Assessing the utility of remotely sensed data and integrated topographic characteristics for determining tree stand structural complexity in a re-forested urban landscape

By

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Abstract

Transformation of natural landscapes into impervious built-up surfaces through urbanisation is known to significantly interfere with urban ecological integrity and its ability to provide environmental goods and services as well as accelerate climate change and associated impacts. Urban reforestation is widely promulgated as an ideal mitigation practice against impacts associated with urbanisation, however reforestation often has to compete with multiple and more "lucrative" urban land uses. This necessitates the optimisation of ecological benefits derived from reforestation within the limited available land. Such optimisation demands spatially explicit monitoring and evaluation (M&E). The recent proliferation of tree stand structural complexity (SSC) – a multidimensional index of the ecological performance of tree stands - offers great potential as an alternative indicator of ecological performance, instead of the one-dimensional traditional indicators such as Leaf Area Index, stem diameter and tree height. Furthermore, the recent advancements in remote sensing (RS) technology offers an improved potential of determining ecological performance across an urban reforested landscape. However, remotely sensed data costs and reliability often hinder their operational adoption. Consequently, the recent advancements in the freely available Sentinel 2 (S-2) data offer great potential for a cost effective operational M&E of SSC. The aim of this study was to i) Examine the utility of the freely available S-2 multispectral instrument imagery to determine SSC using the Partial Least Squares (PLS) regression technique within a re-forested urban landscape ii) Explore the potential of integrating topographic datasets with the S-2 data to determine SSC and iii) To rank the value of these variables in determining SSC. Tree structural data from a re-forested urban area was collected and a SSC index used to determine the area's ecological performance. Multiple vegetation indices (VIs) were derived from the S-2 imagery while topographic variables (i.e. Topographic Wetness Index (TWI), slope, Area Solar Radiation (ASR), and elevation) were derived from a Digital Elevation Model (DEM). Results showed that the PLS model (n = 90) using the most important S-2 VIs (S2 REP, REIP, IRECI, GNDVI) produced a moderate predictive accuracy (0.215 NRMSECV) while topography-based model produced a high prediction accuracy (0.147 NRMSECV). Integrating the S-2 data with topographic information produced the highest prediction accuracy (0.13 NRMSECV). Furthermore, results indicate that SSC significantly varied across all topographic variables, with TWI and slope as the most important determinants of SSC. These results provide valuable spatially explicit information about the ecological performance of the reforested urban areas. Additionally, the study demonstrates the value of topographic data as an alternative predictor

of SSC as well as the value of integrating the S-2 data with topographic characteristics in determining the performance of reforested areas.

Preface

The experimental work described in this dissertation was carried out in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, under the supervision of Doctor John Odindi and Professor Onisimo Mutanga. This dissertation represents original work by the author and has not otherwise been submitted in any form for any degree or diploma to any tertiary institution. Where use has been made of the work of others, it is duly acknowledged in the text.

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I, Kusasalethu Lethukuthula Ortis Sithole, declare that

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For my family

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activated my dormant skills, spread my professional networks and exposed me to great minds. I thank you.

Last but not least, to Institute of Natural Resource (INR) and its staff. The professional exposure and experiences you've provided me and support beyond as your intern thus far, is exemplary and deserves much praise. I deeply appreciate it.

The list of contributions to thank is endless, but specifically for the aforementioned people and institutions, I'm most thankful.

Abbreviations

ANOVA: Analysis of Variance

ASR: Area Solar Radiation

CV: Cross Validation

DAH: Diameter at Ankle Height

DEM: Digital Elevation Model

EM: eThekwini Municipality

GIS: Geographic Information Systems

GNDVI: Green Normalized Difference Vegetation Index

IRECI: Inverted Red-Edge Chlorophyll Index

M&E: Monitoring & Evaluation

PLS: Partial Least Squares

PRESS: Predictive Residual Sum of Squares

REIP: Red-Edge Inflection Point

RMSE: Root Mean Square Error

RS: Remote Sensing

S-2: Sentinel 2

S2REP: Sentinel 2 Red-Edge Position

SEM: Structural Equation Modelling

SSC: Stand Structural Complexity

SWIR: Short-Wave Infrared

TWI: Topographic Wetness Index

UKZN: University of KwaZulu-Natal

VI: Vegetation Index

VNIR: Visible and Near-Infrared

CHAPTER ONE

General Introduction

1.1 BACKGROUND

Urbanisation, the transformation of natural landscapes into impervious built-up surfaces is considered a major driver of environmental change (Jusuf et al. 2007). It is associated with climate change (Nowak and Crane 2002), biodiversity loss (Le-Xiang, Hai-Shan and Chang 2006), thermal stress (Tan et al. 2010), noise pollution (Singh and Davar 2004), air pollution (Nowak, Crane and Stevens 2006), and habitat loss (Hanski 2005). Consequently, urban reforestation is often widely promulgated as the most ideal practice against the above mentioned adverse effects (Grace and Basso 2012, Zomer et al. 2008, UNFCCC 2013). Reforested areas act as carbon sinks, bio-sequestrating carbon through photosynthesis and storing it in their biomass (Luyssaert et al. 2008, Liski et al. 2000, Nowak and Crane 2002, Silver et al. 2004). Also, reforestation using a range of indigenous tree species, mitigates for biodiversity loss by increasing habitat diversity, which accommodates a wider variety and abundance of animal species (Harrison, Wardell-Johnson and McAlpine 2003, Le et al. 2012, UNFCCC 2013, Benayas et al. 2009). Furthermore urban reforestation offers other ecosystems services which include flood attenuation (Dwyer et al. 1992), assimilation of air pollutants (Nowak et al. 2006), water purification (Fiquepron, Garcia and Stenger 2013), job creation (Benayas et al. 2009) and improved livelihoods (Zomer et al. 2008).

However urban reforestation often has to compete for the limited urban land with “more lucrative” land uses such as real estate, industrial establishments, urban agriculture and other commercial establishments (Zhou et al. 2007). Such competition therefore demands that urban reforestation outputs, outcomes and impacts be maximised within the limited urban land by optimising their ecological performance. Such optimisation requires spatially explicit and cost-effective monitoring and evaluation (M&E) of the ecological performance of the re-forested areas. Ecological performance is the level of provision of ecosystem services which incorporates, but not limited to, biomass, biodiversity and structural diversity (Gaston et al. 2008). Unfortunately, reforestation programmes often have to spread their limited resources to planning, implementation and maintenance. According to Zhou et al. (2007), such costs may include land purchase, labour wages, technical expertise, capacity building and planting material. Such strain tends to result in neglect of M&E. Hence there is need for the development of alternative reliable and cost effective M&E approaches for ecological performance of urban reforestation for optimal planning and management of urban landscapes.

Traditionally, studies have relied upon single stand attributes to determine ecological performance of tree stands. These include Leaf Area Index (Davis et al. 2000, Arx et al. 2013, Moser, Hertel and Leuschner 2007), stem diameter (Chave et al. 2005, Zheng et al. 2008), Net Primary Productivity (Girardin et al. 2010, Aragão et al. 2009), tree height (Seavy, Viers and Wood 2009), basal area (Waltz et al. 2003, Liang et al. 2007) and species composition (Valencia et al. 2004, Ruiz-Labourdette et al. 2012). However, these attributes have been identified as limited indicators of ecological performance of tree stands across landscapes (McElhinny et al. 2005). For example, Franklin et al. (1981) found mean tree diamter to be a weak comparator between stands as old-growth and young stands of Douglas-fir had a similar mean tree diameter even though the old-growth stand had approximately twice the coefficient of variation of tree diameter compared to the young stand. Also, Svensson and Jeglum (2001) noted that using tree height as an indicator demanded further information on the horizontal arrangement of the trees. Consequently, other studies have adopted the use of tree stand structural complexity (SSC) to determine tree stands ecological performance. The SSC has been identified as a more reliable indicator of forest ecological performance that includes habitat diversity, biodiversity, ecological restoration and carbon sequestration (McElhinny et al. 2005, Neumann and Starlinger 2001, Lindenmayer, Margules and Botkin 2000, Franklin and Van Pelt 2004, Kane et al. 2010, Lamonaca, Corona and Barbati 2008, McKenny, Keeton and Donovan 2006). For instance, Pastorella and Paletto (2013) found a positive relationship between habitat diversity in Trentino forests and SSC, whilst Tanabe, Toda and Vinokurova (2001) noticed a relationship between SSC to local insect diversity. Wang et al. (2011) found a positive relationship between SSC in spruce-dominated forest stands and aboveground carbon stocks.

The SSC offers a reliable indicator of ecological performance as it is a multi-dimensional index that includes species (i.e. species richness), horizontal (i.e. basal area) and vertical (i.e. canopy height) characteristics. Multiple SSC indices with varying combinations of tree stand attributes have been developed. These include the Structural Complexity Index using ground vegetation, shrub, log and litter attributes (Barnett, How and Humphreys 1978), the Stand Diversity Index using variations in species richness, tree spacing, diameter at breast height (DBH) and crown size (Neumann and Starlinger 2001), the Structure Index based on covariance in height and

DBH (Staudhammer and LeMay 2001) and the Structural Complexity Index (Holdridge 1967) based on canopy height, stem diameter, basal area and species richness. The Structural Complexity Index by Holdridge (1967) has become increasingly appealing due to its processing simplicity and commonality of data inputs within existing forestry inventories.

Ecological performance of tree stands has been traditionally conducted through periodic field surveys and analysis of aerial photographs. Such approaches are cumbersome, time consuming, costly per unit area and may be incomparable across a landscape. Remote sensing (RS) approaches offer spatially explicit, repetitive and quantitatively consistent M&E of the ecological performance of tree stands (Peerbhay, Mutanga and Ismail 2013, Wunderle, Franklin and Guo 2007). Whereas multiple studies have used RS techniques to determine ecological performance indicators such as basal area (Hudak et al. 2006), stem density (Franco-Lopez, Ek and Bauer 2001), tree diameter (Wolter, Townsend and Sturtevant 2009), stand biomass (Foody et al. 2001), basal area (Hudak et al. 2006), canopy cover (Smith et al. 2009), stand age (Wunderle, Franklin and Guo 2009), and species composition (Gillespie et al. 2008), there is paucity in literature on the use of RS approaches to determine SSC. This has been attributed to cost and technical limitations of existing remotely sensed data. These technical limitations include the coarseness in spatial and spectral resolutions of the affordable or freely available remotely sensed data sets such as Landsat and MODIS. The recent technical improvements with the now freely available Sentinel 2 (S-2) multispectral instrument offer a great potential for the cost effective and reliable determination of SSC or urban reforestation initiatives. The S-2 offers 13 spectral channels in the visible/near infrared (VNIR) and short wave infrared spectral range (SWIR) at a 5-day temporal resolution, which range from 10 - 60 m spatial resolution. Specifically, its 3 red edge spectral channels can be used to generate VIs useful for vegetation analysis. For instance, the S2REP is a S-2 based VI sensitive to variation in leaf chlorophyll content, hence valuable in vegetation analysis (Frampton et al. 2013). However, its spectral and spatial data characteristics remain a limitation in discriminating finer variations in tree stand attributes (Frampton et al. 2013). Hence, some studies have proposed the use of ancillary environmental variables such as soil fertility (Wolf et al. 2011), altitude (Gallardo-Cruz, Pérez-García and Meave 2009) and topography (Kuebler et al. 2016) to compensate for these limitations.

Topographic data in particular holds great promise in discriminating ecological variations in SSC. This is attributed to the recent technological advancements that have resulted in high quality and cost-effective Digital Elevation Models (DEMs), allowing for derivation of fine scale topographic data. Since DEMs offer large-area data coverage, they allow for reliable comparisons of ecological performance across large reforested landscapes. While topographic characteristics have been used to determine other tree stand attributes such as tree species (Kuebler et al. 2016), canopy structure (Aiba, Kitayama and Takyu 2004), tree diameter (Aiba et al. 2004), tree community composition (Baldeck et al. 2013), few studies have used topographic characteristics to determine SSC. Topographic characteristics indirectly affect tree growth or SSC through their relationship with biophysical factors that influence vegetation abundance. For instance, slope steepness is closely related to soil erosion and deposition (Webb, Stanfield and Jensen 1999, Vorpahl et al. 2012). Gentle and flat slopes are often characterised by convergence of moisture, soil, nutrients and litter, which promote tree growth, while the steeper slopes are commonly characterised by thinner soil depths, which impede tree growth (Ließ, Glaser and Huwe 2011, Wolf et al. 2011, Oliveira-Filho et al. 2001). The topographic Wetness Index (TWI) - a steady state hydrological model - represents the relative distribution of soil surface moisture based on the terrain surface. Due to the gravitational effect, TWI has shown a positive correlation with soil moisture (Wilcke et al. 2011) and soil fertility (Ou et al. 2014, Wolf et al. 2011). Area solar radiation (ASR) is the variation in solar exposure due to slope face direction. Hence ASR is strongly related to insolation and air temperature (Fries et al. 2009), transpiration (Kuebler et al. 2016) and precipitation (Rollenbeck 2006). While elevation has been found to have a negative correlation to soil moisture (Wilcke et al. 2011), soil nutrient pooling (Tanner, Vitousek and Cuevas 1998, Wilcke et al. 2011), and soil fertility (Wilcke et al. 2008). Therefore, the lower elevations tend to possess a higher tree carrying capacity for growth of tree stands in biomass and structural diversity. Therefore, this study postulates that the heterogeneity of the aforementioned topographic characteristics creates micro-habitat gradients that influence tree growth, which could be used to determine SSC across a re-forested urban landscape.

