ASSESSMENT OF VEGETATION PRODUCTIVITY IN THE UMFOLOZI CATCHMENT USING LEAF AREA INDEX (LAI) DERIVED FROM SPOT 6 IMAGE

By

AZWIFANELI DAVHULA

213574325

Supervisor: Prof. Onisimo Mutanga

Co-supervisor 1: Dr. Abel Ramoelo

Co-supervisor 2: Dr. Moses Cho

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DECLARATION 1

This study was undertaken in fulfilment of a Master’s Degree and presents the original work of the author. Any work taken from other authors or organizations is duly acknowledged within the text and references section.

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Mr. Azwifaneli Davhula

(Student)

………………………

Prof. Onisimo Mutanga

(Supervisor)

……………..........

Dr. Abel Ramoelo

(Co-supervisor 1)

....

Dr. Moses A. Cho

(Co-Supervisor 2)

DECLARATION 2

DETAILS OF CONTRIBUTION TO PUBLICATIONS

Below are two possible publications to be submitted for peer review;

Publication 1: Davhula Azwifaneli [1], Ramoelo A. [1, 2] , Cho, M.A. [1, 2] **,** Mutanga, O[1]. Estimation of leaf Area Index (LAI) using various indices and reflectance from SPOT 6 data (in preparation).

The work was done by the first author under the guidance and supervision of second, third and fourth authors.

Publication 2: Davhula Azwifaneli[1], Ramoelo A. [1, 2]. Cho, M.A [1,2]., Mutanga, O[1]. Investigating the influence of environmental variables on the distribution of LAI in the UMfolozi catchment (in preparation).

The work was done by the first author under the guidance and supervision of second, third and fourth authors.

[1] University of KwaZulu-Natal, Discipline of Geography, Private Bag X01, Scottsville, 3209, Pietermaritzburg, South Africa.

[2] Council for Scientific and Industrial Research (CSIR), Natural Resources and Environment, Earth Observation Unit, P. O. Box 395, Pretoria, 0001, South Africa.

Signed: ....

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Acronyms

ANN- Artificial Neural Network

ANOVA-One-way Analysis Of Variance

ATCOR- Atmospheric / Topographic Correction for Satellite Imagery

DEM-Digital Elevation Model

EVI- Enhanced Vegetation Index

GI- Greenness Index

GPS- Global Positioning System

LAI- Leaf Area Index

LUT- Look-Up-Table

MERIS- MEdium Resolution Imaging Spectrometer

MODIS- Moderate Resolution Imaging Spectroradiometer

NDVI- Normalized Difference Vegetation Index

NIR- Near Infrared Band

OSAVI- Optimised Soil Adjusted Vegetation Index

PPR- Plant Pigment Ratio

R^2- Coefficient of Determination

RDVI- Renormalized Difference Vegetation Index

RGB- Red, Green, Blue bands

RMSE- Root Mean Square Error

RRMSE- Relative Root Mean Squared Error

RF- Random Forest

RTM- Radiative Transfer Model

SAVI- Soil Adjusted Vegetation Index

SIPI- Structured Insensitive Pigment Index

SR- Simple Ratio

SPOT-Système Pour l'Observation de la Terre

SRTM- Shuttle Radar Topography Mission

STASOFT- STATISTICA software

SVM- Support Vector Machine

VI- Vegetation Index

Abstract

Around the world, rural areas rely on the natural resources for their sustenance. These include grazing lands for livestock production and fuel wood harvesting for heating and cooking, as well as for medicinal purposes. These natural resources are barely managed in rural areas which exacerbate the challenge of land degradation due to unsustainable overgrazing and fuel wood collection. Land degradation has been identified as one of the key global problems are the root cause of poverty, food insecurity and malnutrition. In South Africa, the uMfolozi catchment is very vulnerable to disturbance due to slow ecological recovery, growing human populations and episodic droughts. Leaf Area Index (LAI), defined as one half the total green leaves per unit ground surface area, is an inventory of the plant green leaves that defines the actual size of the interface between the vegetation and the atmosphere. Thus, LAI spatial data could serve as an indicator of vegetation productivity. The main aim of the study is to estimate LAI as an indicator of vegetation productivity using remotely sensed data. First, field collected LAI were used to assess LAI models derived from various vegetation indices and bands. Secondly, multivariate statistics were used to combine bands and indices in estimating LAI. Combining reflectance at various bands and vegetation indices yielded higher estimation accuracy of LAI (Bootstrapped: R^2 = 0.71, RMSE = 0.92) as compared to using individual bands or indices. Furthermore the study found that environmental variables such as slope, Digital Elevation Model (DEM) and annual mean temperature significantly influenced the spatial distribution of LAI. There is a scope to estimate LAI empirically using bands and vegetation indices which are more site and data specific, but the study further recommends the use of physically-based models which are known to be robust. In conclusion, estimation of LAI is possible using remote sensing derived variables combined with multivariate statistical techniques, which is critical for assessing vegetation productivity.

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CHAPTER 1: INTRODUCTION

1.1. Background and importance of vegetation productivity

Around the world, rural areas rely on the natural resources for their sustenance. These natural resources include grazing lands for livestock production and fuel wood harvesting for heating and cooking, as well as for medicinal purposes. Natural resources in most rural areas are over-utilised (e.g. overgrazing, unsustainable fuel wood collection) and poorly managed thus exacerbating of land degradation which is typified by soil erosion, loss of soil fertility, bush encroachment and alien species invasion (DEAT, 2006). Land degradation has been identified as one of the key global problems causing rural poverty, food insecurity and malnutrition (DEAT, 2006). Soil erosion for example causes loss of valuable soil nutrients thereby depleting soil fertility with the consequence negative impacts on livestock and crop production (Pimentel, 2006).

Land degradation is also a problem in South Africa, for example sheet and gully erosion are common in the River uMfolozi catchment, of KwaZulu-Natal province. Tsafengenyasha et al., (2010) reported a decrease in vegetation productivity due to soil erosion. It is therefore important to develop techniques for assessing vegetation productivity in rural landscapes.

A biophysical variable that has been used to assess dynamics in vegetation productivity is the LAI (Fernandes et al., 2004). LAI is the total one-sided area of leaves per unit ground area (Nemani et al., 1993). LAI is used to quantify the energy and mass exchange characteristics of terrestrial ecosystems such as carbon and nutrient cycle, rainfall interception, evapotranspiration, photosynthesis, respiration, and transpiration, (Gong et al., 2003 and Kappas et al., 2012). LAI is an importance driver in models of net ecosystem productivity because it provides the surface for exchanges of carbon dioxide, water vapour and energy between the atmosphere and terrestrial ecosystems (Bonan, 1993; Gower et al., 1999 and Myneni et al., 2002). Additionally, it is also an important tool to measure grazing intensity in rangelands, because it decreases as vegetation becomes stressed (Gower et al., 1999).

