difference 1	MNDVI 1	$(R755 - R740)/(R755 + R740)$	Mutanga and Skidmore (2004)
Modified Normalised Vegetation Difference 2	MNDVI 2	$(R755 - R740)(R740 - R705 - 2*R445)$	Sims and Gamon (2002)
Modified Normalised Vegetation Difference 3	MNDVI 3	$(R740 - R705)/(R740 + R705 - R445)$	Sims and Gamon (2002)

Soil Vegetation Index	MSAVI	$\frac{((2 \cdot R_{842} + 1 - \sqrt{(2 \cdot R_{842} + 1)^2 - 8 \cdot (R_{842} - R_{665}))})}{2}$	Qi et al. (1994)
Optimsed Soil Adjusted Vegetation Index	OSAVI	$\frac{(1 + 0.16) \cdot (R_{842} - R_{665})}{(R_{842} + R_{665} + 0.16)}$	Rondeaux et al. (1996)
Transformed Chlorophyll Absorption in Reflection Index	TCARI	$3 \cdot ((R_{740} - R_{705}) - 0.2 \cdot (R_{740} - R_{560})) \cdot (R_{740}/R_{705})$	Haboudane et al. (2004)
Modified Chlorophyll Absorption in Reflection Ratio index	MCARI	$((R_{705} - R_{665}) - 0.2 \cdot (R_{705} - R_{560})) \cdot (R_{705}/R_{665})$	Daughtry et al. (2000)
Revised MCARI	RMCARI	$(((740 - 705) - 0.2 \cdot (740 - 560)) \cdot (740/705))$	
TCARI/OSAVI	TCARI/OSAVI	$\frac{3 \cdot ((R_{705} - R_{665}) - 0.2 \cdot (R_{705} - R_{560})) \cdot (R_{705}/R_{665})}{(1 + 0.16) \cdot (R_{842} - R_{665}) / (R_{842} + R_{665} + 0.16)}$	
MCARI/OSAVI	MCARI/OSAVI	$\frac{((R_{705} - R_{665}) - 0.2 \cdot (R_{705} - R_{560})) \cdot (R_{705}/R_{665})}{(1 + 0.16) \cdot (R_{842} - R_{665}) / (R_{842} + R_{665} + 0.16)}$	
Modified Simple Ratio	MSR	$(R_{842} / R_{665}) - 1 / (\sqrt{R_{842}/R_{665}} + 1)$	Chen (1996)
Modified Normalised Difference Vegetation Index	mND	$((R_{750 \text{ to } R_{900}} - (R_{660 \text{ to } R_{720}})) / ((R_{750 \text{ to } R_{900}}) + (R_{660 \text{ to } R_{720}}) - 2 \cdot R_{445}))$	Sims and Gamon (2002)
Red Edge Bands/ Indices			
Band 5	705		
Band 6	740		
Band 7	783		
Band 8a	865		
Normalised Difference Vegetation Index Red Edge	NDVI RE	$(R_{740} - R_{705}) / (R_{740} + R_{705})$	Rouse et al. (1974)
Normalised Difference Red and Red Edge	NDVI Red RE	$\frac{R_{864} - ((0.5 \cdot R_{665}) + (0.5 \cdot R_{705}))}{R_{864} + ((0.5 \cdot R_{665}) + (0.5 \cdot R_{705}))}$	Xie et al. (2018)
Simple Ratio 740, 560	SR 740,560	R_{740}/R_{560}	
Modified Simple Ratio Red and Red Edge	MSR Red RE	$\frac{R_{864}/((0.5 \cdot R_{665}) + (0.5 \cdot R_{705})) - 1}{\sqrt{R_{864}/((0.5 \cdot R_{665}) + (0.5 \cdot R_{705}))} + 1}$	(Xie et al., 2018)
Modified Simple Ratio Red Edge	MSR RE	$(R_{864}/R_{665}) - 1 / (\sqrt{R_{864}/R_{665}} + 1)$	Xie et al. (2018)
Green Chlorophyll	CI Green RE	$R_{864}/R_{705} - 1$	Xie et al. (2018)
CL Red and Red Edge	CI RED RE	$R_{864}/0.5 \cdot R_{665} + 0.5 \cdot R_{705}$	
Red Edge Inflection Point	REIP	$(R_{705} + 40 \cdot ((R_{re} - R_{705}) / (R_{740} - R_{705}))) / 100$	Guyot et al. (1988)
Reflectance at the Inflection Point	Rre	$R_{665} + R_{783} / 2$	Broge and Leblanc (2001)
Inverted Red Edge Chlorophyll Index	IRECL	$(R_{783} - R_{665}) / (R_{705}/R_{740})$	Frampton et al. (2013)

