Refinement of predictions of forest structure using remote sensing techniques in a topographically complex landscape

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REFINEMENT OF PREDICTIONS OF FOREST STRUCTURE AND BIOMASS USING REMOTE SENSING TECHNIQUES IN A TOPOGRAPHICALLY COMPLEX LANDSCAPE

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A thesis submitted in the fulfilment of the requirements for the degree of Doctor of Philosophy

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“Almost everything - all external expectations, all pride, all fear of embarrassment and failure - these things just fall away in the face of death, leaving only what is truly important. Remembering that you are going to die is the best way I know to avoid the trap of thinking you have something to lose. You are already naked.

There is no reason not to follow your heart”

Steve Jobs (1955- )
DECLARATION

I certify that the work presented in this thesis is, to the best of my knowledge and belief, original, except as acknowledged in the text, and that material has not been submitted, either in whole or in part, for a degree at this or any other university.

I acknowledge that I have read and understood the University’s rules, requirements, procedures and policy relating to my higher degree research award and to my thesis. I certify that I have complied with the rules, requirements, procedures, and policy of the University (as they may be from time to time).

Printed Name: Sisira Ediriweera

Signature: __________________________________________

Date: ______________________________________________
Abstract

Topography has an important influence on forest structure and composition. Understanding of structure, composition, and functions in Australian plant communities in a topographically dissected landscape has been substantially advanced in recent years. While much is known about variations in structure and composition of the plant communities in dissected topography, scant information is available about how to assess such variations using remotely sensed data. Advantages of investigation of forest structure using remote sensing include the ability to obtain measurements from any location in a forested area, the speed with which remotely sensed data can be collected and processed, the relatively low cost of various remote sensing data, and the ability to collect data easily in extensive areas containing diverse topography. In order to improve the understanding of how to examine the variation of forest structure and biomass using remotely sensed data in topographically complex landscape, this study investigated a number of strategies using different forms of remotely sensed data and combined these with modelling techniques. Therefore, the main objective of this study was to refine the predictions of forest structure and biomass of two structurally different plant communities using remote sensing and modelling techniques in topographically complex landscapes.

Small footprint Light Detection and Ranging (LiDAR) and Landsat5 Thematic Mapper multispectral satellite data along with a statistical modelling approach were employed in this study. Two distinct forested areas, eucalypt dominated open-canopy vegetation of the Richmond Range National Park (RRNP) and the tall closed-forest community of the Border Ranges National Park (BRNP) were selected to represent the broad range of vegetation characteristics found throughout north-eastern New South Wales, Australia. As the correction of topographic effects on multispectral satellite data is
a key pre-processing method for remotely sensed data, the study assessed five commonly used topographic correction methods of forested scenes: (i) C, (ii) Minnaert, (iii) Sun Canopy Sensor (SCS), (iv) SCS+C and (v) the Processing Scheme for Standardised Surface Reflectance (PSSSR) to determine impact of each methods on Landsat5 TM data for predicting accuracy of Foliage Projective Cover (FPC). LiDAR derived laser metrics, in conjunction with ground measured structural properties of vegetation data was employed to predict plot scale fundamental forest structure including height, canopy structure and the density related structural parameters of vegetation. Estimation of plot scale above ground biomass was investigated using a fusion of LiDAR derived laser metrics with spectral bands and vegetation indices derived from Landsat5 TM. Furthermore, potential of characterisation of overstorey height and canopy component related structural attributes of forests in relation to the variation of topography was investigated using LiDAR and multispectral satellite data of landscapes.

The key findings of the study were; (1) the physically based radiometric correction method improved the performance of all topographic correction methods, and the PSSSR model performed significantly better in terms of yielding a marked improvement of FPC prediction from Landsat5 TM compared to other correction models under the investigated sun angle; (2) LiDAR derived laser metrics based linear regression models were able to explain 62% of the variability associated with basal area, 66% for mean dbh (diameter at breast height) and 61% for dominant height 60% in subtropical rainforest. In contrast, mean (adjusted R$^2$ 0.90) and dominant (adjusted R$^2$ 0.81) heights were predicted with the highest accuracy for the open canopy study area with LiDAR. Combined rainforest and eucalypt forest sites showed results with intermediate accuracy. The study noted that the magnitude of error for predicting structural parameters of vegetation was much higher in closed-canopy subtropical rainforest than those documented in other studies; (3) fusing LiDAR with Landsat5 TM derived variables increased overall performance for the RRNP and combined sites data
by describing extra variation (3% for eucalypt forest and 2% combined rainforest and eucalypt forest sites) of field estimated plot scale AGB. However, it was noted that the fusion of LiDAR and Landsat derived variables did not improve prediction of above ground biomass across structurally complex closed-canopy subtropical rainforest; (4) employing digital elevation model (DEM) based estimated insolation, topographic wetness index (TWI), and topographic variables enabled a characterisation of the plot scale structural attributes of forests in relation to the variation of topography. The key finding of this investigation was that adopting this methodology to characterise vegetation structure in relation to environmental and topographic variations in eucalypt dominated open canopy is possible. The results indicated that physical and chemical properties of soil, and geology possibly have significant influences on potential vegetation structure more than the TWI, and insolation in subtropical forest BRNP.

Overall, this study presented different investigations for understanding the potential for remotely sensed data including LiDAR to refine the prediction of fundamental forest structure and biomass of two plant communities. This finding is significant because as far as we are aware, this is one of few studies to demonstrate the application of remotely sensed data to investigate forest structure of hilly plant communities in Australia. Thus, this information strengthens the understanding of methods of prediction of Australian woody plant communities over large areas of landscape. Furthermore, despite some limitations, these results add to the existing knowledge base and contribute to a better understanding of how to predict spatial configuration of vegetation structure of plant communities in topographically complex landscapes.
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Finally, immense love and gratitude goes to my wife Nelum who managed excellently with all the difficulties of taking care of our son Ravira (Dinosaur hunter) in spite of her own heavy PhD workload. We can now finally spend more time together.................

Again, my heartfelt thanks to all my supports.......!!!
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<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AGB</td>
<td>Above ground biomass</td>
</tr>
<tr>
<td>ALOS</td>
<td>Japan’s Advance Land Observation Satellite</td>
</tr>
<tr>
<td>ANOVA</td>
<td>Analysis of Variance</td>
</tr>
<tr>
<td>BA</td>
<td>Basal Area</td>
</tr>
<tr>
<td>BRDF</td>
<td>Bidirectional Reflectance Distribution Function</td>
</tr>
<tr>
<td>BRNP</td>
<td>Border Range National Park</td>
</tr>
<tr>
<td>CCA</td>
<td>Canonical Correlation Analysis</td>
</tr>
<tr>
<td>CHM</td>
<td>Canopy Height Model</td>
</tr>
<tr>
<td>CRAFTI</td>
<td>Comprehensive Regional Assessment Aerial Photograph Interpretation</td>
</tr>
<tr>
<td>CSM</td>
<td>Canopy Surface Model</td>
</tr>
<tr>
<td>CV</td>
<td>Coefficient of Variation</td>
</tr>
<tr>
<td>DBH</td>
<td>Diameter at Breast Height</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>DN</td>
<td>Digital Numbers</td>
</tr>
<tr>
<td>DSM</td>
<td>Digital Surface Model</td>
</tr>
<tr>
<td>DTM</td>
<td>Digital Terrain Model</td>
</tr>
<tr>
<td>FPC</td>
<td>Foliage Projective Cover</td>
</tr>
<tr>
<td>GDA 94</td>
<td>Geodetic Datum of Australia 1994</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information Systems</td>
</tr>
<tr>
<td>GLM</td>
<td>General Linear Models</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>INS</td>
<td>Inertial Navigation Systems</td>
</tr>
<tr>
<td>LAI</td>
<td>Leaf Area Index</td>
</tr>
<tr>
<td>Landsat TM</td>
<td>Landsat Thematic Mapper</td>
</tr>
<tr>
<td>LiDAR</td>
<td>Light Detection Ranging</td>
</tr>
<tr>
<td>LPI</td>
<td>Land and Property Information</td>
</tr>
<tr>
<td>MLR</td>
<td>Multiple Linear Regression</td>
</tr>
<tr>
<td>MODIS</td>
<td>MODerate resolution Imagine Spectroradiometer</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Full Form</td>
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<tr>
<td>--------------</td>
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</tr>
<tr>
<td>MSS</td>
<td>Multispectral Scanner</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NRW</td>
<td>Natural Resources and Water</td>
</tr>
<tr>
<td>NSW</td>
<td>New South Wales</td>
</tr>
<tr>
<td>PPSG</td>
<td>Principal Polar Spectral Greenness</td>
</tr>
<tr>
<td>PSSSR</td>
<td>Processing Scheme for Standardised Surface Reflectance</td>
</tr>
<tr>
<td>QRSC</td>
<td>Queensland Remote Sensing Centre</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Squared Error</td>
</tr>
<tr>
<td>RRNP</td>
<td>Richmond Range National Park</td>
</tr>
<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
</tr>
<tr>
<td>SCS</td>
<td>Sun Canopy Sensor</td>
</tr>
<tr>
<td>SLATS</td>
<td>A Statewide Landcover and Trees Study</td>
</tr>
<tr>
<td>SLAVI</td>
<td>Specific Leaf Area Vegetation Index</td>
</tr>
<tr>
<td>SPOT</td>
<td>Satellite Pour l’Observation de la Terre</td>
</tr>
<tr>
<td>SRTM</td>
<td>Shuttle Radar Topography Mission</td>
</tr>
<tr>
<td>STS</td>
<td>Sun Terrain Sensor</td>
</tr>
<tr>
<td>TOA</td>
<td>Top-of-Atmosphere</td>
</tr>
<tr>
<td>TWI</td>
<td>Topographic Wetness Index</td>
</tr>
<tr>
<td>UNFCCC</td>
<td>United Nations Framework Convention Climate Change</td>
</tr>
<tr>
<td>6S</td>
<td>Second Simulation of the Satellite Signal in the Solar Spectrum</td>
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1.1. The Need for Data on Fundamental Forest Structures and Biomass

Australia’s forest estate covers an area of 164 million hectares; this area has significantly diminished in most localities (National Forest Inventory, 2003). There has been an increased awareness in the past two decades of the importance of the remaining Australian forests. Information regarding vegetation structure of these existing forests is increasingly being recognized as fundamental for sustainable forest management and conservation. As a signatory to international agreements, including the United Nations Framework Convention Climate Change (UNFCCC) and the Montreal Process Working Group for sustainable forest management, Australia is increasingly required to provide accurate information on the state of plant communities and forest structure over the entire continent (Richards and Brack, 2004). Furthermore, to effectively respond to changing climate there is a need to improve vegetation assessment methods, particularly as the dynamics (direction and magnitude) of potential change need to be identified (Burrows et al., 2002). This presents many research challenges as a greater range of information is required which previously had not been widely or consistently collected (Thackway et al., 2007). Forest assessment information is also required by governments, industry, private landholders, and the public to investigate commercial uses, biodiversity, and greenhouse values in assessing the performance of management practices and public policies, guide sustainable development, and forecast the future conditions of Australian forest ecosystems (Henry et al., 2002, National Forest Inventory, 2003, Brack, 2007). Furthermore, knowledge of the pattern of variation in vegetation structure of forested areas over time and space can serve as the basis for future forest management strategies that better enable a broad array of sustainable forests goods and services.
In Australia, landscape ecologists, forest managers and remote sensing specialists have long been monitoring fundamental forest structure, composition and species distribution of natural and plantation forests over large-scale landscapes. The Queensland Remote Sensing Centre (QRSC) is one of the leading user groups of remotely sensed data for state and national level vegetation assessments and monitoring. The QRSC has used Landsat data since 1989 for operational mapping and monitoring of the extent of changes to vegetation cover and to provide accurate information on land cover and trends in land clearing, tree growth and re-growth of Queensland’s woody vegetation (Armston et al., 2009). Additionally, during the last decade considerable effort has been devoted by various research groups to study the structure, composition, and biomass of woody vegetation over other areas of Australia. For instance, airborne small footprint Light Detection and Ranging (LiDAR) data has been used to estimate vertical distribution of foliage cover (Weller et al., 2003, Lucas et al., 2006), canopy structure (Lovell et al., 2003, Lee and Lucas, 2007) and other structural elements (Goodwin et al., 2006, Haywood and Stone, 2011) in open-canopy eucalypt forests in Queensland and Victoria states. Moreover, combining LiDAR data with different multispectral data has been utilized to map and monitor Australian woody vegetation over large-scale landscapes (Armston et al., 2009, Arroyo et al., 2010, Johansen et al., 2010). In addition, much effort has been devoted to mapping and monitoring vegetation cover and vegetation cover changes on large-scales using MODerate resolution Imagine Spectroradiometer (MODIS) 250 data (Gill et al., 2009). The findings of these studies have revealed that remote sensing has significantly enhanced the capability for mapping and monitoring of spatial and temporal distributions of biophysical parameters of woody vegetation across landscapes. These findings have enhanced the knowledge of functions, dynamics and significance of natural and managed forest ecosystems. However, all these studies have been restricted to woody vegetation over flat terrain, hence, knowledge gaps remain,
leaving considerable uncertainties about the biophysical structure of vegetation and biomass of hilly plant communities.

