Significance of local topographic variables in commercial forest operations in KwaZulu-Natal, South Africa

By

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A thesis submitted in the fulfilment for the degree of Master of Science in Environmental Sciences, in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal.

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Abstract

The planning and management of forest operations is a complex task. This complexity is attributed to the variability of forest plantations' site and topographic conditions. Therefore, there is a need for an integrated approach towards forest management and decision-making which offer a continuous review of forest operation systems used to increase site productivity. Therefore, the aim of this study was to determine the impact of local terrain on forest operations and forest productivity using GIS and statistical modelling in a commercial forest plantation in KwaZulu-Natal, South Africa. The first objective of the study focused on determining the influence of terrain variation on the productivity of commercial forestry using LiDAR-derived topographic factors. A 1m LiDAR-derived Canopy Height Model (CHM) and 30m digital elevation model (DEM) were used in the study. Four model scenarios were generated using LiDAR data in conjunction with a stepwise multiple linear regression. The results showed that elevation, aspect, clay content and slope were significant variables in influencing tree productivity ($R^2 > 0.9$). Furthermore, a strong correlation was observed between observed tree heights and predicted tree height values ($R^2 = 0.88$). The results of the study suggest that topographic variables strongly influence commercial tree species productivity. The second objective of the study determined optimal terrain classes based on a national terrain classification system developed by Erasmus (1994) for South African forestry regions. The integration of logistic regression in a GIS environment proved to accurately map suitable terrain classes (AUC = 0.93). This was achieved using a cost-effective 30 m DEM and SOTER-based soil parameter estimates (SOTWIS) data which was used to derive site topographic variables. The study demonstrates the use of integrated approaches for providing efficient and feasible means to apply terrain classification for current forestry practices. The study provides an effective framework for classifying ideal terrain conditions for forest management applications and forest operations. Overall, the study establishes the significance of local topography on commercial forest production and contributes towards enhancing management decision-making during spatial planning initiatives and operations.

Keywords: Topography, Forestry, Terrain Classification, LiDAR, Logistic Regression

Preface

The research undertaken in this thesis was conducted in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, from February 2017 to May 2019, under the supervision of Professor Onisimo Mutanga and Dr Kabir Peerbhay.

I, Silungile Dlamini declare that the work submitted in this thesis represents my own original work and has never been submitted for examination at any other university. Where the work of others has been used, I have duly acknowledged it in the text and reference sections of this thesis.

Silungile Dlamini,

Signed: __________________ Date: _________________

As the candidate's supervisor, I certify the above statements and have approved this thesis for submission.

Professor Onisimo Mutanga,

Signed: _____________________ Date: _____________________

As the candidate's co-supervisor, I certify the above statements and have approved this thesis for submission.

Dr. Kabir Peerbhay,

Signed: ________________________ Date: ____________________

Declaration

I, Silungile Dlamini 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 university.

3. This thesis does not contain other persons' data, pictures, graphs, or other information unless specifically acknowledged as being sourced from other persons.

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Signed: ____________________

Dedication

To my Mother.

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I would like to extend my gratitude to the following for their contributions:

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CHAPTER 1

General introduction

1.1 Introduction

The commercial forestry industry contributes significantly to the South African Gross Domestic Product and provides employment and long-term investment opportunities for rural areas in South Africa (DAFF 2017). Commercial forest plantations are largely based on exotic species, such as *Eucalyptus* which cover approximately 1.2% of the South African landscape. Of this 1.2%, approximately 1.5 million hectares of forest plantations are located on the east coast of South Africa (DAFF 2008) with *Eucalyptus* being the most dominant of the hardwood species, followed by *Acacia mearnsii* (Peerbhay et al. 2016). Consequently, information relating to species productivity in plantation forests is significant for effective decision-making across complex terrain to maintain forest timber production (Peerbhay et al. 2013).

Forest management often includes planning for forest operations such as silviculture, harvesting and site-species matching as main objectives because these operations have progressive, long-term economic, social and ecological impacts. The planning of forest operations is a complex task and this complexity is largely a result of a variety of topographic conditions. It is for this reason that there is a need for the integration of multiple sources of information into the decision-making process (Ezzati et al. 2016). Decisions in the implementation of effective planning of forest operations are often based on experience, field surveys and intuition; therefore, falling short of the consideration of sustainable, long-term strategies for resource management (Lüthy 1998). Undoubtedly, such decision-making processes would result in the continuous review and improvement of current systems utilized. Therefore, there is a need for planning and forest management methods to adopt terrain classification procedures and apply such knowledge in relation to forest structural characteristics and tree productivity.

Terrain classification systems offer a standard and consistent means towards categorizing terrain for forest operations (Erasmus 1994). Terrain classification assists to identify low impact means of executing essential forest operations (Upfold 2014) as it provides a constant and justifiable means of classifying various types of terrain for forest operations (Erasmus 1994). Therefore, this technique aid the process of planning effective and resources forest operations as it assists with the selection of appropriate systems to execute forest operations networks (Kühmaier and Stampfer 2010). The South African forestry industry recognizes the need for a formal terrain classification system which is suited for South African forestry conditions (Erasmus 1994). Terrain classification systems from other countries could not be adapted to the South African forestry industry because these systems address conditions which are vastly different from those of the local industry (Erasmus 1994). Furthermore, commercial tree species are exposed to an integrated complex environment due to each site being characterized by unique soil, topographical, biological and climatic factors (Louw and Scholes 2002; Naidoo et al. 2007). However, determining commercial forestry potential in South Africa has been based on climatic considerations with rainfall being the most prominent factor (Schönau and Schulze 1984). There are numerous studies (Eksteen 2012; Grant et al. 2010; Louw 1997; Schutz 1990) which focus on site growth of commercial forest species. However, there is limited literature focusing on local site factors that influence forest productivity, and little is known about the influence of local terrain and its complexities on commercial tree species' productivity (Adams et al. 2014).

Some methods have been applied to understand the relationship between forest structural characteristics, forest productivity and terrain classes (Davis and Reisinger 1990; Du Plessis 2014; Erasmus 1994; Schutz 1990). For instance, for terrain suitability, methods such as field surveys and measurements of ground bearing capacity, ground roughness and slope conditions were required. Moreover, information on forest structural characteristics was also obtained using periodic surveys, aerial photography and repeated ground surveys. The challenge with these traditional methods is that they are time-consuming, labour-intensive, costly (Cho et al. 2009), limited to local scales, require expertise which is often associated with high costs and are often not practical when dealing with large spatial extents (Otunga et al. 2018). Therefore, there is a need for efficient, cost-effective, convenient and spatially explicit methods which are applicable to local and could be upscaled to regional scales.

Even though traditional methods were notably implemented in forest planning operations, forest productivity and terrain suitability, the use of GIS can expand the feasibility and flexibility of successfully planning and managing large scale areas. The use of remote sensing tools such as light detection and ranging (LiDAR) provides a convenient and semi-automated derivation of site features including tree structural characteristics. For example, Saremi et al. (2014a) aimed to address the relationship between local topography and tree diameter at breast height (DBH) with two even-aged pine plantation sites in New South Wales, Australia. LiDAR was used to derive aspect and slope in order to link them with each individual tree. The study showed significant relationships between local topography and DBH with greater DBH at slopes of 20^o and southerly aspects. Results also showed high correlations between measured and observed heights with an R^2 value of 0.87 – 0.9 and an RMSE value of 0.66 - 1.49. Additionally, in another study Saremi et al. (2014b) sought to investigate the relationship between tree height and ALS-derived slope and aspect within 2-even aged radiate Pinus radiata D. Don plantation sites in Nundle, Australia. The results of the study demonstrate that slope ($P< 0.01$) and aspect ($P< 0.001$) show to have a significant relationship with tree height variation across the stands with aspect being more significant than slope.

The rapid development of GIS and remotely sensed datasets provides for strategic implementation of forest planning from local to national scale owing to the convenience of geospatial datasets and analytical procedures. The use of GIS provides a gateway to use spatial modelling which can be feasibly implemented in forest management to maximize forest productivity. For instance, Breidenbach et al. (2008) successfully quantified the influence of aspect, slope, stem density and crown shape on the estimation of forest tree height at plot level using LiDAR and InSAR data using a stepwise model selection based on the Bayesian Information Criterion (BIC) in Stuttgart, Germany. The results showed slope for InSAR (RMSE = 6%) and LiDAR (RMSE = 9%) influence the estimation of tree height at the plot level. Although statistical modelling and GIS has been extensively applied in forestry, however, there is a need for applying an integrated approach to forest management and planning in order to determine the influence of local topographic variables and their complexities on commercial tree species' productivity.

1.2 Aim and Objectives

The aim of this study was to determine the impact of terrain on forest operations and forest productivity using GIS and statistical modelling in a commercial forest plantation, South Africa. The specific objectives of the study were set as follows:

1. Determine the relationship between terrain variation and productivity of commercial tree species using LiDAR-derived topographic factors in a stepwise multiple linear regression model.
2. Evaluate the performance of a 1m LiDAR-derived Canopy Height Model (CHM) in predicting tree height.
3. Determine optimal terrain classes for forest operations based on a cost-effective 30m digital elevation model (DEM) for South African forestry regions using logistic regression.
4. Assess the robustness of logistic regression for the development of a plantation terrain classification system.

1.3 Key research questions

- Do local topographic factors have an influence on tree productivity?
- To what extent can LiDAR CHM predict forest structural attributes?
- Can the application of a cost-effective DEM contribute towards a national terrain classification system for South African commercial forestry using a GIS interface?
- To what extent does logistic regression successfully predict optimal terrain classes?

1.4 Significance of study

Though commercial forestry is multifaceted, the planning of forest operations has been mainly influenced by a focus on the impacts of soil and climate on commercial tree species. This study sets to fill critical gaps through attempting to determine the relationship between local topographic factors and commercial tree species. Furthermore, the study aims to determine the relationship between commercial tree species production and productivity and local topographic variables. Therefore, the study will contribute to the enhancement of decision making from a strategic level to an operational level of forestry planning and operations and implementation of well calculated forest operations that adhere to local topographic features.

1.5 Limitations of study

The study's focus has limited literature that addresses the influence of topographic factors on commercial forestry tree species, especially in a South African context. This resulted in literature utilised in this study to be outdated as most studies focus on the effects of climate and soil.

1.6 Scope of study

In addressing the limitations of determining the relationship between terrain variables and commercial forestry sites, the premise of this work is limited to use of digital elevation models in deriving local topographic variables. The study also demonstrates the capability and efficiency of cost-effective 30m DEM and LiDAR-derived canopy height model in determining commercial tree species productivity as a result of topographic factors. This study assessed the use of statistical methods in determining a relationship between terrain variation and commercial tree species productivity. Further statistical approach was applied by determining optimal terrain classes for forest operations using logistic regression. The use of elevation models and statistical modelling yielded high accuracy when determining relationships between local topographic factors and commercial tree species and forestry operations.

1.7 General thesis structure

The thesis comprises of two papers which address the objectives mentioned in section 1.2. The methodology used in the thesis and the literature review is within the papers. Chapter 1 covers the general introduction and motivation of the study. Chapter 2 investigates the effects of local terrain topographic factors on commercial tree species productivity. A LiDAR-derived canopy height model (CHM) was used to predict tree height and a 1m digital terrain model (DTM) was used to derive site factors. A stepwise multiple linear regression was used to demonstrate the effect of local site factors on tree productivity A R^2 value was also calculated to measure the accuracy between observed tree height against modelled tree height derived from the CHM. Chapter 3 seeks to determine optimal terrain classes for a commercial forest plantation using logistic regression in a GIS environment. Topographic variables were derived from a cost-effective 30m digital elevation model (DEM) and SOTER-based soil parameter estimates (SOTWIS) for Southern Africa. The logistic regression model performance was validated using the Receiver Operating Characteristic (ROC) curve. Chapter 4 provides a synthesis of the findings of the study for both chapter two and chapter three and the recommendations proposed.