Sentinel 2 Red Edge Position	S2REP	$R705 + 35 * ((R783 - R665/2) - R705) / (R740 - R705)$	Frampton et al. (2013)
VI 705	VI705	$(R705 - R665) / (R705 + R665)$	
Standard Bands			
Band 2			
Band 3			
Band 4			
Band 8			
Band 11			
Band 12			

3.2.5. Predicting leaf area index using the RF regression ensemble

The prediction model was generated using the RF regression ensemble. The analyses were performed within the R – environment software package - Rattle, Version 3.5.1. The RF ensemble is a machine learning algorithm that utilises the bootstrapping technique to *bag* data. The *in-bag* data represented groupings of training data, that are randomly selected observations of the spectral bands and VI's, used to train the trees. Decision trees are produced, with a defined number of features. The 'forest' is created from the decision trees, to finally return an average of the probabilities of the created trees. Probabilities are tested against the decision trees to return a class with the highest number of votes. *Out-of-bag* (OOB) data is used to validate how the model performs, as the validation returns an associated OOB error. The ensemble was selected and used in this study because it has demonstrated reliable performance, especially in RS applications including vegetation attributes prediction (Ahmed et al., 2014; Belgiu and Drăguț, 2016; Ismail and Mutanga, 2010). The ensemble requires two parameters, M_{try} and N_{tree} . M_{try} was standardised to 500 observations and N_{tree} ranged from 1 to 5. Here, identification of important predictor variables from S2 MSI data were selected to produce estimates from observed LAI. Training data consisted of 70% ($n = 42$) of the entire dataset while the other 30% ($n = 18$) was used as validation data. Model accuracies from different predictor variables (spectral bands and VIs) were evaluated based on the root mean square error (RMSE) calculated using the following formula:

$$RMSE = \sqrt{\sum \frac{(Y_{ObservedLAI} - Y_{PredictedLAI})^2}{N}}$$

Formula 3.1.

To provide a measure of strength between measured and predicted values, adjusted coefficients of determination (R^2) were determined based on the formula below:

$$R^2 = 1 - \frac{\sum (Y_{ObservedLAI} - Y_{PredictedLAI})^2}{\sum (Y_{ObservedLAI} - \bar{Y}_{PredictedLAI})^2}$$

Formula 3.2.

The closer the coefficient of determination is to 1, the better the fit and the more predictive power will be exhibited by that model. Level of importance of predictors was also computed and used, as rankings returned from the RF model.

3.2.7. Approaches for LAI prediction

Predictor variables, spectral bands and VI's used in the study were categorised. Categorising predictor variables into sets as; traditional VI's, modified VI's and RE bands and indices facilitated the identification of influential predictors in the retrieval of *Podocarpus* LAI. The categories of predictors were grouped into four categories which are referred to as the Multistage Analysis. The variables from the predictor category which exhibited the highest model accuracy was selected and used to generate a LAI prediction model. Similarly, in the backward elimination analysis, the dataset representative of predictors from all categories were pooled. Here, the least performing predictors were omitted from

the subsequent model generation. This facilitated the identification of fewer, more important predictors that improved model estimation accuracy. This is critical as not all predictors are equally important in building the prediction model.

Table 3.3. The two approaches used in LAI prediction models.

Multistage Analysis	Backward Elimination Analysis
Standard Bands	All spectral variables (pooled)
Traditional Vegetation Indices	
Modified Vegetation Indices	
Red Edge Bands and Indices	