The Partial Least Squares (PLS) technique offers great potential for deriving meaningful information from the S-2 and topographic data to determine the SSC (Carrascal, Galván and Gordo 2009, Peerbhay et al. 2013). The PLS technique is one of the new modelling techniques within the family of Structural Equation Modelling (SEM) techniques. These SEM techniques overcome the common limitations of first family modelling techniques such as assumption of simple model structures, requirement for all variables to be observable and assumption that all variables are measured without error (Haenlein and Kaplan 2004). The SEM techniques allow for the construction of latent variables as a function of the predictor variables. They also allow for explicit modelling error of measurement for the predictor variables (Haenlein and Kaplan 2004). The PLS technique compresses explanatory information derived from the predictor variables (i.e. S-2 data and topographic variables) into a few non-correlated latent components that have maximum covariance with the response variable (i.e. SSC) (Maestre 2004, Carrascal et al. 2009). The PLS regression is computed through linear combinations of the latent components and their weighted explanatory power on the response variables. The PLS technique is particularly appealing for its ability to minimise non-explanatory noise, identify relevant predictor variables and is applicable in studies with small sample sizes (Haenlein and Kaplan 2004, Chin and Newsted 1999). However, despite this potential, the utility of the PLS technique to determine SSC across a re-forested urban landscape, using S-2 data and integrated topographic characteristics, remains largely unexplored.

1.2 AIM AND OBJECTIVES

This study aimed to:

- Assess the utility of topographic variables in determining tree stand structural complexity in a re-forested urban landscape.
- Determine tree stand structural complexity using remotely sensed data and integrated topographic characteristics in a re-forested urban landscape.

The major objectives to the study were to:

- Assess the utility of topographic variables (TWI, slope, ASR and elevation) in determining SSC within a reforested urban landscape.
- Rank the importance of the above topographic variables on these SSC patterns.
- Evaluate the utility of S-2-based VIs for determining SSC within a re-forested urban landscape.
- Assess the utility of integrating S-2-based VIs with topographic variables for determining the SSC using the PLS regression.
- Determine the relative importance of the S-2-based VIs/topographic variables on SSC.

1.3 CONTRIBUTION AND SIGNIFICANCE OF THIS RESEARCH

This study forms part of a wider research of the Durban Research Action Partnership (D'RAP) under the eThekwini Municipality (EM) and the University of KwaZulu-Natal (UKZN). The overall aim of D'RAP is to develop knowledge in biodiversity conservation and management within the context of global environmental change, therefore assisting reforestation managers in the Municipality. By developing a reliable, informative and feasible alternative monitoring and evaluation (M&E) approach for determining SSC, using the freely available S-2 imagery and widely available topographic data, this study answers broader questions of the research group of evaluating the growth of the reforested trees and investigating feasible and effective systems of monitoring the reforestation programme. The current study also identifies the spatial differences in SSC within topographic spaces across the landscape. Furthermore, the study determines the relative importance of topographic variables on SSC.

1.4 DESCRIPTION OF STUDY AREA

The study was conducted within the Buffelsdraai landfill site north of South Africa's port city of Durban (Figure 1.1). The reforestation programme was initiated as a buffer zone around the landfill site to offset carbon emissions associated with South Africa's 2010 FIFA World Cup hosted by the city. The programme also aimed to mitigate biodiversity loss and to improve local livelihoods by providing employment opportunities. The buffer zone is 800 ha, with the 117 ha active landfill located at the centre. The buffer zone is mainly surrounded by urban settlements, grazing land and sugar cane farms, a major economic activity in the area. The study area is characterised by humid subtropical climate influenced by the warm Indian Ocean currents. Winter months (May to September) are warm and dry, with average maximum temperatures of 22°C while summer months (November to March) are hot and humid with average maximum temperatures at 27°C. Total mean annual precipitation is approximately 1000 mm. The area is underlain by the Dwyka Tillite - a glacial conglomerate parent material that is base-rich, hard and resistant to weathering, hence its un-even topography. Glenrosa soil dominates the upper- to mid- slopes while the gentle to flat areas are dominated by the Oakleaf soils, due to deposition (McCulloch 2014). The area's variable topography is particularly ideal for determining SSC.

Reforestation in the study area was initiated in 2009/2010 and is conducted on an annual basis (2009/2010, 2010/2011, 2011/2012, 2012/2013, 2013/2014 and 2014/2015) within the buffer zone. As at January 2015, 660 523 indigenous tree species had been planted in 412 hectares of land. Common tree species are the Common hook-thorn (Acacia caffra), Pale-bark sweet thorn (Acacia natalitia), Coastal golden-leaf (Bridellia micranta), Climbing flat bean (Dalbergia obovate), African coral tree (Erythrina caffra), Sausage tree (Kigelia Africana), Umzimbeet (Millettia grandis) and Water berry (Syzygium cordatum). The rest of the buffer zone, previously dominated commercial sugarcane plantation, is now covered by grass (utilized for livestock grazing), scarp forest and pockets of weeds.

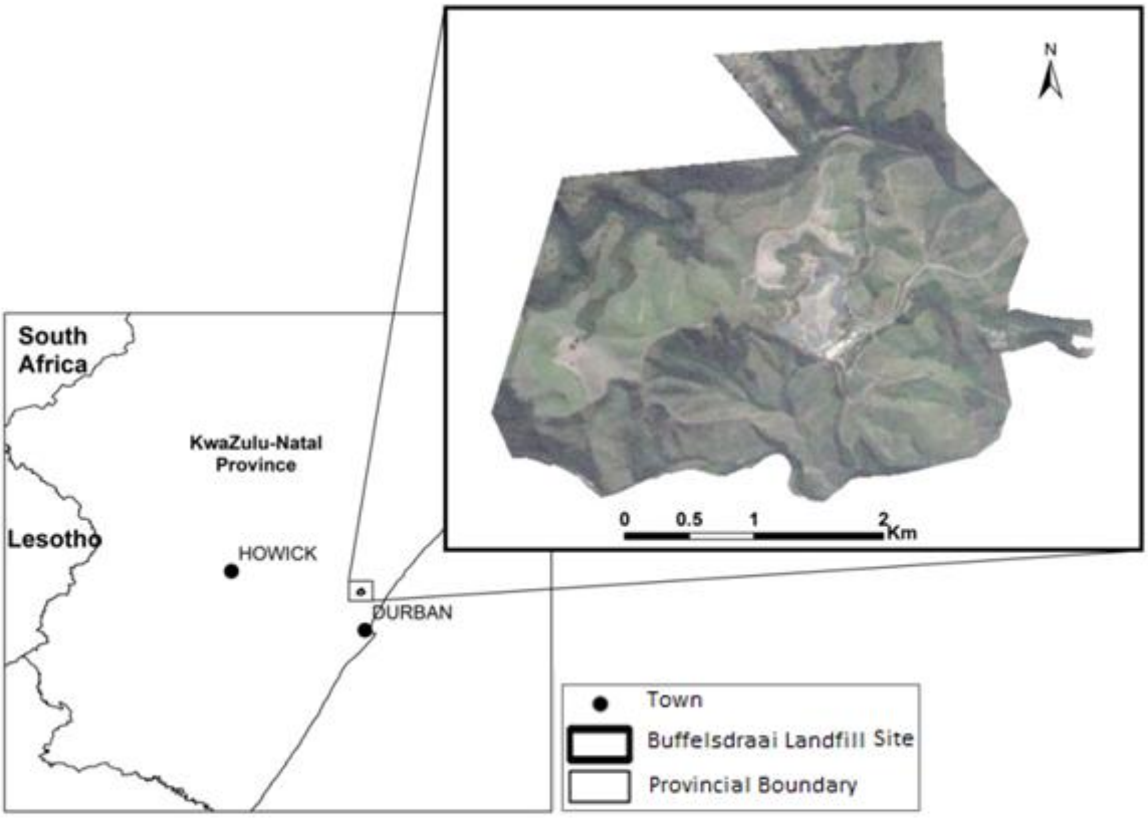

Figure 1. 1: The study area

1.5 THESIS OUTLINE

This thesis is presented in four chapters. The first chapter outlines the theoretical background and the locational setting with relevant biophysical aspects of the study. Chapter 2 and 3 are the main chapters with publishable content in a peer-reviewed journal, with each chapter presenting the theoretical motivation, study methodology, results, discussion and conclusions. Chapter 2 covers the utility of topographic variables for determining the SSC within a reforested urban landscape. It provides the theoretical motivation for this study, identifies the differences in SSC within different topographic spaces, models SSC using the PLS technique, and lastly ranks the importance of topographic variables in determining the SSC. Chapter 3 investigates the utility of freely available Sentinel 2 (S-2) multispectral instrument in determining SSC across a re-forested urban landscape using the PLS technique. The accuracy results of these spatial models are compared with similar past studies, including the results in Chapter 2. Furthermore, chapter 3 investigates the effect of integrating topographic information with the S-2 data. In Chapter 5, the main aim, objectives, limitations and major findings of the entire study are reviewed.

CHAPTER TWO

Assessing the utility of topographic variables in predicting tree stand structural complexity in a re-forested urban landscape

This chapter is based on:

Sithole, K., Odindi, J. and Mutanga, O., 2017. Assessing the utility of topographic variables in predicting tree stand structural complexity in a re-forested urban landscape. Urban Forestry and Urban Greening, Under Revision.

2.1. INTRODUCTION

Urbanisation, characterised by transformation of natural landscapes into impervious built-up surfaces, is regarded as a major driver of environmental change (Deosthali 2000, Jusuf et al. 2007). Such transformation is associated with among others natural landscape fragmentation and associated adverse effects (Hanski 2005), air pollution (Nowak et al. 2006), noise pollution (Singh and Davar 2004), climate change (Nowak and Crane 2002), biodiversity loss (Le-Xiang et al. 2006) and thermal stress (Tan et al. 2010). Consequently, urban reforestation is increasingly becoming a popular approach to dealing with adversities associated with urban natural landscape loss (Luyssaert et al. 2008, Liski et al. 2000, Nowak and Crane 2002, Silver et al. 2004). Reforestation, particularly by a range of indigenous tree species, mitigates for biodiversity loss by increasing habitat diversity, which accommodates a wider variety and abundance of plant and animal life (Harrison et al. 2003, Le et al. 2012, UNFCCC 2013, Benayas et al. 2009). Furthermore, reforested areas act as effective carbon sinks, valuable for climate change mitigation (Luyssaert et al. 2008, Liski et al. 2000, Nowak and Crane 2002, Silver et al. 2004). Other benefits associated with urban reforestation include assimilation of air pollutants (Nowak et al. 2006), recreation (Arnberger 2006) flood attenuation (Dwyer et al. 1992) and water purification (Fiquepron et al. 2013). Unfortunately, urban reforestation is often in competition with "higher return for investment" activities such as real estate, industrial establishments, urban agriculture and other commercial establishments. This necessitates that reforestation benefits are maximised within the limited urban land by optimising their ecological performance, where ecological performance is the extent to which an area provides ecosystem services (Gaston et al. 2008). Such optimisation requires spatially explicit information about the ecological performance of urban reforested areas.

Tree stand structural complexity (SSC) is known to be a reliable indicator of a forest's ecological performance, and has been used to determine among others a forest's carbon sequestration, habitat diversity and biodiversity change (McElhinny et al. 2005, Neumann and Starlinger 2001, Lindenmayer et al. 2000, Franklin and Van Pelt 2004, Kane et al. 2010, Lamonaca et al. 2008, McKenny et al. 2006). Wang et al. (2011) for instance noted a positive relationship between aboveground carbon stocks and SSC in spruce-dominated forest stands in New Brunswickk, Canada, while Pastorella and Paletto (2013) established a positive relationship between SSC and habitat diversity in Trentino forests. Tanabe et al. (2001) established a relationship between SSC to local insect diversity, while McKenny et al. (2006) noted that SSC was useful for monitoring the effect of different silvicultural management practices on eastern red-backed salamander populations in hardwood forests. Other studies e.g. Garbarino, Weisberg and Motta (2009) found that SSC is useful in determining the influence of anthropogenic factors on the health of European larch forests. Based on the above examples, I hypothesize that the determination of SSC would be a useful indicator of the ecological performance of a reforestation initiative within an urban landscape.