CHAPTER 2

Determination of the Statistical Relationship between Terrain Variation and Productivity of Commercial Tree Species Using Lidar-Derived Topographic Factors in SAPPI Highflats, South Africa.

Abstract

Commercial tree species are exposed to complex terrain environments whereby tree productivity is influenced by multiple factors including site-specific variables. However, there is limited literature focusing on which site factors influence forest tree productivity, and little is known about how the variation of terrain may influence tree growth and tree growth distribution. Therefore, this study investigates the relationship between terrain variation and productivity of commercial tree species using LiDAR-derived topographic factors. Using LiDAR data, integrated with a stepwise multiple linear regression, four model scenarios based on topographic variables and tree height were generated. Canopy Height Model (CHM) was used to determine tree height and coefficient of determination was used to validate the accuracy of CHM tree height predictions. The results showed that aspect, slope, elevation and clay content were important variables impacting tree productivity ($R^2 > 0.9$), and a high correlation was observed between predicted and measured tree height ($R^2 = 0.88$). Overall, the study demonstrates topographic variables influence commercial tree species productivity and that CHM can accurately predict tree height. Our results demonstrate the value of LiDAR in determining forest structural characteristics and the integration of statistical modelling and GIS in establishing relationships within integrated complex environments at a regional scale.

Keywords: Terrain variables, Tree productivity, stepwise multiple linear regression, GIS

2.1 Introduction

South Africa is considered a water scarce country (DEA 2011); therefore, the land available for commercial forestry is extremely restricted. The majority of the forestry plantations are located in less than 20% of the country (Eksteen 2012) mainly in the eastern regions of the country, in the provinces of KwaZulu-Natal and Mpumalanga (Peerbhay et al. 2013; Tewari 2001). The forestry industry, along with the agricultural and fisheries sector, contributes 2.4% of the Gross Domestic Product (GDP) and provides people living in rural areas with employment. Also, the industry offers long-term investment opportunities for rural economic development (DAFF 2017). Furthermore, commercial forestry is a well-established feature of the economy and landscape (Le Maitre et al. 2002). Therefore, information relating to the productivity of forest plantation species across the complex terrain is important for effective decision-making on sustainable resource harvesting and improving forest timber production (Peerbhay et al. 2013).

Commercial tree species are exposed to an integrated and complex environment (Naidoo et al. 2007). This is a result of each site comprising of multifaceted topographical, climatic, biological and soil factors (Louw and Scholes 2002; Naidoo et al. 2007). There is a large body of literature focusing on site growth of commercial forest species e.g. (Eksteen 2012; Grant et al. 2010; Louw 1997; Lüthy 1998; Mabvurira and Miina 2002; Schutz 1990). However, determining commercial forestry potential in South Africa has been primarily based on climatic considerations with rainfall being the most prominent factor (Schönau and Schulze 1984). Subsequently, there is limited literature focusing on which site factors influence forest productivity, and little is known about how the variation of terrain may influence tree growth (Adams et al. 2014) and the distribution of tree growth.

Topographic variables have proven to be the prevailing force controlling site productivity in areas of marked relief (Vanclay 1994). For instance, Saremi et al. (2014a) conducted a study which aimed to address the relationship between tree diameter at breast height (DBH) and local topography within two even-aged radiata pine plantation sites in South Wales, Australia. The study shows that slope and aspect are important factors when examining tree growth with results showing that trees on slope below 20^{o} and on southerly aspects displayed significantly large DBH than on steeper slopes and north facing slopes. Similarly, Evans (1974) conducted a study in Swaziland and found that elevation highly correlated with the height of *P. patula* plantations at the age of twelve. Finally, Louw (1997) used a stepwise multiple regression analysis to identify the variables related to the growth of *E.grandis* in Mpumalanga, South Africa. The results of the study showed that the growth of *E. grandis* is primarily influenced by variables controlling available soil moisture, and organic carbon content in the topsoil.

It is essential for forest management to be dependent on spatial information on forest structural characteristics such as height and tree density (St-Onge and Achaichia 2001). This assists forest management to make use of high potential forest sites by assigning the optimal species for afforestation and to identify factors which contribute and enhance species growth. Such information was traditionally obtained using periodic surveys, analyses of aerial photography and repeated field surveys. The use of traditional techniques is time-consuming, labour-intensive, costly (Cho et al. 2009), and often impractical when dealing with large spatial extents (Otunga et al. 2018); however, utilizing remote sensing offers a convenient and accurate method to obtain information regarding forest growth (Peerbhay et al. 2013).

Even though they are regarded as highly accurate, traditional methods have been challenged in favour of remotely sensed (Dube et al. 2014) and GIS techniques. Thus, when compared to traditional methods, GIS coupled with statistical modelling proves to be valuable and potentially offer lower costs for determining forest attributes. The statistical modelling of a species can serve as an important decision support tool in forest management and planning (Louw 1997). Furthermore, statistical modelling can be successfully implemented with excessive feasibility and flexibility. Previous studies show that the stepwise multiple linear regression has been used in demonstrating relationships between remotely sensed data tree attributes with reasonable accuracy rates (Dube et al. 2015).

While studies have shown successful results when determining forest productivity attributes and topographic variables using optical imagery, coupled with statistical modelling, the use of light detection and ranging (LiDAR) has yielded improved results. Advances in LiDAR technology permit feasible, consistent and semi-automated extraction of forest parameters and terrain variables, unlike traditional photogrammetry, whose data quality depends on the photograph's scale and resolution and the photographic interpreter's experience and skills (Lee et al. 2018). LiDAR technology has also been used in forestry to develop very high-resolution digital terrain models (DTMs) (Sharma et al. 2010), due to the added advantage of penetrating through vegetation canopies (Pradhan and Abdulwahid 2017). Soja and Ulander (2013) demonstrated the use of Interferometric TanDEM-X data and a LiDAR DSM to produce digital canopy models for the boreal forests of Krycklan and Remningstorp in northern and southern Sweden. Furthermore, the use of LiDAR has rapidly become the standard for topographic mapping (Hodgson and Bresnahan 2004). For example, Hodgson and Bresnahan (2004) evaluated whether the mean elevation error would vary across land cover categories while holding terrain slope constant in Richland County, South Carolina. This was achieved by using an Optech Airborne Laser Terrain Mapper flying at 1207 meters above ground level to collect airborne LiDAR imagery. The results showed that the RMSE of the land covers used in the study ranged from 17.2 to 25.9 cm with the lowest errors observed for pavement (RMSE = 18.9 cm), high grass (RMSE = 18.9) and evergreen (RMSE = 17.2 cm) forest land covers. Thus, the aim of this study was to determine the influence of terrain variation on the productivity of commercial forestry using LiDAR-derived topographic factors.

2.2 Materials and Methods

2.2.1 Study Area

The study area was the SAPPI Highflats forest plantations in KwaZulu-Natal, situated at a latitude of 30°15'2.47" S and longitude of 30°15'30.12" E. The area is predominantly rural, consisting mainly of large agricultural plantations, natural vegetation and traditional authority land (Ubuhlebezwe Municipality 2017). SAPPI Highflats plantation is situated on a plateau which is 700-1000m above sea level (ICFR 2016). The area receives mean annual precipitation of 800-900 millimetres per year, and has a mean annual temperature of 17^{o}C, with lithology consisting mainly of tillite and sandstone resulting in the different types of soils present in the area. The forest is characterized by extensive commercial forestry dominated by *Eucalyptus* species, namely *Eucalyptus grandis* and *Eucalyptus dunii*.

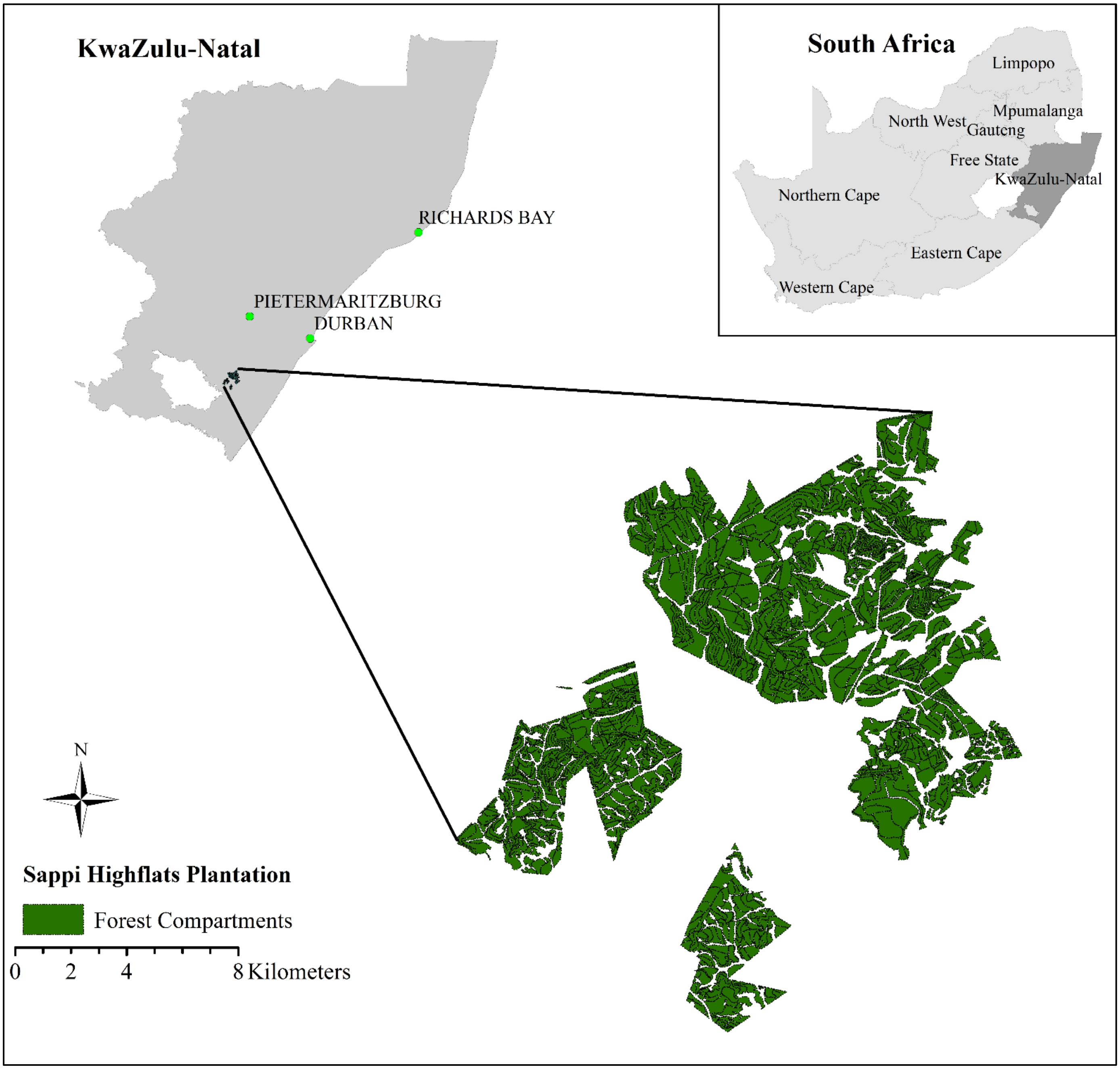

Figure 2.1 Location of the study area and plantation compartments in SAPPI Highflats.