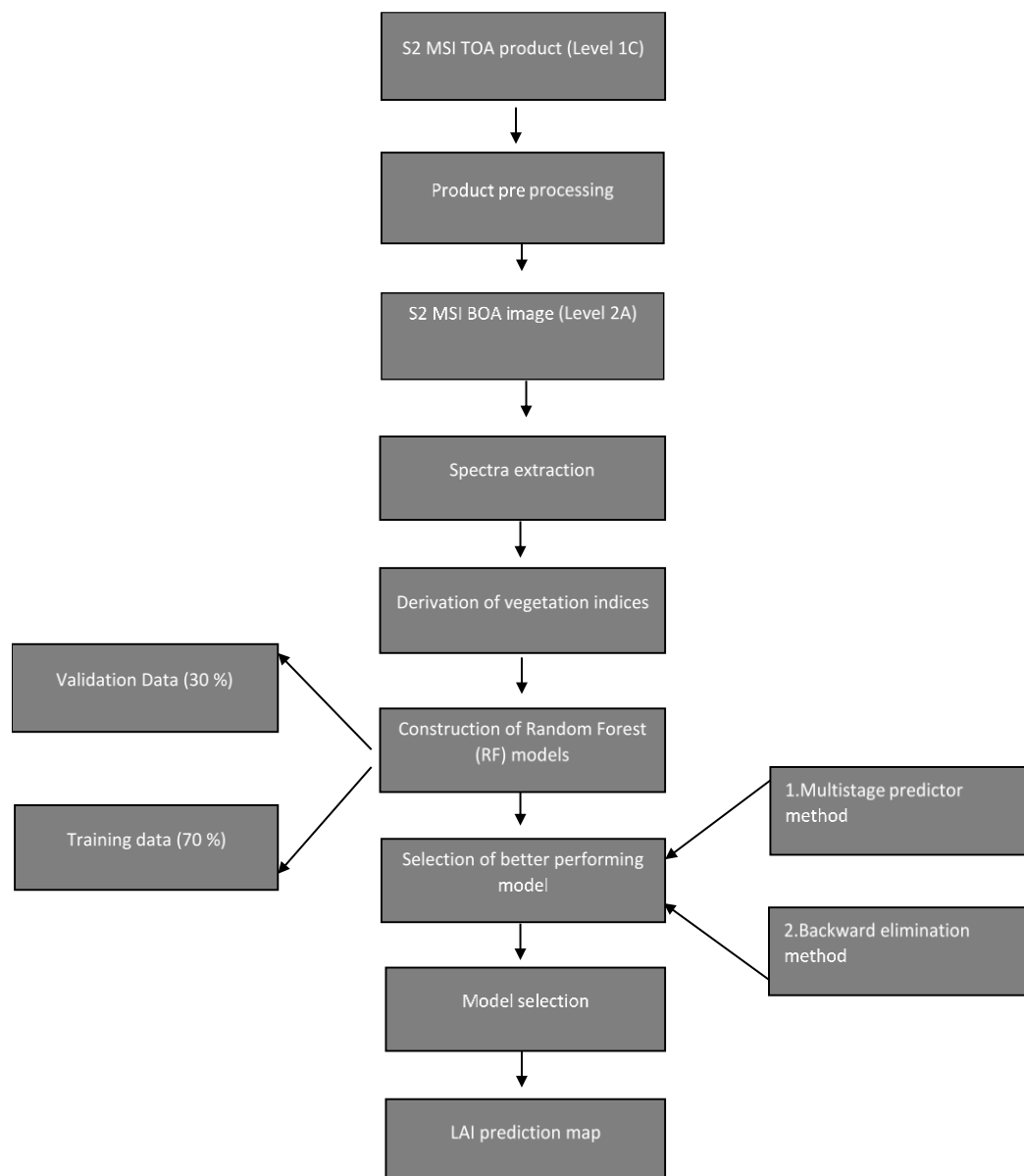


Figure 3.3. Systematic diagram of the methods involved in the estimation of LAI.

3.3. Results

3.3.1. Descriptive Statistics of observed LAI

Yellowwood species LAI measurements ranged between 0.83 and 4.09 ($n = 60$, Mean = 2.24) (**Figure 3.4**). The conducted Shapiro – Wilk normality test on LAI measurements showed a unimodal distribution following a normal distribution curve assumed by the data.