To date, studies have relied on single stand attributes to determine tree stands ecological performance. These include Leaf Area Index (Davis et al. 2000, Arx et al. 2013, Moser et al. 2007), stem diameter (Chave et al. 2005, Zheng et al. 2008), Net Primary Productivity (Girardin et al. 2010, Aragão et al. 2009), tree height (Seavy et al. 2009), basal area (Waltz et al. 2003, Liang et al. 2007) and species composition (Valencia et al. 2004, Ruiz-Labourdette et al. 2012). Other studies have combined multiple attributes to determine tree stands ecological performance. These include the Structural Complexity Index using ground vegetation, shrub, log and litter attributes (Barnett et al. 1978), the Stand Diversity Index using variations in species richness, tree spacing, diameter at breast height (DBH) and crown size (Neumann and Starlinger 2001), the Structure Index based on covariance in height and DBH (Staudhammer and LeMay 2001) and the Structural Complexity Index (Holdridge 1967) based on canopy height, stem diameter, basal area and species richness. The adoption of multiple SSC attributes is particularly appealing as it offers a multi-dimensional index that include species (i.e. species richness), horizontal (i.e. basal area) and vertical (i.e. canopy height) characteristics, which is more robust in determining the value of a reforested area. Hence, Structural Complexity Index, originally proposed by Holdridge (1967) has recently become popular due to among others its commonality with existing data inputs within forestry inventories and processing simplicity.

Generally, existing approaches that seek to determine tree stand structural complexity and ecological performance have been restricted to use of ecological variables. However, surface physical characteristics like variation in topography offer great potential for predicting SSC. Whereas initial adoption of topographic variables in determining ecological characteristics was impeded by lack of good quality topographic data, recent technological advancements that have led to a proliferation of good quality Digital Elevation Models (DEMs) offer great potential in determining urban forest's ecological value. Specifically, DEMs offer large-area data coverage, hence suitable for comparing varied reforestation regimes across a landscape, while recent improvements in their spatial resolutions allow for determination of finer structural variations. Furthermore, the growth in freely available high-resolution DEM data makes them ideal for cost-effective operational use.

Previously, surface topographic characteristics have been used to model other tree attributes like tree diameter (Aiba et al. 2004), canopy structure (Aiba et al. 2004, Webb et al. 1999), tree community composition (Baldeck et al. 2013, Homeier et al. 2010, Zhao et al. 2015), and tree species (Kuebler et al. 2016, Lan et al. 2011). However, there is paucity in literature on the use of topographic characteristics to predict SSC. In this study, I hypothesize that topographically related environmental gradients that influence vegetation growth may influence SSC. The topographic Wetness Index (TWI) for instance is a steady state hydrological model, which represents the relative distribution of soil surface moisture based on the terrain surface. Due to the effect of gravity, TWI has shown a positive correlation with surface soil moisture (Wilcke et al. 2011), soil fertility (Wolf et al. 2011, Wilcke et al. 2008, Ou et al. 2014), soil nutrient pooling (Tanner et al. 1998, Wilcke et al. 2011, Oliveira-Filho et al. 2001) as well as soil's microbial activity (Lan et al. 2011). Slope steepness determines soil erosion and deposition (Webb et al. 1999, Vorpahl et al. 2012). Steeper slopes for instance are often characterised by thinner soil depths, impeding tree growth (Ließ et al. 2011, Wolf et al. 2011, Oliveira-Filho et al. 2001), while gentle slopes and flat surfaces are commonly characterised by moisture, soil, nutrients and litter convergence, hence nutrient pooling. An area's solar radiation (ASR) is the variation in solar exposure due to slope face direction. Therefore, ASR is strongly related to insolation and air temperature (Fries et al. 2009), precipitation (Rollenbeck 2006) and transpiration (Wang et al. 2009, Kuebler et al. 2016). Elevation has been found to influence soil fertility (Wolf et al. 2011, Wilcke et al. 2008, Ou et al. 2014), soil moisture (Wilcke et al. 2011), soil nutrient pooling (Tanner et al. 1998, Wilcke et al. 2011, Oliveira-Filho et al. 2001) and surface air temperature (Fries et al. 2009). Therefore, as topographic heterogeneity creates micro-habitat gradients that influence tree growth and consequently SSC, this study used SSC derived from local ecological stand structural attributes (canopy height, tree diameter, stem density and species richness) to: i) predict the spatial patterns in SSC within a reforested urban landscape using stand age and topographic variables (TWI, slope, ASR and elevation) and ii) to rank the value of the above named variables in determining SSC.

2.2. METHODS AND MATERIALS

2.2.1. Sampling Plots

Ninety sampling plots were selected for the study using stratified random sampling (Figure 2.1a). The sampling plots were deemed an adequate representation of the major topographic variations within the study. Whereas new areas have been reforested annually since 2009 (Figure 2.1b), only reforested zones that were at least two years old (i.e. planted in 2009/2010, 2010/2011 and 2011/2012) were sampled as they were deemed to have attained sufficient growth and cover. Using coordinates of the sampling plots' central points as reference, sampling plots measuring 30 x 30 m and at least 60 m apart (to avoid overlap in topographic coverage) were selected.

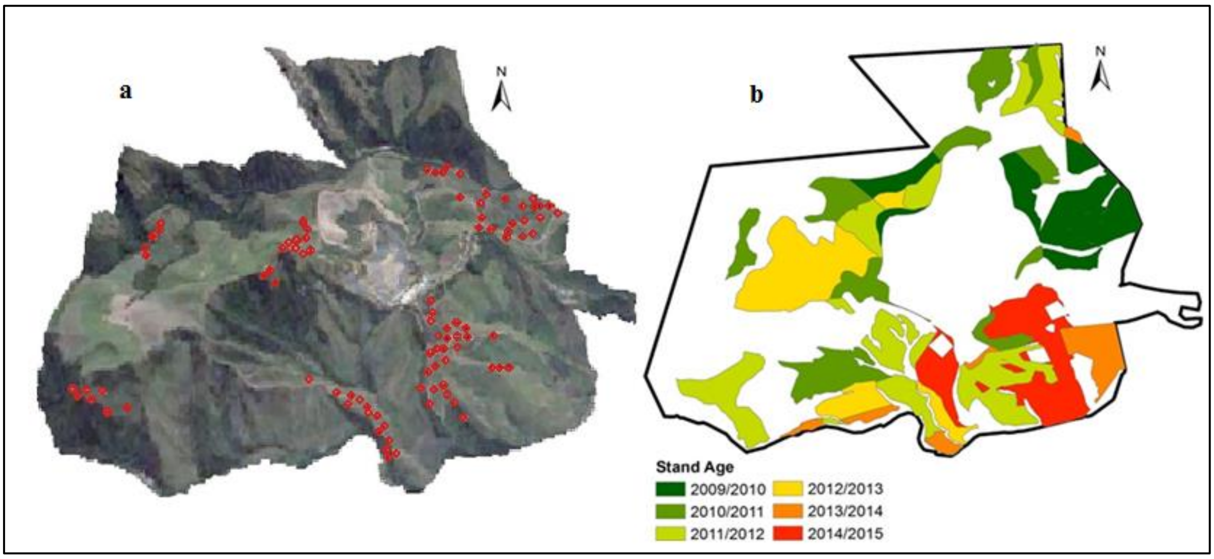

Figure 2. 1: Sampling points and stand ages

2.2.2. *Data for Stand Structural Complexity*

To determine SSC, stand structural attributes (canopy height, tree diameter, stem density and species richness) were measured at each sampling plot. A levelling rod was used to measure canopy height with ~0.05 m accuracy (canopy height in this study refers to the height of the highest branch of the tree). In this study, tree diameter-at-ankle-height (DAH), instead of diameter-at-breast height (DBH) was used to determine tree diameter as recommended in literature (Van Leeuwen and Nieuwenhuis 2010, Maltamo et al. 2009, Pommerening 2002, Wolter et al. 2009). Paradzayi et al. (2008) and Way, Wickersham and Wickersham (2006) note that DBH measurement, as a determinant of tree diameter at ~1.3m height is not suitable in an area with tree canopy height of approximately 1.3 m. Furthermore, multiple studies (Tietema 1993, Van Sambeek and McBride 1991, Paradzayi et al. 2008, Way et al. 2006) have found DAH to be as useful as DBH in determining tree diameter. To determine stem density, the total number of trees per plot was divided by the plot area. Species richness was established by counting the number of species within each plot.

The four aforementioned ecological stand attribute data were used to determine structural complexity index (HC) using simple linear combination of common stand structural parameters (equation 2.1) as proposed by Holdridge (1967). The approach's incorporation of species diversity and horizontal and vertical stand dimensions in determining SSC makes it an attractive indicator of other forest attributes such as habitat diversity, biodiversity, ecological restoration and carbon sequestration (McElhinny et al. 2005, Neumann and Starlinger 2001, Lindenmayer et al. 2000, Franklin and Van Pelt 2004, Kane et al. 2010, Lamonaca et al. 2008, McKenny et al. 2006). Tree diameter and stem density informs the index's horizontal dimension, while canopy height informs the index's vertical dimension and is expressed as;

$$HC = H \times DAH \times n \times N \qquad [\ 2.1\ ]$$

Where HC is the Structural Complexity Index, H is the canopy height, DAH the diameter at ankle height, n the number of stems per ha, and N is the number of species.

2.2.3. Predictor Data

Topographic variables and stand age was the predictor variables used to determine SSC. All topographic variables (i.e. TWI, slope, ASR and elevation) were derived from a high resolution (2 m) contour map of the area. The contour map was first converted into a Digital Elevation Model (DEM), with a Pearson correlation of 0.99 using ground elevation measurements from a Trimble GPS unit. The DEM was then used to derive all the above named topographic variables. The TWI was determined for each pixel by combining local upslope contribution area using equation 2.2.

$$TWI = \ln (FA + 0.001)/ ((S/100) + 0.001) \qquad [2.2]$$

Where TWI is the topographic wetness index, FA is the flow accumulation, and S is the slope percentage.

As aforementioned, stand ages were determined from the reforestation ages of the sampling plots. Stand age accounts for the factor of time that the tree stands had to grow, and therefore increase in SSC.

2.2.4. Statistical analysis

To determine differences in SSC within each topographic variable, class ranges were delineated as shown in Table 2.1 and spatial depictions generated. One Way ANOVA was then conducted to determine whether there were significant differences in SSC between the respective topographic classes. Where post-hoc testing was necessary, Tukey's tests were conducted to evaluate pairwise differences among the topographic classes. A significance *p value* of 0.05 was used as the threshold. *P* values below 0.05 meant the paired topographic classes where significantly different, whereas those with *p* values above 0.05 were not significantly different.

Table 2. 1: Classes of topographic variable ranges.

Topographic variable	Class Name	Class Range
TWI	Ridges	<10
	Intermediate	10 - 15
	Depressions	>15
Slope	Fairly Flat	<10o
	Intermediate	10 - 15o
	Steep	>15
ASR	Low	<585 999
	Intermediate	586 000 - 632 999
	High	> 633 000
Elevation	Low Altitude	<190 m
	Intermediate	190 - 230 m
	High Altitude	>230 m

2.2.5. Predictive Model

The adoption of Partial Least Squares (PLS) technique in ecological studies has recently grown significantly (Serbin et al. 2015, Ramoelo et al. 2013, Luedeling and Gassner 2012, Peerbhay et al. 2013, Carrascal et al. 2009). The PLS technique is one of the new modelling techniques within the family of Structural Equation Modelling (SEM) techniques. These SEM techniques overcome the common limitations of first family modelling techniques such as assumption of simple model structures, requirement for all variables to be observable and assumption that all variables are measured without error (Haenlein and Kaplan 2004). The SEM techniques allow for the construction of latent variables as a function of the predictor variables. They also allow for explicit modelling error of measurement for the predictor variables (Haenlein and Kaplan 2004). The PLS technique compresses explanatory information derived from the predictor variables (i.e. topographic variables) into a few non-correlated latent components that have maximum covariance with the response variable (i.e. SSC) (Maestre 2004, Carrascal et al. 2009). The PLS regression is computed through linear combinations of the latent components and their weighted explanatory power on the response variables, and can be statistically expressed by Equation 2.3 and Equation 2.4. The PLS technique is particularly appealing for its ability to minimise non-explanatory noise, identify relevant predictor variables and is applicable in studies with small sample sizes (Haenlein and Kaplan 2004, Chin and Newsted 1999).

$$X = TP' + E \qquad [2.3]$$

$$Y = UQ' + F \qquad [2.4]$$

where X represents the matrix of the predictor variables (topographic variables), Y is a matrix of the response variable (SSC), T is a factor score matrix, U is the scores for Y, Q is the Y loadings, P is the X loadings, E is the residual for X or a noise term, and F is the residuals for Y (Peerbhay, Mutanga and Ismail 2014, Mehmood et al. 2012).

In this study PLS was used to predict SSC using topographic variables within the MATLAB statistical environment (PLS Toolbox).

2.2.6. Model pre-treatment

The PLS technique is informed by the variance in the response variable as a function of the predictor variables. Without pre-treatment, the actual data sample values of the predictor variables would influence the PLS regression differently, based on sample size instead of variance (van den Berg et al. 2006). The current study used the auto-scale pre-treatment method, making topographic data samples of all sizes equally important in predicting SSC. This was conducted by selecting the auto-scale option within the preprocessing tab of the PLS Toolbox in the MATLAB statistical environment. Auto-scaling first scales all variables to unit variance by dividing them by their standard deviations according to equation 2.5, and then centres them by subtracting their means according to equation 2.6, hence ensuring that all variables are equally important regardless of their units and value size.

$$\tilde{x} = \frac{x-\bar{x}}{s} \qquad [\ 2.5\ ]$$

$$\hat{x} = \tilde{x} - \bar{x} \qquad [\ 2.6\ ]$$

where x represents the value of the variables, $\tilde{x}$ is variables' values after scaling, $\hat{x}$ is variables' values after mean centring, $\bar{x}$ is the means of the variables, and s is the standard deviations of the variables (van den Berg et al. 2006).