2.2.2 Methods of data acquisition

Using a Leica ALS50-2 with multi-pulse (Table 2.1), airborne LiDAR data were acquired during the 15^{th} and 22^{nd} March 2014. The sensor had a 50% minimum flight line overlap at an average flying height of 820 m above ground level with a flight speed of 95 Kt (Table 2.2). The number of returns was four at a pulse rate of 126 000 Hz and a scan rate of 53 Hz. Digital terrain models (DTM) and digital surface models (DSM) with a spatial resolution of 1 m were generated using triangulated surface models and LAS dataset tools in ArcGIS 10.4. LAS file format is a standard binary file format for storing airborne LiDAR data such as feature classes that contain surface constraints (Sumerling 2011). Both DTM and DSM are derived from a Digital Elevation Model (DEM). A DTM is a representation of the bare-earth containing the natural terrain's elevation whereby non-ground objects (vegetation and buildings) have been digitally removed and a DSM contains elevations of natural terrain without digitally removing other objects on the surface such as buildings or trees (Holmes 2011). A canopy height model (CHM) represents the difference between the top canopy surface and the underlying ground topography (Panagiotidis et al. 2017). The CHM used in this study was created as the difference between DTM and the DSM. The CHM was used as a proxy for tree height because tree height best reflects the site productive capacity (Panagiotidis et al. 2017).

Tree heights were measured from 30 m x 30 m plots within the study area. A random sampling technique was adopted in this study. A total of 200 points were randomly generated within a GIS environment using Arc GIS 10.4. Thereafter, the field data were collected during November 2017 whereby the points were transferred into a handheld Trimble Global Positioning System (GPS) to a sub-meter level of accuracy (50 cm) was used to navigate to the random sample points within the forest plantation. The points were randomly divided into 70 % (n =140) for training the stepwise multiple linear regression models and 30% (n = 60) for validation.

Sensor Name	Leica ALS50-2 with multi-pulse
No of Returns	4
Pulse Rate	150 000Hz
Scan Rate	55Hz
Maximum Field of View	75°

Table 2.1 Acquisition parameters of the LiDAR sensor used in this study.

Sensor Name	Leica ALS50-2 with multi-pulse
Pulse Rate	126 000Hz
Scan Rate	53Hz
Field of View	25°
Average flying height	820m AGL
Minimum flight line overlap	50%
Swath Width	343.5m
Flight Speed	95Kt

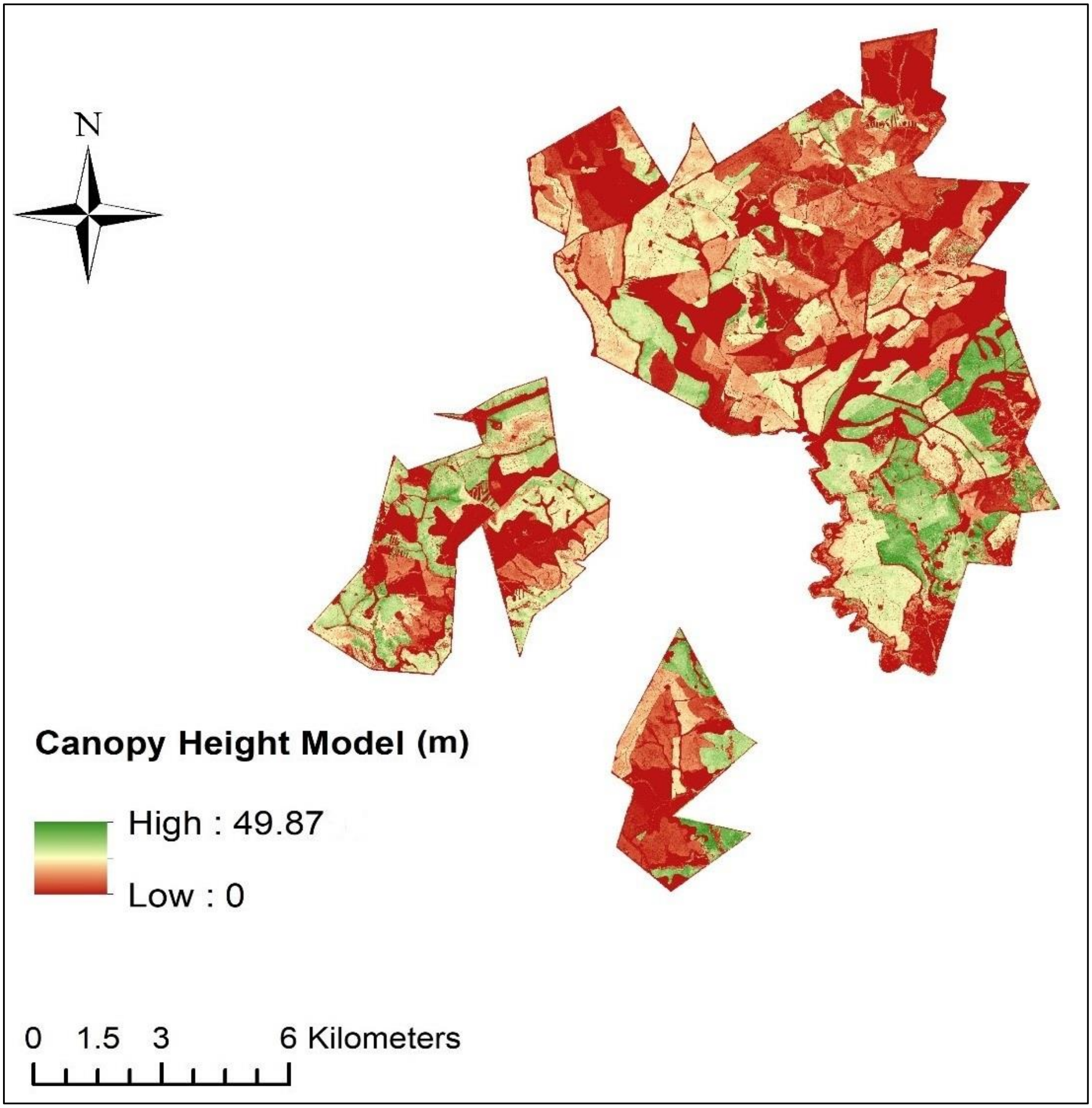

Figure 2.2 Canopy Height Model derived from a Leica ALS50-2 with multi-pulse.

A 1m x 1m LiDAR digital terrain model (DTM) was used to derive elevation, slope, aspect and Topographic Wetness Index (TWI) using ArcGIS 10.4, and average clay content data was acquired from SOTER-based soil parameter estimates (SOTWIS) for Southern Africa.

TWI is used to determine the tendency of a landscape to become saturated and produce runoff. TWI was computed using the following formula:

$$\text{TWI} = \text{In}\ (A_s / \tan \beta)$$

whereby A_s is the catchment area (m^2/m), and β is the slope in degrees (Yilmaz 2010). This is established on the assumption that topography has an effect on the near-surface position of the groundwater table (Thomas et al. 2017). TWI is widely utilized as an explanation for soil moisture and water levels. Low TWI values represent possibly drier areas related to diverging terrain, and high TWI values represent possibly wetter areas related to converging terrain. Landscape-scale studies of relationships between topography and tree growth discover that growth responds to soil moisture conditions across gradients such as aspect and elevation (Adams et al. 2014).

2.2.4 Methods of data analysis

A stepwise multiple linear regression was used to determine the site factors that impact tree growth using SPSS software 25.0 (Inc.) and an R-squared value was calculated as a measure of accuracy.

An R-squared is a number between 0 and 1, the number measures the degree to which changes in the dependent variable can be estimated by changes in the independent variable(s), whereby a precise regression has a high R-squared value close to 1 and an inaccurate regression has a low R-squared value of close to 0 (AICPA 2012). The advantage of this method is that variables selected in one step can be removed in the steps that follow; therefore, this model ensures that all independent variables are introduced in the initial step. Thereafter, independent variables that are not insignificant to the regression are discarded (Marquínez et al. 2003). Variables showing no statistical significance ($p > 0.05$) were subsequently eliminated from the model

Each variable was classified using ArcGIS 10.4. The slope was classified according to the South African national terrain classification system (Erasmus 1994). Elevation (Table 2.4) and clay content (Figure 2.3) were classified into equal intervals classes. Lastly, aspect was reclassified into compass direction classes (ranging from 0° to 360° - North, North East, East, South East, South, South West, West and North West) (Figure 2.3). The classes were assigned values based on ascending order of each topographic variables range.

To evaluate the accuracy and performance of the CHM in predicting tree height a coefficient of determination (R^2) was calculated.

Table 2.2 Slope classes adapted from Erasmus (1994).

Slope	**Designation**	**Slope Class**
≤ 11	Gentle	1
≤ 20	Moderate	2
≤ 30	Steep 1	3
≤ 35	Steep 2	4
≤ 40	Steep 3	5
≤ 50	Very Steep 1	6
50 ≥	Very Steep2	7

Table 2.3 Elevation classified by 100 m contour interval.

Elevation (m)	**Classes**
688 – 788	1
788 – 888	2
888 - 988	3
988 – 1088	4
1088 – 1136	5

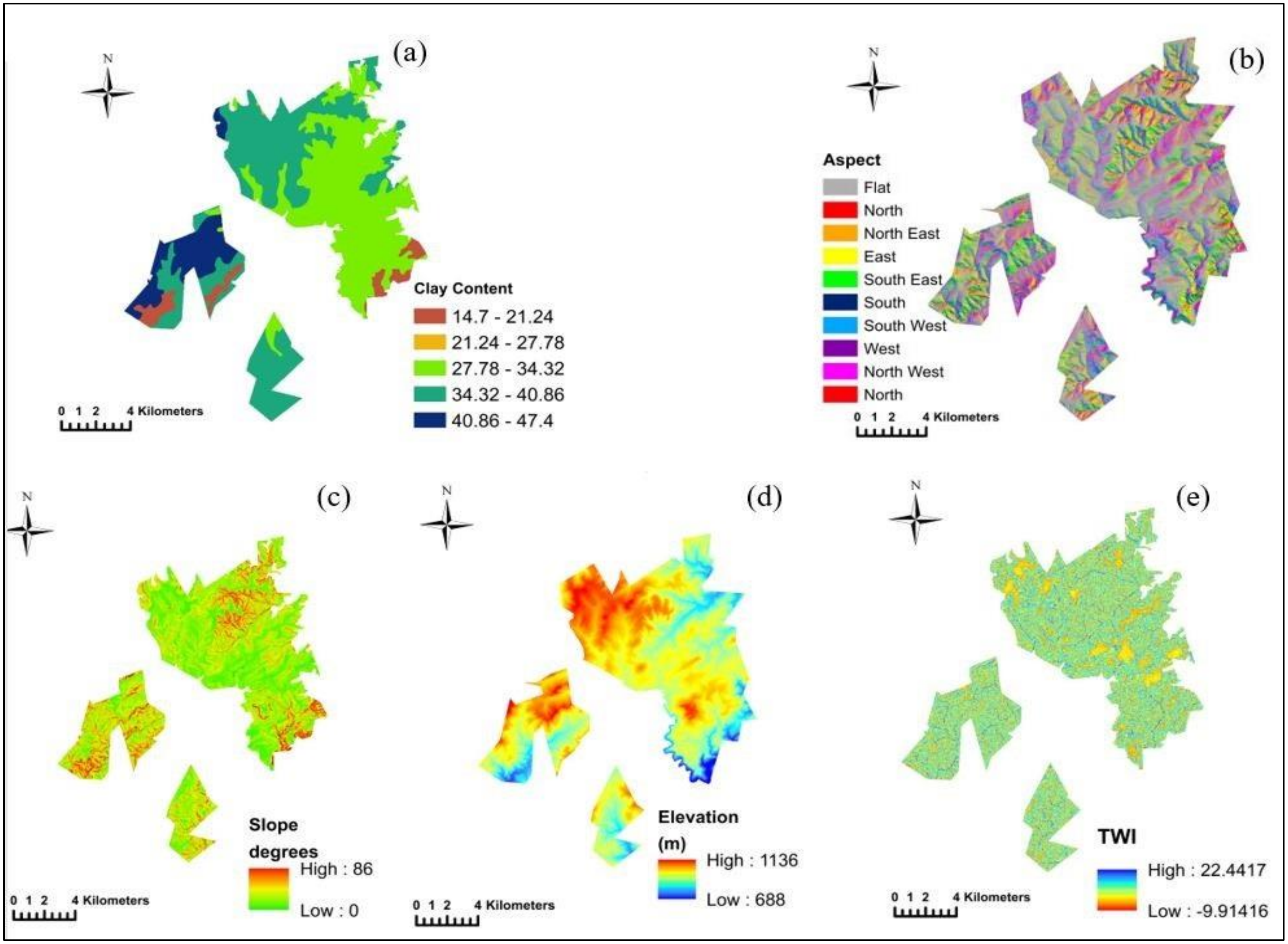

Figure 2.3 LiDAR-derived site factors (a) clay content, (b) aspect, (c) slope, (d) elevation and (e) TWI.