1.2. Forest structure in Topographically Complex Terrain in North-Eastern Australia

The vegetation of north-eastern New South Wales (NSW) exists in a series of pockets, varying greatly in size, with those along the Eastern coast restricted to topographically dissected landscapes (Summerbell, 1991, Groves, 1994). A unique characteristic of this vegetation is its floristic variation in relation to changes in topography through the distribution of sclerophyll forests particularly on ridges or upper slopes, while subtropical rainforests are restricted to the gullies or lower slopes (Florence, 1996). Subtropical rainforests represent the common closed-canopy forest type of this region, and these occur in patches from northern NSW south to the Illawara region of NSW (Summerbell, 1991). This region is one of the most biologically diverse areas of Australia, with many endemic species and many others at the extremes of their distributional ranges (Burbidge, 1960, Keast, 1981, Pianka and Schall, 1981, Webb et al., 1984). For instance, a hectare of this subtropical rainforest can contain more than 100 tree species, 60 species of vines, 70 fern species and a host of other plant forms (Churchett, 1982). Furthermore, the region encompassing the north-east of NSW through to the south-east area of Queensland supports many endemic terrestrial vertebrates, and is the national distributional stronghold for many other species (Scotts, 2003). Additionally, these forests are economically important (Summerbell, 1991).

Since early European settlement, these forests have been cleared for timber extraction, agriculture and residential development. Further, at present there are additional pressures on these forests by several agents, with the following generally considered as important anthropogenic-related threats to vegetation in NSW: land clearance for agriculture, grazing, forestry, road works,
urbanisation, industrial development, altered fire regimes, spread of exotic species, and land degradation (Leigh et al., 1984, Boyd, 1989, Environment Protection Authority NSW, 1995). Of these, agriculture presents a major threat to many forest patches, primarily due to the large land areas involved, and the intensive nature of agricultural activities. Forests, therefore, are limited to fragmented areas and are mostly affected when the vegetation types contained within the patch are cleared for purposes such as cropping or to improve pasture. Furthermore, dieback of vegetation associated with canopy damage is frequently being recorded through sclerophyll forested areas, and dieback-affected areas contain severely deteriorated canopies (Stone et al., 2008). Consequently, this modifies the species composition and vegetation structure through establishment of understorey weeds such as Lantana camara. Thus, study of the fundamental vegetation structure of these remaining forested areas is required to efficiently assess and monitor these changing and often deteriorating vegetation states and conditions.

Globally, most remote sensing applications including LiDAR for characterizing forest structure have been carried out in plantations with a uniform overstorey, temperate coniferous forests (Næsset, 2002, Næsset and Okland, 2002, Holmgren et al., 2003, Næsset, 2004, Jensen et al., 2006), deciduous forests (Brandtberg et al. 2003, Brandtberg, 2007), or mixed forest vegetation with simple forest structure (Heurich and Thoma, 2008), with gentle topography. While investigation of forest structure and its distribution and dynamics using remote sensing measurements in Australian woody plant communities has advanced considerably during the last decade, knowledge gaps remain regarding remote sensing of hilly forest structure over large areas. Additionally, Phua and Saito (2003), Clark et al. (2004) and Tonolli et al. (2011) argued that only a few studies have purposefully examined the structural variations of vegetation using remotely sensed data over landscape scales in topographically complex terrain in other regions of the world. Available literature regarding the structural assessment of forests using remote sensing
including LiDAR in topographically rugged terrain in Australia is very limited or not available and relatively a few studies in elsewhere. For example, according to the literature only one study, (Zhang et al., 2011) has investigated the application of small footprint LiDAR for characterising forest structure of cool temperate rainforests in hilly terrain. Available literature regarding the structural assessment of forests using remote sensing including LiDAR in topographically rugged terrain in Australia is very limited or not available. For example, according to literature only one study, (Zhang et al., 2011) has investigated the application of small footprint LiDAR for characterising forest structure of cool temperate rainforests in hilly terrain. Flat terrain conditions with fairly simple forest structures are ideal for precise remotely predicted forest structures. These circumstances are significant in facilitating the extraction of biophysical information of forests that is of high fidelity and, hence, conducive to enabling precise estimates of forest structure. Therefore there is need to improve understanding of fundamental forest structures and biomass in rugged terrain; and enhanced understanding may help to unlock information regarding the history, functions and futures of plant communities in topographically extensive and varied landscapes. These requirements form the basis of the primary research objectives to be achieved in this study and are the subject of this thesis.

1.3. Rationale and Objectives

Section 1.1 identified the knowledge gaps regarding remote sensing of fundamental forest structure in topographically complex terrain, and the need for a strategy to assess the structure of vegetation utilizing remote sensing technology to improve the prediction of forest structure and biomass of Australian woody plant communities in topographically complex landscape. Airborne small footprint LiDAR and multispectral data such as Landsat data have shown promise in being able to meet many of the requirements for measuring forest structure in Australia and elsewhere, however, there exists a lack of investigation into the utility of LiDAR and multispectral data for
Australian vegetation structural assessments in topographically rugged terrain. LiDAR and multispectral data are mutually exclusive, thus, the combination of these technologies should lead to more accurate applications in ecological and forest studies.

Forest structure is broadly defined according to the research orientation of the examiner and it is defined generally as the horizontal and vertical configuration of vegetation components. The assessment of a forest structure can encompass a wide range of metrics and may be valid on a range of scales (Lund, 2002). For example, Specht and Specht (1999) states that plant community structure reflects its position in space and time, and illustrates the spatial distribution of a plant community biomass, as well as indicating the effects of prevailing disturbance patterns. However, for the purpose of this study, the concept of forest structure is defined as a measure of density; that is the density of tree stems within unit area, density of crown components including branches and foliage originating from those stems and the density of foliage at different heights throughout a landscape structure or stand structure. Landscape or stand structure refers to the pattern of organisation of these structural attributes at a particular scale.

A combination of optical sensor data and LiDAR with a statistical modelling approach should allow for a better understanding of forest structure in topographically complex landscape. However, the influence of terrain on optical satellite data in forested hilly areas cannot be ignored, and methods that indicate how to accurately retrieve surface reflectance in hilly areas is one of the most significant remote sensing problems (Civco, 1989, Meyer et al., 1993). Hence, topographic correction is a necessary pre-processing step in the remote sensing of data acquired over topographically complex terrain. In this study, particular emphasis was placed on assessment of the impact of the different topographic corrections on Landsat data for accurate predictions of vegetation cover in topographically complex landscapes.
The overall aim of this study is to refine the predictions of forest structure and biomass of two structurally different plant communities using remote sensing and modelling techniques in topographically complex landscapes.

In order to achieve this primary research aim, the aim translates into the following four targeted objectives:

- To predict plot scale biophysical attributes of vegetation using airborne LiDAR over a eucalypt-dominated open-canopy forest and a closed-canopy subtropical rainforest
- To assess the impact of topographic corrections on estimation accuracy of Foliage Projective Cover (FPC) in a topographically complex landscape
- To investigate the influence of topographic variation on forest structure in two woody plant communities using a remote sensing approach
- To predict above ground biomass in a eucalypt dominated open canopy-forest and a closed-canopy subtropical rainforest using airborne LiDAR and multispectral data


This thesis is presented as a series of multiple scientific publications with each objective constituting a separate paper. This format is accepted by the Higher Degree Research Committee of Southern Cross University. However, at times; there is some overlap, particularly some repetition in the methodology and interpretation of results which were unavoidable.

There are a total of eight chapters in this thesis. The current chapter, Chapter 1, has presented an introduction to the central research objective. It has discussed the requirements for information on forest structure, limitations of current measurements of forest structures, forest remote sensing strategies, and the present state of vegetation in hilly terrain in north-eastern Australia. The need to investigate how remote sensing can be improved for use in hilly forest structure assessments has been indentified.
Chapter 2 will synthesise published literature to provide a review of forest structure, its role in forest ecosystems and the limitations and difficulties of its measurement. Application of different remotely sensed data such as multispectral satellite data and LiDAR for obtaining measurements of vegetation is reviewed.

Chapter 3 will outline the vegetation of north-eastern NSW and provides a detailed description of study areas including the geographical locations, topography, climate, geology and soil, forest structure, and species composition.

Each of the papers (labelled as Chapters 4, 5, 6, and 7), will include a general introduction, methodology employed, results, discussion and conclusion sections for use in structuring future scientific papers for publications. Chapter 4 will examine the application of LiDAR derived laser metrics to estimate structural attributes of two woody plant communities. The impact of five commonly used topographic correction methods on the accuracy of prediction of a biophysical variable, FPC using Landsat5 TM data will be assessed in Chapter 5. Chapter 6 characterises the variation in structural elements of forest in relation to variations in topographic position using airborne discrete return LiDAR, and multispectral satellite data over landscapes. In order to improve the capacity of estimating plot scale above-ground biomass for eucalypt dominated forest and subtropical rainforest Chapter 7 will present fusion of small footprint LiDAR and Landsat5 TM multispectral data.

Finally, Chapter 8 will be a synopsis of findings of the research and a discussion of the theoretical and practical limitations, and provides recommendations for further research. This final chapter will revisit objectives outlined in Chapter 1 and state the extent to which the study has achieved the main research objectives.
Chapter – 2
Remote Sensing of Forest structure in Complex Landscapes

2.1 Introduction

The main objective of this study is to refine prediction of forest structure and biomass of hilly forests using different remote sensing techniques and modelling strategies. As such, it is inherently about improving vegetation monitoring strategies in order to provide better understanding of site productivity, vigour of wildlife habitats, watershed areas, and ecosystem functions through the monitoring of biophysical variables. Further, findings would assist with sustainable forest management decision making and meet national and international reporting needs.

This chapter provides a review of the relevant literature and background of the components of forest structure, and overviews different strategies in the measuring and monitoring of structural components in forests using different remote sensing techniques. Section 2.2 of this chapter particularly examines published literature to outline forest structure through components, and similarly discuss variations in relation to the topography. Furthermore, this section outlines components of vegetation structure with their function in relation to forest ecosystem functions and services. The section also reports the limitations of the studying and monitoring of forest structure due to the variations in components, and the important element of linking field and remote sensing approaches as an alternative method for studying vegetation in large scale geographical and long-term temporal entities. Section 2.3 introduces vegetation measurement, using both passive (e.g. Landsat TM) and active (e.g. LiDAR) methods. An extensive overview of
multispectral and LiDAR based remote sensing of vegetation is provided their use for structural assessment of forests.

**2.2 Forest structure- A Key to Understanding Ecosystem Functions**

Forest structure is defined generally as the horizontal and vertical configuration of vegetation components. MacArthur and MacArthur (1961) refined this broad concept of forest structure by defining foliage height as a measure of canopy layering, and suggesting its use as an indicator of biodiversity. However, the definition for forest structure is not clearly fixed in the same manner as traditionally measured attributes of vegetation, such as stand basal area, that are used to characterise vegetation (Maltamo et al., 2005). The definition of forest structure seems to vary from one application to another. From an ecological perspective, forest structure at the stand level is of special interest for instance when considering disturbance dynamics, successional and growth stages, biomass and wildlife habitat (biodiversity issues) (Clark et al., 2004, Lee et al.). On the other hand, for forest management forest structure can be defined as the frequency of distribution of stems, the percentage of contribution of major life forms such as trees and palms, and the spatial organization of structurally distinct patches such as tree fall gaps (Clark and Clark, 2000). Thus, the definition of forest structure is broad and may depend on a research interest.

The term “forest structure” therefore characterises different components and it is possible to describe in numerous ways. Essential components of forest structure include structural type, size, shape and spatial distribution (horizontal and vertical) of components. According to (Zimble et al., 2003), the components for forest structure are vertical (e.g. number of strata, understorey tree species) and horizontal structures (e.g. tree groups and spatial pattern) as well as species richness. For the sake of simplicity in this discussion; the component of forest structure will be
broadly grouped into four important components: (a) vertical foliage distribution (b) horizontal canopy distribution (c) tree size/age distribution and (d) dead wood as described by (Spies, 1998).