2.2.7. Model Optimisation

Selection of the optimal number of latent variables is a critical step in the optimisation of the PLS model (Mehmood et al. 2012). Due to its simplicity and reliability for optimizing the PLS model through latent component selection, Cross-Validation (CV) has become a common PLS process. Cross-Validation (CV) is computed by iteratively dividing the data into a number of subgroups with one of the subgroups reserved for validation. At each data division, their respective PLS models is generated from sub grouped data over a multiple number of latent components. After developing each model, differences between actual and predicted response variables are computed for validation data at each number of latent components. The sum of squares of the differences in actual and predicted response variables computed at each number of latent variables is used to compute the predictive residual sum of squares (PRESS), which estimates the predictive ability of the model at each latent variable number. During this iterative process, the number of latent components is systematically increased until the PRESS shows that increased latent components does not improve model predictive power. Hence, latent variables that retain high level of noise and multi-collinearity among variables are removed from the PLS model (Tobias 1995, Mehmood et al. 2012, Peerbhay et al. 2014). There are multiple cross validation methods available, which divide these subgroups differently. The current study used the venetian blinds cross validation method as the data was relatively large with randomly ordered samples. The latent components selected through this optimisation process were used to develop the final model to predict the SSC. The PLS models were derived and used to generate spatial maps of the SSC.

2.2.8. Ranking of predictor variable importance

To determine the relative importance of the topographic and stand age variables in predicting the SSC in the reforested areas, the PLS process offers the computation of Variable Importance in Projection (VIP). The VIP computes scores which are informed by the importance of each predictor variable (i.e. topographic variables) in explaining the response variable (i.e. 5) (Wold, Sjöström and Eriksson 2001). These are ranked scores as defined by equation 2.7. It is on the basis of the VIP scores that the importance of the topographic variables on the SSC was ranked. The higher the VIP score of a predictor variable, the higher that predictor variable is ranked for determining SSC.

$$\text{VIPk} = \sqrt{K \sum_{a=1}^{A} [(q_a^2 t_a^T t_a)(w_{ak}/||w_k||^2)] \,/ \sum_{a=1}^{A} (q_a^2 t_a^T t_a)} \qquad [2.7]$$

Where VIPk is the importance of the kth topographic variable based on a PLS model with a latent variables, K is the total number of topographic variable, w_{ak} is the corresponding loading weight of the kth topographic variable in the ath latent variable, and qa, ta and wa are the column vectors.

2.2.9. *Assessment of Prediction Accuracy*

To evaluate the predictive power of a PLS model - which refers to how close the predicted values of a model are to the actual values in the field - the Root Mean Square Error of Cross Validation (RMSECV) was used. This is the accuracy of the final selected PLS model from the cross validation process. RMSE is the overall deviation of the predicted SSC values from the field tree community structure and diversity values, expressed as equation 2.8. For comparing predictive models of differing SSC units, the normalized RMSECV was used (equation 2.9). The smaller the NRMSE of Cross Validation, the stronger the predictive power of the PLS model.

$$RMSE = \frac{1}{N}\sum_i^N (p_i - o_i)^2 \qquad [2.8]$$

$$NRMSECV = \frac{RMSECV}{\bar{x}} \qquad [2.9]$$

Where RMSE is the Root Mean Square Error, NRMSECV is the Normalized RMSE of Cross Validation, p is predicted complexity index value, O is the observed complexity index value, N is total number in predicted to observed complexity index value comparisons, $\bar{x}$ is the mean observed SSC value.

2.3. RESULTS

2.3.1. Relationships between structural complexity and topographic variables

Figure 2.2 shows the spatial distribution of the topographic variables (TWI -a, slope-b, Area Solar Radiation – c and elevation - d) on the reforested area.

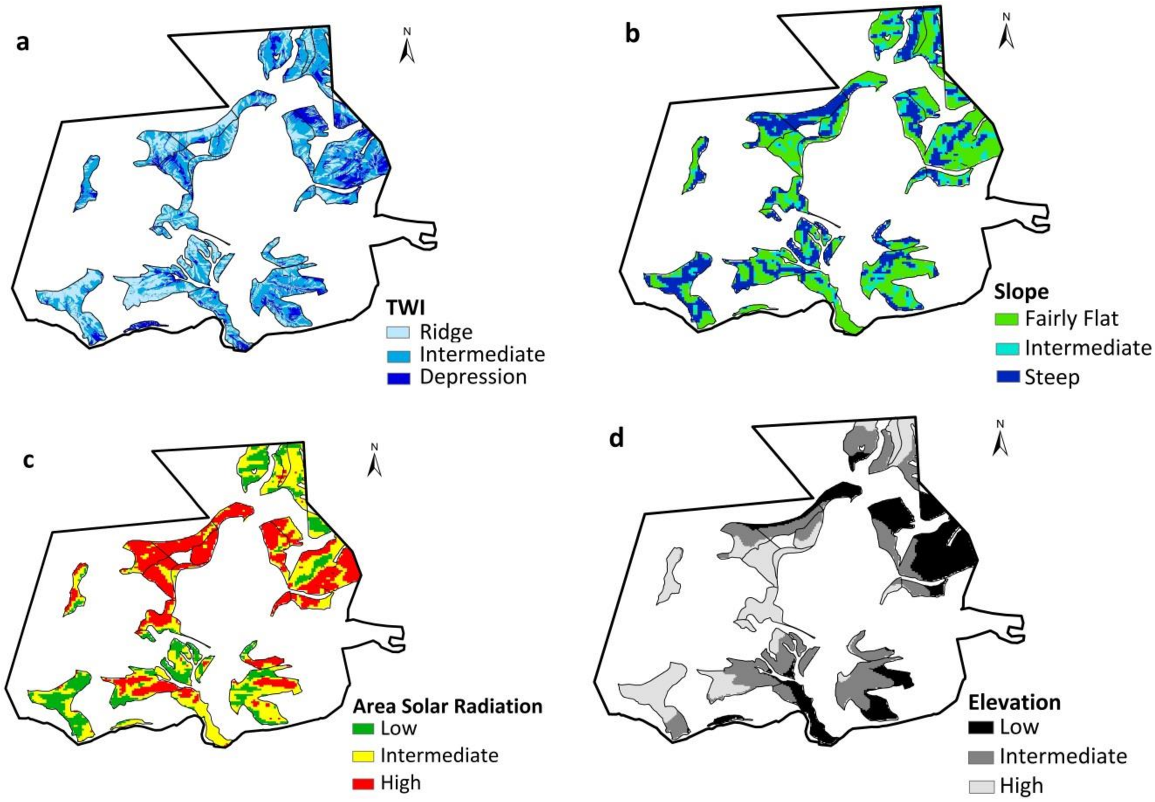

Figure 2. 2: The spatial distribution of the topographic variables extracted from the reforested area (a – TWI, b – slope, c- Area Solar Radiation and d – Elevation).

Based on a 95% confidence interval, all the topographic variables had a significant effect on stand structural complexity (SSC). Results for the TWI classes One Way ANOVA were (F (2,85) = 22.563, p = 0.0005), with SSC difference between all TWI classes (Table 2.2). The slope classes had a significant difference on SSC ($F(2,85)$ = 37.638, p = 0.0005), with only the fairly flat slopes having a different SSC from the intermediate and steep (Table 2.2). Area Solar Radiation (ASR) were ($F(2,85)$ = 10.018, p = 0.0005), with only the fairly flat slopes having a different SSC from the intermediate and high slopes (Table 2.2) while elevation were ($F(2,84)$ = 6.294, p = 0.003) with only the low and high elevations with different SSC (Table 2.2). Stand age were ($F(2,84)$ = 3.422, p = 0.037) - post-hoc test for age classes, with only the 2009/2010 and 2011/2012 sites having different SSC (Table 2.2). A summary of the mean stand structural complexities for the topographic classes and stand age is provided in Figure 2.3. A correlation analysis showed that the

TWI had the strongest correlation (R= 0.72), while stand age had the weakest correlation (R= 0.27) with SSC. Slope, ASR and elevation had a correlation of 0.69, 0.55 and 0.34, respectively.

Table 2. 2: Tukey's Post-Hoc Test of differences in SSC between classes.

Variable	Class		Class	
TWI		Ridges	Intermediate	Depressions
	Ridges	1		
	Intermediate	0.036	1	
	Depressions	0.0005	0.0005	1
Slope		Fairly Flat	Intermediate	Steep
	Fairly Flat	1		
	Intermediate	0.0005	1	
	Steep	0.0005	0.523	1
ASR		Low	Intermediate	High
	Low	1		
	Intermediate	0.04	1	
	High	0.0005	0.116	1
Elevation		Low Altitude	Intermediate	High Altitude
	Low Altitude	1		
	Intermediate	0.079	1	
	High Altitude	0.002	0.338	1
Stand Ages		2009/2010	2010/2011	2011/2012
	2009/2010	1		
	2010/2011	0.893	1	
	2011/2012	0.049	0.149	1

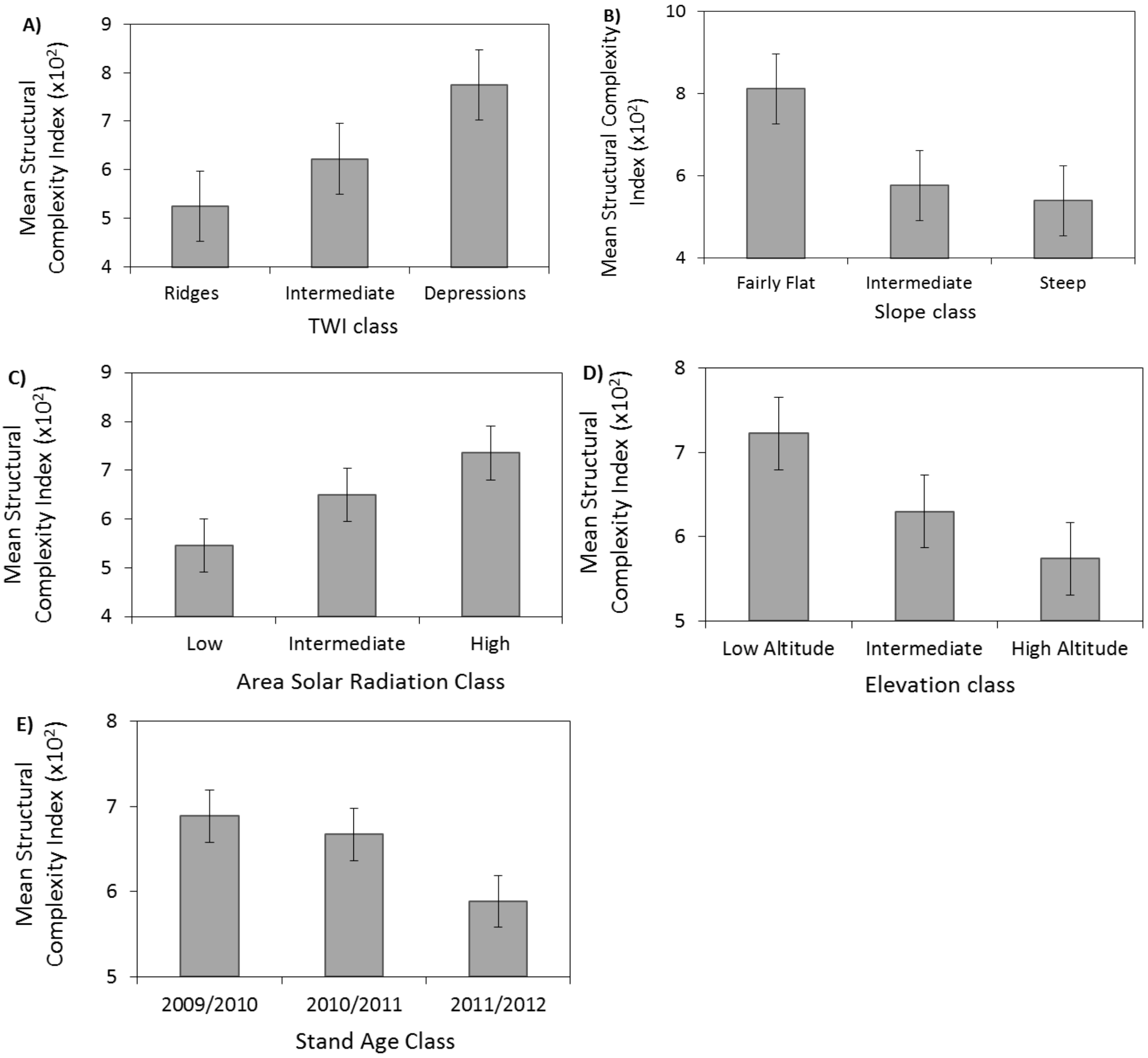

Figure 2. 3: Relationship between SSC and topographic variables a-TWI, b-Slope, c-Area Solar Radiation, d-elevation and d-Stand age (MSCI – Mean Structural Complexity Index).