2.3 Results

The analysis of the Pearson correlation matrix (Table 2.5) showed significant correlations between independent variables, and between independent variables and tree height. Significant correlations were between tree height and elevation, aspect and slope, and between elevation and slope, aspect and elevation, as well as aspect and slope. However, Table 2.5 shows that there is no significant correlation between tree height and TWI, tree height and clay content and TWI and clay content. The stepwise multiple linear regression provides four significant models (a – d) (Table 2.6), all with an R^2 above 0.9 as shown by Table 2.6. Elevation, slope, aspect and clay content proved to be statistically significant ($p < 0.05$). Although a potential predictor, TWI was excluded from all models as it was not a statistically significant variable; thus, proving to insignificantly contribute to tree height. Thus, model 4 was selected as it had a higher R^2 value and shows that clay content, slope, elevation and aspect significantly predict the dependent variable.

Table 2.4 Pearson correlation matrix among the major topographic, soil and tree variables

	Tree Height	***Elevation**	***Slope**	**TWI**	***Aspect**	***Clay Content**
Tree Height	1.000	0.976	0.577	-0.021	0.919	-0.020
Elevation	0.849	1.000	0.588	-0.030	0.893	0.088
Slope	0.577	0.558	1.000	0.017	0.536	-0.042
TWI	-0.021	-0.030	0.017	1.000	-0.002	-0.062
Aspect	0.812	0.893	0.536	-0.002	1.000	-0.039
Clay Content	-0.020	0.088	-0.042	-0.062	-0.039	1.000

statistically significant at *p*-value <0.05 (*****).

Furthermore, it can be observed that for any increase in slope, elevation and aspect, the odds of tree growth increase by a factor of 0.183, 0.804 and 0.027 respectively (Table 2.6). For example, every 1-degree increase in slope will result in an increase in the odds of tree height by a factor of 0.183, and with every 1 m elevation increase in elevation, tree height will increase by a factor of 0.804. However, the results show that a decrease in clay content (-0.083) increases the likelihood of tree height by 0.083. Therefore, it can be concluded that elevation has a greater effect on tree height, followed by slope, aspect and clay content.

Figure 2.4 is a regression graph illustrating the correlation between CHM predicted tree height and measured tree height. Strong correlations between predicted tree height from CHM and measured tree height were observed (R^2 = 0.88).

Table 2.5 Model summary of the stepwise multiple linear regression.

Model	R Square	Std. Error of the Estimate
a.	.952	54.37151703
b.	.963	47.46646868
c.	.970	42.97647025
d.	.970	42.64375165

a. Predictors: (Constant), Elevation

b. Predictors: (Constant), Elevation, Clay Content

c. Predictors: (Constant), Elevation, Clay Content, Aspect

d. Predictors: (Constant), Elevation, Clay Content, Aspect, Slope

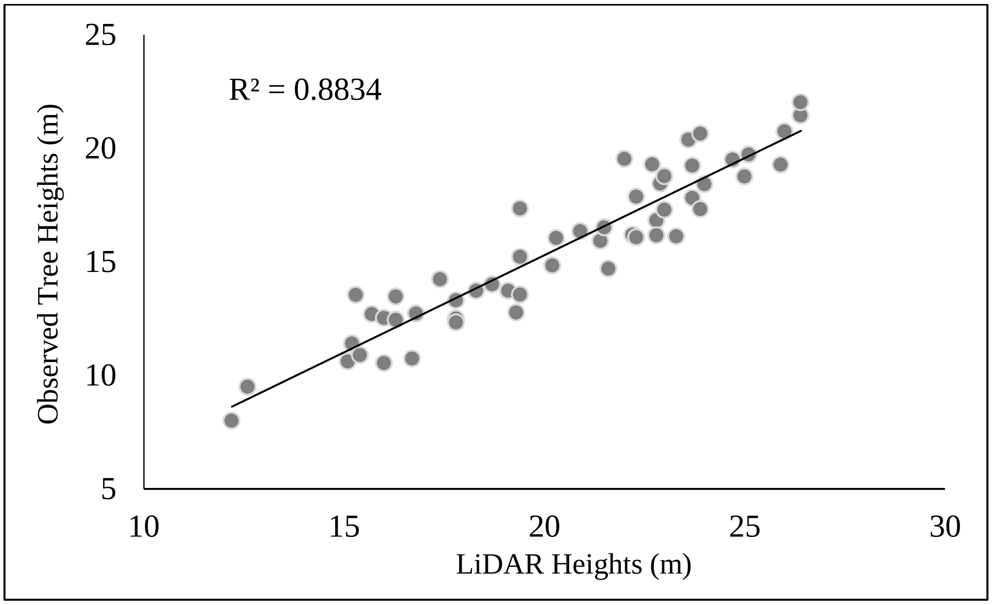

Figure 2.4 Linear regression model of the estimated tree height from LiDAR CHM and measured (ground truth) tree heights for SAPPI Highflats.

2.4 Discussion

The principal aim of this study was to determine the influence of terrain variation on the productivity of commercial forestry. This was achieved using stepwise multiple linear regression, tree height as a proxy for tree growth and terrain variables in SAPPI Highflats plantation, South Africa, which is a small-scale area with a relatively constant climate.

The results of the study show that elevation, clay content, aspect and slope significantly influence tree growth and tree growth distribution. This is consistent with White (1990) and Millner (2006) who state that these variables have significant effects on vital environmental factors that influence tree growth such as temperature and solar radiation. Furthermore, these findings are consistent with several studies which note that *Eucalyptus* tree growth is influenced by elevation above 500m (Grant et al. 2010), generally flat terrain (Wichert et al. 2018), north-facing slopes (Hocking 1995; Spurr and Barnes 1980), with clay content being a beneficial predictor of *Eucalyptus* tree productivity (Du Plessis 2014).

In contrast, in this study, tree productivity is shown to not only be influenced by north-facing slopes but by west and north-west facing slopes as well. This finding is consistent with Greaves et al. (1996) who note that west aspects showed to be favourable for *Eucalyptus* nitens wood density. This is also in agreement with Ashton (1975) who found that the northwestern aspect of *Eucalyptus* regnas stands was denser than those in southeastern aspect. Of all the terrain variables, elevation has the greatest influence on tree growth. This is because the effects of elevation on plants are mostly indirect as these effects modify other site factors (primarily climate and soil) (Latifah et al. 2014). Additionally, the Highflats plantation is also dominated by *E.dunni* which demonstrates increased growth in cooler sites. This contributes to the likelihood of elevations above 500m being a significant variable to tree growth in the Highflats plantation. This is consistent with Pierce (2000) who suggests that through light intensity and solar radiation, elevation contributes to the growth potential of a forest. Therefore, an increase in elevation is accompanied by a decrease in temperature (Villanueva 2005). Thus, elevation has a significant influence on tree growth and distribution owing to its direct relationship with climatic variables such as temperature (Latifah et al. 2014; Villanueva 2005)

Aspect and slope have a significant influence on key environmental factors such as temperature (Millner 2006). Furthermore, literature shows that soils and topography are closely related because topography has an influence on soil depth, texture, profile development and the structure of subsoil as well as the topsoil (Pierce 2000; Spurr and Barnes 1980). A site's positioning, concerning the magnitude of wind and sun, is largely influenced by slope as steeper slopes generally receive and experience more insolation than flatter slopes (Pierce 2000). Furthermore, Wichert et al. (2018) note that tree growth generally increases on flat terrain as steep slopes are more susceptible to erosion.

Clay content has a significant influence on soil fertility; thus, having a direct effect on tree productivity. High clay content of soil has high cation exchange capacity for Eucalyptus spp. (Mensah et al 2016). Soils with high cation exchange capacity have high ability to hold nutrients which is a defining factor of soil fertility compared to low cation exchange capacity have a deficiency in cations. TWI was used as a proxy for soil moisture because soil moisture contributes to soil shear strength. Soil moisture content is often lower in Eucalyptus spp. as the species transpires significant amounts of water in order to produce a unit of dry matter because Eucalyptus spp. is a broad-leaved plant (Demessie et al 2012). Furthermore, soil moisture decreases from steep to gentle slopes (Zhang et al 2010) and has an inverse relationship to soil shear strength (Zydroń and Dąbrowska 2012); therefore, having an impact on ground strength and commercial tree species productivity.

The results show that LiDAR-derived CHM provides dependable information for the extraction of forest structural attributes ($R^2 = 0.88$). This is consistent with Tesfamichael et al. (2010) who explored the utility of LiDAR data in deriving significant forest structural attributes such as plot-level dominant tree height, mean tree height and volume of *Eucalyptus grandis* commercial plantations with a R^2 of 0.82-0.94 for observed and predicted volume. Therefore, the result indicates that the CHM used in this study offers dependable, convenient information regarding tree height data and is a reliable and effective means of retrieving forest structural parameters and terrain mapping (Mweresa et al. 2017). Furthermore, the results demonstrate the potential of LiDAR-derived data approaches for forest structural assessment of commercial tree species (Tesfamichael et al. 2010).

The study provides effective means of assigning commercial tree species to optimal potential sites using terrain variables. Furthermore, the study enhances the ability for forest management to assign optimal species for afforestation. This will improve forest management decision-making process through the application of spatial and statistical modelling techniques in forest planning activities. Additionally, the study will result in the improvement of planning forest operation's physical accessibility and terrain classification applications. Given the prioritization of cost reduction measures in forestry, the application of high-resolution remote sensing sensors such as LiDAR is associated with multiple limiting factors such as availability and cost (Dube et al. 2015; Matongera et al. 2017). Therefore, the use of freely available DEMs and Synthetic Aperture Radar data is recommended for future studies, as such technologies will potentially prove to be a speedy means of predicting tree productivity for a specific site. Additionally, the use of freely available remote sensing technologies will improve continuous monitoring and revision of forest systems such as terrain classification.

To improve the practicability of using methods demonstrated in this study to advance forest operations' management, future studies need to employ evaluations similar to this study to know whether local site factors have an effect on tree growth of other key commercial tree species such as *Eucalyptus smithii*, *Eucalyptus nitens, Pinus patula*, *Pinus elliotii and Acacia mearnsii*, and their structural attributes such as tree diameter at breast height (DBH).

2.5 Conclusion

This study sought to determine the influence of local terrain variables on tree productivity of commercial forest tree species in Highflats plantation, South Africa using GIS, LiDAR and stepwise multiple linear regression. Based on the results of the study we can conclude that this study shows the value of LiDAR-derived CHM in determining forest structural characteristics such as tree height with an accuracy of R^2 = 0.88. Furthermore, the stepwise multiple linear regression yielded pleasing results (R^2 = 0.97) and elevation above 500m, clay content, west and northwest facing slopes and aspect influence tree growth than TWI, with elevation being the most influential in *Eucalyptus* tree productivity.