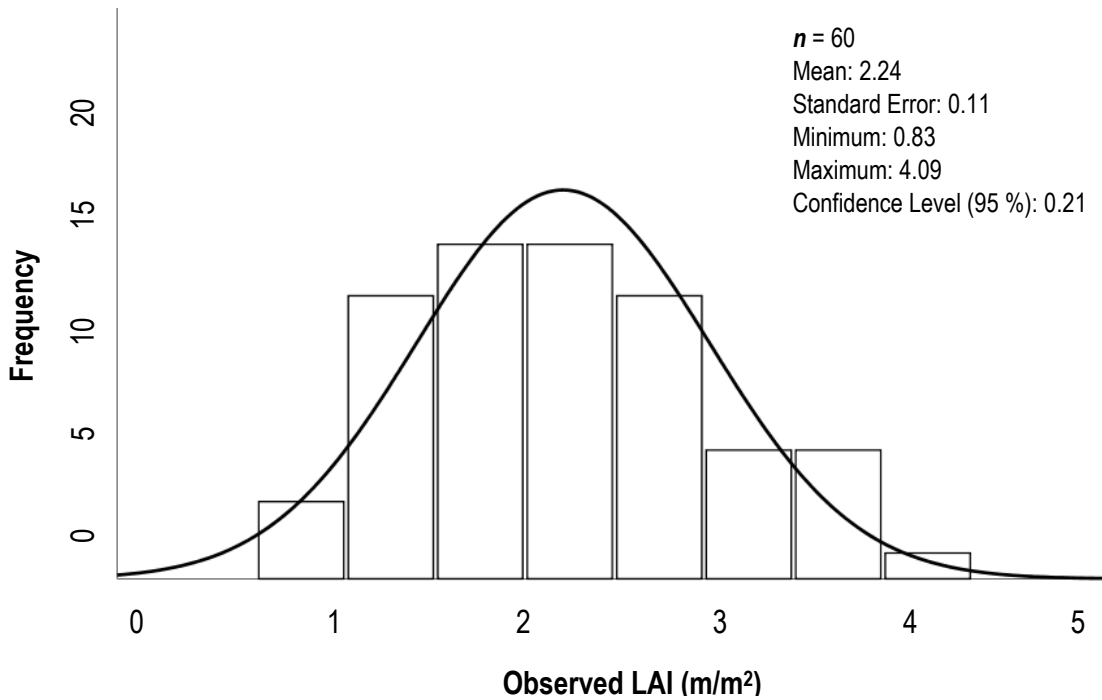


Figure 3.4. Descriptive statistics of observed LAI of the Yellowwoods.

3.3.2. Comparison of S2 MSI spectral bands and vegetation indices in estimating leaf area index

Low to moderate levels of accuracy were returned by the RF multistage models, using the S2 MSI product. Low model accuracy was observed for the Modified Vegetation Indices, which returned a RMSE of 0.74 m²/m² and R^2 of 0.35 in the categorised data management approach. Similarly, the Traditional Vegetation indices exhibited a RMSE of 0.55 m²/m² and a R^2 of 0.16. RE bands and indices showed the highest accuracy most optimal model (RMSE = 0.48 m²/m²; $R^2 = 0.50$), which also has more numbers of predictors. Lowest model variability was observed for Traditional Vegetation indices. While the RE bands and indices maintained the highest model, variability explained. Explained variability (%) indicates the cumulative contributions of predictors to the model.

Table 3.3. RF model accuracies from the multiage approach.

Predictor variables	Number of predictor variables used	RMSE (m ² /m ²)	R ²	Explained variability (%)
Standard Bands	6	0.61	0.23	41.60
Traditional Vegetation Indices	16	0.55	0.16	33.40
Modified Vegetation Indices	12	0.74	0.35	46.84
RE Bands and Indices	16	0.48	0.50	57.08

In comparison, the backward elimination method models showed an improvement and increased model performance when more variables were eliminated with each successive stage. From Stage 1, a large proportion of eliminated predictors were of the traditional and modified indices (**Table 3.4.**) A gentle progression in terms of the R² values was observed from Stage 1 to Stage 6. Although Stage 7, returned a slightly lower R² value that deviated from the progression, it exhibited a decrease in terms of the RMSE from 0.60 to 0.54 m²/m². Stage 8 exhibited the most performing model with a R² of 0.59 and the lowest RMSE recorded in this study equivalent to 0.48 m²/m² as well as the highest percentage of explained model variance of 70%.

Table 3.4. RF model accuracies from the backward elimination approach.

Elimination stage	No. of predictor variables used	Eliminated variables	R ²	RMSE (m ² /m ²)	% Model variability explained
1	50	NPCI, MNDVI 2, CI Red RE, SR, MSR, PSSRb, GVI	0.41	0.62	48.82
2	44	Band 11, Band 3, OSAVI	0.41	0.64	50.91
3	41	CI RE, PSSRa, Band 2, VI710, GRg, SAVI, REIP, NDVI, MCARI/OSAVI, MCARI, CI Green RE, MSR RE	0.41	0.63	52.86
4	29	G, RMCARI, Band 4, PVR, EVI	0.42	0.61	53.23
5	23	CI Green, MNDVI 1, Band 8, TVI, DVI, MSR RED RE, S2REP, mND, Band 12, MSR RE	0.43	0.64	54.42
6	15	MSAVI, CI Green, SR750	0.55	0.60	55.59
7	12	GNDVI, Rre, IRECL	0.48	0.56	66.92
8	7	-	0.59	0.48	70.09

3.3.3. The comparison of the multistage and the backward elimination data management approaches

Figure 3.5(a) shows the final one-to-one relationship between measured and predicted LAI, derived using the variables from the multistage approach. That is, the RE bands and indices which exhibited a RMSE of 0.48 m²/m² and

a R^2 of 0.50, whereas the final model derived based on the backward elimination method resulted in a R^2 of 0.59 and a RMSE of 0.48 m^2/m^2 (**Figure 3.5.**), comprising predictors from all categories. Correspondingly, the backward elimination method also identified RE bands and VI's as the most optimal predictor variables, in terms of variable importance. (**Figure 3.5 (b)**). Of the two model approaches, the backward elimination method was the best prediction model, for observed LAI.