2.3.2. Modelling stand structural complexity

To spatially model stand structural complexity (SSC) in relation topographic variables, PLS regression models were developed and their algebraic formulae derived (Equation 2.10). At an optimal latent variable number of 2, the PLS model for structural complexity index performed strongly at an RMSECV of 91.793 and R2 CV of 0.736. Its NRMSECV was 0.147. Figure 2.4 shows the spatial distribution of the structural complexity based on this PLS model. Based on the variable importance (VIP) function, TWI had the highest value of determining SSC (1.729), which was above slope (1.575), ASR (1.065), elevation (0.480) and stand age (0.350) (Figure 2.5).

HC= 10.018*TWI-14.881*Slope+0.0012*ASR-0.3016*Elevation+14.370*Stand Age-13.441 [2.10]

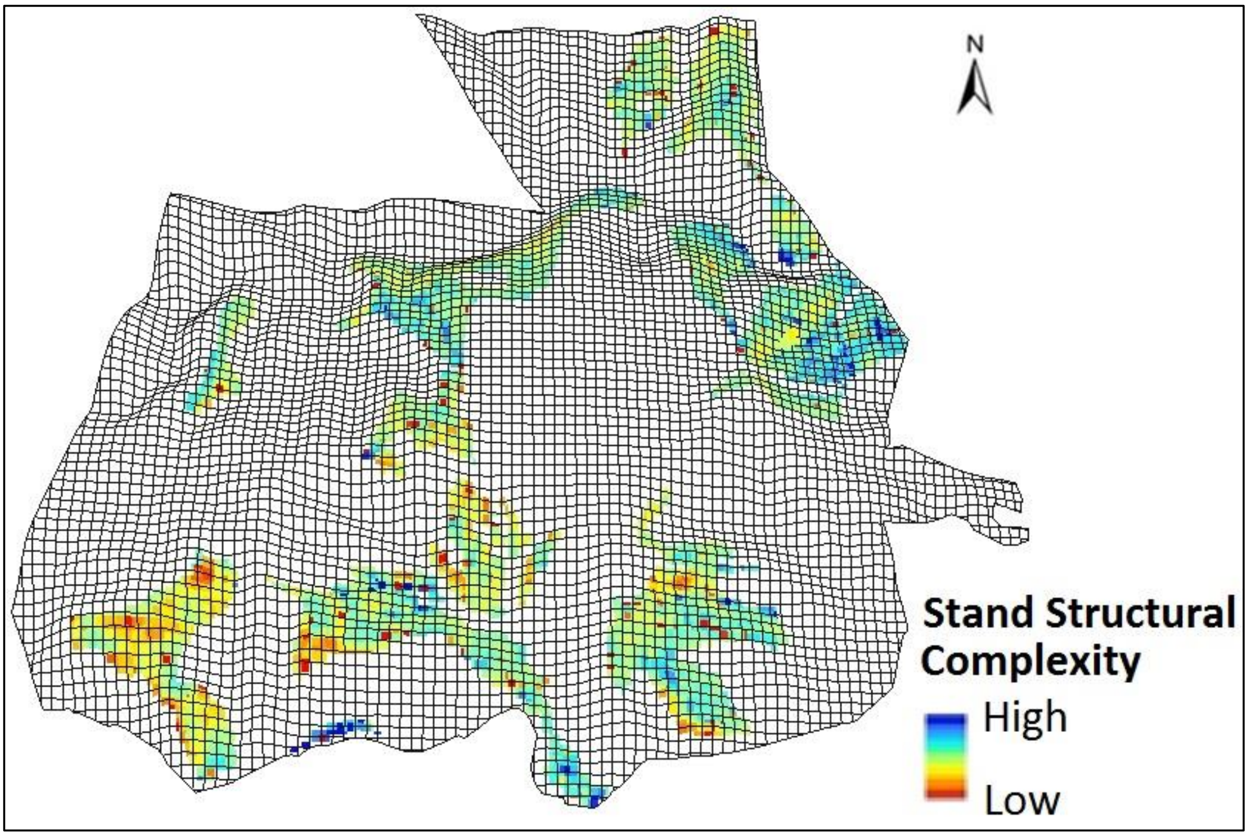

Figure 2. 4: The spatial distribution of the predicted SSC.

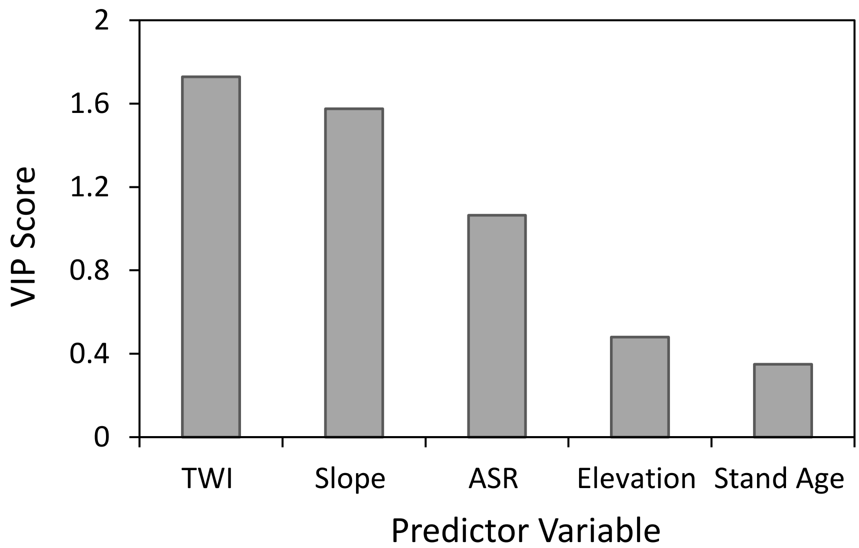

Figure 2. 5: VIP scores of predictor variables in determining SSC.

2.4. DISCUSSION AND CONCLUSIONS

2.4.1 Discussion

The emergence of SSC as a superior indicator of ecological performance has increased the need for its spatially explicit information. This study sought to i) use topographic variables to predict SSC within a reforested urban landscape and ii) to rank the importance of the topographic variables on these topographic patterns. To date, studies to determine SSC have been mainly restricted to ecological data that include Leaf Area Index, stem diameter, Net Primary Productivity, basal area, tree height and species composition (Valencia et al. 2004, Aragão et al. 2009, Chave et al. 2005, Girardin et al. 2010, Ruiz-Labourdette et al. 2012, Zheng et al. 2008). Others have used remotely sensed image characteristics. Ozdemir and Karnieli (2011) for instance predicted SSC to a Gini coefficient 0.214814815 NRMSECV using the image texture derived from WorldView-2 imagery, while Jinghui et al. (2016) achieved a Pielou Index of 0.274 NRMSECV using the Spectral and Textural Information Derived from SPOT-5 Satellite Images. Using LIDAR composite metrics and machine learning, Zhao et al. (2011) predicted aboveground biomass and Leaf Area Index to 0.18 and 0.166 NRMSECV respectively while Castillo-Santiago, Ricker and de Jong (2010) estimated basal area and canopy height to 0.228 and 0.161 NRMSECV respectively, using SPOT-5 satellite imagery. Using topographic variables and multispectral airborne imagery based on a redundancy analysis, Pasher and King (2010) captured only 35% of the total field variance, with an RMSE of 19.9%, while Cohen et al. (2001) attained a 12-23 % RMSE prediction accuracy using forest cover attributes with the Landsat TM. Similar to Carrascal et al. (2009) and Luedeling and Gassner (2012), this study achieved a high prediction accuracy (0.147 NRMSECV). I attribute this higher prediction accuracy to the adoption of the PLS technique that reduced the complex and interrelated data into explanatory components of SSC, maximizing covariance with the topographic variables.

There was a visible spatial variation in SSC in different topographic variables, with TWI as a strongest predictor of SSC. TWI is determined by soil moisture's downslope gravitational movement, hence TWI typically increases downslope (Sörensen, Zinko and Seibert 2006). As noted by Homeier et al. (2010) and Balvanera et al. (2002), this downslope soil moisture gradient increases downslope vegetation carrying capacity and SSC. According to Paoli and Curran (2007), the downslope soil moisture also creates nutrient pooling, hence trees in a depression or lower altitude benefit from relatively higher amounts of soil nutrients. In this study, the effect of the soil moisture gradient and associated nutrients is evident in the significant differences in SSC between all the slope ranges. Areas characterised by higher TWI (i.e. valley moisture sinks) had higher SSC than areas with lower TWI (i.e. ridge moisture drains).

In this study, slope was the second strongest predictor of SSC. The strong negative correlation between slope and SSC is consistent with Homeier et al. (2010) and Joseph et al. (2008). According to Webb et al. (1999), slope gradient represents the level of relative disturbance within a landscape. Steeper slopes are often more vulnerable to processes influenced by gravitation such as soil erosion and mass soil movement. Such processes result in erosion on steep slopes and deposition at gentle slopes and flatter areas, causing a topsoil and nutrient gradient, which influence SSC (Joseph et al. 2008, Yirdaw et al. 2015, Takyu, Aiba and Kitayama 2002).

Area Solar Radiation (ASR) had a moderate effect on the spatial distribution of SSC. ASR represents the variation in solar exposure as a result of the slope face direction. As aforementioned, its topographic variation creates a gradient in insolation, precipitation and transpiration (Wang et al. 2009, Kuebler et al. 2016, Webb et al. 1999), which may determine SSC. As insolation, precipitation and transpiration are known to strongly influence tree growth, ASR gradient creates a corresponding carrying capacity gradient, which influences SSC. In the southern hemisphere, north/east facing slopes are often characterised by higher SSC than the south/west facing slopes (Yirdaw et al. 2015, Balvanera et al. 2002). This is attributed to the southern hemisphere's often wetter and more humid north east -facing slopes and drier south west-facing slopes. However, due the moderate correlation between ASR and SSC in this study, it can be concluded that the limited variation in topography and insolation is a weaker determinant of SSC. Furthermore, the area experiences significant insolation throughout the year.

Although elevation was the least important topographic determinant of SSC, there was a significant difference in SSC between lower and higher altitudes. The downslope gravitational pull of loose soil acts as a practical proxy of edaphic gradients that directly affects tree growth (Oliveira-Filho et al. 2001, Wilcke et al. 2011, Clark and Clark 2000). Other factors that may be influenced by altitude include soil fertility, soil moisture and soil and surface temperature (Wolf et al. 2011, Wilcke et al. 2008, Ou et al. 2014, Fries et al. 2009, Wilcke et al. 2011). Hence, Homeier et al. (2010) and Clark and Clark (2000) conclude that trees at the low elevations are often characterised by higher stand structural complexities. However, in contradiction to a number of studies (Homeier et al. 2010, Clark and Clark 2000, Joseph et al. 2012), this study found a weak relationship between elevation and SSC. This can be attributed to the study area's "constrained geographic space" noted by Raes (2012) that leads to a weaker co-relation between elevation and vegetation growth.

Stand age is known to significantly influence tree size (Boninsegna et al. 1989, Burley, Phillips and Ooi 2007), however in this study, stand age showed a weak positive correlation with SSC. Unlike single dimension tree attributes such as canopy height and stem diameter, SSC is influenced by other stand attributes like species richness, which do not necessarily increase linearly over time. For example, within the establishment and developmental years of reforestation, species richness change may be dramatically influenced by tree mortality (Van Mantgem et al. 2009, Lutz and Halpern 2006), which could influence SSC.

As noted by Balvanera et al. (2002), an area's spatial extent strongly determines the influence of bio-physical factors on SSC. At a localized landscape, the current study has shown that topographic variables like TWI and slope are strong determinants of SSC. In consistency with Gallardo-Cruz et al. (2009), this study established that different topographic variables, characterised by varying biophysical processes, have varying influences on the SSC. Hence, a combination of different topographic variables in this study was useful for predicting SSC in the re-forested urban landscape. In this study the PLS technique and topographic datasets were useful in determining a re-forested landscape's SSC. Such determination is valuable in the management of urban environment and mitigation of climate change, biodiversity loss and associated impacts.

2.4.2 Conclusions

This chapter sought to i) predict the spatial patterns in stand structural complexity (SSC) within a reforested urban landscape using topographic variables and ii) rank the importance of the topographic variables on these topographic patterns. The chapter findings show that;

- The PLS model performed with high accuracy in predicting SSC.
- The highest SSC was located at lower elevation in flatter depressions that were facing north/east.
- The importance of the variables in predicting SSC in decreasing order were TWI, slope, ASR, elevation and stand age.

CHAPTER THREE

Determining tree stand structural complexity using remotely sensed data and integrated topographic characteristics in a re-forested urban landscape

This chapter is based on:

Sithole, K., Odindi, J. and Mutanga, O., 2017. Determining tree stand structural complexity using remotely sensed data and integrated topographic characteristics in a re-forested urban landscape. South African Journal of Science, In Preparation.

3.1 INTRODUCTION

Urban reforestation has been identified as one of the best practices against the adverse impacts associated with urbanisation. Reforestation mitigates for climate change as reforested areas act as carbon sinks (Luyssaert et al. 2008). Furthermore, urban reforestation reverses biodiversity loss and promotes ecological succession (Catterall et al. 2004, Kanowski et al. 2003). Reforestation has also been found to improve other ecological functions such as water purification (Fiquepron et al. 2013), flood attenuation (Dwyer et al. 1992) and absorption of air pollutants (Nowak et al. 2006).