LAI can be measured using direct and indirect methods. The most accurate direct method involves destructive harvesting of leaves and measuring their actual areas. This approach is extremely labour intensive and cannot be extended to broad areas. Indirect methods make use of optical instruments. For example, a field-based sensor such as LICOR 2200 plant canopy analyser derives LAI estimates by measuring the intercepted light below the vegetation canopy. LAI field measures using the LICOR can then be used to calibrate satellite images for broader landscape application or mapping of LAI (Gong et al., 2003). Wider area assessment of LAI using satellite images (i.e. space-borne remote sensing) is relevant to inform decision making processes pertaining to land degradation (Qi et al., 2000).

In general, remote sensing of earth is the science of acquiring information about targets on the earth's surface using instruments which are not in contact with the targets. The sensors may use visible and infrared spectral regions to obtain reflectance data from the earth's surface. Air or space-borne remote sensing offers the ability to observe and collect data for large areas very quickly, and is an important source of data for geographic information system (GIS) (Lwin, 2008 and Pidwirny, 2006). According to (Gong et al., 2003 and Darvishzadeh et al., 2008), huge progress has been made in developing methods that correlate remotely sensed data with regional estimation of a number of ecosystem variables including LAI in the last three decades. In the past three decades, traditional broadband vegetation indices (VI's) such as normalised difference vegetation index (NDVI) have been widely used in the estimation of LAI. For example, Ghebremicael et al. (2004) estimated LAI of black wattle from Landsat ETM+ satellite imagery. Also Pope and Treitz (2013) used the vegetation indices to estimate LAI in the Boreal Mixed wood Forest of Ontario, Canada using high resolution WorldView-2 Imagery. These techniques assume that there is a statistical relationship between LAI and vegetation greenness and or cover as captured by vegetation indices (Prospastin and Kappas, 2012). While, empirical models are site, season and data specific, they are quick and easy to implement (Prospastin and Kappas, 2012).

In addition to local and regional level estimation of LAI, there are several existing global LAI products derived from sensors such as MODIS, SPOT Vegetation and MERIS (MERIS sensor was discontinued in 2012). Often these products are not validated in our ecosystems and not accurate for South African environments (Cho et al., 2014). High resolution sensors such as the newly launched SPOT 6 data provides high spatial resolution (<6m) which can be used to accurately estimate LAI at the local to regional scale when compared to the coarser and moderate resolution images such as Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS). High resolution estimation of LAI could be critical for calibration and validation of coarser resolution images such as MODIS for broader landscape assessment of LAI. Consequently degradation of land at the sub-continental to continental scale can be determined. Therefore, this study intends to develop and investigate empirical LAI models based on individual bands, band combinations, and vegetation indices derived from SPOT 6 imagery in uMfolozi river catchment, South Africa.

1.2. Problem statement

In South Africa there have been limited attempt to use remote sensing images to predict LAI e.g. Cho et al. (2014). There are existing global LAI products derived from sensors such as Moderate Resolution Imaging Spectroradiometer (MODIS), MEdium Resolution Imaging Spectrometer (MERIS) and Satellite Pour l'Observation de la Terre (SPOT) Vegetation, with relatively coarse spatial resolutions. These LAI products are not well validated and may not be conducive for understanding vegetation productivity or land degradation at the catchment scale. There is a need to further develop techniques to estimate LAI for regional ecosystems which are locally parameterized. In this study, the utility of SPOT 6 high spatial resolution for estimating LAI shall be assessed.

1.3. Aim of the study

The aim of this study is to assess the utility of SPOT 6 for estimating LAI as an indicator of vegetation productivity in the uMfolozi river catchment, South Africa.

1.3.1. Specific Objective

In order to achieve the aim of this study, the following objectives were set;

- To investigate whether vegetation indices or bands derived from SPOT 6 significantly correlate to LAI

- To investigate if combining vegetation indices and bands improves the estimation of LAI using SPOT 6.
- To determine environmental variables that influences the spatial distribution of LAI in the River uMfolozi catchment.

1.3.2. Hypothesis

- LAI is significantly related to vegetation indices and spectral bands
- Combining vegetation indices and bands improves the estimation of LAI.
- LAI is influenced by various environmental variables e.g. Spadavecchia et al., (2008).

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter reviews existing literature which includes books and scientific articles focusing on the definition of LAI, its importance, and the methods for estimating LAI. The definition of LAI will be presented in the next section followed by...

Grasslands comprise 26% of the total global land area and 80% of agricultural productive land. Most grassland areas are found in the tropical developing countries (Boval and Dickson, 2012). Boval and Dickson (2012) indicated that about one billion people in poor communities live in and depend on in grassland resources. Southern Africa, from 1650 to 1850 people provided their daily needs through cattle farming and was nomadic in nature, i.e. migrating from one place to the other for good grass condition for grazing (Tainton, 1999). Today in South Africa, grassland covers almost one third of the land surface, covering about seven provinces (SANBI, 2013). There is a need to assess these resources for improved livelihood of the poor communities.

2.2 LAI – a measure of vegetation productivity

2.2.1 Definition

LAI is a dimensionless indicator of vegetation structure. LAI defined as total one sided green leaf area per unit soil area (McAllister, 2005 and Nemani et al., 1993). The definition of LAI is often dependent on the purpose of the study or the background of the scientist, in which some preferred a certain definition over others (McAllister, 2005 and Nemani et al., 1993). Watson, 1947 proposed a definition for agricultural purposes, which accounts for leaf structure, particularly with respect to shape.

2.2.2 Importance of LAI

According to Baldocchi (2012) LAI is one of the most important bio-meteorological variables. LAI provides the effective surface for absorbing light and momentum and for exchange of heat, moisture; CO_2 and trace gases between the vegetation and the atmosphere (Baldocchi, 2012) highlighted the importance of LAI estimates for understanding the eco-physiology of plant. LAI is an important determinant of photosynthetic and transpiration activities of the vegetation (Wulder et al., 2004 and Chen, 2013). The green LAI determines the amount of visible to near-infrared (NIR) that is absorbed or reflected. For example the higher the density of leaves, the higher absorption of blue and red light and the higher the reflectance of energy in the green and near infrared spectrum (Gobron et al., 1997; Zheng and Moskal, 2009).

LAI can be used to assess vegetation productivity and land degradation because it is an important biophysical variable that controls ecosystem processes such as plant production and evapotranspiration (Jensen et al., 2011). Another study used by (McAllister, 2005) uses remote sensing techniques to estimate LAI within an ecosystem and to use the values to estimate net primary productivity. The study region was located in the Fundy National Forest and LAI estimates were derived from seventeen stands. The authors determined that a weak relationship existed between NDVI and LAI for all stands.

2.2.3 Methods of estimating of LAI

This section will review various literature including books and scientific literature concerning the direct, indirect and remote sensing based methods for estimating LAI.

2.2.3.1. Direct method for measuring LAI

Direct methods involve destructive harvesting of green leaves from the sampled plot and measuring actual area of the leaves (Jonckheere et al., 2004). Direct methods are limited in the sense that they are laborious, expensive, time consuming and sampling can only be done in small plots (Gower et al., 1999). The disadvantages of direct methods have been dealt with by indirect methods which depend on optical measuring instruments e.g.

handheld sensors and satellite sensors which have great potential to estimate LAI over large areas.