CHAPTER 3

Determination of Optimal Terrain Classes for Forest Operations Based on Cost Effective 30 M DEM Using Logistic Regression

Abstract

Terrain classification is an important aspect of forestry planning as it allows for the grouping of commercial forest land according to a site's ground conditions. Owing to the fixed land base of commercial forestry there is a need for efficient means of classifying terrain. Therefore, this study sought to develop a terrain classification system for a commercial forest plantation using logistic regression in a GIS environment. Topographic variables were derived from SOTER-based soil parameter estimates (SOTWIS) for Southern Africa and a cost-effective 30 m digital elevation model. Integration of GIS and logistic regression framework showed that suitable terrain areas can be mapped with an accuracy of 93% in the landscape under study. The study provides an efficient and effective means of classifying ideal terrain conditions for forest management applications, specifically related to silviculture practices and harvesting operations. Also, the study demonstrates the use of GIS coupled with statistical modelling for providing a feasible and accessible means towards the application of terrain classification in an effective measure while contributing towards a national level analysis.

Keywords: Terrain Classification, Logistic Regression, GIS

3.1 Introduction

In forestry, terrain classification is interpreted as the categorisation and characterization of an area's physical accessibility for forest operations. These operations require planning through the knowledge of dominant terrain conditions (Erasmus 1994), with the overall goal of grouping forest land according to the supporting capacity of the site's ground conditions (Löffler 1986). Terrain classification forms a part of the tactical planning in order to identify low impact techniques for key forest operations (Upfold 2014). It also forms an integral component of forest management planning such as site-species matching (Dykstra and Heinrich 1996). Terrain classification offers a constant and customary means of categorizing a variety of terrain types for forest operations such as silviculture and harvest planning (Erasmus 1994). Development of a planning system for road route location in forests and calculation of forest road construction costs are some of the benefits that can be attained using terrain classification and forest road networks (Kobayashi 1984).

Terrain classification has become essential to forest operations considering the expansion of forest operations into inaccessible and least investigated areas characterized by steep terrains (Löffler 1986). The prolific mechanization of key forest operations, as well as the pressing demand for operational methods and equipment which will ensure high financial returns and environmental safety, also necessitate strategic harvesting techniques that are grounded on in-depth knowledge of the terrain categories (Löffler 1986). Terrain classification assists in planning and facilitating effective and resourced harvesting operations. This is achieved through the selection of the most suitable equipment and machinery for appropriate forest system deployed, and carefully planned forest road networks (Kühmaier and Stampfer 2010). There are a few studies that address classifying terrain for harvesting in the South African forestry industry (Erasmus 1994; Ezzati et al. 2016) because terrain conditions are an important element in determining the success of forest operations. Thus, the South African forestry industry has acknowledged the necessity of a formal terrain classification system of areas occupied by the South African forest plantations.

Traditionally, the selection of optimal systems for forest operations is based on the intuition and experience of forest planners which is based on factors such as tree characteristics, terrain, environmental factors and availability of appropriate technology (Lüthy 1998). However, forest planning relies on expert knowledge and results in a continuous review of forest management and current operations. This is due to the adoption of new machinery and future improvement in operational systems (Kühmaier and Stampfer 2010). For instance, timber harvesting provides practitioners, harvest planners and harvesting managers with a variety of challenges. Amongst these challenges, is the selection and optimal application of harvest equipment and systems for ground-based harvesting operations (Längin 2010).

Owing to the complexity and varying demand in the forestry industry, there are multiple variables that are considered in the terrain classification process for forest operations (Shemwetta 1997). Adams et al. (2003a) state that the planning and management of forest activities can be problematic owing to various terrain and soil factors (slope, aspect, elevation, soil type, soil moisture and geology) that influence forestry activities. Davis and Reisinger (1990) and Pentek et al. (2008) suggest that there is a need for forest planners to consider the site's terrain variables. Therefore, terrain classification is dependent on 3 key features, namely: ground bearing capacity, ground roughness and slope conditions (Erasmus 1994; Löffler 1986). Ground bearing capacity includes factors that affect the soil's bearing capacity which is determined by variables such as soil type and geology. Ground roughness addresses the presence of obstacles on the land surface which affects the movement of vehicles. Slope conditions can be classified using the topographic form and the gradient of the slope. These key features aid in the planning of long term environmentally sound and economically viable forest operation systems, and to recognize the most suitable systems and techniques for particular terrain conditions.

In South Africa, multiple ground-based harvesting equipment and systems are available to the forestry industry. However, timber harvesters are faced with two critical tasks which are: (1) to select an optimal system and equipment for a site; and (2) to utilize the selected equipment in the best manner possible (Längin 2010). Specifically, terrain classification for forest operations enables managers to evaluate the various aspects of terrain for accurate budget planning, cost control and the use of best-suited machinery for site management as these are heavily influenced by variations in the machines' ability to work diverse terrain within the forest (Erasmus 1994). There are numerous methods that have been applied in terrain classification of plantation forests. For instance, traditional methods such as surveys and ground measurements of ground bearing capacity, ground roughness and slope conditions, where each category is classified in five suitability classes as in Erasmus (1994). However, the challenge with these traditional methods is that they are monotonous, limited to local scales and require expertise which is often associated with high costs. In that regard, the use of GIS and remotely sensed data provide a spatially explicit, cost-effective and efficient method that could be applied both at local and regional scales.

The rapid development of GIS and remotely sensed datasets offer significant prospects for the improvement in the implementation of terrain classification to forest operations (Fournier et al. 2000). Many geospatial datasets and analytical procedures are now feasible and accessible through developments in software applications and computing power. This has, therefore, enabled spatial modelling which is relevant to the management of resources in areas such as plantation forests. The use of geospatial data through spatial modelling could offer new and robust approaches of forest resource monitoring and management which are urgently required in assessing various aspects of terrain decision making by managers in site management (Fournier et al. 2000). Though traditional methods assisted extensively in terrain classification for forest operations, the use of spatial modelling coupled with GIS can expand the scope as it provides the ability to successfully plan and manage large scale areas (Davis and Reisinger 1990).

Therefore, there is an increased need for forest managers to apply GIS-based planning tools for enhanced implementation of integrated management as it is more profitable than independent planning at different stages of forestry (Sullivan et al. 2005). For example, Davis and Reisinger (1990) developed a terrain evaluation model in Northern Maine, USA, using slope, soil moisture, soil texture and surface roughness variables in a GIS environment and a decision support system for large scale harvesting operations. Sullivan et al (2005) used GIS in conjunction with MAGIS eXpress modelling system to investigate the application of the method in creating an ideal vegetation pattern suitable for efficiently scheduling timber harvesting and road accessibility in a 4700 acres' forest in Helena National Forest, USA. The integration of GIS and MAGIS express effectively reduced the total projected construction costs of the new road from 62.5 million to 3.44 million dollars.

Numerous studies (Arekhi 2011; Felicísimo et al. 2002; Myat et al. 2009; Nahib and Suryanta 2017) have demonstrated the use of GIS coupled with statistical models such as logistic regression in forestry applications. Logistic regression is a generalised linear model and a multivariate statistical technique with the capability to determine the strength of binary response data as a function of multiple predictors (Lee 2005). It has been considered to be appropriate for studies which have a dichotomous outcome (Achia et al. 2010; Hosmer and Lemeshow 1989). The advantage of logistic regression, when compared to other multivariate techniques, is that the dependent variable is limited to two values (e.g. absence = 0, and presence = 1) which makes it easy to implement. For instance, Bavaghar (2015) illustrated the utility of logistic regression coupled with GIS to predict the spatial distribution of deforestation, and detect factors influencing forest degradation of Hyrcanian forests of western Gilan, Iran to an RMSE of 23% and ROC curve = 0.81. The studies that have used logistic regression in forestry applications did not attempt to conduct a terrain classification process for forest operations. In that regard, there is still a need to assess its utility in characterising terrain for facilitating efficient forest operations. This study, therefore, aims to determine optimal terrain classes based on a national classification system developed by Erasmus (1994) for South African forestry regions using logistic regression in a GIS environment.

3.2 Materials and Methods

3.2.1 Study Site

This study was conducted at the SAPPI Highflats forest plantations in KwaZulu-Natal, situated at a latitude of 30°15'2.47" S and longitude of 30°15'30.12" E. The area is predominantly rural, consisting of mainly of large agricultural plantations, natural vegetation and traditional authority land (Ubuhlebezwe Municipality 2017). According to ICFR (2016), the SAPPI Highflats plantation is situated on a plateau which is 700-1000m above sea level. The area receives mean annual precipitation of 800-900 millimetres per year, and has a mean annual temperature of 17^{o}C, with lithology consisting mainly of tillite and sandstone resulting in the prevalence of different soil types in the area.

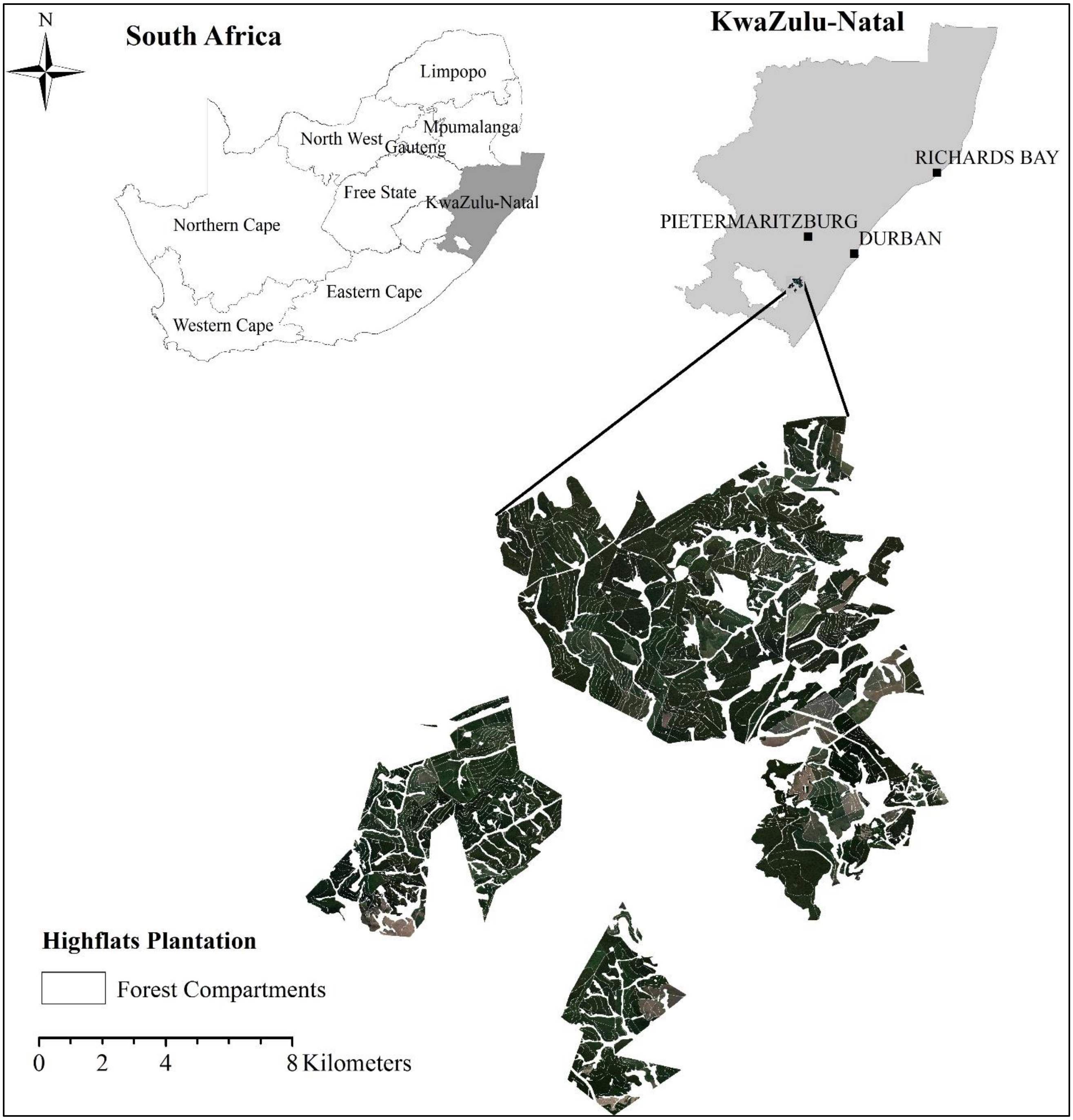

Figure 3.1 Location of the study area in the SAPPI Highflats plantation.