Implementation of effective urban reforestation decisions requires quantitative and spatially explicit monitoring of the ecological performance of reforested areas across an urban landscape. Due to the high demand of urban spaces, these decisions involve determination of areas with potential to maximise ecological performance (Sithole, Odindi and Mutanga 2017).

Stand structural complexity (SSC) provides researchers with an improved indicator to compare the ecological performance of tree stands across landscapes (McElhinny et al. 2005). Hence, SSC has been identified as a reliable indicator of ecological performance, and has recently been used to compare ecological performance between tree stands and to determine carbon sequestration, habitat diversity and biodiversity change (Lindenmayer et al. 2000, Franklin and Van Pelt 2004, Lamonaca et al. 2008). SSC is a multi-dimensional index that includes horizontal (i.e. basal area), vertical (i.e. canopy height) and species (i.e. species richness). There are numerous SSC indices that have been developed through varying mathematical combinations of different structural attributes, which offer varying estimations of ecological performance. These include Structural Complexity Index by Zenner (2000) which combines tree height and their spatial arrangement and Stand Diversity Index by Neumann and Starlinger (2001) that combines species richness, tree spacing, diameter at breast height (DBH) and crown size. Adopted in this study is the Stand Structural Complexity Index (SSCI) originally proposed by Holdridge (1967) that combines canopy height, stem diameter, basal area and species richness. This approach is particularly appealing due to its wide adoption in existing forestry databases and its processing simplicity.

To date ecological performance of tree stands has been commonly conducted through recurring field surveys and processing of aerial photographs. Such techniques are cumbersome, time consuming, costly per unit area and may be inconsistent within a landscape. The emergence of remote sensing (RS) approaches offers spatially explicit, repetitive and quantitatively consistent means of monitoring the ecological performance of tree stands (Peerbhay et al. 2013, Wunderle et al. 2007). Whereas remote sensing has been used to determine useful ecological performance indicators such as tree diameter (Wolter et al. 2009), basal area (Hudak et al. 2006), leaf area index (Pekin and Macfarlane 2009), canopy height (Lefsky et al. 2005), canopy cover (Smith et al. 2009), stand age (Wunderle et al. 2009), stem density (Franco-Lopez et al. 2001), species composition (Gillespie et al. 2008) and stand biomass (Foody et al. 2001), there is a lack of studies that have used RS data sets to predict SSC. The recent technical improvements in the freely available multispectral satellites, the now freely available Sentinel 2 (S-2), offer great potential in determining SSC. The S-2, using its multi-spectral instrument (MSI) technology, offers 13 spectral channels in the visible/near infrared (VNIR) and short wave infrared spectral range (SWIR) ranging from 10 - 60 m spatial resolution at a 5-day temporal resolution. Its three red edge spectral channels can be used to generate VIs, useful for vegetation analysis. The S2REP for instance is an S-2 based VI sensitive to variation in leaf chlorophyll content, hence valuable in vegetation analysis (Frampton et al. 2013).

However, despite the S-2 potential, its spectral and spatial data characteristics remain a limitation in determining finer variations in stand attributes. Consequently, some studies have proposed the use of ancillary environmental variables such as soil fertility (Wolf et al. 2011), altitude (Gallardo-Cruz et al. 2009), soil moisture (Fries et al. 2009) and topography (Kuebler et al. 2016) to compensate for these limitations. Topographic variables, despite their influence on vegetation have particularly received little attention in predicting SSC. Topographic variables do not directly affect tree growth or SSC, but indirectly though their relationship with forest-influencing factors such as nutrient availability (Paoli and Curran 2007), soil moisture

(Fries et al. 2009), precipitation (Rollenbeck 2006) and surface temperature (Fries et al. 2009). For instance, slope steepness determines soil erosion and deposition (Webb et al. 1999, Vorpahl et al. 2012), while the Topographic Wetness Index (TWI) represents the relative distribution of soil surface moisture based on the terrain surface. The Area Solar Radiation (ASR) is the representation of the variation in solar exposure as a result of the slope face direction, which influences surface air temperature (Fries et al. 2009) and micro-precipitation (Rollenbeck 2006). Elevation on the other hand has been found to be correlated to soil moisture (Wilcke et al. 2011) and soil nutrient pooling (Oliveira-Filho et al. 2001) Previously, good quality DEMs, for deriving fine scaled topographic characteristics were not readily available. However, a recent proliferation of freely available high resolution DEMs make them ideal for cost-effective operational use. Therefore integrating S-2 imagery with topographic information provides an improved ability to accurately determine SSC whilst minimizing operational costs. Hence this study sought to evaluate the utility of integrating S-2-based VIs with topographic variables for determining the SSC in a reforested landscape.

3.2 METHODS AND MATERIALS

3.2.1. Sampling plots

Although the buffer zone has been reforested annually (Figure 3.1a), only the 2009/2010, 2010/2011 and 2011/2012 reforestation zones were sampled as they were considered to be of adequate age to allow for sufficient growth for SSC analysis (Figure 3.1b). Using stratified random sampling, 90 sampling plots were identified across these reforestation zones. The sampling plots were 30 x 30 m and at least 60m apart to avoid overlap in landscape coverage.

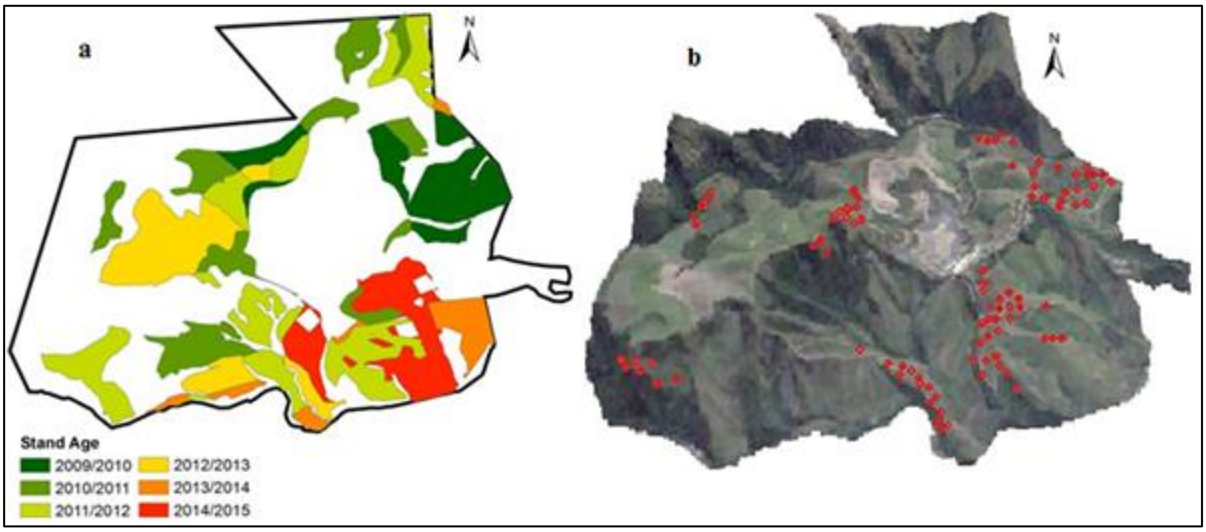

Figure 3. 1: Reforestation stand ages and sampling points.

3.2.2. *Stand Structural Complexity data*

To determine the SSC index, stand structural attributes (canopy height, tree diameter, stem density and species richness) were captured at each sampling plot. Using a levelling rod with ~0.05 m accuracy, mean stand canopy height was captured in each sampling plot (in this study canopy height refers to the height of the highest branch of a tree). To determine the tree diameter, the tree diameter-at-ankle-height (DAH) was used as recommended in literature (Van Leeuwen and Nieuwenhuis 2010, Maltamo et al. 2009, Pommerening 2002, Wolter et al. 2009). The total tree count in a plot, divided by the plot area represented the stem density. Species richness was a count of the number of species within each plot.

The four aforementioned stand attributes data were used to compute the SSC index (SCCI) (equation 3.1) (Holdridge 1967). Its multi-dimensionality - species diversity, horizontal (tree diameter and stem density) and vertical stand dimensions (canopy height) - makes it appealing as an ecological performance indicator of forest characteristics such as carbon sequestration, habitat diversity and biodiversity change (McKenny et al. 2006, Neumann and Starlinger 2001, Lindenmayer et al. 2000).

$$SSCI = H \times BA \times n \times N \qquad [\ 3.1\ ]$$

where SSCI is the Stand Structural Complexity Index, H is the canopy height, BA is the surface area covered by tree stems, n is the number of stems per ha, and N is the number of species.

3.2.3. *S-2 Imagery*

Imagery Acquisition

A cloud-free S-2 A Level 1C acquired on 5 January 2016 was downloaded from the European Space Agency's (ESA's) online Sentinel Data Hub (https://scihub.copernicus.eu/), pre-processed (radiometric, geometric and terrain corrected) into a S-2 B image using ESA SNAP software and used to derive VIs. S-2 captures spectral data at 13 bands detailed in Table 3.1. S-2's unique spatial and spectral characteristics offer a great opportunity for determination of SSC.

Table 3. 1: Spectral attributes of S-2

Spectral Band	Central Wavelength (nm)	Bandwidth (nm)	Resolution (m)
Band 1 - Coastal / Aerosol	443	20	60
Band 2 - Blue	490	65	10
Band 3 - Green	560	35	10
Band 4 - Red	665	30	10
Band 5 - Vegetation Red Edge	705	15	20
Band 6 - Vegetation Red Edge	740	15	20
Band 7 - Vegetation Red Edge	783	20	20
Band 8 - NIR	842	115	10
Band 8A- Vegetation Red Edge	865	20	20
Band 9 – Water Vapour	945	20	60
Band 10 – SWIR - Cirrus	1380	30	60
Band 11 - SWIR	1610	90	20
Band 12 - SWIR	2190	180	20

Derivation of vegetation indices

Using ESA SNAP, 21 vegetation indices (VIs) were generated from the image. The VI values corresponding to the sampling plots were extracted and correlated with SSC. This was conducted through using a Pearson correlation between the SSC from the field and the generated VIs within Excel 2013. The four VIs that had the strongest correlation with SSC were selected for the predictive modelling process. These included – Sentinel 2 Red-Edge Position (S2REP), Red-Edge Inflection Point (REIP), Inverted Red-Edge Chlorophyll Index (IRECI), and Green Normalized Difference Vegetation index (GNDVI) (Table 3.2).

Table 3. 2: Equations of vegetation indices and the S-2 equations formulae

Vegetation Index	S-2 Bands Used	Sources
S2REP	705 + 35 * (0.5 * (B7 + B4) - B5) / (B6 - B5)	(Frampton et al. 2013)
REIP	700 + 40 * [(B4 + B7)/2 - B5)/(B6 - B5]	(Guyot, Baret and Major 1988)
IRECI	[(B07 - B04) * B06 / B05]	(Frampton et al. 2013)
GNDVI	(B8 - B3)/(B8 + B3)	(Gitelson, Kaufman and Merzlyak 1996)

3.2.4. Topographic data

A high resolution (2 m) contour map was used to derive all the topographic variables i.e. elevation, Area Solar Radiation, slope and the Topographic Wetness Index. This was achieved by first converting the contour map into a Digital Elevation Model (DEM). The produced DEM had a high (0.99 Pearson) correlation with the elevation measured using the Trimble GPS. The Topographic Wetness Index (TWI) was determined on a per pixel basis by combining local upslope contributing area (equation 3.2).

$$TWI= \ln (FA + 0.001)/ ((S/100) +0.001) \qquad [\ 3.2\ ]$$

Where TWI is the topographic wetness index, FA is the flow accumulation, and S is the slope percentage.

3.2.5. Predictive Model

Currently, there are multiple regression techniques available to integrate the S-2 indices and the topographic variables to predict SSC. However, the Partial Least Squares (PLS) technique has recently generated a lot of interest within the remote sensing community (Peerbhay et al. 2014, Wolter et al. 2008, Carrascal et al. 2009). The PLS is useful for its ability to compress a set of predictor variables into a few latent variables that have maximum covariance with the response variables. The key advantages of PLS is its relative ease of application and its ability to suppress multicollinearity in data and identify relevant predictor variables amongst numerous predictor variables with their estimate magnitudes of importance on the response variable (Wolter et al. 2009). Therefore, the PLS technique offers great potential for integrating topographic variables and S-2 indices to predict the spatial patterns in SSC within a re-forested urban landscape. Hence, the PLS was chosen in this study due to its previous success in landscape analysis. The current study used the PLS tool within the MATLAB statistical environment (PLS Toolbox) to predict SSC.

Model Optimisation

To reduce the potential of overfitting due to correlated predictor variables, cross-validation optimisation was conducted. The CV optimisation iteratively processes and adds each latent component to the PLS model for the determination of the predicted SSC. The differences between actual and predicted SSC are calculated for validation data at each number of latent components. To determine the model’s predictive ability at each latent variable number, the predictive residual sum of squares (PRESS) is calculated through the sum of the squared differences in actual and predicted SSC. This process is repeated until the addition of more latent components to the model does not produce an improvement in the PRESS. Thus the latent components which possess high non-explanatory noise and multicollinearity among predictor variables are excluded from the PLS model. There are various methods which offer different ways of subdividing the data for cross validation. As the current study's data was relatively large with randomly ordered samples, the venetian blinds cross validation was used. The CV selected latent components were used to derive the end-point PLS model and generate the SSC spatial maps.