2.2.3.2. Indirect method for measuring LAI

Handheld optical sensors used to indirectly measure LAI include LAI-2000 Plant Canopy Analyzer (LICOR) and digital hemispheric photography (Schiffman et al., 2008), LICOR instrument measures the diffused sunlight at various zenith angles ranges based on the canopy gap size distribution (Wittamperum et al., 2012). A disadvantage of LAI meters is that they are based on a number of assumptions; for instance, random foliage distribution which is less likely to occur in nature (Ghebremicael et al., 2004). Air or space borne remote sensing is another indirect method with the greatest potential to characterize variations of LAI at different spatio-temporal scales due to the multiple spatiotemporal resolutions of the available satellite data (Shen et al., 2014).

2.2.4. Remote sensing based methods for the estimation of LAI

Remote sensing is the science of acquiring information about the earth using instruments which are remote to the earth's surface, usually from aircraft or satellites (Lwin, 2008 and Pidwirny, 2006). It offers the ability to observe and collect data for large areas relatively quickly, and is an important source of data for GIS (Lwin, 2008). Remote sensing also provides a unique perspective for vegetation studies on the regional and continental scale and uses the red and near-infrared portions of the electromagnetic spectrum for characterizing vegetation and its processes (McAllister, 2005 and Darvishzadeh et al., 2008a).

There are three categories of methods to derived LAI from spectral data; the first type is called the empirical-based approach. This approach uses regression models to acquire a relationship between the target variable e.g. LAI and its spectral reflectance (Darvishzadeh et al., 2008a and 2012). Models used in empirical-based approach are categorized by univariate regression and multivariate regression; (1) Univariate regression relates the target variable to either the reflectance at a specific waveband or a spectral index and (2) multivariate regression relates several spectral bands to estimate biophysical concentrations

(Majeke et al., 2008). Various studies have estimated LAI from vegetation indices derived from various remote sensed (RS) data (Table 1).

Table 1: Examples of studies used Indices

Vegetation index	**Acronym**	**Modified formulae**	**Reference**
Normalized Difference Vegetation Index	$NDVI_{53}$	$(R_{805}-R_{657.5})/(R_{805}+R_{657.5})$	(Rouse et al., 1974)
Soil-Adjusted Vegetation Index	SAVI	$(1+0.2)*R_{805}-R_{710})/((R_{805}+R_{710})+0.2)$	(Huete, 1988)
Simple Ratio	SR_{52}	$R_{805}/R_{657.5}$	(Jordan, 1969)
Enhanced Vegetation Index	EVI	$2.5*(R_{805}-R_{657.5})/R_{805}+(6*R_{657.5})-(7.5*R_{455})$	(Huete et al., 1997)
Greenness Index	GI	$R_{555}/R_{657.5}$	(Smith et al., 1995)
Structure Insensitive Pigment Index	SIPI	$(R_{805}-R_{475})(R_{805}-R_{657.5})$	(Peñuelas et al., 2001)
Near Infrared region of the Reflectance Index	NRI	$(R_{555}-R_{657.5})/(R_{555}+R_{657.5})$	(Schleicher et al., 2001)
Plant Pigment Ratio	PPR	$(R_{555}-R_{475})/(R_{555}+R_{475})$	(Metternicht, 2003)
Renormalized Difference Vegetation Index	RDVI	$(R_{800}-R_{670})/(SQRT(R_{800}+R_{670})$	(Roujean and Breon, 1995)
Soil-Adjusted Vegetation Index	SAVI1	$((1+0.2)*(R_{805}-R_{657.5})/(R_{805}+R_{657.5})+0.2)$	(Huete, 1998)
Optimized SAVI	OSAVI	$(1+0.16)*(R_{805}-R_{657.5})/(R_{805}+R_{657.5}+0.16)$	(Rondeaux et al, 1996)

Kross et al., (2014) used seven RapidEye vegetation indices and evaluated them for estimating LAI and biomass of corn and soybean crops with contrasting leaf structures, canopy architectures and photosynthetic pathways. Overall, most of the indices had good linear or exponential relationships with LAI and showed sensitivity along the entire range of LAI values from emergence to $8m^2/m^2$. The study demonstrates the potential of using Landsat and SPOT images in multi-sensor virtual constellation approach for continuous field LAI monitoring over time and space.

Potithep et al., (2010) also investigated the actual relationships between LAI and VI's in the deciduous broad leaf forest; the results concluded that (1) NDVI and EVI can show the seasonal variations of LAI, but presents the value earlier than *in situ.* LAI values started due to the effects of forest floor; (2) for the single relationship, NDVI and EVI had the linear relationship with *in situ* LAI, and (3) the different patterns between LAI and VI were clearly illustrated in the double relationship, then it can improve the LAI estimations better than single relationship.

LAI can also be derived from remote sensing data through the inversion of radiative transfer (RT) or physical process models. RT models (RTM) are biome-independent because they are based on geometrical optical and radiative transfer theories by taking the interactions between LAI and influencing factors (Shen et al., 2014). These models can be applied to various remote sensing data acquired over the same vegetation cover and they are more accurate and easy to apply on a larger scale (Darvishzadeh et al., 2011 and Liang, 2007)). Amongst RT models, the leaf reflectance model, there is PROSPECT (Jacquemoud and Baret, 1990) and canopy reflectance model called SAIL (Verhoef, 1985) are the widely used models on the estimation of LAI in various biomes.

The PROSPECT is a leaf reflectance model used to simulate leaf optical properties from visible to mid-infrared based on leaf chemical composition (Jacquemoud and Baret, 1990), while SAIL is the canopy reflectance model used to calculate the bi-directional reflectance factor of a vegetative cover with inclined leaves (Verhoef et al,. 1987 and Verhoef et al., 2003) as a function of leaf optical properties (such as LAI), measurement conditions

(Verhoef, 1984) and the peak in the reflectance when the sun is directly behind the sensor (Kuusk, 1985).

The advantage of the physically-based models is that; that they are robust, not site specific and can be generalized for various vegetation cover. However, the disadvantages of RT models are; they are time consuming computation and difficultly obtained input parameters (Shen et al., 2014).

RTM inversion methods include Look-Up-Table (LUT) based inversions and neural networks. LUT are easy to implement and provide a search across the entire parameter space (Hadi et al., 2015). The traditional inversion and table look-up methods are designed to handle any arbitrary set of Sun-view angles (Hadi et al., 2015). However neural networks have not been generalized to handle any arbitrary set of angles (Kimes et al., 2000).

Examples of studies that have used RTM include (Darvishzadeh, 2008) by estimating and predicting canopy characteristics, such as LAI and chlorophyll contents in heterogeneous Mediterranean grassland by inverting the canopy radiative transfer model PROSAIL. A LUT-based inversion algorithm has been used; the result shows that there is the potential of model inversion for estimating vegetation biophysical parameters at the canopy scale using hyperspectral measurements. Another example is study done by Vuolo et al., (2010) wherein they used radiative transfer model to retrieve the biophysical vegetation products from RapidEye imagery. A well-known and widely used coupled PROSPECT+SAIL model was used. The results show that physically based approaches outperformed the empirical methods, with a slightly higher retrieval accuracy of the look-up table (LUT) than of the neural network (NN) approach.