2.2.1 Vertical Foliage Distribution

The quantity and distribution of foliage are fundamental components of forest ecosystems. Primary productivity of plant communities depends upon spatial distribution of foliage and abiotic factors normally associated with photosynthesis (Kinerson et al., 1974). Forests can have distinctive horizontal layers of vegetation, however typically foliage is distributed more from the forest floor to the overstorey with peaks in profiles (Spies, 1998). There are several techniques to quantify foliage profiles such as the destructive method (Fujimori, 1971) point quadrat sampling described by Warren (1960), foliage profiles by field method MacArthur and Horne (1969) litter collection and a modified camera point quadrat sampling techniques (Aber, 1979). Most of these methods measure the interception of canopy elements in a series of vertical transects throughout the forest stand, and inventory-based foliar-profiles estimates derived from measurements of crown dimensions assuming a uniform foliage density within a crown volume (Walker and Hopkins, 1990). However, efficiency in application of these methods is not satisfactory hence are not much in use, as the use of detailed field-based methods to quantify the horizontal and vertical distribution of elements in a canopy is an extremely labour intensive task, especially if a large number of sampling sites need to be measured (Hall et al., 2005).

2.2.2 Horizontal Canopy Distribution

Forests are horizontally structured into a mosaic of different canopy densities and gaps (Whitmore, 1984). A forest canopy can be defined as “the combination of all leaves, twigs, and small branches in a stand of vegetation; it is an aggregate of all the crowns” (Parker, 1995). It can vary in species composition, total height, as well as in thickness of foliage density (Lieberman et
al., 1989). It is the key element in the ecology and function of a landscape. Furthermore, in forested areas with dissected topography, aspect and slope variations influence canopy structure through changing intensities of solar radiation (Ackerly et al., 2002). Canopy disturbances in forest landscapes due to various reasons create canopy openings (which may range from single branches or trees, to areas of hundreds or thousands of hectares) within the forest landscape (Spies et al., 1988). Variations of topography influence the variation in gap sizes; the largest gaps are in valleys and the smallest on ridgetops (Ashton, 1992, Ediriweera et al., 2008). Canopy gaps allow light to penetrate into the understory, and hence alter microclimates on the forest floor.

The foliage component of a canopy is the primary surface that controls mass, energy and gas exchange between the photosynthetically active vegetation and atmosphere (Fournier et al., 2003). Forest canopy also determines ecosystem processes and functions such as microhabitats for plants and wildlife (Dial, 2004). Furthermore the amount and arrangement of canopy foliage are associated with stand structure and canopy architecture, thereby determining light penetration and foliage aggregation through a forest canopy (Oker-blom and Kellomaki, 1983). Prior to forest canopy disturbance, light is the resource that appears to be most limit survivorship and growth of advance regeneration in the forest understory of moist forests (Chazdon and Pearcy, 1991). Gaps contribute to spatial diversity, facilitate seedling regeneration, and enable herb and shrub species to grow and reproduce within late-successional forests (Gray and Spies, 1996).

Understanding canopy structure is critical to provide insight into functional characteristics and the process of tree growth, and can reveal important information on a forest’s response to disturbance at the individual tree, stand, community and ecosystem level (Parker et al., 2004). On an ecosystem scale, a thorough characterization of a foliage component of forest canopy can provide valuable information about nutrient cycles, biogeochemical processing and for hydrologic forecasting of a forest ecosystem. The spatial and temporal properties of these
biophysical processes are directly related to the horizontal and vertical configuration of forest canopies, and their changes at multiple temporal scales (Parker and Tibbs, 2004). However, quantification and measurement of canopy structure of vegetation is not an easy task. Stratified clipping of biomass samples is one direct measurement method. However, its application in the field is limited due to the destructive and laborious nature of the process. Indirect methods have thus become a popular alternative. The first indirect method that was developed is the point-quadrat method (Warren, 1960), in which a probe with a sharp point is inserted into the canopy at a known inclination and azimuth angle, and the number of times the point contacts leaves or stems is counted. Leaf Area Index (LAI) can then be estimated by calculating the contact frequency. However, this method is also very laborious (Norman and Campbell, 1989). Another indirect method, the gap-fraction method, is widely applied in field surveys and uses commercially available tools such as cameras with a fish-eye lens and optical sensors (e.g., the LI-COR LAI-2000 Plant Canopy Analyzer; (Norman and Campbell, 1989)). This method allows automatic estimation of LAI without destruction of the plants and is less laborious. However, it depends on the assumption that the foliage distribution is random, which leads to errors when the foliage distribution is non-random. Similarly, hemispherical photographs are used to estimate canopy cover and this technique measures total gap as a function of elevation in a canopy. Foliage Projective Cover (FPC) is yet another technique used to characterize the architecture of the foliage in all strata in a plant community (Specht and Specht, 1999) and has a logarithmic relationship with effective LAI (Chen and Cihlar, 1995). FPC measures the interception of canopy elements in a series of vertical transects throughout the sampling plot, and yields percentages of horizontal and vertical distribution of elements in the canopy. The limitation of these applications is that it is not efficient to use them on a broad landscape scale, especially in topographically rugged terrain. Additionally, LAI is merely the projected area of foliage on the horizontal plane.
providing no information on the vertical distribution of leaf area through the canopy (Coops et al., 2004).

2.2.3 Tree Size/Age Distribution

The traditional and most common measure of forest structures are size and age distribution of trees (Smith, 1986). Information on forest structure is summarised using structural elements (e.g. mainly dbh) and give an idea about the development stage of the forest (e.g. stem exclusion, understorey initiation or old growth). Each development stage of the vegetation has various structural features. For instance, old growth forest is represented by large trees, different species, several canopy layers and some component of rotting wood, snags and logs (Oliver and Larson, 1996). In forested areas, size distribution of living trees is closely connected with many other structural elements of vegetation (e.g. foliage distribution, crown attributes) or potential to produce other elements (e.g. dead wood, different size). The size distribution of trees in a given stand is an important factor that affects the fate of trees (Kohyama, 1993). Crowns of taller trees control the light penetration to the lower strata, thus reducing the growth and survival of trees in lower strata and affect seedling regeneration as well. Within any forest landscape the variation in stem size distribution of stands depends to a large extent on the periodicity, magnitude and spatial and temporal stochasticity of any particular disturbance even. Similarly it has been shown that size class distribution of individual species varies as a function of broad scale ecological factors such as topography (Basnet, 1992, Oliver and Larson, 1996).

Size distribution of trees in vegetation is an important factor related to the provision of habitats for wildlife. For example rotting wood, snags and logs are common in old-growth forests and these spaces provide more nesting opportunities for wildlife. In the forest plantation sector, size distribution and density per unit area are used to calculate growth and yield as well as make decisions regarding harvesting or thinning (Oliver and Larson, 1996). Similarly understanding
age and size distribution of vegetation provides insight into the history of vegetation and the site productivity. Although there are several ways of acquiring information on age and size distribution of vegetation these measurements remain difficult hence today data acquisition has been expedited by different new technologies.

2.2.4 Dead Wood

Ecologists consider dead wood, i.e. snags (standing dead trees) and logs (fallen dead trees) as important structural elements in forests. These are important components of diversity in forest ecosystems (Fridman and Walheim, 2000, Lindenmayer et al., 1999). Conservation biologists increasingly recognise the value of deadwood as a key substrate for a vast, but often overlooked, component of forest biodiversity (Speight, 1989, Hanski and Hammond, 1995, Hammond, 1997). Species dependent on decaying wood microhabitats (e.g. many invertebrates and fungi) are called saproxylic (Speight, 1989), while those that colonise its surface (e.g. many lichens and bryophytes) are known as epixylic (Laaka, 1992). Saproxylic species are a speciose functional group in native forests (Grove, 2002). However, the role of dead wood in site productivity is less clear apart from a role as habitat, although it can contribute nitrogen to soil ecosystems via fixation (Spies, 1998).

The amount of dead wood in forested ecosystems is related to the intensity of forest management (Guby and Dobbertin, 1996). There are several causes of dead trees (e.g. senescence, pathogens and insects, wind, drought, lightning or catastrophic wild fire). This is a crucial process for gaps formation especially in old-growth forest. These disturbances result in snapped trunks and uprooted trees, which create gaps in the forest canopy that allow light to penetrate into the understory. The classification of logs or snags into decay classes is crucial in a dead inventory as different stages of decay attract different organisms (Soderstrom, 1988).
In conclusion, forest structure is directly related to the functioning of plant communities. Understanding of forest structure is crucial as it is a key indicator in monitoring long-term vegetation changes in an ecosystem. Thus, in order to understand the composition requires measurements of changes in these characteristics over time (Brokaw, 1982). Accurate measurement of forest structure using conventional methods of an extensive landscape is not always straightforward. However, the rapid advancement of remote sensing instruments and methods may provide ecologists and foresters with new ways of solving conventional problems related to the estimation of forest structure. Innovative remote sensing applications can be developed in connection with the development of instruments with the ability to calculate unique configurations. Thus, “the advancement of the remote sensing instruments is one of the most significant “driving” forces in the progress of new remote sensing applications” (Hyyppä et al., 2008).

2.3 Remote Sensing of Forest structure – An Overview

“Global understanding is an impossible task [for the discipline of ecology] to achieve without extensive and intensive use of remotely sensed data” (Graetz, 1990). Passive remote sensing sensors record the spectral reflectance from the surface of the Earth, and are a vital source of information about the spatial distribution of vegetation. Applications for mapping the locations of vegetation, its quality, quantity and dynamics using remotely sensed data are numerous and continually expanding. There is also a correspondingly intensive research effort for improving analytical methods (Dungan, 2001). The scale of the land surface unit under observation (pixel size) and spectral range combine to determine the amount of information that can be derived from these sensors; thus understanding of potential scale effects is critical to effective use of remotely sensed data (Hay et al., 2005).
Use of remote sensing within forest inventory has been steadily increasing over the last 60 years. The first use began with black and white aerial photography after the First World War, with major utilisation and colour photography occurring after World War II. There has been an ever expanding use of satellite remote sensing from the 1970’s, with the spatial resolution, extent, diversity (multispectral, hyper-spectral, microwave/radar), and reliability of remote sensing technologies improving rapidly over the last decade (Wulder, 1998). Additionally, the increasing adoption of a range of remote sensing instruments in multi-resources inventories has produced more accurate information, particularly for defining forest boundaries and producing national level maps (McRoberts and Tomppo, 2007).

Methods for processing moderate spatial resolution (~20 m+) remote sensing to produce forest and landcover information are well developed and accepted (Patenaude et al., 2005). Broad scale forest mapping and monitoring worldwide has been undertaken primarily using NASA’s Landsat series, the Advanced Very High Resolution Radiometer (AVHRR) (Lu et al., 2003), the Satellite Pour l’Observation de la Terre (SPOT) series, and more recently with the MODIS series (Wulder, 1998). Processing methods for determining biophysical structure of vegetation from moderate spatial resolution sensors like Landsat TM can be varied. Wulder (1998) described the most widely used methods in vegetation analysis including spectral relationships, spectral vegetation indices, texture, multispectral image classification, change detection, data fusion, linear mixture modelling, bidirectional reflectance methods, geometric optical models, hyperspectral image analysis, individual tree isolation and data discriminators.

Spectral response is often related to ground validation of data allowing for the extrapolation of the calibration relationship of the entire image (Wulder, 1998). Spectral band ratios or linear combination of visible red and near infrared bands derived vegetation indices are used in conjunction with correlation methods to estimate structural parameters of forest (Vogelmann,
This is the agreement between remotely sensed data (i.e. spectral signatures, vegetation indices, simple ratios) and ground truths. Regression techniques are often used due to the simplicity of the analysis (Wulder, 1998) and are important tools for relating field measured biophysical variables to spectral characteristics (Cohen et al., 2003). Typically, the process involves analysing empirical relationships between remotely sensed spectral data (spectral signatures, vegetation indices, or simple ratios) and structural attributes of forest using a variety of linear or non-linear correlation and regression techniques (Salvador and Pons, 1998). The regression approach can yield accurate predictions, at times however the assumptions underlying regression are difficult to satisfy (Foody et al., 2003).