3.2.6. Variable Importance in the Projection

A powerful ability of the PLS technique is to determine the relative importance of the predictor variables in predicting the SSC, through the Variable Importance in Projection (VIP). The VIP calculates the importance score of each predictor variable in explaining the SSC, which are then used for ranking the predictive power of each predictor variable as expressed by equation 3.3 (Wold et al. 2001). The higher the VIP score of a predictor variable, the higher that predictor variable is ranked for determining SSC.

$$\text{VIPk} = \sqrt{K \sum_{a=1}^{A}[(q_a^2 t_a^T t_a)(w_{ak}/||w_k||^2)] \,/ \sum_{a=1}^{A}(q_a^2 t_a^T t_a)} \qquad [3.3]$$

Where VIPk represents the importance of the kth predictor variable based on a PLS model with a latent components, K is the total number of predictor variables, w_{ak} is the corresponding loading weight of the kth predictor variable in the ath latent component, and qa, ta and wa are the column vectors.

3.2.7. Prediction Accuracy

The predictive power of the end-point PLS model was evaluated using the Root Mean Square Error of Cross Validation (RMSECV). RMSE represents the overall deviation of the predicted SSC values from the observed SSC values as defined by equation 3.4. The normalized RMSECV was used for comparison with predictive models of differing SSC units in other studies, expressed in equation 3.5. The strength of the PLS model's predictive power is negatively correlated with its NRMSE of Cross Validation,

$$RMSE \ = \frac{1}{N}\sum_{i}^{N}(p_i - o_i)^2 \qquad [3.4]$$

$$NRMSECV = \frac{RMSECV}{\bar{x}} \qquad [3.5]$$

Where RMSE is the Root Mean Square Error, N is total number in predicted to observed complexity index value comparisons, p is predicted complexity index value, O is the observed complexity index value, NRMSECV is the Normalized RMSE of Cross Validation, $\bar{x}$ is the mean observed stand structural complexity value.

3.3 RESULTS

3.3.1. Relationship between structural complexity with vegetation indices and topographic variables

Fig. 3.2 depicts the correlation between SSC and the predictor variables (VIs, topographic variables and stand age). Whereas the S-2 VIs had weak Pearson correlations with SSC, the topographic variables had strong correlations. For instance, TWI had the strongest coefficient of correlation (R = 0.72), while Slope and ASR had a coefficient of correlation of 0.69 and 0.55 respectively. The S2REP and REIP had the strongest coefficient of correlation (0.36) amongst the S-2 VIs, which was better than that of elevation (R = 0.34), while IRECI and GNDVI had a weak coefficient of correlation with SSC of 0.31 and 0.29 respectively. Stand age had the overall weakest coefficient of correlation (R = 0.27) with SSC among all the variables.

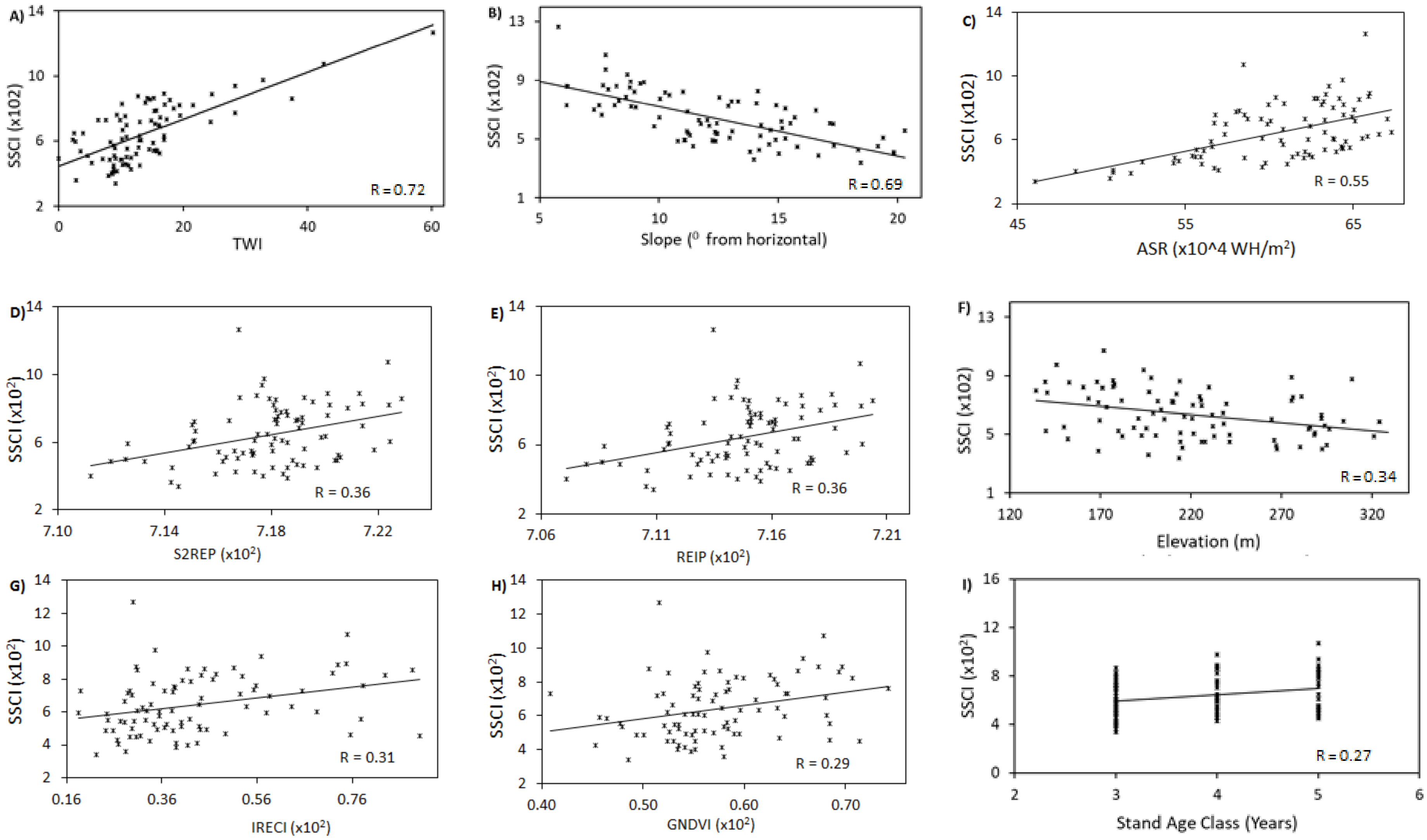

Figure 3. 2: Relationship between stand structural complexity with a) TWI, b) slope, c) area solar radiation, d) S2 REP, e) REIP, f) elevation, g) IRECI, h) GNDVI, and i) stand age. Where SSCI = Stand Structural Complexity Index.

3.3.2. *Predicting stand structural complexity based on topographic variables and S-2-based vegetation indices.*

The PLS regression models were developed and their algebraic formulae derived as expressed in Equation 3.6, 3.7 and 3.8 for VI-only, Topography-only and the combination of VIs and topography respectively. Table 3.3 describes the accuracy of the models. With the NRMSECV as the basis of model comparison, the PLS model of SSC based on VIs only performed moderately at 0.215 compared to the NRMSECV of the topography based model at 0.147. The combination of VIs and topography produced the highest accuracy (0.130 NRMSECV).

Table 3. 3: Description of models accuracies in predicting stand structural complexity

Model	R2CV	RMSECV	NRMSECV
VIs Only	0.281	134.043	0.215
Topography Only	0.736	91.793	0.147
Combination	0.790	80.937	0.130

$$SSC = 9.71559*S2REP + 8.50128*REIP + 170.142*IRECI + 387.505*GNDVI - 12713.5 \quad [3.6]$$

$$SSC = 10.02*TWI - 14.88*Slope + 0.0012*ASR - 0.3016*Elevation + 14.37*Stand\ Age + 431.73 \quad [3.7]$$

$$SSC = 8.281*TWI - 18.38*Slope + 3.80922*S2REP + 3.33284*REIP + 62.9459*IRECI + 228.897*GNDVI - 0.5963*Elevation + 0.0004*ASR + 12.07*Stand\ Age - 4701 \quad [3.8]$$

Based on the variable of importance (VIP) function, slope and TWI had the highest importance on SSC distribution at 2.416 and 2.228 respectively. The VIs were of relative importance at 0.7852, 0.7852, 0.6803 and 0.6342 for S2REP, REIP, IRECI and GNDVI respectively. Area Solar Radiation and stand age were the least important variables on the SSC distribution at 0.4316 and 0.3728 respectively. Fig. 3.3 provides a visual display of the variation in SSC as explained by the three PLS models.

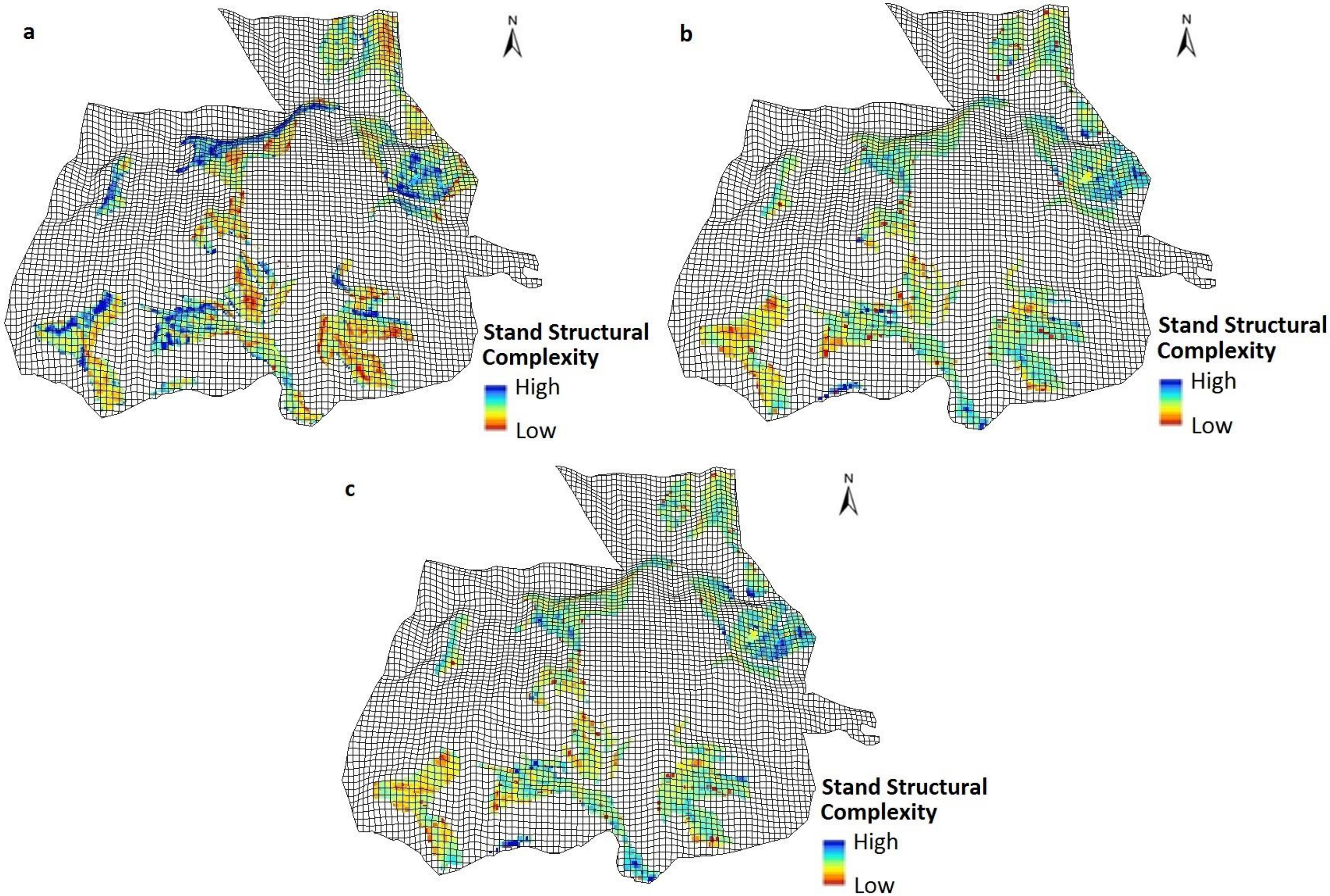

Figure 3. 3: Spatial distribution of predicted of SSC using (a) VIs only, (b) topographic variables only, and(c) a combination of VIs and topographic variables

3.4 DISCUSSION AND CONCLUSIONS

3.4.1 Discussion

The recent proliferation of SSC and the advances in S-2 and topographic data has increased the potential of an alternative cheaper approach to generate spatially explicit information about ecological performance of urban reforestation. The current study sought to i) evaluate the utility of S-2-based VIs for predicting SSC within a re-forested urban landscape, and ii) evaluate the utility of integrating S-2-based VIs with topographic variables for predicting the SSC using the PLS regression.