Even though it is a relatively simple method, the look-up table (LUT) approach has been applied in combination the PROSAIL model by a number of studies; e.g. Darvishzadeh et al., 2008, Weiss et al., 2000) successfully retrieving biophysical variables of different crop type and at different sites.

The main disadvantage of the RTM's that they are computational intensive and not easy to implement. That is why they are not applied everywhere.

CHAPTER 3: MATERIALS AND METHODS

3.1 Study area

The study area covers ten per cent of KwaZulu Natal Province. The River uMfolozi is the second largest catchment in KwaZulu Natal province. The study area lies between 28°00'00" S and28°10'00" S; 30° 37'00" E and 30°55'00'' E. The land use of uMfolozi catchment is mainly comprised of dryland agriculture, which combines communal livestock grazing and rain fed agriculture (Tafangenyasha et al., 2010).

The area is known for extreme temperatures with hot summer and cold winter months. The average summer rainfall of the region is 350 mm per annum which ranges between 60 to 129 mm. The rainfall is available between October and February. Mean annual temperature ranges from 12° to 23°C. Frost is also a common feature and it appears from April to September (Tafangenyasha et al., 2010).

The area understudy is known for extensive subsistence farming. The topography of the area consists of mountains, hilly and undulating veld and flat surface. The vegetation of the study area is mainly comprised of typical Karoo veld (Acocks, 1988). The climate, slope and soil conditions combine to determine the potential of the study area to erosion. According to the Natal Town and Regional Planning Commission (1984), 54% of the catchment is highly prone to natural erosion. The study area is drained by two major tributaries which are the White uMfolozi and Black uMfolozi Riverstional Park (Tafangenyasha et al., 2011).

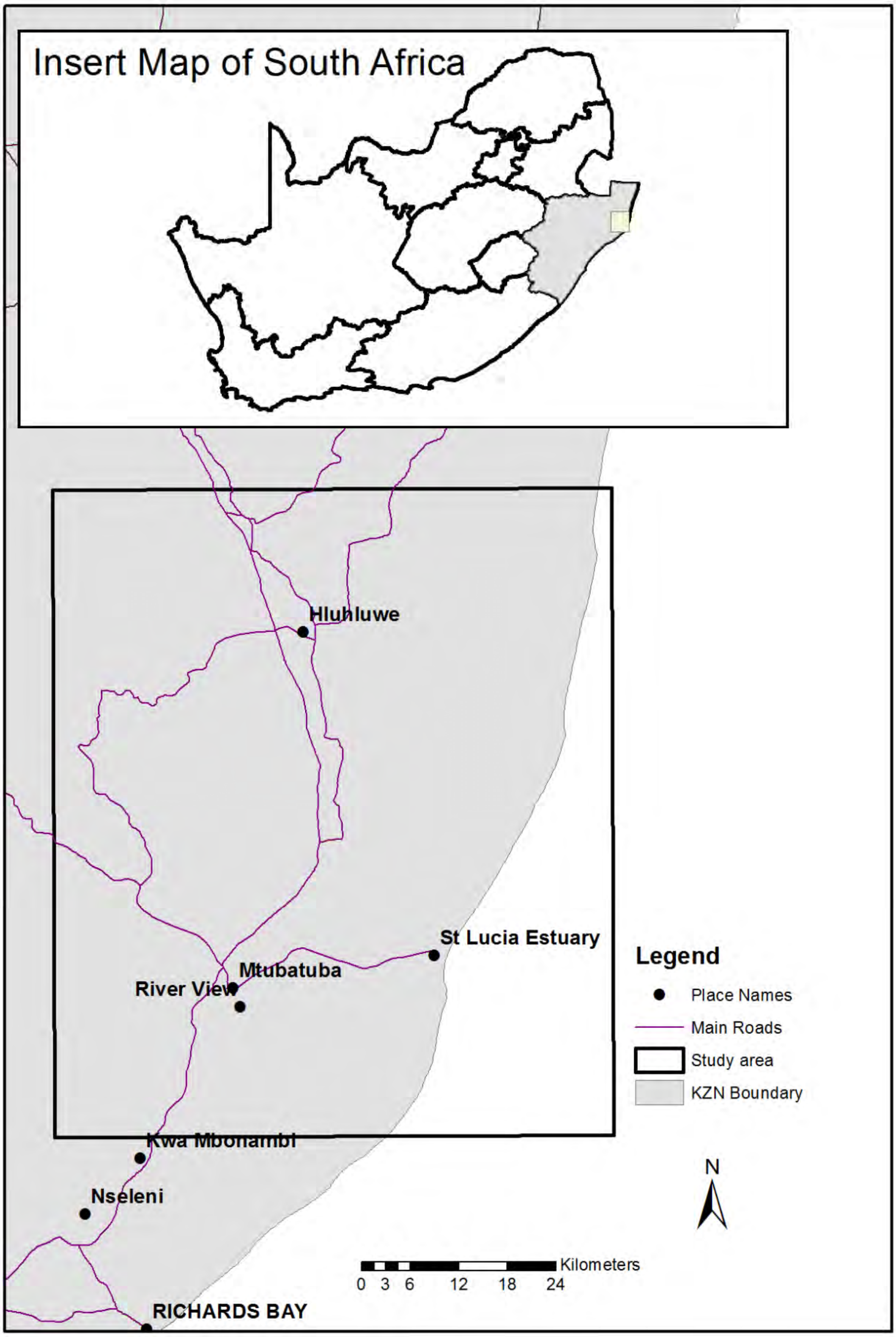

Figure 1: Study area map

3.1.1. Vegetation types on the study area

UMfolozi catchment is characterized by a variety of vegetation types such as Maputaland coastal belt, Northern coastal forest, Zululand low veld and Zulu-land coastal veld (Scott-show and Escott, 2011). Table 2 shows vegetation types found in the uMfolozi catchment.

Table 2: Vegetation types (Scott-show and Escott, 2011)

Vegetation types	Description
Maputaland Coastal Belt	It is composed of pockets of various forest types (separated into different vegetation units), thickets, primary and secondary grasslands, extensive timber plantations and cane fields.
Northern Coastal Forest	It is consisted by species-rich, tall/medium-height subtropical coastal forests occur on coastal (rolling) plains and stabilised coastal dunes.
Zululand Lowveld	Extensive flat or only slightly undulating landscapes supporting complex of various bushveld units ranging from dense thickets of Dichrostachys cinerea and Acacia species, through parklike savanna with flat-topped A.
Zululand Coastal Thornveld	This is mainly consisted of wooded grassland dominated by Themeda Triandra

3.1.2. Soil types on the study area

The catchment has various types of soils including Arenosols, Luvisols, Regosols, Phaeozems, Leptosols and Fluvisols**.** Table 3 shows the types of description of soils in the uMfolozi catchment (FAO 1974; 1988).