Furthermore, processing methods for determining structural attributes of forests from more complex modelling, for example, Geo-Optical (GO) and radiative transfer methods (Li and Strahler, 1985) have been developed. With GO methods for example, pixel radiance is modelled as the area-weighted combination of the range of sunlit and shaded tree objects and background components visible to the sensor. GO models are used to estimate the bidirectional reflectance distribution function using discrete 3D objects, where the shape, density and patterns control the reflectance response to illumination and different view angles. In the Li-Strahler GO model a spherical shape is assumed for the partially illuminated tree crowns that make up the vegetation canopy (Jupp and Waker, 1996).

The Landsat series of satellites have been in operation since 1972, and have been utilised for a broad range of applications in Australia. The latest sensors-Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper (ETM) have 30 m spatial resolution across 7 spectral bands, with Landsat 7 having and additional 15 m panchromatic band (NASA, 2004). A fault developed in Landsat 7 during 2003 resulting in data gaps, rendering its data unusable for
vegetation application; however, more recent research into increasingly sophisticated data blending algorithms incorporating MODIS and Landsat, the SLC-off limitation is becoming less of an issue (Gao et al., 2006). In Australia, one of the major users of Landsat TM imagery for state and national level vegetation measurements and monitoring is the QRSC (former name: Queensland Statewide Land-cover And Trees Study (SLATS) programme) (Armston et al., 2009).

The QRSC use Landsat TM imagery from 1989 to present for estimating the extent and change in woody vegetation. A multiple regression vegetation index developed using field site data sampled throughout Queensland, is used to calculate a gradient of woody FPC, and seeks to detect woody vegetation to the lowest possible detection limit (Lucas et al., 2006a, Armston et al., 2009). This vegetation index compensates for the difference in background soil colour which can otherwise cause significant overestimation (for black soil) or underestimation (for red soil) of woody vegetation cover. Dry season imagery (July-September) is used to minimise the variability in image quality due to atmospheric haze and cloud, and to provide the maximum differentiation between pasture and forest canopy (Lucas et al., 2006a). For purpose of vegetation management, QRSC detects all woody vegetation, with a minimum threshold of approximately 7% FPC in most cases, however, the minimum threshold may be up to 12% where image quality is poor (Armston et al., 2009). Recently airborne LiDAR data were collected at a number of test sites, and successfully used to improve the Landsat TM derived FPC estimation models (Armston et al., 2009). In the above study, Landsat TM visible and near infrared spectral wavelengths or wavelength combinations spectral responses, and LiDAR, and field measured FPC, have been modelled using Multiple Linear Regression, General Linear Models and machine learning techniques such as a Random Forests, Support Vector Machines (Armston et al., 2009). Moreover, a recent study has incorporated a more complex vegetation index, in an effort to minimize the influence of canopy background noise (Moffiet et al., 2010). Model development is supported by
an extensive set of ground measured data which includes ground measured FPC covering a range of different woody plant communities from sparse low open woodland to tall closed-forests.

Synthetic Aperture Radar (SAR) is another potential source of forest information. Knowledge of the information content of this data source acquired over forest environments, and in particularly microwave interaction with different components (leaves, trunks, branches) is required to support the retrieval of their biomass, structure and floristic composition at an operational level (Hyyppä et al., 2000). Such knowledge is increasingly important given the deployment of lower frequency spaceborne radar sensors (e.g. Japan’s Advance Land Observation Satellite (ALOS) Phase Array L-band SAR) to complement the current suit of C-band sensors observing the Earth. Active microwave sensors can penetrate the canopy and so provide information about the entire vertical depth of the vegetation, as well as being sensitive to a range of structural parameters of forest, including the geometric structure of tree components (Liang et al., 2005).

Another benefit of SAR systems is the ability to make all-weather (although results can be negatively impacted by wet conditions (e.g. de Jong et al., 2002) and night-time observations at high spatial resolution, and at a range of frequencies and polarizations. In gaining such knowledge, a number of approaches can be adopted, including the use of empirical relationships (Lucas et al., 2000) and modelling by distributing tree components of varying size, geometry and dielectric properties within two-dimensional (2D) layers (Lucas et al., 2004). Similarly modelling have utilised 3D cubes (Sun et al., 2002) and simulated microwave interaction, overall backscatter coefficient, and the magnitude of contributory mechanisms (e.g. single bounce, volume scattering). In the latter case, the cubes or “voxels” (volumetric pixels) have typically been constructed around artificial trees or those that have been measured from field data. However, at the present time these systems and methodological approaches tend to be best suited for
structurally homogeneous forest types, and those in the lower biomass range (30-200 Mg ha\(^{-1}\)) due to issue of sensor saturation (Lucas et al., 2006a).

LiDAR remote sensing directly measures both horizontal and vertical spatial elements of forest structure. Many studies utilising either both small footprint (<0.5 m radius) or large footprint (10 m +) waveform digitization airborne LiDAR, have demonstrated an ability to recover structural elements such as tree and canopy height, canopy cover and volume, canopy height profiles, biomass and basal area at accuracies near equivalent to (and sometime better than) field survey (Magnussen and Boudewyn, 1998, Lim et al., 2003, Riaño et al., 2004, Lefsky et al., 2005). LiDAR remote sensing of forest structure will be covered in more detail in section 2.3.1

2.3.1 LiDAR Remote Sensing of Forest Structure

In recent years, the retrieval of structural attributes of forest across the landscape has been advanced considerably following the development of remote sensing technology, and particularly multiple (discrete) return and full waveform LiDAR (Lim et al., 2003). Small footprint LiDAR, an active sensor that uses a laser beam in the near infrared spectral range directed towards the ground. The time and intensity of any return signals from the original pulse are used to measure the distance to an object. Depending upon flying height, the footprint size may vary from 0.1 m to 5 m and the interval between laser returns may range from 0.25 m to 5 m. With the aid of real-time differential GPS (with base stations) and sophisticated inertial navigation systems (INS) that measure aircraft pitch, yaw and roll, most LiDAR are now capable of achieving absolute spatial accuracies of < ± 1 m in the x and y directions, and < 0.25 m in the z direction (i.e. elevation). In most systems, the laser pulse is emitted via a rotating mirror, which creates a zigzag swath of laser returns either side of the aircraft. For vegetation assessment purposes, LiDAR provides a highly precise dataset of points representing a sample of terrain and vegetation. The
high geo-registration accuracies now makes it possible to “image” individual tree crowns, and to locate the same tree on the ground using, for example, hand-held GPS (Lovell et al., 2003).

Over the last few decades, the use of small footprint airborne LiDAR for retrieving ground surface and vegetation parameters has been documented. The data have been used primarily to retrieve commonly measured attributes of forest structure, namely tree-based estimates of tree height and crown dimension (Leckie et al., 2003, Solberg et al., 2006), or stand-based estimates of mean or maximum canopy height (Næsset, 2002, Means et al., 2000), basal area and stem volume (Holmgren et al., 2003), canopy cover (Todd et al., 2003, Weller et al., 2003, Riaño et al., 2004), timber volume (Maltamo et al., 2004, Tesfamichael et al., 2010), and biomass (Lim and Treitz, 2004). Algorithms have typically been developed through empirical relationships with ground data, and their success was reported by referring to a testing ground dataset and utilizing standard statistical descriptors (i.e. the root mean squared error, $R^2$). This investigation is now mature to the state where direct estimates of structural variables (e.g. tree heights, canopy cover) routinely $R^2$ values approaching or exceeding 0.90 in open canopy plantations, or temperate forests (Suarez et al., 2005). Hyyppä et al. (2001) demonstrated that LiDAR could provide more precise stand-based estimates than conventional ground based inventory.

To date, the research and development effort have been undertaken by timber companies, government organizations and academic scientific community. Research into LiDAR applications have often been in close collaboration due to the cost of acquisition, mission planning, collection of associated field data, along with computer storage and processing software. A considerable work has been conducted in US and Canada (Hudak et al., 2001, Lim et al., 2003, Streutker and Glenn, 2006, Coops et al., 2007, Skowronski et al., 2007, Lefsky et al., 2008), and in Europe (Næsset, 1997, Hyyppä et al., 2000, Ronnholm et al., 2004, Morsdorf et al., 2006), while only a few studies were found in Australasia (Lovell et al., 2003, Goodwin et al., 2006, Lucas et al., 2006a, Lee
and Lucas, 2007, Lucas et al., 2008, Arroyo et al., 2010, Johansen et al., Zhang et al., 2011). When retrieving structural parameters of forests, the majority of studies have utilised LiDAR height information, which has generally been in the form of canopy height surface or models (CHM) interpolated from point data from the outer surface on the canopy. In previous studies using LiDAR data, emphasis was placed on retrieving tree or stand height from the canopy height models or information on the vertical stratification of foliage and branch elements (Magnussen and Boudewyn, 1998, Todd et al., 2003, Lovell et al., 2005, Lee and Lucas, 2007).

At present, attention is increasingly turning to the estimation of a greater range of structural elements of vegetation using canopy surface models. Desirable attributes include tree density (Holmgren et al., 2003, Leckie et al., 2003), basal area or biomass (Lefsky et al., 1999, Lim and Treitz, 2004, Lefsky et al., 2005), and measures of canopy cover (Raino et al., 2004, Chen et al., 2006). For the purpose of retrieving these attributes, measures derived from the LiDAR CHM (maximum, mean or percentile) and / or the percentage of canopy strikes per unit area or volume have typically been considered. For estimating stem density, several studies have simply counted crown delineated using CHM (Hyyppä et al., 2001, Leckie et al., 2003, Suarez et al., 2005), whilst other have used more complex transfer functions based on specific percentiles of the height distribution of canopy LiDAR pulse or mathematical functions e.g. Weibull (Lovell et al., 2003, Maltamo et al., 2004); or Johnson’s SB (Jerez et al., 2005) that describe apparent profiles. Furthermore, plot and strand-level descriptions (e.g. density, mean height and canopy cover) have been obtained through aggregation of tree level information (Popescu et al., 2002, Popescu et al., 2003). However, the success in locating and attributing stems occurring in high density forest (i.e. tropical and subtropical rainforests) or beneath overstorey canopies, and integrating these with those of the overstorey trees for stand-based estimates could be limited.
Some studies have examined the potential of integrating existing aerial photographic interpretation (API) and LiDAR. For example, (St-Onge et al., 2004) assessed the potential for improved utilisation of historical aerial photography for tree height measurement by using LiDAR derived ground Digital Terrain Model (DTM). The study used LiDAR to derived ground elevation (base of tree), and then using stereo photogrammetry to measure tree height. This allowed the improvement of photo interpretation and measurements of height even in more dense forests, which were more difficult to interpret due to higher cover in lower or understorey strata. As the ground terrain was unlikely to change in a major way (unless there has been significant disturbance/ erosion), then the same DTM could be used with historical photography, thus expanding the utility of historical aerial photo achieves.

2.3.2 Remote Sensing of Structural Parameters of Forests- Issues and Limitations

The investigation of biophysical structure of vegetation using remotely sensed data include reference data that are assumed to represent the ground measured and remotely send data. This investigation has inherent issues and limitations for both ground measured and remotely sensed data. However, the following discussion will be limited to the relevant issues and limitations recognised for optical remotely sensed data and LiDAR data.

The issues and limitations can be recognised within the scope of estimating biophysical structure of vegetation using multispectral data particularly acquired over topographically complex terrain. The influence of variations in topography on satellite data in forested hilly areas is one of the most significant issues for application of optical satellites to estimating biophysical structure of vegetation. The variations in topography can seriously affect the radiometric quality of remote sensing data. This change affects both the amount of light illuminating the surface and the amount of light entering the sensor. As a result, similar forest structure and composition can produce a wide range of pixel values under different illumination conditions (Gu and Gillespie,
This leads to the creation of unique challenges in estimating and monitoring of biophysical parameters of forest structure and estimating changes that are not encountered on flat terrain. Thus, topographic correction is a necessary pre-processing step in the remote sensing application for topographically complex terrain (Teillet et al., 1982).

Furthermore, the understory and background materials substantially contribute to the reflectance signal received by the sensor (Nemani et al., 1993, Huete et al., 1985). This issue may have implications for the estimation of structural elements of forests by optical remote sensed data particularly in open woodland and savannah vegetation. For example, Armston et al. (2004) reported influence of soil brightness and colour, particularly in areas of dark cracking clay soils for overestimation of FPC; and Spanner et al. (1990) claimed the influence of understory reflectance on the accuracy of estimation of LAI. Additionally, it has been recognized that moderate resolution images like Landsat TM with broad wavelength data are susceptible to saturation due to similar canopy structure (intact large rainforest crowns), and the impact of shadowing (Lu, 2006). Moreover, optical sensors do not provide three dimensional (3D) profiles of forest structure on direct measurement on forest height, and vertical distribution of foliage hence, this may be another major limitation of this data sources. Similarly, Wulder (1998) reported that understanding of scale as a fundamental concept in effective utilization of remotely sensed data is required for assessing forest landscapes, primarily because scale determines the quality and type of information that can be extracted from data. Additionally, although satellite images have been shown to be successful monitoring and mapping broad vegetation types, Leckie (1990) pointed out that very basic attributes such as species and crown closure, can not be consistently mapped and monitored.