3.2.2 Methods of data acquisition

A total of 200 points were randomly generated within the SAPPI Highflats forest plantation with various compartments of *Eucalyptus grandis and Eucalyptus dunnii* species. The points were randomly divided into 70 % (*n* =140) for training and 30% (*n* = 60) for assessing the accuracy of the derived logistic regression model. A stratified sampling technique, which divides the population into non-overlapping strata, was first applied based on species type (Hashemian et al 2004). Thereafter, a cluster sampling method was applied to Eucalyptus grandis and Eucalyptus dunnii species and n=30 points were randomly selected from each commercial tree species type.

The field data were collected during November 2017 whereby a handheld Trimble Global Positioning System (GPS) with a sub-meter level of accuracy was used to navigate to the random sample points within the forest plantation. Plots measuring 30 m x 30 m were delineated around the sample point with observations recorded on slope conditions, ground strength and ground roughness. Each plot was then scored and assigned as either an optimal terrain condition (1) or a non-optimal terrain condition (0) for forest operations using expert field technical assistance. Erasmus (1994) states that ground roughness is assessed by height (Table 3.1.2) and by incidence (Table 3.1.1). Table 3.1 shows the four classes observed in the field based on four classes of ground roughness assessment by Erasmus (1994).

Table 3.1 Assessment of ground roughness based on Erasmus (1994) national terrain classification.

Height Class Limit (m)				Ground Roughness Class	
H20	H40	H60	H80+		
Infrequent	Isolated	Isolated	Isolated	1	Smooth
Moderately Frequent	Infrequent	Isolated	Isolated	2	Slightly even
Frequent	Moderately Frequent	Infrequent	Isolated	3	Uneven
Moderately Frequent	Moderately Frequent	Moderately Frequent	Infrequent	4	Rough
Frequent	Frequent	Infrequent	Infrequent	4	Rough

All surfaces with ground roughness more difficult than class 4 are considered class 5 (Very Rough).

Table 3.1.1 Height classes for ground roughness assessment.

Height Class Limit (m)	
H20	0.10 - < 0.30
H40	0.30 - < 0.50
H60	0.50 - < 0.70
H80+	< 0.70

Table 3.1.2 Incidence classes for ground roughness assessment.

	Distance between obstacles (m)	Number of obstacles per hectare
Isolated	> 16	< 40
Infrequent	> 5 – 16	40 - < 400
Moderately Frequent	2.2 – 5	400 - 2000
Frequent	< 2.2	> 2000

.

A 30 x 30 m digital elevation model (DEM) was used to derive slope, Terrain Ruggedness Index (TRI), and Topographic Wetness Index (TWI) using ArcGIS 10.4, and average clay content data was acquired from SOTER-based soil parameter estimates (SOTWIS) for Southern Africa (*www.isric.org*). Slope and clay were reclassified according to Erasmus (1994) (Table 3.2).

Topographic Wetness Index (TWI) is used to determine the tendency of a landscape to become saturated and produce runoff. In this study, it was also derived from the 30 x 30 m DEM. Thereafter, TWI was computed in ArcGIS 10.4 using the formula:

$$\text{TWI} = \text{In}\ (A_s / \tan \beta)$$

whereby A_s is the catchment area (m^2/m), and β is the slope in degrees (Yilmaz 2010). This is established on the assumption that topography has an effect on the near-surface position of the groundwater table (Thomas et al. 2017) and is widely utilized as an explanation for soil moisture and water levels (Pradhan and Abdulwahid 2017).TWI was then classified to optimal and non-optimal using the guidelines below (Table 3.2) (Erasmus 1994).

Table 3.2 Criteria used for the classification of terrain variables based on Erasmus (1994).

Terrain Classification	**Map Variables**	**Optimal**	**Not Optimal**
Slope Conditions	Slope	$x < 20^o$	$x > 20^o$
Ground Strength	Clay Content	36 % - 47.4%	12% - 15%
	TWI	$x < 10$	$x > 10$

Owing to limited access to digital ground roughness data, in this study, Terrain Ruggedness Index (TRI) was used as a proxy for ground roughness. TRI is a measurement which indicates the elevation difference between cells in digital elevation grid. It is the difference between the mean of an 8-cell neighbourhood of surrounding cells and the value of a cell (Riley 1999). It was calculated in ArcGIS 10.4 using the following equation:

$$\text{TRI}=\sqrt{max^2 - min^2}$$

whereby *Max* is the maximum focal statistic and *Min* is the minimum focal statistic type used to generate the TRI using the DEM (Pradhan and Abdulwahid 2017). Erasmus (1994) states that ground roughness is the most difficult terrain classification component. Therefore, to have all components of terrain classification, we used guidelines by Riley (1999) to classify TRI into level, nearly level and slightly rugged classes (Table 3.3).

Table 3.3 TRI classification (Riley 1999).

TRI Range (m)	Designation
0 – 80	Level
81 – 116	Nearly Level
117 – 161	Slightly Rugged
162 – 239	Intermediately Rugged
240 – 497	Moderately Rugged
498 – 958	Highly Rugged
959 – 4367	Extremely Rugged

The study area contains humic and orthic soils which are characterized by high trafficability compared to melanic and vertic soils. This is very common in forest areas as vertic and melanic soils containing high clay content, and are usually wet because of their mineral composition (Erasmus 1994). The study area has dry conditions and areas with clay content greater than 16%. Such areas considered as having very good ground strength (Erasmus 1994). However, should the soil moisture content increase owing to runoff, areas with less than 16% clay content have more ground strength (such as the humic soils) as they have high water holding capabilities which can reduce trafficability (Erasmus 1994). Table 3.2 visually describes each terrain condition calculated in this study and used in the statistical analysis.

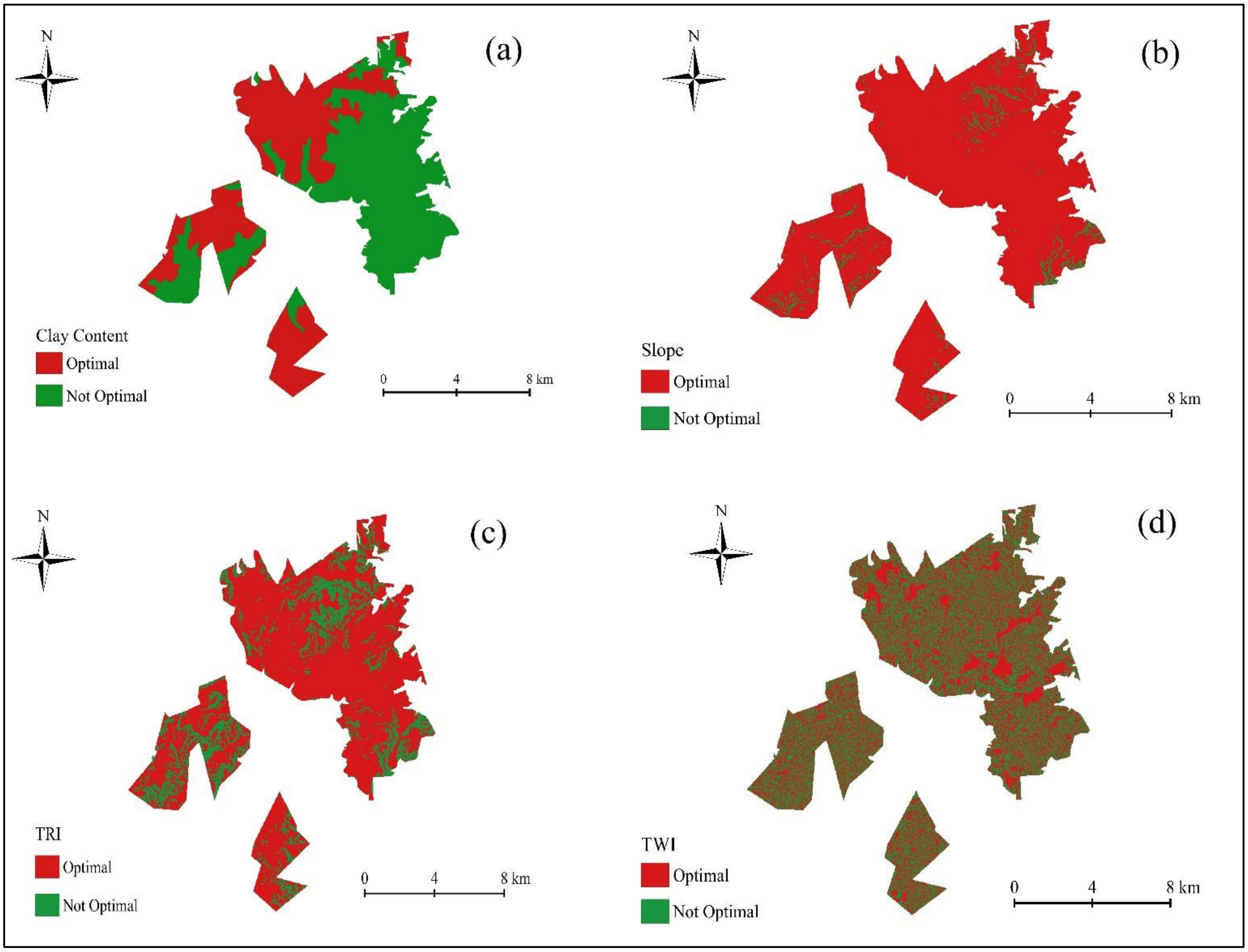

Figure 3.2 Terrain variables classified into optimal and not optimal classes derived from 30 m DEM.

3.2.4 Methods of data analysis

3.2.4.1 Logistic Regression

In this study, logistic regression was used to determine the optimal terrain classes based on a national terrain classification system developed by Erasmus (1994) for South African forestry regions. The dependent variable is a binary variable, whereby points of optimal terrain classes were assigned the value of 1, and those that were not optimal were assigned the value of 0. Terrain variables (slope, average clay content, TWI and TRI) were used as independent variables. In this analysis, the independent variables comprised of categorical data (average clay content) and continuous data (TWI, TRI and slope).

Logistic regression coefficients were utilized for the estimation of ratios for each of the independent variables in the model. Optimal terrain classes were calculated using this equation:

$$p = 1 / (1 + e^{-z}) \quad \text{……………………………………………} (1)$$

Where p is the probability of terrain classes being optimal, whereby the probability varies from 0 to 1 on an S-shaped curve (Hosmer and Lemeshow 1989). And z represents the linear combination. The lean combination can be calculated as follows:

$$z = b_o + b_1x_1 + b_2x_2 + b_3x_3 + b_nx_n \quad \text{………......................................} (2)$$

where b_o represents the intercept, b_i (i = 1,2 …. n) represents the logistic regression coefficients and x_i (i = 1,2 …. n) represents the variables produced as conditioning factors for the prediction of the optimal terrain classes (Pradhan and Abdulwahid 2017).

The assessment of the relationship between optimal terrain classes and the terrain variables influencing the suitability of the study area for operations was achieved through the logistic regression model.

3.2.5 Model Performance Assessment

This study used 200 randomly selected sample points which were randomly split to 140 points (70%) training data and 60 (30%) testing data as it is necessary to create training and testing datasets in order to create and evaluate a model (Hong et al. 2015). The training data was used to train the logistic regression model and the testing data set was used to validate the model. In order to map optimal terrain classes, the model assumed a binary classification. Thereafter, each layer was converted to TIFF files that possessed the same coordinate system and imported into R studio to model optimal terrain classes. A comprehensive data matrix was then prepared where columns and rows represented the dependent and independent variables.