Table 3: Soil types (FAO 1974; 1988)

Soil type	Description
Arenosols	Loamy sand or coarser soils
Luvisols	Soils with high activity clays
Regosols	Soils with unconsolidated finely grained materials
Phaeozems	Dark soils rich in organic matter
Leptosols	Shallow soils
Fluvisols	Soils developed in alluvial deposits

3.2 Materials

3.2.1. Field data collection and sampling design

Field sampling was conducted in the morning (8h30- 12h00) and afternoon (12h00 – 17h00) in November 2012. Stratified random techniques were used for data collection in 51 different plots. The ground plot was precisely geo-located using a hand held GPS (GARMIN GPSMAP 76, Garmin Ltd) devise (accuracy of <5m) within the area of study to obtain ground-truth data. In each plot three subplots of 1m x 1m were randomly selected. In each subplot effective LAI measurements were collected using the Plant Canopy Analyzer LAI- 2200 (LICOR Inc., Lincoln, NE, USA). The strata were defined by various land cover classes, e.g. grassland, forest, agriculture (sugarcane) and savannah (mixture of grass and trees). In each class, several sampling points were randomly located, and grassland was allocated about 38 sampling points, 5 for forest, 4 for agriculture or sugarcane and 4 for savanna class totalling to 51.

The LAI-2200 Plant Canopy Analyzer computes LAI and a variety of other canopy structure attributes from radiation measurements was made with a “fish-eye” optical sensor. Measurements made above and below the canopy are used to determine the interception of light by the canopy at 5 zenith angles. The biasness of the result from LAI-2200 has been minimized by circumventing high level of light scattering off the leaf surface which could reach LAI -2200 sensor. This has been achieved by using transect oriented perpendicular to the solar azimuth during the measurement with LAI-2200.

LAI measurement of each plot is obtained by calculating the average LAI values in each plot, based on the one above canopy measurement and one below-canopy measurements. The measurement of LAI comprises of one reading above-canopy followed by below-canopy reading.

3.2.2. High resolution image: SPOT 6

The images acquired by SPOT Earth Observation Satellite are useful for studying, monitoring, forecasting and managing natural resources and human activities. Because of its multiple sensor instruments and revisiting frequencies, SPOT satellites are capable of obtaining an image of any place on earth every day with an advantage of mapping vegetation at flexible scales (regional, national, continental or global); in addition, SPOT imagery is also effective in monitoring the distribution and growth of vegetation (Xie et al., 2008).

A multispectral image; SPOT 6 imagery was acquired on the 24th of September 2013. The image spatial resolution is 1.5 m for the panchromatic band and 6.0 m for the multispectral bands. It is consisted of 4 visible to NIR bands. The image swath is 60 km at nadir. Table 4 shows the spectral regions of the SPOT 6 sensors.

Table 4: SPOT 6 spatial bands

Band	Band coverage (µm)	Spectral description
1	0.455µm-0.525µm	Blue
2	0.530µm-0.590µm	Green
3	0.625µm-0.695µm	Red
4	0.760µm-0.890µm	Near Infrared

3.2.3. Vegetation indices computed for this study

Several vegetation indices which are commonly used for estimating vegetation parameters were computed; namely NDVI (Rouse et al., 1976), SAVI (Huete, 1998), EVI (Huete et al., 1997), GI (Smith et al., 1995), SIPI (Peñuelas et al., 2001)), NRI (Schleicher et al., 2001), PPR (Metternicht, 2003), RDVI (Roujean and Breon, 1995), OSAVI1 (Rondeaux et al., 1996), SAVI1 (Huete, 1998) and SR_{52} (Jordan, 1969). Details of bands used for computation of these indices are presented in Table 1.

3.2.4. Environmental variables

Studies have shown that climate, topography, and geologic substrate influence the distribution of primary environmental regimes such as moisture and nutrients in soils or plants; for details see the review by (Skidmore et al., 2011). Several environmental variables influence the spatial distribution of LAI this include precipitation, temperature, geology, soil, DEM, slope, and aspect (Table 7 and 8).

The world climate database (worldclim) (www.worldclim.com) was used to acquire mean annual precipitation and mean annual temperature. Slope and aspect were derived from DEM using ArcGIS 10x. DEM (Digital Elevation Model) which was used was SRTM 4.1 with high spatial resolution of 90m (Javis et al., 2008). A soil layer was obtained from the soil and terrain database of Southern Africa (SOTERSAF) (Dijkshoorn, 2003). The soil layer used was acquired at 1:1 000 000 scale.

3.2.5. Pre-processing of SPOT 6 imagery

The image was radiometrically corrected and digital numbers were converted to reflectance values, i.e. atmospheric correction, to reduce the effects associated with atmospheric interference (e.g. clouds and noise) using Atmospheric Correction (ATCOR 2) software for flat surfaces. The SPOT 6 image was geometrically corrected to the acceptable accuracy. ATCOR is a widely used software for atmospheric correction; and the advantage of ATCOR 2 is that it was developed specifically for satellite remote sensing data and includes a large database of atmospheric correction functions (look-up tables computed with the Modtran® 5 radiative transfer code) covering a wide range of weather conditions, sun angles, and ground elevations (Richter, 2011). The workflow for implementing ATCOR for atmospheric correction in any terrain is outlined in Richter, (2011).

3.2.6. Statistical analysis

Two main statistical analyses were undertaken. The first was the univariate and the second was multivariate statistical analyses.

3.2.6.1. Univariate analysis: Estimation of LAI using vegetation indices and bands

Univariate analysis involves the use of the simple linear regression between LAI, different bands and vegetation indices. The selection of the best vegetation index and band was based on the high coefficient of determination (R^2) and the root mean square error (RMSE) (Bunke and Droge, 1984; Efron and Tibshirani, 1997; Fox, 2002; Fox and Weisberg, 2010). The validation of these models was achieved by using bootstrapping (see section 3.2.5.3).

3.2.6.2. Multivariate analysis: Estimation of LAI using a combination of vegetation indices and bands

The multivariate analysis was undertaken using stepwise multiple linear regressions (SMLR). Only significant wavelengths were used in the model development using SMLR. Wavelengths were selected using the conventional rule for selecting independent variables in SMLR ("in" if $p<0.05$, and "out" if $p>0.01$). SMLR is a commonly used multivariate statistics for extracting vegetation parameters (Grossman et al., 1996, Ramoelo, 2012). The combination of vegetation indices and bands for estimating LAI using SMLR were done in the following order;

(1) Use of reflectance at all bands to estimate LAI
(2) Use of several vegetation indices
(3) Use of combined data sets from bands and vegetation indices

The main disadvantage of combining bands and vegetation indices is the issue of multi-collinearity and overfitting of multivariate statistics such as stepwise multiple linear regressions (SMLR). In this study, two stage SMLR was implemented to reduce such a problem. The first stage was to use all the variables for estimating LAI, and secondly, only the significant variables were used to develop the final model. SMLR is a commonly used statistical method, and is not only used for estimating LAI, but for leaf nitrogen concentration (Ramoelo et al., 2012) and biomass measurement (Ullah et al., 2009).

Forward SMLR was used to acquire the significant bands or indices for estimating LAI. The approach was adopted to determine the best and significant model for estimating LAI based on R^2 and RMSE.