In the context of LiDAR remote sensing of forest structure, several issues and limitations have been recognised. These issues on LiDAR estimates have been discussed as acquisition inherit,
environmental and vegetation-related error. The error at the data acquisition is caused by a
number of factors including sensor attitude (Goodwin et al., 2006), point spacing density, foot
print size and sensor configurations which are likely to affect accuracy (Hyyppä et al., 2008).
Similarly the effect of topography and forest structure on accuracy of estimates has been
documented (Gatziolis et al., 2010). Additionally, due to integration of different sensors (dGPS,
INS and laser scanners) the error budget of a single laser point is a combination of several error
components (Crombaghs et al., 2002). These errors Hyyppä et al. (2008) categorise roughly into
four components: an error per point, error in a strip section (covered during one dGPS
observation), error per strip and error within an entire block. The quality of the DTM is
determined by the density of penetrated points on the ground surface, understorey vegetation
and slope angle. In addition to that applied methodology and algorithms (Sithole and Vosselman
2004), characteristics of data (e.g. point density, first/last pulse, flight height, scan angle) and
complexity of the target (nature of terrain, density of overstorey canopy cover) may influence a
DTM. Further, underestimation of tree height due to inadequate return density, lack of
comprehensive pulse coverage of the laser scanned area, imperfection in the algorithms used to
generate the CSM and DTM, and other issues related to pulse penetration into the canopy are
also commonly documented (Lefsky et al., 2002, Gaveau and Hill, 2003, Gatziolis et al., 2010).
Therefore Hyyppä et al. (2004) points out that developing suitable corrections has been
challenging due to the range of factors contributing to the underestimation. Developing universal
correction factors for the underestimation may be difficult, since correction appears to be
dependent on terrain and vegetation type, flying altitude, sensor system type and the algorithm
being used. Accuracy of laser canopy height may be improved by acquiring laser data under
other leaf-on and leaf-off conditions and also using calibrated field based tree height information
collected from survey grade instruments (Gatziolis et al., 2010). However, due to the lack of
significant influence of variation in seasons on vegetation this method is not valid for evergreen conditions in tropical or subtropical forested regions.

2.4 Summary

This chapter outlined current literature to gain an understanding of the structural component of forests, why forest structural measurements need improving and how remote sensing (multispectral and LiDAR) and modelling techniques may assist with this task. The first part of the chapter identified different structural elements of forests with their important ecological functions and also discussed prevailing field based methods to measure for their measurements. However, these methodologies are well not suited to effective measurements and monitoring of forest structure, especially in topographically complex terrain. Application of remotely sensed data is an efficient way to measure the landscape in detail, and involve taking fine scale measurements from a few well-selected ground measured data and calibrating LiDAR and medium scale satellite data that can be applied across the landscape. Therefore, several studies related to applications of different remotely sensed data for forest structure measurements discussed. Furthermore, there are critical issues and limitations related to the application of remotely sensed data including LiDAR remote sensing were reviewed. Enhanced understanding of these issues and limitations is an opportunity for effective application of remotely sensed data. Moreover, more specific literature related to the each objective of the study will be discussed in detail in the introduction section of each objective chapter.
3.1 Vegetation in North-eastern NSW

North-eastern NSW is one of the most biologically diverse areas of Australia with many endemic species and other flora at the extremes of their distributional ranges (Pianka and Schall, 1981, Webb et al., 1984). The vegetation of this region demonstrates intricate patterning of plant communities due to natural site factors including substrate, topography, and aspect, in addition to human interference and fire. Vegetation formations are based on forest structure, specifically canopy cover and growth form, and have provided the basis for vegetation description throughout north-eastern NSW (Specht et al., 1995). This region supports a range of vegetation formations including (i) closed-forests, (ii) open-forests, (iii) heathlands, (iv) freshwater wetland complex, (v) coastal wetland complex, and (vi) coastal sand dunes (Specht et al., 1995, Specht and Specht, 1999). Within each of these formations are a variety of sub-forms and alliances (Specht and Specht, 1999).

(i) Closed-forests: Closed-forests are characterised by a forest canopy with more than 70% FPC of the overstorey (Specht and Specht, 1999). Specht and Specht (1999) further describe sub-formations of the closed-forests including subtropical rainforests and cool temperate rainforest which are common in this region. These closed-forests have been almost entirely cleared by European settlers leaving only remnants associated with hilly terrain (Floyd, 1990).

Subtropical rainforest: Subtropical rainforest is closely related to the lowland rainforest of the tropics and can be regarded as a latitudinal variant of the true tropical rainforest with its floristic composition predominantly of Indo-Malayan affinities (Baur, 1962b). Subtropical rainforest is a tall, closed-forest growing to a maximum height of 40 m with a moderately dense canopy and more open sub canopy and ground layer (Specht and Specht, 1999). This forest occurs in deep
valleys, usually with a south to easterly aspect and at lower altitudes (< 500m) with fertile soils derived from basic igneous rocks and in areas receiving more than 1300 mm of rain annually (Floyd, 1990). *Geissois benthamiana* F.Muell., *Sloanea woollsii* F.Muell, *Endiandra muelleri* Meisn., *Sloanea australis* (Benth.) F.Muell. and *Archontophoenix cunninghamiana* (H.Wendl.) H.Wendl. & Drude are common tree species recognised in the overstorey (Tweedie et al., 1995).

**Cool temperate rainforest:** Cool temperate rainforest occurs at higher altitudes (>800 m) and occupies less favourable areas (Baur, 1962b). There is typically a single, dense tree layer with a scattered middlestorey. Buttressing and lianas are rare or absent. Cool temperate rainforest is characterised by *Nothofagus moorei* (F.Muell.) Krasser.

**(ii) Open-forests:** Open-forest communities dominated by evergreen eucalypts trees with a FPC 30-70% (Specht and Specht, 1999). There are two main subforms in open-forests including tall open-forest or wet sclerophyll forests and open-forest or dry sclerophyll forests (Specht, 1970).

**Wet sclerophyll forests:** An open-forest with trees more than 30 m tall and occurring in the higher rainfall areas on fertile soils along the coast, and lowlands areas (Specht and Specht, 1999). These forests are generally restricted to sedimentary origin with some metamorphosed shales and sandstones (Tweedie et al., 1995). Wet sclerophyll forests also develop transition zones between closed-forest and open-forest eucalypts. This forest type is characterised by *Lophostemon confertus* (R.Br.) Peter G.Wilson & J.T.Waterh. and *Eucalyptus grandis* W.Hill ex Maiden. and occurs in the alluvial gullies of the coastal lowlands, where with time it tends to be replaced by rainforest (Baur, 1962a).

**Dry sclerophyll forests:** Dry sclerophyll forests occur throughout north-eastern NSW and occupy low-nutrient, free-draining soils of the upper slopes (Tweedie et al., 1995). Trees vary from 10 m to 30 m in height (Specht and Specht, 1999). The understorey is likely to be shrubby or grassy (Groves, 1994, Specht et al., 1995, Florence, 1996). The shrubs may be more xerophytic in
character, and their distribution is varied from sparse to dense. The upper canopy is composed of *E. pilularis* Sm. and *E. pyrocarpa* L.A.S.Johnson & Blaxell, and associated species include *Corymbia maculata* (Hook.) K.D.Hill & L.A.S.Johnson, *E. fibrosa* F.Muell., *E. carnea* R.T.Baker and *Angophora floribunda* (Sm.) Sweet (Tweedie et al., 1995). Frequent moderate fires occur approximately every two years (Tweedie et al., 1995).

(iii) **Heathland:** Heathland typically occurs near the coast on exposed coastal sands and dune systems. It also occurs further inland on exposed or seasonally wet and poorly drained areas, and on skeletal soils (e.g. Triassic sandstone and granite rock types). Heath vegetation comprises species of the Proteaceae, Fabaceae, Mimosaceae, Myrtaceae and Epacridaceae families (Specht and Specht, 1999).

(iv) **Freshwater wetland complex:** Freshwater wetlands on coastal floodplains of north–eastern NSW are dominated by herbaceous plants and woody species. The structure and composition of the community varies both spatially and temporally depending on the water regime (Yen and Myerscough, 1989). Wetlands or parts of wetlands that lack standing water most of the time are usually dominated by dense grassland or sedgeland vegetation, often forming a turf less than 0.5 m tall. However, swamp sclerophyll forests on coastal floodplains of this region have an open to dense tree layer of eucalypts (e.g. *E. robusta* Sm) and paperbarks (*Melaleuca ericifolia* Sm. and *M. quinquenervia* (Cav.) S.T.Blake), which may exceed 25 m in height, but can be considerably shorter in re-growth stands or under conditions of lower site quality (Specht and Specht, 1999).

(v) **Coastal wetland complex:** Sedgeland and wetland types include riverine, estuarine and coastal habitats, such as the swamps and waterlogged areas. Sites where soil conditions do not permit tree growth are dominated by scrub, heath, grassland, sedgeland and other wetland vegetation (Specht, 1981, Beadle, 1981).
(vi) Coastal sand dunes: Above the stand-line where the beach meets the dune, creeping grasses such as Spinifex spp are able to bind the loose sand (Specht and Specht, 1999). Coastal dune vegetation is usually of low height (<10 m), though in protected sites it may attain greater height and contain a wider range of species (Baur, 1965). This vegetation type serves a valuable protective function in both stabilising the dunes and protecting the commercially more valuable types further inland from salt-laden winds.

3.2 Selection of Study Sites

The north-eastern NSW region is a recognised hub, and national refuge, for a large number of flora species (Ferrier et al., 2001). A common pattern of terrestrial vegetation in north-eastern NSW forests involves a topographic mosaic of eucalypt dominated sclerophyll forest on ridges and upper slopes, and closed canopy rainforest on lower slopes or valleys. A vegetation assessment of this environment provides a preliminary perspective of vegetation structure and vegetation structure-topographic relationships. Therefore, two plant communities, closed canopy subtropical rainforest and open canopy dry sclerophyll forest were chosen for this study. The selected plant communities are occupied in the Richmond Range National Park (RRNP) and the Border Ranges National Park (BRNP) (Figures 3.1 and 3.2). Though relatively close in geographic proximity (approximately 40 km), each study area exhibits contrasting characteristics with regard to the topography and vegetation structure, and species composition. Both study areas are managed by the NSW Office of Environment and Heritage. Sections 3.3 and 3.4 provide the detailed description, including geographical locations, climate, geology and information on structure and composition of the vegetation of the study areas.
Figure 3.1 The Border Range National Park, the Richmond Range National Park study sites and LiDAR acquisition areas
Figure 3.2 Digital Elevation Models of the Border Range National Park and Richmond Range National Park
3.2 (a) The Border Ranges National Park

The Border Ranges North and South Biodiversity Hotspot refers to the closed canopy rainforest and related vegetation communities that occur in the Border Ranges region of north-east NSW and south-east Queensland (Department of Environment Climate Change and Water NSW, 2010). This forested region is one of Australia’s most diverse area; and comprises different significant plant communities: subtropical rainforest, wet sclerophyll forest, mountain headlands, rocky outcrops and transition zones between forests (Department of Sustainability Environment Water Population and Communities, 2009).

Location: The BRNP is a subtropical rainforest (approximately 31,508 ha), in north-east NSW and is located west of Murwillumbah, just south of the Queensland border (28.36º S, 153.86º E).

Topography: The topography of the region varies from coastal floodplains to hilly ranges. The eroded calderas of Mt Warning and Focal Peak form a series of radiating ranges that connect through the McPherson Range that runs along the NSW–Queensland border and joins the Great Dividing Range at Wilsons Peak (Stevens, 1977). Within the study area elevation varies from 600 m to 1200 m above mean sea level.