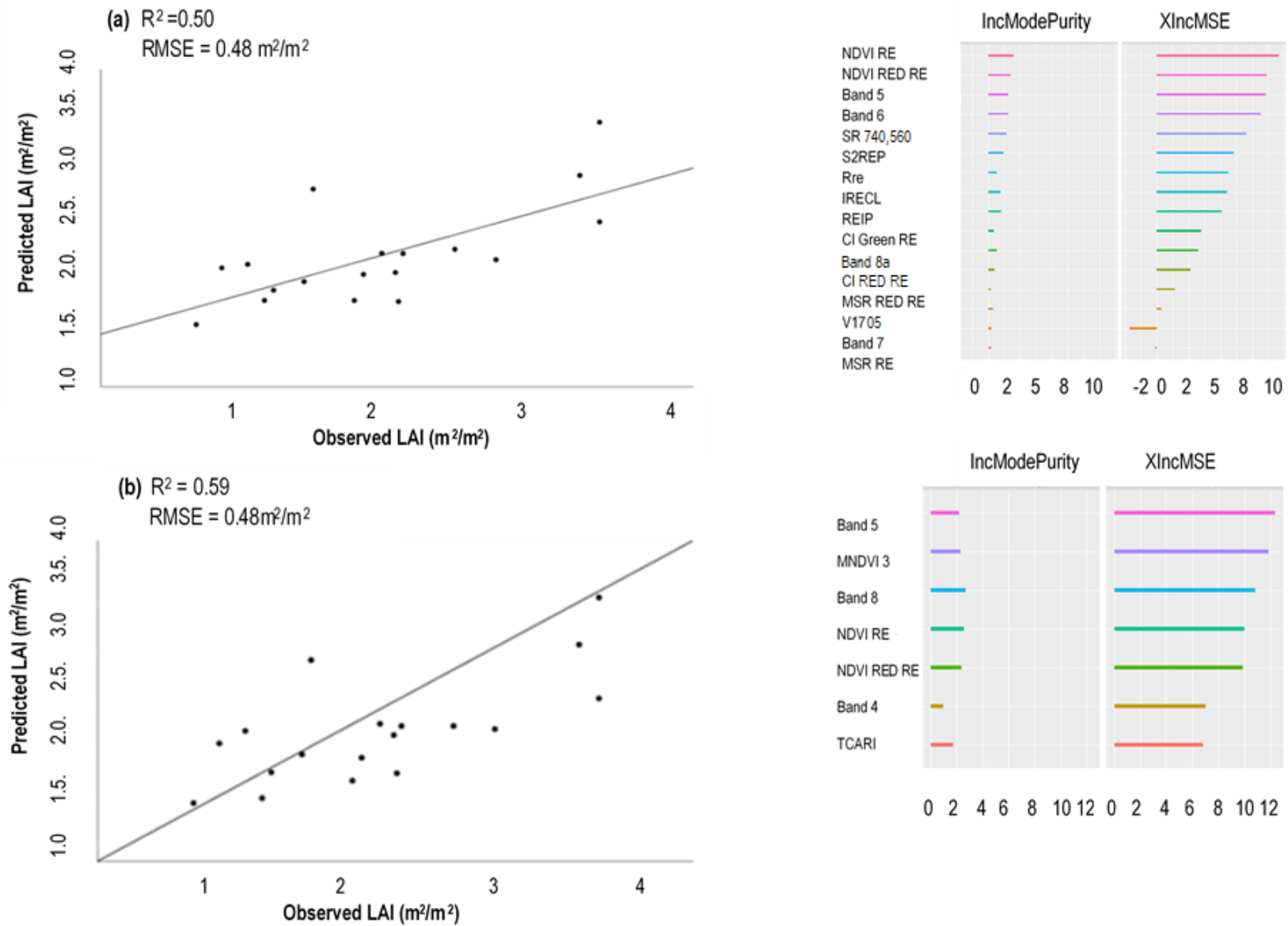


Figure 3.5. Relationship between the predicted and observed leaf area index and relative variable importance for the data management approaches, **(a)** multistage (categorisation) and **(b)** backward elimination method, of the best overall prediction models for each case.

3.3.3. Mapping the spatial distribution of *Podocarpus* spp. LAI

Figure 3.6 illustrates the spatial distribution of LAI in the study area. Predicted LAI values are shown, with varying measurements within the Ingeli forest. The largest proportion of LAI values are predicted for the 2.38 – 3.02 range. Higher LAI predictions are noted in western, eastern, and southernmost parts of the forest. Lowest LAI values can be seen in the middle part of forest, showing no distinctive pattern.