3.2.6.3. Validation using Bootstrapping for the univariate and multivariate models

Validation of the LAI models was done using bootstrapping implemented in R programming language because of a small sample size. Bootstrapping is an unbiased way to validate models as it has an iteration component (Efron and Tibshirani, 1997). It samples the data a number of times, which makes it a more robust way of validating models, as well as extremely efficient when only few samples are collected. As a common practice, 1000 iterations were used. The highly accurate bootstrapped model was inverted and applied to the SPOT image to derive LAI.

3.2.7. Determining the relationship between LAI and other environmental variables

Simple regression was used for determining the relationship between LAI, slope, altitude and aspect as well as annual average temperature. The relationship between LAI and other environmental parameters was done using simple linear regression, because the dependent variable (LAI) and independent variables such as slope, aspect, DEM, mean annual temperature, mean annual precipitation are continuous variables. To test the hypothesis, the *p*-value at 95% confidence level was recorded when $p<0.05$. The variable was considered significantly influencing LAI when $p<0.05$.

One-way analysis of variance (ANOVA) was computed to test the significance difference between LAI and vegetation, geology and, soils. ANOVA is a known statistical technique for testing the significance difference especially when the dependent variable is continuous and the explaining variables are categorical. When $p<0.05$, the variables were known to significantly influence the LAI distribution. The significant variables were plotted showing high and low values of LAI per category or type (Vegetation, soil and geology).

CHAPTER 4: RESULTS

4.1. Introduction

A total of 51 points were used for development of the model. Table 5 below shows the number of points collected, minimum and maximum values of LAI obtained and the average/mean LAI values. The mean LAI was 3.13 across the study area.

Table 5: Descriptive statistics for the measured LAI values

	Number of points	**Minimum**	**Maximum**	**Mean/Average**
LAI values (*m^2/m^2*)	51	1.26	7.27	3.13

4.2. Relationship between LAI with vegetation indices and spectral bands

Simple ratio (SR) vegetation index yielded the highest accuracy (Bootstrapped: R^2=0.29, RMSE=1.29) compared to other vegetation indices. Band 2 (Green) also achieved the highest amongst other bands (Bootstrapped: R^2=0.25, RMSE=1.32). Equally Band 3(Red) and 4(Near Infra-red) relate significantly with LAI. EVI, SIPI and SAVI were not significant to LAI ($p < 0.05$). Table 6 shows the relationship between LAI and various indices.

Table 6: Univariate statistics: relationship between LAI (*m^2/m^2*) and various indices

LAI with(*m^2/m^2*)	**R^2**	**RMSE**	**RRMSE (%)**	**B**	***P***
SR	0.29	1.29	41.23	0.53	0.00
B 2	0.25	1.32	42.17	-0.50	0.00
B 3	0.23	1.33	42.38	-0.48	0.00
B 4	0.20	1.37	43.73	0.44	0.00
B 1	0.19	1.37	43.84	-0.43	0.00
PPR	0.17	1.39	44.30	0.41	0.00
RDVI	0.17	1.33	42.38	0.42	0.00
GI	0.16	1.41	45.00	-0.39	0.00
SAVI	0.15	1.41	45.07	0.38	0.01

NRI	0.14	1.40	44.82	-0.37	0.01
OSAVI1	0.13	1.37	43.84	0.35	0.01
NDVI	0.09	1.46	46.53	0.30	0.03
EVI	0.04	1.50	47.88	0.19	0.18
SIPI	0.00	1.53	48.75	0.02	0.88
SAVI1	0.00	1.32	42.17	-0.04	0.78

B1-Blue, B2-Green, B3-Red,B4-Near Infra-red, NDVI- normalized difference vegetation index , SAVI-soil-adjusted vegetation index, SR- simple ratio , EVI-Enhanced Vegetation Index , RDVI-renormalized difference vegetation index , NRI-near infrared region of the reflectance , SIPI-structure insensitive pigment index , PPR-Plant Pigment Ratio, GI-Greenness Index, OSAVI-Optimized SAVI.

4.3. LAI prediction using multivariate statistics: stepwise multiple linear regression

Integrating vegetation indices and bands achieved a higher estimation accuracy (bootstrapped: R^2=0.71, RMSE=0.92) than the model using all bands or all vegetation indices; Table 7. The second highest model for estimating LAI was obtained on the integration of all vegetation indices (bootstrapped: R^2=0.67, RMSE=0.98).

Table 7: Multivariate statistics: predicting LAI using combined bands and vegetation indices (VI's) using stepwise multiple linear regression

Stepwise regression:LAI with (m^2/m^2)	R^2	RMSE	RRMSE (%)	*P*	Significant variables
All bands and all Vi's	0.71	0.92	29.39	0.00	B2,B3,SR,EVI,NDVI,SAVI,PPR,GI
All VI's	0.67	0.98	31.30	0.00	SR,EVI,NDVI,SAVI,PPR,RDVI
All bands	0.43	1.19	38.02	0.00	B1,B4

B1-Blue, B2-Green, B3-Red,B4-Near Infra-red, NDVI- normalized difference vegetation index , SAVI-soil-adjusted vegetation index, SR- simple ratio , EVI-Enhanced Vegetation Index , RDVI-renormalized difference vegetation index , PPR-Plant Pigment Ratio, GI-Greenness Index

4.4. Relationship between LAI and environmental parameters

One-way analysis of variance (ANOVA) was used to test if LAI significantly varies among vegetation, geology and soil. LAI varied significantly between vegetation (F=3.28, p=0.03). Geology and soil were not significant which shows that they do not influence LAI (Table 8). Figure 2 shows the effect of various classes of vegetation, geology and soil on LAI. In Figure 2, the Northern Coastal forest showed a significantly higher LAI as compared to Maputaland Coastal belt, Zululand Lowveld and Zululand Coastal Thornveld with lower LAI values. Though geological types did not show significantly influence on the distribution of LAI, high values are associated with class Basalt and lower values of class Sandstone. On the other hand, soil type Leptosols showed higher LAI values as compared to Fluvisols, Luvisols, Phaeozems, Luvisols-Regosols and Arenosols.

Linear regression was used to test the relationship between of LAI vs slope, aspect, DEM, mean annual temperature and mean annual precipitation. Mean annual temperature provided the highest coefficient of determination (R^2= 0.29, $p < 0.05$) when compared to the other variables. Aspect and precipitation were not significantly related to LAI ($p > 0.05$) Table 9.