Geology and Soil: The predominant features of the BRNP and around the region are the two eroded shield volcano calderas of Mt Warning in the Tweed Valley and Focal Peak to the west near Mt Barney, both of which were formed about 20–30 million years ago (Stevens, 1977). The following discussion has been derived from discussions in Stevens (Stevens, 1977) and interpretation of the various geological 1:250 000 map sheets covering the Border Ranges region (Brunker et al., 1972, Olgers et al., 1972, Geological Survey of Queensland, 1973, Geological Survey of Queensland, 1974). These two volcanoes underwent a series of eruptions creating two considerably different types of lava flows. The most extensive flows were of Tertiary basalt that weathered to form the deep fertile red soils. These soils usually support subtropical rainforest in
wetter areas and dry rainforest in areas where the rainfall is lower. Much of these once extensive basalt plateaus have eroded to expose the older underlying geologies and form the coastal floodplain of the major river valleys. The other type of lava flow was of rhyolite, which weathers slowly to form low-nutrient, free-draining soils. A third lava type present in the BRNP, trachyte, generally did not occur as a flow but formed volcanic plugs and dykes. Rhyolites and trachytes are particularly resistant to erosion and can be seen as prominent cliffs, mountains and outcrops such as Mt Warning, Mt Lindesay and the cliffs of the Tweed caldera.

The most extensive flows were of Tertiary basalt that weathered to form the deep fertile red soils and these soils lay in moist, sheltered sites at lower altitudes. Soil is friable, with clay content generally more than 50% in the surface soil, and as high as 70–90% in the subsoil, with good infiltration and is nutrient rich Ferrosols also known as krasnozems (Beckman and Thompson, 1976). The second major soil is fine structured, friable clay loam, and dark brown to dark grey coloured prairie soils which are derived from basalt (Beckman and Thompson, 1976). Prairie soils occupy steep ridges which are subject to continuing erosion (Beckman and Thompson, 1976). On slopes, prairie soils are associated with lithosols, chocolate soils, and shallow black earths on basalt and with lithosols and shallow podzolic soils on rhyolite (Natural Resources Audit Council, 1996).

Climate: North-east NSW and south-east Queensland are located in a transition zone between a belt of steady trade winds to the north and an anticyclonic belt to the south (Department of Environment Climate Change and Water NSW, 2010). The fluctuation of these two features over the region results in a climate that is largely subtropical. In general, rainfall is received in December through to April, and the annual rainfall is approximately 3000 mm (Bureau of Meteorology, 2010). Although there is no month without significant rainfall, there is a pronounced maximum of about 160 mm per month in late summer from February to March, and a minimum
of about 40 mm per month in late winter from August to September (Bureau of Meteorology, 2010). However, rainfall is augmented by fog-drip. December through April is warm and wet with daytime temperatures ranging from about 25–31 °C, and humidity levels above 70%. Mean monthly temperature ranges from 3–19 °C in winter and 15–31 °C in summer, and the annual mean minimum and maximum temperature are 10 °C and 24 °C respectively (Bureau of Meteorology, 2010).

**Vegetation:** Vegetation of the BRNP is described as a tall closed-forest community, while subtropical and cool temperate rainforests are prominent sub-formations in the target area (Specht and Specht, 1999). The BRNP has a complex structure with a number of fairly distinct storeys and shrubs. Overstorey trees greater than 30 m in height, with stem buttressing is common, and overstorey FPC vary 70–100% (Specht and Specht, 1999). Below the overstorey trees, different tree species are abundant, but many are incapable of sufficient height growth to become part of the overstorey species, mixed together with seedling or sapling of overstorey species which are capable of growing into the overstorey (Kariuki, 2004). The most common species based on basal area dominance are *Planchonella australis* (R.br.) Pierre, *Heritiera actinophylla* (F.M.Bail) Kosterm, *Diospyros pentamera* (Woods & F. Muell.), *Neolitsea reticulate* (Meisn.) F. Muell, *Polyscias elegans* (C. Moore & F. Muell.) Hanns, *Callicluva paniculosa* (F. Muell.) Hoogl., *Endiandra discolour* Benth. and *Euodia macrococca* F. Muell.(Horne and Gwalter, 1982). There are understorey shade tolerant trees and shrub species such as *Actephila lindleyi* (F.Muell), *Denhamia celastroidestrees* (F. Muell), *Wilkiea huegeliana* (Thul.) ferns and herbaceous plants and vines (Kariuki, 2004, Smith et al., 2005) (Plate 3.1 A, B and 3.2 A, B). Cool temperate rainforests occur in the high elevation area (>800m) of the BRNP. The vegetation structure and composition is simple and the Antarctic floristic elements (*Nothofagus moorei* (F.Muell.) Krasser) are well represented (Specht and Specht, 1999).
Plate 3.1 A-Subtropical rainforest BRNP
Plate 3.1 B-Subtropical rainforest BRNP
3.2 (b) The Richmond Range National Park

The RRNP is a significant part of a system of conservation reserves in the north-eastern NSW. It is significant because it incorporates five World Heritage listed areas that are part of the Central Eastern Rainforest Reserves of Australia, and contains a diversity of vegetation communities (Department of Environment Climate Change and Water NSW, 2005). Alone, it is also important due to its biodiversity, cultural, landscape and nature-based recreation values.

**Location**: The RRNP (approximately 15,420 ha) is located approximately 50 km west of Lismore (28.69° S, 152.72° E). Kyogle and Casino to the east of the National Park are the nearest major centres. The RRNP falls within the local government areas of Kyogle and Richmond Valley.

**Topography**: The RRNP lies predominantly along the Cambridge Plateau which is north-south orientated along part of the Richmond Range. It is flanked on both sides by moderate to steep slopes that give rise to many creeks that fall into the Richmond River valley to the east and the Clarence River valley to the west (Department of Environment Climate Change and Water NSW, 2005). The elevated relief of the RRNP contrasts with the surrounding gently undulating broad valleys. Elevation ranges from around 150 m to 750 m, and has an irregular topography where small valleys alternate with ridges.
Geology and Soil: The basalt flows of the RRNP region associated with Focal Peak shield volcano which was active 24 million years ago (Stevens, 1977). In higher rainfall areas, soils often support areas of dry rainforest along elevated ranges, along with enrichment from the overlying basalt outcrops. Basalt weathers to form Ferrosols and chocolate soils which are fertile, relatively stable and well drained and support rainforest communities (Natural Resources Audit Council, 1996). Other underlying major volcanic rock in the RRNP region is Triassic sedimentary rocks (Brunker et al., 1972, Olgers et al., 1972, Geological Survey of Queensland, 1973, Geological Survey of Queensland, 1974, Stevens, 1977) and typically comprise sandstones, claystones, mudstones, and conglomerate which erode to form low-nutrient, free-draining soils. In these areas of the RRNP such as the more exposed ridges and slopes, the sedimentary parent material has been exposed by erosion and created red and yellow podsolic soils of lower fertility, stability and permeability than those of basaltic origin (Murphy, 1991). Dry sclerophyll forests mainly inhabit areas with lower soil fertility.

Climate: Climate in this area is subtropical, with warm to very warm wet summers and cool dry winters (Bureau of Meteorology, 2010). The average minimum daily temperature in winter is 12 °C, and maximum is 21°C, while the daily temperature in summer varies around 25 °C with a maximum of 31°C. Annual rainfall is approximately 1200 mm while regional rainfall distribution is characterised by an average of between two and four times more rainfall in summer than in winter (Bureau of Meteorology, 2010).

Vegetation: Vegetation of the RRNP is mostly as open-forest community (Specht and Specht, 1999) and two major sub-forms are distinguished, wet sclerophyll and dry sclerophyll. The RRNP represents sparse vegetation with 30-70% FPC (Specht and Specht, 1999). The most common species based on basal area dominance are found in the overstory of dry sclerophyll in the RRNP, include C. maculata (Hook.) K.D.Hill & L.A.S.Johnson, E. propinqua H.Deane & Maiden, E.
siderophloia Benth., L. confertus (R.Br.) Peter G.Wilson & J.T.Waterh., E. saligan Sm., E. seeana Maiden, E. moluccana Roxb. and E. acmenoides Schauer. The understorey is mainly covered by grass and shrubs species. This understorey is fire tolerant; rapidly regenerating from underground organs or by seed (Specht and Specht, 1999) (see Plates 3.3 A, B and 3.4 A, B). Wet sclerophyll forests patches are common in gullies and lowland areas. In the upper stratum of wet sclerophyll forest patches, Brush Box (L. confertus (R.Br.) Peter G.Wilson & J.T.Waterh.) and E. seligna Sm., E. grandins W.Hill ex Maiden and Hoop Pine (Araucaria cunninghamii Aiton ex A.Cunn) are common (Specht and Specht, 1999). Ferns and shrubs are common in the understorey of these wet rainforest patches. Wet dry sclerophyll forests develop a transition zone between closed-forest and eucalypts open-forest (Plate 3.5).

**Canopy dieback:** Populations of Bell-Miners (Manorina melanophrys), also known as bellbirds, are one of the major threats to biodiversity as they appear to be associated with eucalypt dieback areas (Wardell-Johnson et al., 2005). Bell-Miner associated dieback affects both wet sclerophyll and dry sclerophyll forest communities (Stone et al., 2008). This issue is particularly evident in the RRNP study site. The impact of previous logging activities has altered the forest structure and encouraged the establishment of weeds, particularly lantana (Lantana camara L.) in the understorey (Plate 3.6 and 3.7). Bell-Miners favour these disturbed forest habitats and aggressively protect their territories from other birds, including insectivorous birds (Stone et al., 2008). This may result in sap-sucking psyllid populations rising to damaging levels and leading to tree dieback.
Plate 3.3 A-Dry sclerophyll forest in RRNP
Plate 3.3 B-Dry sclerophyll forest in RRNP

Plate 3.4 A and B-Canopy view of the dry sclerophyll forest RRNP
Plate 3.5 Wet sclerophyll forests in RRNP
Plate 3.6 Bell-Miner-associated dieback of the dry sclerophyll forest RRNP
Plate 3.7 Distribution of *Lantana camara* in canopy dieback area in the dry sclerophyll RRNP
3.3 Summary

North-eastern NSW is a region of extreme ecological complexity, with considerable variation in climate, geology types and topography, and with consequent variation in the plant communities. Six dominant plant communities including closed-forests, open-forests, freshwater wetland complex, coastal wetland complex, heathlands, coastal sand dunes with their sub-forms are distinguished in this region. The two selected study areas (subtropical rainforest, and wet sclerophyll and dry sclerophyll) represent a diverse assemblage of different plant communities with different structural variations, geology, and climatic conditions. There are two major soil types in region with well structured Ferrosols (red clay loam) and red and yellow podsolic soils, both formed due to the weathering of volcanic rocks such as basalt and Triassic sedimentary rocks. The rainfall of this area is modified by topography, however, with higher orographic rainfall occurring in the mountainous areas and lower rainfall in the low-lying valleys and floodplains. In summer, easterly to southeasterly winds predominate, while in winter, dry westerly to south-westerly winds predominate. These result in a distinct summer–autumn rainfall maximum, relatively dry springs, and fine sunny days with cool nights in winter. Both selected study areas are in Biodiversity Hotspots harbouring a large number of flora and fauna species. Nevertheless, Bell Miner associated dieback continues to be a major cause of eucalypt vegetation decline and this has led to localised fundamental change in vegetation structure, species composition, and more general effects on the biota and landscape of the region.
Chapter 4
Uses of LiDAR to Characterise Plot Level Biophysical Attributes of Vegetation in Eucalypt Dominated Open-canopy Forest and Structurally Complex Subtropical Rainforest

This chapter has been submitted to the Journal of Forest Research as: EDIRIWEERA, S., PATHIRANA, S., DANAHER, T. & NICHOLS, D., ‘Estimating structural parameters using airborne LiDAR in subtropical rainforest and eucalypt forest in topographically complex terrain in North-eastern Australia’ Journal of Forest Research, under review

Declaration of Authorship

Components of this chapter relating to assessment of different topographic corrections were done in entirety by Sisira Ediriweera in partial fulfillment of his PhD. Sisira Ediriweera led the writing of the paper. S. Pathirana, T. Danaher, and D. Nichols reviewed the manuscript prior to submission to the Journal of Forest Research. The relative contributions of the four authors to the manuscript are indicated below.

Conception of the study: SE (60%), SP (20%), TD (20%)
Design of the study: SE (50%), SP (25%), TP (25%)
Collection of data: SE (70%), SP (20%), DN (10%)
Analysis of data: SE (70%), TD (30%)
Interpretation of data: SE (60%), TD (15%), SP (15%), DN (10%)
Conclusions: SE (60%), TD (20%), SP (20%)
Writing up manuscript: SE (100%)
4.1 Introduction

The biophysical structure of vegetation is increasingly being recognized as a fundamental source of data for sustainable forest management and investigations of climate change. Collecting information about forest structure and composition requires measurements of changes in its structural characteristics over time (Brokaw, 1982), however, field methods are a proven method and likely to be part of any monitoring program but not efficient over large areas. Field based assessments are time consuming and often not economically viable. Access may be challenging, especially in extensive rugged terrain, resulting in important areas of targeted vegetation being inadequately sampled. Thus, forest managers and ecologists have long sought efficient ways to estimate vegetation structure in forested systems. The rapid advancement of remote sensing instruments provides methods by which it is possible to acquire information of forest structure over space and time that can serve as the basis of forest management strategies.