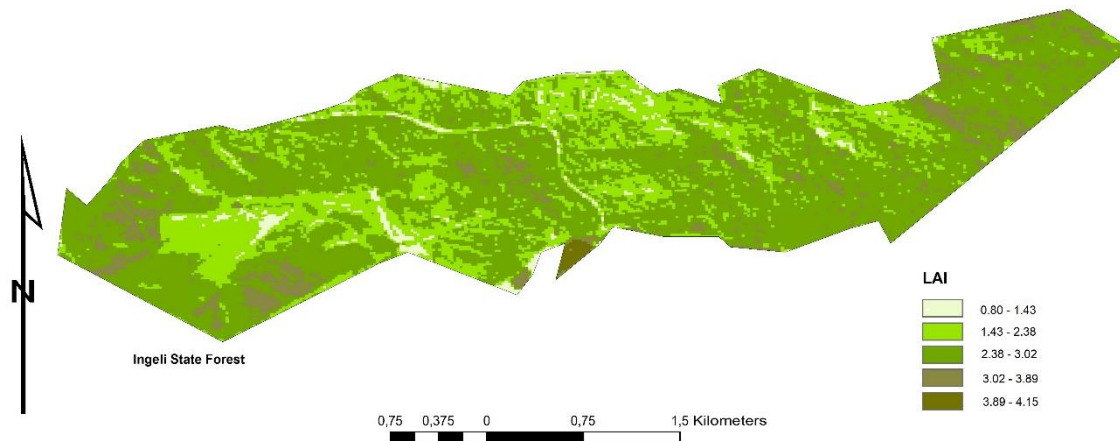


Figure 3.6. LAI map estimated with the backward elimination derived model, for the *Podocarpus* spp LAI.

3.4. Discussion

The main objective of this study was to predict and map the spatial distribution of the *Podocarpus* tree spp. LAI using a model derived using RF and S2 MSI data in an Afromontane mistbelt forest located in South Africa.

3.4.1. Predicting LAI of *Podocarpus* spp.

The comparative analysis of data management approaches showed that the backward elimination method exhibited better results ($RMSE = 0.48 \text{ m}^2/\text{m}^2$; $R^2 = 0.59$) in relation to the multistage approach ($RMSE = .50 \text{ m}^2/\text{m}^2$, $R^2 = .48$), in estimating LAI of the *Podocarpus* spp. in the Ingeli State Forest. The most influential variables of the optimal backward elimination model were RE VI's and bands. Although, the backward elimination method had higher coefficient of determination (59%) than the other method, their RMSE were the same. These findings suggest that there is no clear-cut, best variable selection method of estimating LAI of the podocarps in an Afromontane forest. Our findings are supported by Mehmood et al. (2012) who concluded that there is no best variable selection method when considering the fact that there is likely to be a relation between the method and the data characteristics. This assertion is also mirrored through the selection of three similar spectral variables by both methods, in this study. Specifically, Band 5, NDVI RE and NDVI Red RE were all selected by these two methods - multistage and backward elimination - as optimal variables for predicting and mapping the LAI of *Podocarpus* spp. in this study. The presence of the RE band and indices in both models could also explain their similar accuracy illustrated by a RMSE of $0.48 \text{ m}^2/\text{m}^2$. The RE section of the EM spectrum is widely renowned in

literature for being insensitive to high foliage density and LAI associated with tropical forests such as the Yellowwood forest (Cross et al., 2019; Gitelson et al., 2003). This relationship is explained by the fact that the canopy reflectance in the RE region mainly results from multiple scattering between the leaf layers. Hence, the shape of the RE section of the EM spectrum is strongly associated with high foliage density and LAI (Sun et al., 2019). Taking into consideration that the *Podocarpus* spp. are characterised by glossy evergreen long and narrow, pendulous leaves (Mucina et al., 2006; Van Wyk, 2013) as illustrated in **Figure 3.2 (b)**, the distribution of Yellowwood tree leaves results in high leaf angle distribution (LAD) and LAI estimates. The high LAI and LAD is generally associated with a shift of the RE to longer wavelengths, hence the remarkable influence of both models since they are characterised by RE spectral variables. In a related study, Croft et al. (2014) evaluated specific LAI, in different leaf types, with a wider range of LAI observations based on the MEdium Resolution Imaging Spectrometer (MERIS) data. They noted that the most influential spectral variables were derived from the RE, especially for the broader leaf types.