Table 8: Relationship between LAI and various continuous environmental variables

ANOVA: LAI (m^2/m^2)	DF	F	P	Significance
Veg. Type	3	3.28	0.03	S
Geology	1	0.03	0.85	N.S
Soil	5	2.22	0.07	N.S

Table 9: Relationship between LAI and environmental parameters

LAI with	Pearson R	R^2	P	Statistical significance
Slope	0.25	0.06	0.08	N.S
Aspect	0.08	0.01	0.58	N.S

DEM	0.28	0.08	0.05	S
Precipitation	0.11	0.01	0.45	N.S
Mean annual temperature	0.29	0.09	0.04	S

DEM- Digital Elevation Model, temp- temperature

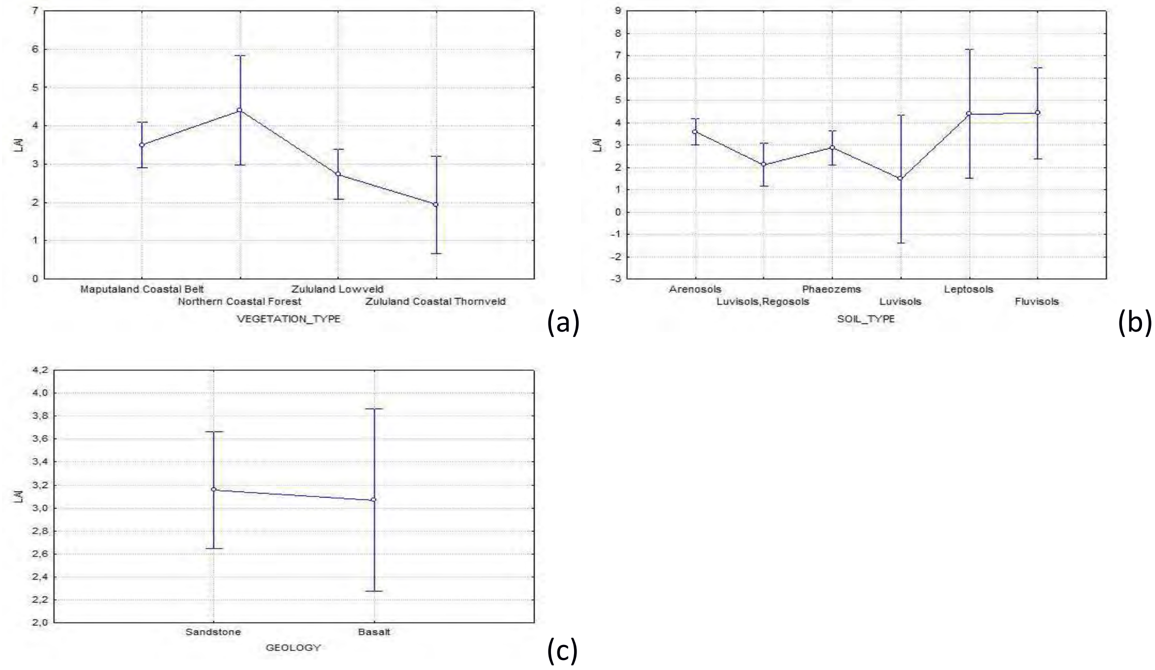

Figure 2 (a), (b) and (c): Influence of (a) vegetation type, (b) soil type and geology on LAI distribution.

4.5. Spatial distribution of LAI

The best model based on integrating or combining vegetation indices and bands was inverted on the SPOT 6 image to estimate and map LAI over the landscape of the uMfolozi river catchment (R^2= 71, RMSE = 0.92);

$$LAI\ (m^2/m^2) = 2.3895*SR-109.9841*B2+97.7260*B3+1.7131*EVI+19.7243*SAVI-20.9562*NDVI+41.8245*GI-16.3628*PPR-39.7293$$

Where *SR = simple ratio, B2 = band 2, B3 = band 3, EVI = Enhanced Vegetation Index, SAVI= Soil-adjusted vegetation index, NDVI = Normalized difference vegetation index, GI = Greenness index, PPR = Pigment ratio*

The general patterns of LAI in Figure 3; shows that higher values of LAI are found in the forested areas such as the DukuDuku forest and the riparian zones, while low LAI values are found in the communal rangeland areas. The predicted LAI values for the forest are higher than 5, while the communal rangelands have LAI values ranging from 1. The DukuDuku forest is found in the south eastern part of the study area. Riparian zones also have high LAI values following the type of vegetation in that zones. Soil type, topography and the annual precipitation have a significant influence on the distribution of vegetation. The Northern coastal forest vegetation type yielded high LAI values ranging from 3 – 6 than the other three types of vegetation. On the other hand, Leptosols have high LAI values ranging between 1.5 and 7.2, than the other five types of soil.

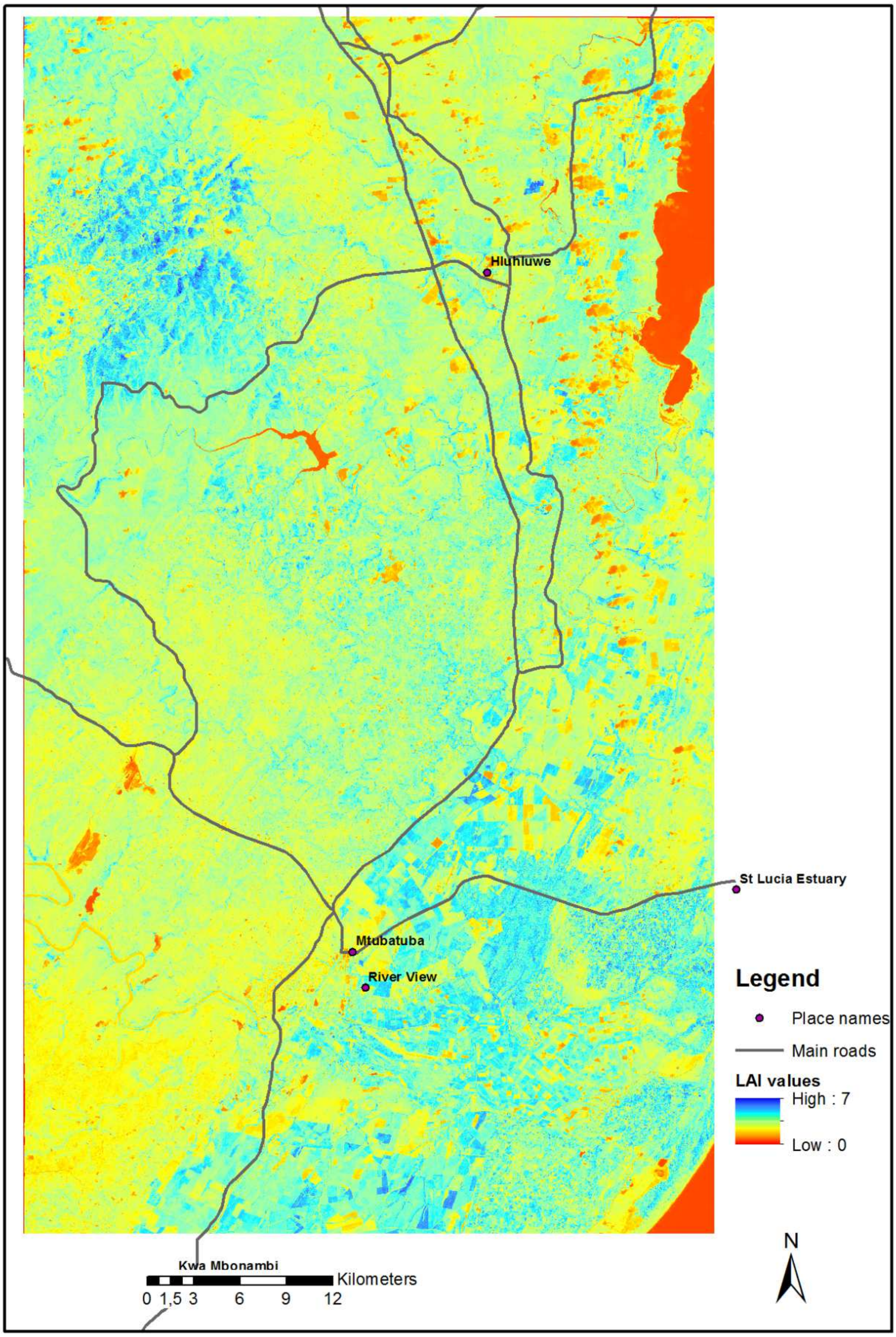

Figure 3: LAI distribution map

CHAPTER 5: DISCUSSION

The objective of this study was to assess the utility of SPOT 6 for estimating LAI in the River uMfolozi catchment, KZN South Africa. A number of vegetation indices extracted from SPOT 6 image were extracted and correlated with spectral bands and LAI. This section will interpret and explain the findings of the study.