Evaluating the performance of a model is a vital step in the selection and comparison of the influence of variables. This study used the Receiver Operating Characteristic (ROC) curve (Bui et al. 2016) to measure logistic regression prediction performance in mapping optimal terrain classes. The ROC curve method provides a visual measure of model performance (Peerbhay et al. 2016) which is constructed by plotting the true positive rate (sensitivity) against false positive rate (specificity) (Hong et al. 2015). The Area Under the ROC Curve (AUC) can be used as model validation, whereby the AUC value of 1 is indicative of a perfect model and the value of 0 is indicative of a poor model (Walter 2002). An AUC value of 0.5 to 1.0 indicates that the model is good, whereas values higher than 0.9 indicate an extremely accurate prediction (Bui et al. 2016; Kavzoglu et al. 2014; Walter 2002).

3.3 Results

3.3.1 Logistic Regression Analysis

Table 3.4 summarizes the output results of the logistic regression model analysis. TWI and slope were significantly related to the suitability of the study area for the optimal terrain classes ($p < 0.05$). However, TRI and clay content were non-significantly related to the suitability. Therefore, it can be observed that for any additional slope and TWI the odds of terrain conditions being optimal decrease by a factor of -0.99188 and -0.45177 respectively, i.e. a 1-m increase in slope and TWI will result in a 0.99188 and 0.45177 decrease of the odds of the probability of optimal terrain conditions.

The map of optimal terrain classes (Figure 3.4) was derived from classifying the probability of optimal terrain classes (p) into 2 classes. Figure 3.3 shows the ROC curve plot and it can be observed that the logistic regression method yielded high-performance results in mapping optimal terrain classes with an AUC = 0.93. Figure 3.5 shows terrain classes for each compartment at SAPPI Highflats.

Table 3.4 Results of the logistic regression model showing – β (estimate) is the estimated logit coefficient, s.e is the standard error of the coefficient significant (indicated by *) and non-significant variables, Wald like the p-value shows the significance level of the coefficient.

Variables	***β(estimate)***	***s.e.***	***Wald***	***p-value***
Constant	22.58067	7.776813	8.430827	0.003689
Av. Clay Content	7.75E-06	5.14E-06	2.275227	0.131456
Slope	-0.99188	0.32433	9.35287	0.002226*
TRI	-0.02628	0.014876	3.12163	0.077259
TWI	-0.45177	0.206837	4.770755	0.028947*

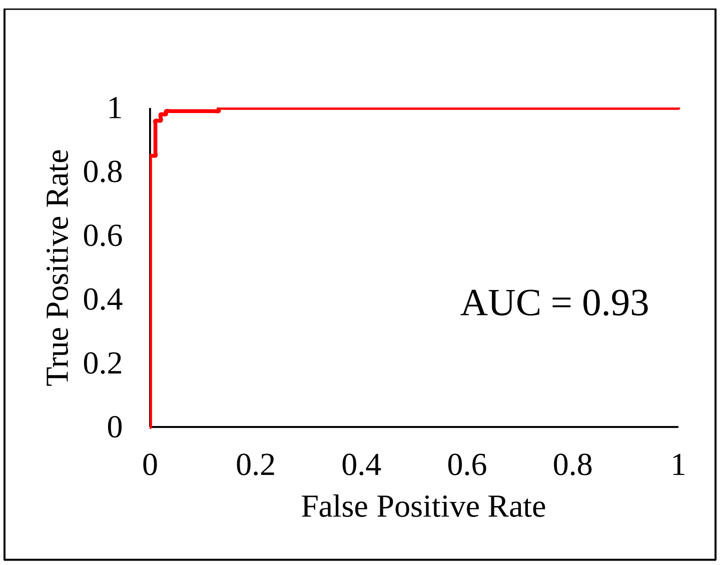

Figure 3.3 ROC curve for the mapping of optimal terrain classes derived from validation dataset (n=60).

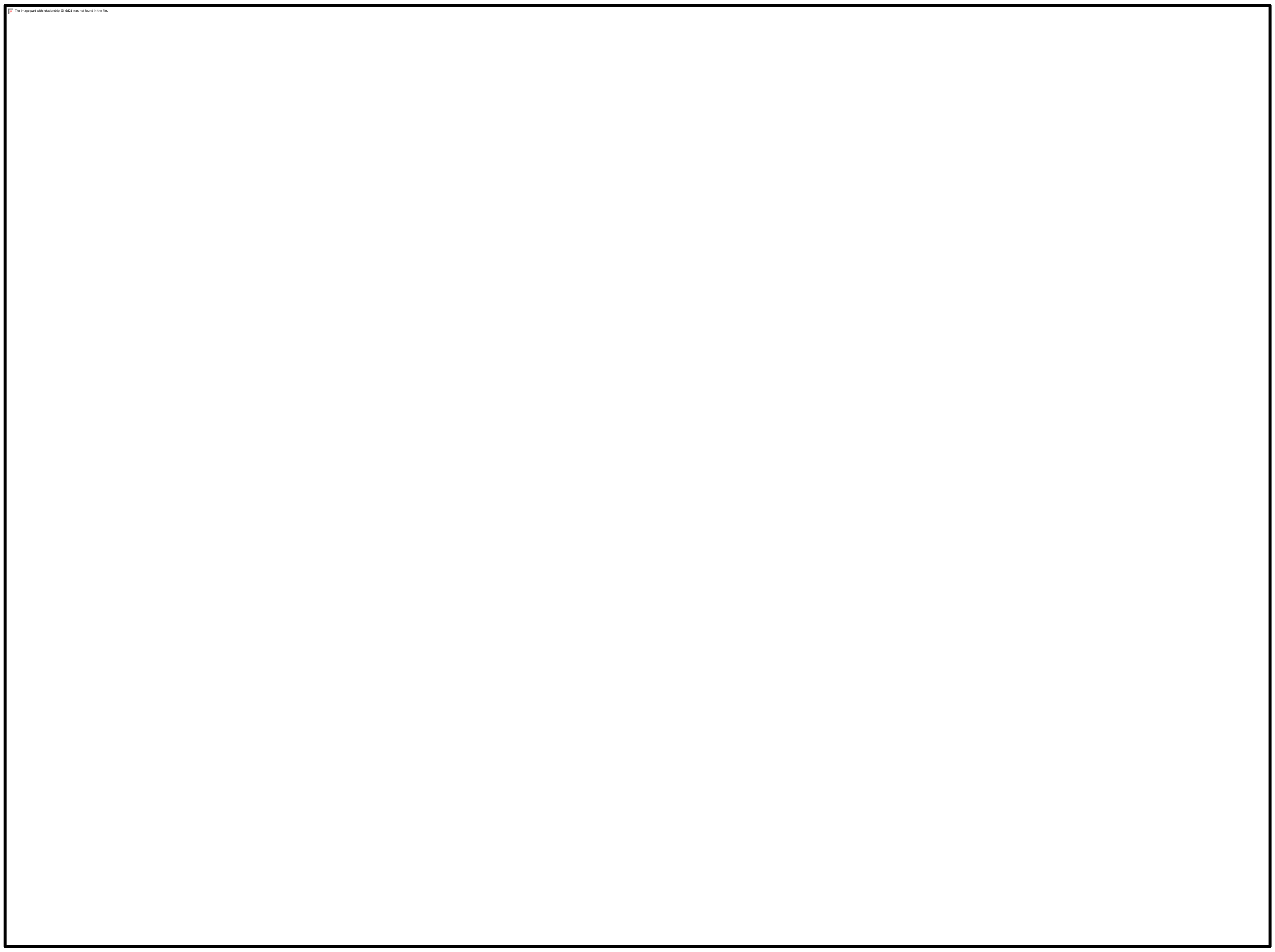

Figure 3.4 Terrain classification for optimal and not optimal for forest areas.

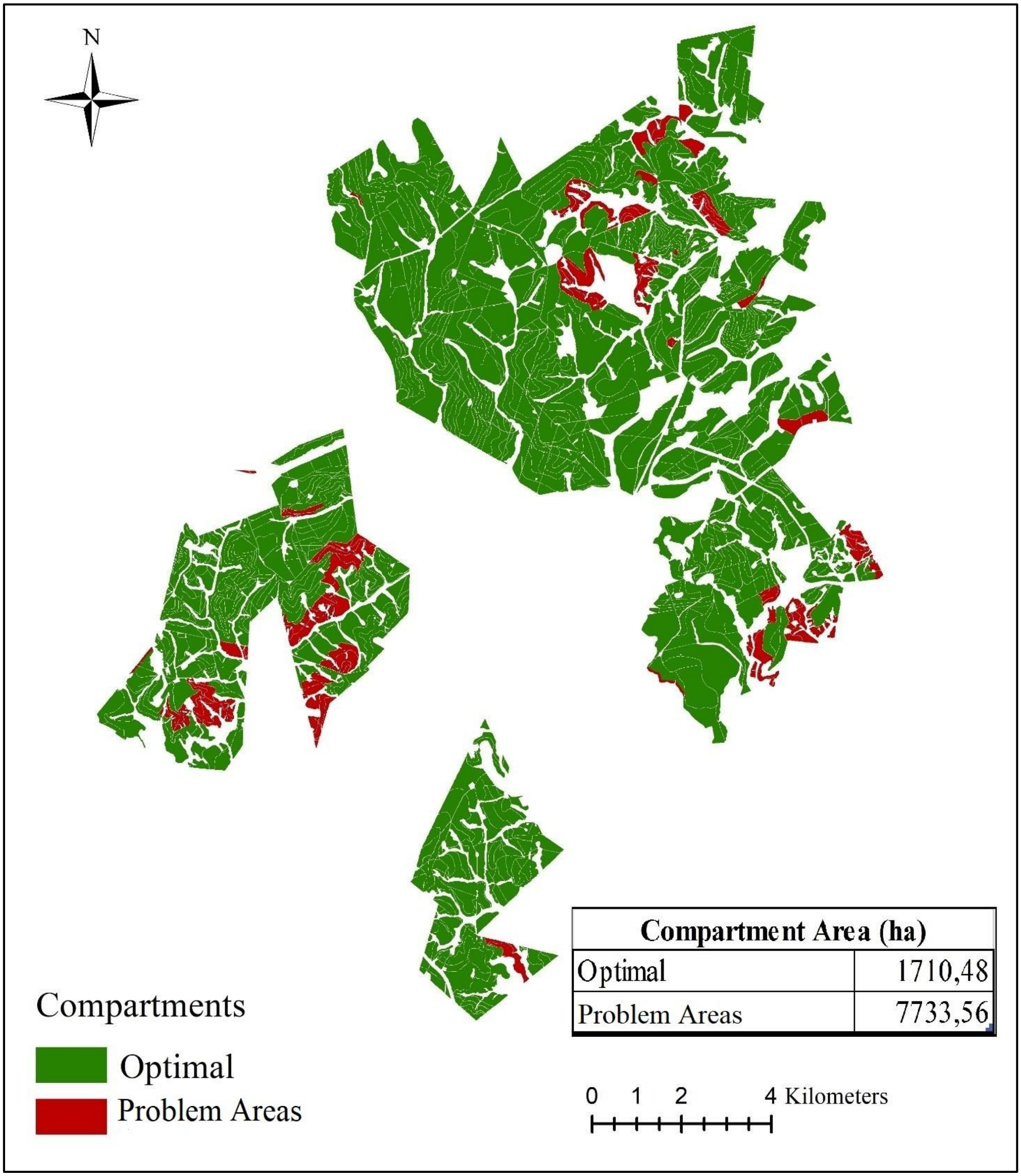

Figure 3.5 Optimal and not optimal SAPPI Highflats compartments for forest operations.

3.4 Discussion

The principal aim of the study was to determine optimal terrain classes based on a terrain classification system developed by Erasmus (1994) for South African forestry regions using logistic regression in a GIS environment. Topographical variables and logistic regression were used to determine optimal terrain classes and a ROC curve was applied for model validation.