Interestingly, the S-2 VIs had weak Pearson correlations with SSC. This may be attributed to the nature of both the RS technology and SSC. RS captures the electromagnetic radiation reflected off surfaces, therefore it can be related to the vegetative activity (as vegetation indices) of surfaces (Nagendra 2001, Turner et al. 2003). Consequently RS VIs have been used to quantify various vegetative attributes such as stand biomass (Foody et al. 2001), canopy cover (Smith et al. 2009), species composition (Gillespie et al. 2008), and Leaf Area Index (Moser et al. 2007). The weak correlation between VIs and SSC can therefore be attributed to the fact that SSC are multidimensional indices of ecological performance, which are mathematically informed by various vegetative attributes such as basal area, canopy height, tree diameter and species richness. Hence, the particular vegetative attributes of the SSCI by Holdridge (1967) may be biased against VIs. As seen in the spatial map for instance, the S-2 based model tended to falsely exaggerate the differences in SSC across the landscapes. The areas which had higher biomass seemed to be depicted as areas with higher predicted SSC, which did not necessarily have actual higher SSC based on the field measurements.

Nonetheless the current study has demonstrated that the S-2-based model (0.215 NRMSECV) generated results with moderate prediction accuracy compared to past studies (Listopad et al. 2015, Torontow and King 2012, Kane et al. 2010). For instance Ozdemir and Karnieli (2011) predicted SSC to a Gini coefficient 0.214814815 NRMSECV using the image texture derived from WorldView-2 imagery, while Jinghui et al. (2016) achieved a Pielou Index of 0.274 NRMSECV using the Spectral and Textural Information Derived from SPOT-5 Satellite Images. Cohen et al. (2001) on the other hand attained a 0.12-0.23 NRMSE prediction accuracy using forest cover attributes with the Landsat TM. Due to spatial and spectral resolution limitations of multispectral RS datasets, past RS studies have been limited to LIDAR and hyperspectral RS to predict SSC (Lamonaca et al. 2008, Pasher and King 2010) . The predictive accuracy of the S-2 model may be attributed to both the improved technical abilities of S-2 instrument and the derivative ability of the PLS technique. The improved spatial and spectral resolution of S-2 compared to other freely available multispectral sensors, allowed the S-2 data to capture information about finer variations in vegetative activity of tree stands, which was then related to SSC. The PLS technique on the other hand offered the ability to exploit these fine vegetative variations in data by reducing the complex and interrelated S-2 VIs data into explanatory components of SSC, concurrently sieving out the noise, which maximized covariance with the S-2 VIs (Wolter et al. 2009).

The VIP ranking of the VIs provided another useful indication for the predictive accuracy of the S-2 based model. S2REP and REIP were the most important variables in predicting SSC. Interestingly these two VIs do not make use of the popular spectral bands amongst VIs (namely, the NIR and red band). The NIR/red band VI slope is known to be susceptible to reflectance saturation, as the NIR band experiences minimised absorption due to the tree cell structure and the red band is heavily influenced by the reflectance absorption due to the trees' chlorophyll content (Freitas, Mello and Cruz 2005). The S2REP and REIP make use of the three vegetation red edge bands, which have become popular for their ability to avoid reflectance saturation. The red edge band, a recent addition to VIs, is known to be sensitive to the steep changes in absorption and reflection between the red spectral range and the near infrared spectral range (Li et al. 2014). Although not significantly, the three S-2 RE bands may have improved the model's sensitivity to SSC, therefore improving the S-2 based model's ability to determine SSC.

Interestingly, the PLS model based only on topographic variables (0.147 NRMSECV) produced a higher accuracy than the PLS model based only on VIs (0.215 NRMSECV). This indicates that the topographic variables are stronger predictors of SSC compared to the multispectral S-2 VIs, in line with the combined VIP ranking. In agreement with (Torontow and King 2012), the topographic characteristics had the ability to discriminate SSC variations, which the multispectral S-2 image did not capture. This may be attributed to the higher spatial resolution of the topographic data (2 m) compared to that of the S-2 data (10 m and 20 m). Therefore, despite the good prediction accuracy of S-2 data compared to other multispectral RS, its spectral and spatial resolution is still a limitation to the extent to which it can predict SSC.

Consequently, there was a visible spatial variation in SSC with change in TWI and slope. These were also the most important determinants of SSC. The spatial maps show SSC to be highest at the low altitudes compared to the high altitudes. This is consistent with the earlier observation in the current study of TWI and slope having the highest correlation on SSC. TWI is determined by soil moisture's downslope gravitational movement, which creates downslope gradient in both soil and nutrients (Homeier et al. 2010, Paoli and Curran 2007). Hence there is the downslope gradient in vegetation carrying capacity and SSC. While slope represents the level of relative disturbance within a landscape (Yirdaw et al. 2015, Takyu et al. 2002). Steeper slopes tend to be more vulnerable to processes influenced by gravitation such as litter and soil movement. Such processes result in a topsoil and nutrient gradient which influences SSC. Whereas the "constrained geographic space" noted by Raes (2012) limited the influence of elevation on the SSC spatial variation. Therefore, the correlation of topographic variables with environmental gradients was important for predicting SSC.

Importantly, integrating topographic information with the S-2 data improved the overall prediction accuracy (0.130 NRMSECV), which was significantly improved from the S-2 only based model. Therefore, the topographic characteristics allowed for the model to capture ecological variations, which would otherwise not be discriminated. Hypothetically, the topographic variables captured patterns in SSC which are consistent with environmental gradients such as soil nutrients, soil moisture, insolation and vulnerabilities to disturbances (Baldeck et al. 2013, Bader and Ruijten 2008, Colgan et al. 2012, Homeier 2008, Vormisto, Tuomisto and Oksanen 2004, Jarvis 2005). For instance, Pasher and King (2010) used a combination high-resolution multispectral airborne imagery and topographic variables to predict SSC using a redundancy analysis, and achieved a prediction accuracy of 0.00398 bootstrapped NRMSE. This study achieved a high prediction accuracy of 0.130 NRMSE through combining the S-2-based VIs and topographic variables, a significant improvement to VI-only model. The improved prediction accuracy of the combined S-2/topographic variables model is a result of aforementioned explanatory power of the PLS technique and topographic information.

Furthermore, it is visually evident from the spatial maps that the topography only based map closely resembles the combined S-2/topography based map, unlike the S-2 only based map. This is in agreement to the prediction accuracies of these spatial maps, which indicate that the S-2 only based map is significantly lower in predictive accuracy compared to the combined S-2/topography, whilst the topography only based map had a smaller difference in prediction accuracy compared to the combined S-2/topography. As aforementioned, the S-2 based model tended to falsely exaggerate the differences in SSC across the landscapes, which is not useful for accurately comparing spatial variation in SSC. This result supports the argument that topographic characteristics may be valuable for not only solely predicting SSC but also further improving the prediction power of remotely sensed data.

The current study's use of the stand structural complexity index (SSCI) by Holdridge (1967) as an indicator of ecological performance makes it ideal for application in other study areas, as its input data sets are traditionally captured within forestry inventories. Furthermore, multiply studies have reliably used multispectral remotely sensed data to predict these data inputs (Wolter et al. 2008, Yu et al. 2006, Hudak et al. 2006, Franco-Lopez et al. 2001). Overall, the current study has shown that integrating S-2 data and topographic variables can be a viable alternative of predicting SSC, and beneficial for easily and cheaply informing monitoring and evaluation systems of reforestation programmes.

3.4.2 Conclusions

This chapter set out to i) evaluate the utility of S-2-based VIs for predicting SSC within a re-forested urban landscape, ii) evaluate the utility of integrating S-2-based VIs with topographic variables for predicting the SSC using the PLS regression, and iii) determine the relative importance of the S-2-based VIs and the topographic variables on SSC. The chapter findings show that;

- S-2-based VIs on their own produced a moderate predictive accuracy.
- Integrating the S-2-based VIs with topographic data produced a high predictive accuracy, which performed well compared to past studies.
- The importance of the variables in predicting SSC in decreasing order were Slope, TWI, ASR, S2REP, REIP, elevation, IRECI, GNDVI and stand age.

CHAPTER FOUR

Conclusion

4.1 INTRODUCTION

In an attempt to develop an alternative cost effective approach for monitoring and evaluation (M&E) of reforestation programmes, the current study set out to determine the utility of Sentinel 2 data and integrated topographic characteristics to determine tree stand structural complexity across a re-forested urban landscape. In this chapter, aims and respective objectives presented in Chapter One are reviewed against the findings. Furthermore, the major conclusions, limitations and recommendations for future research are also highlighted.

4.2 REVIEWING OF AIMS AND OBJECTIVES

4.2.1. The first aim and objectives

Aim: Assessing the utility of topographic variables in predicting tree stand structural complexity in a re-forested urban landscape.

Objectives: - Assess the utility of topographic variables (TWI, slope, ASR and elevation) in determining SSC within a reforested urban landscape.
- Rank the importance of the above topographic variables on these SSC patterns.

For effective implementation of urban reforestation, monitoring and evaluation (M&E) is vital. Tree stand structural complexity (SSC) indices have offered a useful alternative indicator and comparator of ecological performance of reforested tree stands across a re-forested landscape. Nonetheless, field based M&E of SSC are cumbersome and inefficient. This study has shown that topographic information derived from Digital Elevation Models is useful in predicting the spatial variation in SSC of the re-forested trees across a landscape. Furthermore, the topographic variables are of different importance on the SSC. Slope and TWI had the most influence on SSC due to the underlying tree growth factors, which are strongly correlated to these topographic variables. However due to the “constrained geographic space” noted by Raes (2012), elevational range was small and of limited influence on the SSC of the landscape. These results reiterated the importance of topographic gradients on SSC, and their importance as aids to urban environmental management.

4.2.2. The second aim and objectives

Aim: Determine tree stand structural complexity using remotely sensed data and integrated topographic characteristics in a re-forested urban landscape.

Objectives: - Evaluate the utility of S-2-based VIs for predicting SSC within a re-forested urban landscape.

- Assess the utility of integrating S-2-based VIs with topographic variables for predicting the SSC using the PLS regression.
- Determine the relative importance of the S-2-based VIs/topographic variables on SSC.

The advancements in the Sentinel 2 (S-2) instrument offer an improved potential of using freely available multispectral RS to effectively and efficiently monitor SSC across re-forested urban landscapes. However, despite the weak correlation between the S-2 VIs and SSC, the results indicate that S-2 had moderate SSC predictive ability. Furthermore, the results showed the ability of the PLS technique to compress and derive the most important information to predict the SSC, and also determine the relative importance of the predictor variables. Amongst the S-2 VIs, it was the VIs which made use of two or more of the red edge bands, which performed most accurately. The red edge bands are well known for overcoming the limitation of reflectance saturation within the NIR and red bands. Interestingly, the topographic variables were of more importance in determining the SSC. Overall, this study has demonstrated the value of integrating the freely available S-2 data with topographic characteristics to monitor and evaluate the ecological performance of reforested urban landscape, and serve as an aid to urban environmental management.

4.3 LIMITATIONS & RECOMMENDATIONS

- Although the topographic information proved beneficial to determining SSC, the integration of other biophysical variables would be useful for improving the accuracy in future studies. For example, soil gradients may capture SSC variations which are not discriminable from topographical gradients.

- The spatial variation in SSC across the reforested urban landscape was limited by the age of reforestation. The oldest reforested trees were 5/6 years old. Future studies should assess older reforested study sites, as the differences in growth rates of reforested tree stands may be more pronounced.

- The determination of SSC using the S-2 data was hindered by the mixed pixel phenomena. As much as there was an effort to exclude these, some of the sampling plots had remnants of previous vegetation such as sugarcane, alien invasive plants, and a few non- reforested trees. Future studies should preferably target study areas with completely reforested vegetation.

- The weak Pearson correlations between the S-2 VIs and SSCIs demand that future studies explore the relationship of S-2 VIs with other SSC indices. Due to the wide spectrum of available SSCIs, with their varying combinations of vegetative attributes, these correlations may vary widely dependent of SSC index used.

- The performance of other regression techniques in comparison to this PLS technique should also be pursued in future studies.

4.4 CONCLUDING REMARKS

It is concluded that the PLS was useful as a technique to determine SSC. It was as accurate, as models developed in previous studies undertaken to tree stand structures and structural complexity.

SSC often vary across topographic gradients. These are driven by the underlying topography-correlated factors which affect tree growth. The topographic gradients are of different importance on SSC, and these can be used to predict the spatial patterns in reforested tree growth.

The multispectral S-2 data had moderate ability in determining SSC, surpassed by the topography-based model. Nonetheless the S-2 was still useful in determining SSC, especially as a freely available multispectral instrument.

The S-2 data with integrated topographic information offered the highest prediction accuracy amongst the predictor combinations. This is encouraging for future researchers looking to improve RS-based predictions of ecological infrastructure. This has contributed to other studies which have sought to improve the predictions of RS through integrating it with other data sources. Specifically, it has contributed to the determination of SSC as an improved indicator of ecological performance across re-forested urban landscapes.

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