5.1. Estimation of LAI using vegetation indices and bands

Amongst all tested vegetation indices used to estimate LAI, SR achieved the highest prediction capability. SR is based on the ratio of NIR to red, which is sensitive to chlorophyll concentration and vegetation structure (Jordan, 1969). Heskanen (2006), indicated that simple ratio yielded higher accuracy (R^2=0.81) in estimating aboveground tree biomass and LAI in a mountain birch forest environments. The results from this study are comparable to those of (Xavier and Vettorazzi, 2003) who mapped LAI through spectral vegetation indices in a subtropical watershed and achieved very strong LAI-NDVI and LAI-SR relationships (R^2=0.72 and 0.70) respectively. On the other hand NDVI was amongst the least performing in estimating LAI. The image was acquired during peak productivity; it is highly likely that there was saturation of the spectral signal during peak productivity. It is known that NDVI saturate at LAI value above 3 (Zhao et al., 2012).

The estimation of LAI is based on using reflectance from specific bands. Amongst all four bands, Band 2 (Green) explained higher and comparable variability of LAI as compared to Band 1 (Blue), Band 3 (Red) and Band 4 (Near Infra-Red). Band 4 is known to relate to vegetation structure and Band 3 and Band 2 are known to relate to chlorophyll concentration (Shen et al., 2014). Darvishzadeh et al., (2008), also tested the effects of soil and plant architecture on the retrieval of vegetation LAI from the hyperspectral data. The bands in the visible to near infra-red were used, together with the spectral vegetation indices. The results suggested that, when estimating LAI using vegetation indices, there is a need to obtain the knowledge of plant architecture and soil background.

5.2. Combining bands and indices for predicting LAI

Combining vegetation indices and reflectance from various bands yielded the highest accuracy (R^2 = 0.71, RMSE = 0.92) as compared to using bands and vegetation indices alone. This approach used the concerted capability of bands and vegetation indices. The significant vegetation indices and bands for the combined model to estimate LAI were band 2, band 3, SR, EVI, NDVI, SAVI, PPR and GI. Amongst these, SR, band 2 and band 3 were shown to perform better in estimating LAI using univariate statistics (Table 6).

The key influence of these results was that LAI is a component of vegetation structure which influences reflectance in the red and near infrared. Darvishzadeh et al., (2008) found out that combining absorption features and indices achieved higher estimation accuracy for LAI in the Majela grassland, Italy. The use of bands is common using hyperspectral data, but this study further demonstrated the importance of this approach using multispectral data.

5.3. Influence of environmental variables on LAI spatial distribution

Environmental variables such as altitude (DEM), vegetation types and mean annual temperature found to significantly play the distribution of LAI, (see Table 8 and 9).

Vegetation types influence the LAI distribution. Forests dominated vegetation types are associated with high LAI values because of the closed canopies. The light is fully intercepted, thereby increasing the LAI values. Sparse vegetation which could be associated with vegetation types (e.g. savanna), for example there are likely to have lower NDVI as compared to the forest closed canopies.

Topographic features such as DEM, slope and aspect influence the distribution of vegetation cover, hence LAI in this study, DEM significantly influence the LAI. Low–lying areas including the riparian zones are known to have high density of vegetation, hence LAI. The valleys have the low LAI values as compared to the bottom areas.

Climate plays a crucial role on the distribution of vegetation, hence LAI. In this study, LAI was significantly plays a vital role in determining the moisture in the soil and in plants. Areas of high temperature and low precipitation are likely to have low vegetation cover, hence LAI.

5.4. Implications of spatial mapping of LAI for land degradation assessment

LAI can and has been used as a proxy of vegetation productivity. Generally, the interpretation of LAI values can be related to the amount or quantity of vegetation as measured by LAI. This approach can be used effectively when there are multiple dates for LAI assessments, to avoid phenology influences (seasonal greening and drying/ loss of leaves for grass and trees. Figure 3 was generated for peak vegetation productivity period and should be treated with caution for understanding land degradation. Generally, areas of high LAI values are associated with low levels of degradation, while areas of low LAI values are normally associated with high rate of degradation. The most degraded area is likely to have thin soil layers which support less nutritious vegetation than the area with low degradation e.g. see communal areas (blue in colour) in Figure 3, particularly west of Hluhluwe.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS OF THE STUDY

The study aimed to determine the spatial distribution of LAI as an indicator to vegetation productivity in the uMfolozi river catchment. Its main objective is to estimate vegetation productivity using LAI models derived from VI's and bands and multivariate statistics.

6.1. Conclusions

Combining vegetation indices and bands from SPOT 6 provides opportunity to estimate LAI with acceptable accuracies in the KZN region. The first objective in this study was to investigate the potential of vegetation indices and bands to predict LAI. Simple ratio (SR) and band 2, 3, and 4 showed significant relationships with LAI. The second objective was to integrate vegetation indices and bands altogether, yielded a better accuracy, with SR, EVI, NDVI, SAVI, PPR, RDVI, contributing highly to model accuracy. The third objective was to determine the most important environmental variables influencing the spatial distribution of LAI. Results of this study showed that altitude, slope, vegetation types and mean annual temperature play a crucial role in explaining the distribution of LAI. The results for this study produce a basic on the calibration and validation of the existing course resolution products. LAI could be used for understating the vegetation productivity which is important information for planning and management of natural resources. Findings in this study can be used to determine the level of land degradation in uMfolozi catchment, characterised by slow vegetation recovery, increasing human population and intermittent droughts.

6.2. Recommendations

- Seasonality – acquire images for different seasons to ascertain properly the variation of vegetation productivity. This way, a proper assertion of land degradation in the UMfolozi catchment could be eminent.

- Acquired field data for various seasons and develop inter-seasonal models for estimating LAI. This will provide the opportunity to identify which Bands and indices consistently significant in estimating LAI.

- Testing methods such as physically based models to estimate LAI; physical based model are known to be robust and transferable but computational intensive and not easy to implement.

- Testing of machine learning techniques for estimating LAI; the machine learning techniques such as Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machine (SVM) are known to minimise the over-fitting and multi-collinearity.

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