3.4.1. Terrain classification using DEM and derivatives

The results showed that slope and TWI exhibited statistically significant relationships ($p<0.05$) for determining terrain classes. The results also showed that optimal terrain classes were those areas with slope gradient ranging from gentle to moderate (0^o to 20^o). The slope has a direct effect on soil temperature, soil moisture and soil erodibility. Slope determines the magnitude of solar radiation an area receives; therefore, having a direct impact on temperature and soil moisture. Furthermore, regions with steep slopes are more susceptible to erosion particularly through the use of heavy machinery (Wichert et al. 2018). In comparison to gentle slopes, regions with steep slopes are more susceptible to erosion particularly when heavy machinery is utilised (Wichert et al. 2018). In addition, slope also dictates machine stability and the speed at which a machine can travel during harvesting (Davis and Reisinger 1990). The potential of damage to equipment and injury of workers increases with an increase in slope or gradient (Adams et al. 2003b); therefore, slope can also be the primary limiting terrain variable in the harvesting of a site by a certain type of harvesting equipment (Davis and Reisinger 1990). Consequently, steep slopes are regarded as non-optimal for harvesting operations as the use of heavy machinery will result in increased soil erosion. Therefore, this study’s findings are in agreement with Ezzati et al. (2016) who note that zones, where harvesting is most feasible, are those with slope gradient of less than 20%.

The results demonstrated that TWI has a significant relationship in determining optimal terrain classes using terrain classification. TWI was used in this study as a proxy for soil moisture because soil moisture content contributes to ground strength as there is an inverse relationship between soil moisture content and soil shear strength (Zydroń and Dąbrowska 2012). Zhang et al. (2010) noted that soil moisture increased from lower slopes to upper slopes, therefore making areas of gentle slopes optimal because they are areas of improved ground strength than steep slopes.

The logistic regression model used in this study had a predictive accuracy of 93 % with 88.8% of the compartments being optimal terrain classes. Otunga et al. (2018) examined the effect of topographic variables on the spatial distribution of C3 *Festuca* grass species in Fort Nottingham Commonage in KwaZulu-Natal, South Africa. The study utilised GIS and logistic regression, along with topographic variables, and showed that *Festuca* grass species can be accurately mapped with an accuracy of 80%, with slope and elevation being the most important factors in the spatial distribution of the *Festuca* grass species. Also, Ayalew and Yamagishi (2005) who investigated the application of logistic regression to landslide susceptibility mapping in the Kakuda-Yahiko mountains in Central Japan using variables such as lithology, lineaments, aspect, bed rock-slope relationship, slope gradient, road network and elevation. In this study, logistic regression proved to accurately map landslide susceptibility with an accuracy of 83.5 %, with road networks, aspect and slope gradient being the most influential of all the variables used in the model. Although these studies do not focus on the application of logistic regression in terrain classification for forestry, they prove that logistic regression is capable of producing high predictive accuracies.

3.4.2. Implications of this study

This study provides an efficient and effective means of classifying terrain for forest management applications. This was achieved through the use of terrain variables that are important to a site's suitability for forest operations. Therefore, this study demonstrates that planners should examine the terrain data of their site of interest in order to make informed decisions with regards to the planning of forest operations. We demonstrated that the use of GIS coupled with statistical modelling can assist to provide a feasible and accessible means towards the selection and application of terrain classification and suitable harvesting and silviculture systems in an effective measure. Therefore, mitigating hazards because poorly planned forest operations can result in workers on the ground being injured and equipment being damaged (Adams et al. 2003b).

Through this integration, forest planners possess the ability to easily evaluate terrain for forest operations. To improve forest production, information relating to the productivity of forest species across a forest site terrain is important as it ensures effective decision-making from a strategic to an operational level. Therefore, terrain classification can assist to increase tree productivity as there is limited literature focusing on how terrain can influence tree productivity. The use of GIS can extend to a framework for forest management at a strategic level for forest operations (Ezzati et al. 2016) as there is no agreement that has been reached on a national forest classification system that is best suited for South African conditions (Louw and Scholes 2002).

The study used outdated information from Erasmus (1994) to develop a digitised terrain classification and there was a need to improvise from variables provided by Erasmus (1994). Therefore, the authors recognise the need to explore more terrain variables such as stream power index, soil type, stream network and geology, as well as high-resolution DEMs to optimise the utility of terrain classification in forestry applications. Utilising statistical modelling alongside GIS possesses the possibility to further explore the potential of GIS in effective planning of forest applications. Furthermore, the application of GIS has shown to have no limit to the number of variables that one can use to determine optimal terrain areas. This is beneficial to planners because forest operations demand environmental caution and cost reduction, indicating that one could include economic, social and/or environmental variables in order to determine the suitability of an area for the planning of silviculture practices and harvesting operations.

3.5 Conclusion

The current study sought to develop a framework for determining optimal terrain classes for forest planning and operations using GIS, coupled with statistical modelling techniques. The study provides evidence that terrain classifications using DEM and GIS are fast, feasible and very user-friendly, in assessing key attributes in terrain classification, especially for a large region. Based on the findings of this study it can be concluded that slope and TWI are variables significant for mapping optimal terrain classes (with $p<0.05$) than average clay content and TRI. Furthermore, logistic regression yielded high accuracy results with AUC = 0.93. The findings of this study also underscore the potential and robustness of integrating statistical modelling with GIS techniques as an approach for strategic future forest planning. However, to further implement environmentally friendly and cost-effective planning, the inclusion of non-terrain variables such as climatic, economic and social factors can assist to improve and widen the scope of predicting optimal terrain classes.

CHAPTER 4

Summary, Conclusions and Future Work

4.1 Summary and Conclusions

Effective decision-making is a significant component of commercial forestry plantations and timber production. Therefore, information relating to commercial tree species and the terrain in commercial plantation sites is crucial for forest management because the nature of timber production creates long-standing social and ecological consequences. Additionally, planning for forest operations is an intricate and multifaceted task. This is often a result of variable topographic conditions, among other factors. Consequently, understanding the relationship between commercial tree species and a site's topographic variables is crucial for optimising forest planning and management.

Traditional methods of implementing forest planning, species' structural attributes and productivity have been suspended in favour of GIS and remote sensing techniques. GIS and remote sensing approaches are cost-effective, convenient and spatially explicit in comparison to traditional methods. The relationship between commercial tree species and topography has not been extensively researched. There is much to understand concerning the planning and management of forest operations and the relationship between topography, structural attributes and forest productivity. Thus, the primary focus of this research study was to determine the impact of local terrain variability on forest operations and tree productivity using GIS and statistical modelling in SAPPI Highflats, South Africa. In this chapter, the aim and objectives established in the general introduction chapter (Chapter 1) are reviewed against conclusions and the chapter continues to highlight major conclusions and recommendations.

The study's objectives were set as follows:

1. Determine the relationship between terrain variation and productivity of commercial tree species using LiDAR-derived topographic factors using stepwise multiple linear regression.
2. To evaluate the performance of a LiDAR-derived Canopy Height Model (CHM) in predicting tree height.
3. Determine optimal terrain classes for forest operations based on the cost-effective digital elevation model (DEM) for South African forestry regions using logistic regression.
4. Assess the robustness of logistic regression for the development of a terrain classification system.

Based on the results of the study, there is a relationship between terrain variables and tree productivity as all the selected local topographic factors influence tree productivity. Elevation showed to have a significant influence on tree productivity and distribution owing to its direct relationship with climatic variables (Villanueva 2008; Latifah et al 2014). Furthermore, the results of the study showed that LiDAR-derived CHM provides a convenient and practical means of predicting tree height with an R^2 value of 0.88 and stepwise multiple linear regression yielded exceptional results in predicting the relationship between tree height and local topographic variables. The study provides an effective means of assigning commercial tree species to optimal potential sites. This provides forest managers with the ability to assign optimal species for afforestation at a particular site based on reliable information and methods.

Traditional methods of selecting optimal terrain classes are time-consuming and labour intensive. Knowledge of terrain conditions is an important aspect of forest planning as it determines the success of forest operations. Therefore, this study aimed to determine optimal terrain classes based on Erasmus (1994) national terrain classification system for South African forestry regions using logistic regression. Based on the results, cost-effective DEM proved to successfully determine optimal terrain classes. Slope and TWI showed statistically significant relationships for determining terrain classes ($p<0.05$). Gentle slopes (0^o – 20^o) demonstrated to be areas of optimal terrain classes. TWI was used as a proxy for soil moisture because soil moisture contributes to ground strength owing to the inverse relationship existing between soil shear strength and soil moisture content (Zydroń and Dąbrowska 2012). The logistic regression model used in this study had a predictive accuracy of 93%; therefore, logistic regression proves to be an applicable and robust method of developing a terrain classification system with a dichotomous output. The study demonstrates the feasibility towards the selection and application of terrain classification to silviculture, harvest planning and the selection of appropriate methods for the execution of these forest operations using GIS and statistical modelling.

4.2 Conclusion

The principal aim of this study was to determine the impact of terrain variability on forest operations and forest productivity using GIS and statistical modelling in a commercial forest plantation in, South Africa, KwaZulu-Natal. The findings from the study have shown that local topographic variables have a relationship with tree productivity. In addition, LiDAR-derived CHM proved to successfully predict tree structural attributes. Furthermore, the application of a cost-effective DEM and logistic regression presented successful results in determining optimal terrain classes for forest operations in a GIS environment. The conclusions drawn on this study were established from observations of results derived from research objectives specified in Chapter 1 and discussed in Chapter 2 and 3.

Based on the results of the study, local topographic variables have a relationship with tree productivity. Elevation, slope, aspect and clay content proved to influence tree productivity. Stepwise multiple linear regression showed to be reliable in determining a relationship between topographic variables and commercial tree species productivity within a complex environment at a regional scale. Also, it can be observed from the results that the CHM yielded highly accurate predictive result when utilized to estimate tree height with an R^2 of 0.88. Therefore, the study shows the value of LiDAR-derived CHM in determining reliable information regarding forest structural attributes such as tree height.

Subsequently, optimal terrain classes were predicted from topographic variables derived from a cost-effective DEM. The results indicate that slope and TWI are significant topographic variables in determining optimal terrain classes, with regions of 0^o – 20^o and low TWI being optimal. Different studies have shown that flat slopes with low soil moisture are optimal for forest operations. Though vital in forest operations such as harvesting, TRI and clay content were not significant in determining optimal terrain classes. Such results prove that the application of a cost-effective DEM showed to be beneficial to a national classification system for South Africa.

Based on the results (achieved in Chapter 3), logistic regression proved to be a robust means of developing a terrain classification system with a dichotomous output. Furthermore, the use of digital surface representation (DTM and DEM) in conjunction with GIS and logistic regression offers fast and dependable information for the evaluation of key attributes in terrain classification over areas of large spatial extent.

The study demonstrates the significance of local topography on timber forest production and productivity and provided an efficient means of classifying terrain for the planning of forest operations. Furthermore, the study demonstrated the use of GIS coupled with statistical modelling can provide a feasible and reliable means to improved decision-making regarding management and planning of timber forest production and forest operations such as site-species matching. This study has the potential to contribute to the limited body of literature concerning the effect of topographic factors on tree productivity and terrain classification in the South African forestry industry. Further research relating to the effect of terrain on commercial tree species productivity should explore more terrain variables and commercial tree structural attributes to further understand the relationship and for improved planning and management of systems.

Based on the findings of this study, we recommend that future studies should investigate the significance of social and environmental variables in mapping suitable sites for forest operations. Furthermore, futures studies should also evaluate the utility of remote sensing in determining the impact of topographic variables on commercial tree species at a regional scale using new generation sensors such as Sentinel-2 MSI. This will assist forest managers gain a holistic view when planning for forest operations from a strategic to operational level. Furthermore, this will aid forest managers to bridge the gaps of local terrain classification, and expand the applications and evaluation of terrain for commercial tree species to a regional scale.

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