LiDAR offers the possibility to retrieve detailed three-dimensional (3D) information about the biophysical structure of forests. The small-footprint airborne discrete return LiDAR system is based on laser range measurements from an aircraft and the precise orientation of these measurements. LiDAR data consist of a set of points, or “returns”, accurately and precisely georeferenced in three dimensions (Baltsavias, 1999). These returns are the location where laser pulse energy emitted from a scanning instrument is backscattered off a target. Even in areas with high canopy cover, where most returns are from a tree canopy, some measurements will be returned from the differing strata and ground surface. Recently, LiDAR technology has become an important component in quantifying forest structure for ecological and commercial purposes. The continual technological advancements and commercial competition has resulted in substantial reduction in the cost of acquiring LiDAR data (Gatzios et al., 2010), which provides an opportunity to integrate this technology for forestry and ecological studies.
During the last few years, the application of discrete LiDAR to estimate at single tree, and plot scale forest structure (e.g., tree height, basal area, timber volume, aboveground biomass, foliage cover) has created interest among the scientific community. The structural variation in forest will affect the spatial distribution of the laser returns (Åorka et al., 2009), thus laser metrics can be employed to characterize structural elements of vegetation. These laser metrics are included as independent variables in regression analyses that examine correlations with measured structural data of vegetation. For example, laser height percentiles provide information on forest canopy structure at different canopy height levels (Donoghue et al., 2007), while further maximum, mean and other height related laser metrics provide statistical information related to the vertical distribution of canopy height levels. Several studies have already demonstrated that the inclusion of laser metrics derived from laser height distribution, rate of laser penetration through the canopy and in combination with selected laser height percentiles have proven potential to estimate basal area (Means et al., 2000, Naesset, 2002, Heurich and Thoma, 2008, Haywood and Stone, 2011), stem density (Naesset, 2002, Heurich and Thoma, 2008, Haywood and Stone, 2011), and timber volume (Means et al., 2000, Naesset and Okland, 2002, Maltamo et al., 2006). Additionally, satisfactory results could be obtained for crown length (Naesset and Okland, 2002), and leaf area index (Magnussen and Boudewyn, 1998). Thus, inclusion of information on the height and density related attributes of forest may allow enhancement of quantification of the horizontal and vertical structure of vegetation.

The use of laser metrics in conjunction with regression equations may improve the prediction of plot scale structural elements of vegetation in Australian woody plant communities, even in topographically dissected terrain. However, the predictions of structural attributes of vegetation using airborne LiDAR have been poorly investigated for subtropical and tropical plant communities in topographically complex terrain. Globally, most LiDAR applications for
characterizing forest structure have been carried out in plantations with a uniform overstorey, temperate coniferous forests (Næsset, 2002, Næsset and Okland, 2002, Holmgren et al., 2003, Næsset, 2004, Jensen et al., 2006), deciduous forests (Brandtberg et al. 2003, Brandtberg, 2007), or mixed forest vegetation with simple forest structure (Heurich and Thoma, 2008), with gentle topography. In Australia, the application of LiDAR data to characterise forest structure in multiple layered rainforest areas is limited (Zhang et al., 2011). Sparse or structurally simple canopy conditions may provide sufficient laser returns to allow the generation of height and density related attributes at high fidelity. These circumstances probably facilitate accurate and precise estimation of forest structure. However, such conditions are not common in forest areas in subtropical and tropical regions, including structurally complex subtropical rainforests which are located on hilly terrain in eastern Australia. Additionally, studies have shown that forest structural attributes predictive models are dependent on the tree species and topography, and are consequently site specific. The objective of this chapter is to investigate the potential application of LiDAR derived different height and density related laser metrics to quantify plot scale forest structure (i.e. mean tree height, dominant tree height, mean dbh, dominant dbh, mean basal area (BA), and stem density) of two structurally different plant communities. To determine how well vertical and horizontal forest structure can be modelled and estimated by laser metrics for plot scale woody plant communities, two dominant vegetation types in hilly terrain in north-eastern NSW were considered: (1) closed-canopy subtropical rainforest, and (2) open-canopy eucalypt forest. This study presents an extreme application of LiDAR technology, that is (a) structurally complex canopy in highly stratified forest, and (b) topographically complex terrain compared to the eucalypt dominated open canopy with moderate topographic variation.
4.2 Material and Methods

4.2.1 Field Data Collection and Processing

Field data collection was conducted between July and December 2010. A total of 50 sampling plots representing 25 plots for each study site were used to measure and estimate structural parameters. Each sampling plot was 0.25 ha in area. A random sampling method was adopted to ensure that sampling measurements acquired all possible variability of forest conditions. Sampling plots were considered undisturbed if they consisted of mature vegetation with uniform slope and aspect, and had not been recently exposed to fire or tree felling. The centre of each plot was determined by using a GPS unit (GARMIN GPSMAP (R) 62stc). Five GPS points were recorded in the centre of each sample plot over a 20 minute period and then averaged. The accuracy of the GPS under the trees varied with the density of overstorey canopy with standard deviation of the five measurements ranging from 5 m to 8 m in the closed-canopy BRNP, and from 3 m to 6 m in the open-canopy RRNP. Mean tree height, dominant tree height, dbh, dominant dbh, mean basal area (BA) and stem density at plot scale in both forests were recorded.

4.2.1 (a) Tree Height Measurements

Heights of all trees at dbh 10 cm or greater than 10 cm were measured, and the average of those measures was used as arithmetic mean height vegetation in each plot. In each sample plot, tree heights were measured using a Nikon Forestry 550 Laser Rangefinder/Heightmeter. Tree height measurement in the BRNP plot was challenging since midstorey tends to obscure the overstorey crowns. Accurate measurement of overstorey tree height in the closed-canopy BRNP plot was dependent on clear visibility of overstorey tree crowns from the ground. Hence, the height measurements recorded were to the furthest visible point of the crown from ground level.
4.2.1 (b) Diameter at Breast height (dbh) Measurements and Calculation of BA

Stem diameter of tree measurements were taken in all plots at both study areas. All trees with dbh greater than 10cm were marked, and diameters at 1.3 m height were measured using a diameter tape. Diameters for buttressed trees were measured immediately above the buttress. Dbh of all dominant trees in each plot were separately measured then averaged.

The sum of the BA of all living trees in each plot is expressed in m²/ha. BA was calculated from measurements of the diameter (dbh in cm) of all trees in a sample plot using equation 1:

\[
BA = \frac{\pi}{4000} \times \frac{\sum \text{dbh}^2}{a} \quad (1) \quad \text{where, } a \text{ is area}
\]

In order to investigate the potential of estimation of plot scale structural parameters of vegetation (i.e. mean tree height, dominant tree height, dbh, dominant dbh, mean basal area (BA), stem density) using laser metrics, overall 1937 and 2207 trees were measured of the BRNP and RRNP respectively (Table 4.1).

Table 4.1 Statistical summary of structural parameters of vegetation of the sample plots

<table>
<thead>
<tr>
<th>Target parameter</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BRNP</td>
<td>RRNP</td>
<td>BRNP</td>
<td>RRNP</td>
</tr>
<tr>
<td>Mean tree height (m)</td>
<td>32</td>
<td>27</td>
<td>17.5</td>
<td>12.5</td>
</tr>
<tr>
<td>Dominant tree height (m)</td>
<td>40.6</td>
<td>34.3</td>
<td>28.4</td>
<td>25.2</td>
</tr>
<tr>
<td>Mean dbh (cm)</td>
<td>31</td>
<td>20.1</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Dominant dbh (cm)</td>
<td>64.8</td>
<td>49.2</td>
<td>41</td>
<td>34</td>
</tr>
<tr>
<td>Mean Basal Area (m² ha⁻¹)</td>
<td>32.3</td>
<td>16.8</td>
<td>24.3</td>
<td>11.3</td>
</tr>
<tr>
<td>Stem density (ha⁻¹)</td>
<td>388</td>
<td>264</td>
<td>272</td>
<td>148</td>
</tr>
</tbody>
</table>
4.2.2 LiDAR Data

The LiDAR data was supplied by the NSW office of Land and Property Information (LPI). LiDAR data was captured using a Leica ALS 50-II infrared laser scanner, mounted on a small aircraft, a Piper Navajo PA-31. The Leica ALS50-II is an infrared laser configured to record up to four returns per laser pulse. LiDAR surveys covered different slopes and aspects; two transects in the RRNP covering approximately 7 km length of each transect while the BRNP was covered by an 8 km transect. The aircraft flew at a nominal altitude of 2 km in both study areas, which resulted in a footprint of approximately 50 cm, and swath widths were approximately 1 km. Due to the large topographic variation, the range from the sensor to the ground for individual pulses varied between individual sampling points. The average point density was 1.3 points/m². All ranges were measured by the laser scanner at the off-nadir angle (Table 4.2). Data was projected into the UTM zone 56 (GDA94). Data was supplied in the American Society for Photogrammetry and Remote Sensing (ASPRS) LiDAR Exchange Format (LAS), specification 1.2. LiDAR returns were classified as ground or non-ground using proprietary software. The average range varied between 524 m and 1018 m (mean 800 m) for the BRNP, and 157 m and 460 m (mean 256 m) for the RRNP. The mean rate of penetration through the vegetation varies from 4.3% in the BRNP and 19% in RRNP (Table 4.3).
Table 4.2 System and mission parameters for the LiDAR data collection mission for the BRNP and RRNP study plots, August 2010

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>LiDAR system</td>
<td>ALS50-II Oscillating mirror, sinusoidal scan pattern</td>
</tr>
<tr>
<td>Wave length</td>
<td>1,064 nm</td>
</tr>
<tr>
<td>Pulse length</td>
<td>&lt; 9 ns</td>
</tr>
<tr>
<td>Scan rate</td>
<td>54 Hz</td>
</tr>
<tr>
<td>Pulse repetition rate</td>
<td>109 KHz</td>
</tr>
<tr>
<td>Aircraft altitude</td>
<td>Approximately 2 km</td>
</tr>
<tr>
<td>Data recording</td>
<td>Multiple</td>
</tr>
<tr>
<td>Size of footprint</td>
<td>50 cm</td>
</tr>
<tr>
<td>Point spacing in flight direction</td>
<td>1.02 m</td>
</tr>
<tr>
<td>Point spacing across flight direction</td>
<td>1.5 m</td>
</tr>
<tr>
<td>Average point density</td>
<td>1.3 pts / m²</td>
</tr>
</tbody>
</table>

Table 4.3 Sampling density of LiDAR data

<table>
<thead>
<tr>
<th>Study area</th>
<th>No. sampling sites</th>
<th>Mean no. of transmitted pulses (ha⁻¹)ᵃ</th>
<th>Mean no. of canopy (&gt; 2 m vegetation) hits (ha⁻¹)ᵇ</th>
<th>Mean rate of penetration (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BRNP</td>
<td>25</td>
<td>29476</td>
<td>28200</td>
<td>4.3</td>
</tr>
<tr>
<td>RRNP</td>
<td>25</td>
<td>25636</td>
<td>20840</td>
<td>19</td>
</tr>
</tbody>
</table>

ᵃ-Refers to first pulse data

4.2.3 LiDAR Data Processing and Computation

All subsequent processing routines were implemented with the LiDAR processing code developed by Armston et al., (2009) in the IDL 8.0 and ESRI Inc. ArcGIS 9.3. As the sensor recorded multiple returns, all returns were considered for subsequent analysis in both study areas. Firstly, ground and non-ground returns were separated. A 1 m DTM was produced using filtered returns classified as representing the ground via Kriging interpolation. For each cell in the DTM, the 6 closest points were used for the interpolation. To evaluate the accuracy of the
LiDAR DTM, post-processed differential GPS points (dGPS) were collected using MobileMapper from Thales Navigation Systems™ in different locations. GPS points were distributed over LiDAR transects with 70 points (4 transects) for the BRNP, and 55 points (3 transects) for the RRNP. GPS points were collected from flat to slope terrain in open ground (e.g. park roads) and under forest canopy of different densities. In order to assess the accuracy of the LiDAR DTM, ground collected dGPS points were overlaid on the LiDAR DTM. To evaluate the quality of LiDAR-derived DTMs, root mean square error (RMSE) were calculated. The calculated RMSE for the closed-canopy BRNP was 5.7 m and 1.9 m for the open-canopy RRNP.