3.4.2. Comparison of standard bands, traditional and novel vegetation indices in predicting LAI of Podocarpus spp. in an Afromontane forest

In the multistage approach to modelling LAI, traditional vegetation indices were outperformed by the standard bands by an error magnitude of 0.06. Traditional vegetation indices then outperformed the modified vegetation indices by an error magnitude of 0.19 whereas the modified vegetation indices were outperformed by the RE vegetation indices to an error magnitude of 0.26. Although outperformance of traditional vegetation indices by standard bands was surprising, there are studies such as that of Wang et al. (2018) that have exhibited similar findings. Results by Wang et al. (2018) showed that the spectral bands exhibited an increased level of accuracy, when compared to traditional vegetation indices in the retrieval of LAI.

The smallest RMSE of 0.48 m²/m² to be recorded in this study exhibited by the standard bands suggests model over fitting related issues. The coefficient of determination as well as the variance explained associated with this model were very low, implying that the relationship between the predicted and measured datasets was relatively poor. VI's derive strength from two or more sections of the EM in relation to a single standard band. In this regard, there is bulk literature that attests to the poor performance of standard spectral bands in relation to vegetation indices when characterising vegetation attributes (Cross et al., 2019; Moreno-García et al., 2018; Thenkabail et al., 2013). Specifically, VIs circumvent the effect of topography, sun and view angle, soil background as well as atmospheric noise while being sensitive to the vegetation spectral characteristics such as high foliage density and chlorophyll content (Thenkabail et al., 2011) associated with evergreen tree species such as the *Podocarpus* spp.

Despite the model performance improvements associated with vegetation indices, Traditional and Modified vegetation indices did not improve the accuracies in estimating LAI of *Podocarpus* species in this study. This points to the fact that the original intent of many of these indices is for general vegetation detection and not suited for specific species attributes characterisation. Most of these indices such as GNDVI and OSAVI were developed to

surpass saturation issues in areas characterised by dense vegetation (Cross et al., 2019). In a related study, Cross et al. (2019) also reported a poor performance of Traditional and Modified VI's in determining the appropriate resolution data and VI's for tropical forest tree species characterisation. Similarly, Chrysafis et al. (2017) also noted no improvement in model accuracies when traditional vegetation indices were used to estimate volume of growing stock using S2 MSI data in a Mediterranean forest.

Meanwhile, the RE bands and indices model outperformed all the other models derived based on the multistage variable selection method. As aforementioned, the *Podocarpus* tree species are evergreen which implies that they generally have chlorophyll content levels other than high foliage density. The RE section of the EM has been extensively proven to be sensitive to high chlorophyll content hence the optimal performance of RE VI's in the multistage approach of estimating LAI of the Yellowwoods in this study. Furthermore, it is worth noting that the S2 MSI RE bands are narrower than other wavebands (Chrysafis et al., 2017; Fernández-Manso et al., 2016; Louis et al., 2016). Broader wavebands tend to mask out critical information that is required in characterising vegetation attributes. Sensitivity of the RE bands and indices noted in this study could be attributed to their narrow nature which makes them more sensitive to the variations of *Podocarpus* spp. LAI.

3.5. Conclusion

The study sought to test the utility of the S2 MSI in the estimation of LAI in the Ingeli State Forest using the RF algorithm based on the backward elimination and multistage data analyses. Grounded on the findings of this study we conclude:

1. Sentinel 2 MSI data particularly RE bands and VI's can be used to accurately predict LAI of Afromontane vegetation species such as *Podocarpus* spp.
2. The backward elimination method performs better in characterising tree specific vegetation attributes such as LAI.

The findings of this study are critical foundational steps for coming up with effective monitoring, management, and conservation strategies of the species diverse Afromontane forest of southern Africa. This research further supports the applicability of spectrally derived information, in the retrieval of LAI, within unique forest types. Furthermore, the findings of this study underscore the use of new multispectral instruments in the conservation of the natural resources and capital.

Chapter Four

Synthesis and Conclusions

4.1. Introduction

Implementing appropriate and meaningful conservation strategies for degraded indigenous forests requires up to date, holistic information for those ecosystems. Such unique landscape settings therefore require new age methods of surveying such as RS and GIS applications. RS is cost effective, and offers a continuous data source, that is incomparable to traditional field surveys. Local surface topography assumes a pivotal role in the distribution and productivity of specialist forest species, such as the Yellowwood tree species. However, the relationship between emergent tree properties such as LAI and topography is not well understood, and there is much to be explored in this regard. Similarly, the predictive capacity of “new generation” satellite remotely sensed data in understanding LAI of such unique forest tree species has not been extensively explored. Specifically, the Yellowwood trees species; *Podocarpus henkelii* (Henkel's Yellowwood), *Podocarpus latifolius* (Real Yellowwood) and *Podocarpus falcatus* (Outeniqua Yellowwood) function as keystone features of the Afromontane forest as they are emergents, with large spreading crowns which support many species. For instance, insects, birds and mammals depend on the trees for habitat and foraging sites. In this regard, they contribute to the maintenance of biodiversity among an assortment of ecological and environmental services. However, the population of these tree species as well as their spatial extent is drastically being reduced by human activities. Subsequently, there is a need to develop comprehensive frameworks for inventorying, monitoring, and drawing up effective conservation strategies for such critical indigenous forest species.

This study, therefore, aimed to characterise the LAI of the Ingeli Yellowwoods in a southern African mistbelt Afromontane forest, using SRTM DEM and the S2 MSI remotely sensed data products. Therefore, the objectives of the study were to:

- (i) evaluate the role of SRTM DEM derived topographic variables, in the explanation of LAI, using PCA and stepwise regression analysis, and
- (ii) to assess the utility of S2 MSI imagery, in the estimation of LAI, using the RF regression ensemble.

4.2. The role of topographic variables in explaining leaf area index, of the Yellowwood tree species in an Afromontane mistbelt forest of southern Africa

In investigating the relative importance of topographic controls in estimating LAI of the endangered Yellowwood species in a recovering indigenous Afromontane mistbelt forest within southern Africa, results of the study showed that catchment area, mass balance and SVF and topographic variables (in order of importance) optimally ($SEE = 35\text{m}^2/\text{m}^2$ and $R^2 = 0.85$) explained the spatial variation of the observed leaf area index. This underpins the applicability of the study for forest management; specifically, the inclusion of topographic indices in understanding emergent tree properties.

4.3. Estimating leaf area index of the Yellowwood tree in an indigenous, southern African forest, using Sentinel 2 Multispectral Instrument imagery and the Random Forest regression ensemble

Freely accessible medium resolution remotely sensed data are important in the retrieval of ecological biophysical characteristics, such as leaf area. Specifically, the ability of S2 MSI data, which covers the critical RE section of the electromagnetic spectrum for vegetation mapping, was tested in the study. The methodology to achieve this included the application of a range of vegetation indices, and the RF regression ensemble. A novel approach was used in constructing the LAI prediction model based on individual bands, traditional indices, modified indices and RE bands and indices in a multistage approach. This was then compared to the backward elimination approach. Yellowwood tree species LAI was optimally predicted ($R^2 = 0.59$) based on the backward elimination prediction model using Band 5, MNDVI 3, Band 8, NDVI RE 2 and NDVI RED RE, Band 4 and TCARI. The prediction of LAI distribution using S2 MSI imagery demonstrated the applicability of the “new generation” sensor in the monitoring of essential biodiversity variables (EBV's), such as leaf area.

4.4. Implication to indigenous forest species monitoring and management

The study is a contribution to the limited body of literature on the effects of topography on tree condition in ecology and forestry in southern Africa. The study's approach to characterising leaf area in terms of topographic controls on the keystone Yellowwood tree species highlights the importance of ecosystem resources movement and distribution facilitated by topography. This implies that the distribution of ecosystem resources, such as water which are highly influenced by terrain affect critical tree properties such as LAI, hence they need to be considered in understanding indigenous forest species distribution and management. Similarly, the prediction of forest species-specific LAI, may be used to produce maps that can be used in the assessment of forest condition, carbon assimilation and productivity. The procedures used in this study provide the required insight to conservationists, ecologists, land use managers and the broader remote sensing community, in identifying appropriate datasets as well as plausible approaches for manipulating RS data to derive spatial information required in monitoring Yellowwood tree species productivity. This is important for accurate and up to date indigenous forest monitoring, especially in highly disturbed forest environments. Overall the successful application of the SRTM DEM and S2 MSI imagery, PCA, stepwise linear regression and the RF regression ensemble in characterising the LAI of the protected Yellowwood tree species, in an indigenous Afromontane mistbelt forest illustrates the potential of remotely sensed data in developing comprehensive frameworks for inventorying, monitoring and devising effective conservation strategies for such critical indigenous forest species.

4.5. Recommendations for future studies

Integrating the topographic variables with geomorphological, soil and climatic data could supplement the understanding of LAI distribution, at a local scale. Climatic data, radiation, and temperature indices could help better understand the sky view factor, as the effects of seasonality particularly on temperature works in concert with the topographic metrics. This has the potential to explain residual variation, especially considering the unique

landscape of the Afromontane forest. Still, it is recommended that the findings of this study be validated with existing forest research inventory such as the recently published Cape Parrot and Mistbelt Forest Conservation Action Plan.

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