Secondly, laser metrics were calculated from separated non-ground laser returns. Observations with height values less than 2 m for the RRNP and 0.5 m for the BRNP were discarded from existing non-ground data. These threshold values were appropriate to remove undulation of the terrain and other objects such as herbaceous vegetation, litter, logs, and boulders thus most reflectance was represented only from understorey and overstorey vegetation. Several studies have used height thresholds up to 3 m to remove laser returns from understorey vegetation (Næsset, 2002, Riaño et al., 2004, Heurich and Thoma, 2008). The chosen lower threshold heights were appropriate for the BRNP as the closed-canopy overstorey vegetation leads to suppressions of understorey layers and weak penetration of laser pulses through the canopy close to the ground. In the RRNP (sparse overstorey trees with dense understorey) a 2 m height threshold was applied to eliminate laser returns from vegetation and non-ground objects. The non-ground returns were used to extract co-located 50 m x 50 m sample plots of each study area, and a series of laser metrics comprising height and density related variables were computed.
4.2.3 (a) Height and Density Related Laser Metrics

Laser height percentiles provide information on forest canopy structure at different canopy height levels (Donoghue et al., 2007), while further maximum, mean and other height related laser metrics provide statistical information related to the vertical distribution of canopy height levels. The standard deviations of LiDAR pulse dispersal provide a simple measurement of the variation within laser height distribution in a planning unit. Moreover, the coefficient of variation (CV) provides information related to the dispersion of laser height distribution within a sampling plot. As a measure of crown density, the higher CV values indicate an open canopy situation, and lower values for closed-canopy forests. The addition of CV values has been successfully used for estimating different structural elements of vegetation including basal area, biomass, and volume (Næsset and Okland, 2002, Nelson et al., 1997). When only the returns from the forest canopy are considered, Skewness and Kurtosis of the laser height distribution change as trees increase in height and the canopy develops (Watt, 2005), hence it can be assumed that inclusion of this information as explanatory variables would improve prediction of structural elements of vegetation even in closed canopy conditions.

Additionally, various measures of canopy penetration rate of laser reflectance are considered to be a good source of data to estimate timber volume derived from LiDAR (Means et al., 2000, Næsset, 2002, Næsset, 2004, Heurich and Thoma, 2008, Nord-Larsen and Riis-Nielsen, 2010). In this study, different canopy penetration rates were used, and different density related metrics were computed from laser reflectance. Moreover, LiDAR fractional cover estimates were calculated by aggregating all points into 50 m spatial bins. LiDAR fractional cover (Lovell et al., 2003) is defined as one minus the gap fraction probability at a zenith of zero. The following height and density related laser metrics were computed using LiDAR for all sample plots in both study sites (Table 4.4).
### Table 4.4 Summary of all LiDAR derived laser metrics computed from all returns of registered laser returns

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>((Z_{\text{max}}))</td>
<td>Maximum laser height</td>
</tr>
<tr>
<td>((Z_{\text{m}}))</td>
<td>Mean laser height</td>
</tr>
<tr>
<td>((Z_{\text{med}}))</td>
<td>Median laser height</td>
</tr>
<tr>
<td>((Z_{\text{rmed}}))</td>
<td>Relative Median laser height [Z_{\text{rmed}} = \frac{Z_{\text{med}}}{Z_{\text{max}}} \times 100]</td>
</tr>
<tr>
<td>((p_{10^{\text{th}}} \ldots, p_{90^{\text{th}}}))</td>
<td>Laser height percentile 10(^{\text{th}}), 20(^{\text{th}}), 30(^{\text{th}}), 40(^{\text{th}}), 50(^{\text{th}}), 60(^{\text{th}}), 70(^{\text{th}}), 80(^{\text{th}}) and 90(^{\text{th}}) percentiles</td>
</tr>
<tr>
<td>((Z_{\text{sd}}))</td>
<td>Standard Deviation of height dispersion</td>
</tr>
<tr>
<td>((Z_{\text{k}}))</td>
<td>Kurtosis - Distribution form parameter</td>
</tr>
<tr>
<td>((Z_{\text{cv}}))</td>
<td>Coefficient of variation- Distribution form parameter</td>
</tr>
<tr>
<td>((\text{PR}_{\text{gl}}))</td>
<td>Proportion of LiDAR points at ground layer [\text{PR}_{\text{gl}} = \text{sum of penetrated all laser pulses (pr) } &lt; m^2/\text{total number of all pulses measured (TP)}; \ m^2 \text{ for BRNP-1.5m, RRNP -1m}]</td>
</tr>
<tr>
<td>((\text{PR}_{\text{ol}}))</td>
<td>Proportion of LiDAR points at overstorey [\text{PR}<em>{\text{ol}} = \text{pr } &lt; 0.75 \times Z</em>{\text{max}}/ \text{TP}]</td>
</tr>
<tr>
<td>((\text{PR}_{\text{ml}}))</td>
<td>Proportion of LiDAR points at middlestorey [\text{PR}<em>{\text{ml}} = \text{pr } &lt; 0.5 \times Z</em>{\text{max}}/ \text{TP}]</td>
</tr>
<tr>
<td>((\text{PR}_{\text{ul}}))</td>
<td>Proportion of LiDAR points at understorey [\text{PR}<em>{\text{ul}} = \text{pr } &lt; h^a \times Z</em>{\text{max}}/ \text{TP} \ \ h^a \text{ for BRNP-8m and RRNP-3m}]</td>
</tr>
<tr>
<td>((P_1, P_2, P_3 \ldots \ldots, P_9))</td>
<td>Proportion of LiDAR point within different height bins: (Z_{\text{max}}) divided into 10 equally size bins the proportion of LiDAR points were calculated within different bins of vertical forest profile</td>
</tr>
<tr>
<td>((\text{Fra}_{\text{ccov}}))</td>
<td>LiDAR fractional cover which is defined as one minus the gap fraction probability (P_{\text{gap}}) at a zenith of zero</td>
</tr>
</tbody>
</table>
4.2.4 Statistical Analysis

Multiple Linear Regression (MLR) was performed with the LiDAR derived laser metric as the explanatory variables and field measured forest structural parameters as the response variables. MLR is a standard statistical technique which is widely used in biophysical modelling of remote sensing applications (Næsset, 2002, Heurich and Thoma, 2008, Haywood and Stone, 2011). There
were thirty-one different independent laser metrics computed (Table 4.4). Many different MLR models can be created with a set of thirty-one independent variables. The plot scale MLR models were fitted using the linear regression in the IBM SPSS -20 statistical software. General model structure can be as follows:

\[ y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \beta_6 x_{i6} + \beta_7 x_{i7} + \epsilon_i \]  

(2)

Here, \( y_i \) is different vegetation structural parameters for \( i^{th} \) plot \((I = 1, 2, 3, 4……50)\), \( x_i \) is a LiDAR metric, \( \epsilon_i \) is the plot-level error with \( \epsilon_i \sim N(0, \sigma^2) \), and \( \beta_1 - \beta_7 \) and \( \sigma^2 \) that are constants that must be estimated. The root mean squared error (RMSE), which is \( \sigma \), as a summary statistic for unexplained variation.

For model fitting, each vegetation type represented in the study area was considered separately and the data set of each study area was combined for regional models as both data sets were acquired using the same sensor and on average a similar footprint. Initially, the strength and potential relationships of ground measured vegetation attributes and laser metrics were assessed using scatter plots and this investigation showed that data transformation was not required. The independent variables were laser metrics for each sampling plot whilst ground measured vegetation structural parameters were dependent variables. Each model used stepwise MLR, independent variables with a partial \( F \) statistic and with a significance greater than 0.1 were not included. A variance inflation factor (VIF) greater than 10 was considered to detect multicollinearity of independent variables (LiDAR derived laser metrics) used.

Regression diagnostics including adjusted \( R^2 \) and coefficient of variance of the root mean square error RMSE (CVRMSE) and residual plots were used to select optimal models. Adjusted \( R^2 \) measures the proportion of the variation in the dependent variable accounted for by the explanatory variables. Unlike \( R^2 \), adjusted \( R^2 \) allows for the degrees of freedom associated with
the sums of the squares. Even though the residual sum of squares decreases, or remains the same, as new explanatory variables are added the residual variance remains constant. For this reason, adjusted $R^2$ is generally considered to be a more accurate goodness-of-fit measure than $R^2$ (Harrell, 2001). The coefficient of variance of the RMSE was computed as follows:

$$CV_{RMSE} = \frac{1}{N} \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n} O_i}}$$

(3)

where $O$ is observed value, $P$ is predicted values, and $N$ is number of observations.

RMSE is the square root of the mean square error and is directly interpretable in terms of measurement units. RMSE of two models both measure the magnitude of the residuals, however they cannot be compared in order to determine which model provides better performance. The RMSE of model and mean of the predicted variable are expressed in the same units, so taking the ratio of these two allows the units to cancel. This ratio can then be compared to other such ratios in a meaningful way: between two models, the model with the smaller coefficient of variance $CV_{RMSE}$ has predicted values that are closer to the actual values. Thus, $CV_{RMSE}$ was used in this study for model selection (equation 3). The applied methodology for data processing and model development is summarised in Figure 4.1.

4.2.5 Validation of the Regression Model Predictions

The accuracy of a regression model is demonstrated in its ability to predict data from other samples of the target population. The best procedure is to reproduce the study and test the accuracy of the prediction rule with the ground collected vegetation structural measurements. However, this method is expensive and delays the final establishment of a model. Since all ground-truth data were used for the model calibration, there was no data available for the validation process. Therefore, in order to determine the accuracy of the estimations cross-validation was performed. Bias and $CV$ were used to assess prediction error of candidate models.
4.3 Results

4.3.1 Regression Model Performance

4.3.1 (a) Dominant and Mean Heights

The results for the structural parameters of forest (Table 4.5) showed that the different height related parameters were relatively accurate. The overall adjusted $R^2$ ranged between 0.81-0.90 for the RRNP, 0.40 - 0.61 for the BRNP closed-canopy, and 0.60 - 0.66 adjusted $R^2$ observed combined dataset (BRNP+RRNP). The summarised statistics showed that highly accurate results were obtained for mean tree height, and dominant tree height in the RRNP, however the least accurate results reported for mean tree height were in the BRNP sites. The results for dominant tree height in the BRNP and mean height for combined data were also relatively high. Mean tree height and dominant tree height in the RRNP were the most accurate. The coefficient of variation of the RMSE was greatest (7 %) for dominant overstorey height combined data. For the mean tree height, dominant tree height in the RRNP, the coefficient of variation of the RMSE was below 5%. The best subset of models for tree height with least error was obtained for the open-canopy RRNP sites; followed by the combined data (RRNP+BRNP). However, the findings for the closed-canopy BRNP site were less satisfactory.

4.3.1 (b) Dominant and Mean Dbh

The different diameter related parameters yielded acceptable results, however the accuracy was not as high as the height related parameters in all sites. The adjusted $R^2$ ranged between 0.35 to 0.85 for all sites. The highest adjusted $R^2$ value was obtained for mean dbh for combined sites with adjusted $R^2$ value of 0.85. The respective coefficient of variation of the RMSE was 13.6%. Estimation of mean dbh was satisfactory for the BRNP site and correspondence coefficient of variation of the RMSE was 11.3%. The least accurate result for mean dbh estimation was obtained for the RRNP site and its coefficient of variation of the RMSE was 14.5%. The findings suggested
that estimation of dominant dbh at acceptable accuracy was possible for the open-canopy RRNP site rather than the mean dbh. The best result for dominant dbh estimation was produced for the RRNP sites and combined sites data provided the best subset of a model with least error for mean dbh estimation.

4.3.1 (c) Basal Area

The adjusted $R^2$ for basal area ranged between 0.62-0.76. The most accurate results were obtained for the combined site data and adjusted $R^2$ and coefficient of variation of the RMSE were 0.76 and 11.9% respectively. The second most accurate height results for basal area were produced for the RRNP site with 9.4 % coefficient of variation of the RMSE. However, the BRNP data computed the least accurate results for estimation of basal area with coefficient of variation of the RMSE at 10.8%.

4.3.1 (d) Stem density

The estimation of number of trees per hectare for RRNP and BRNP and combined site data were less satisfactory. The adjusted $R^2$ was between 0.18 and 0.21. The coefficient of variation of the RMSE for the BRNP was 29.1 % and this value was greater than the other sites investigated. The coefficient of variation of the RMSE for estimation of number of trees per hectare for combined site data was 27.8%.

All other developed equations were parsimonious models containing four, or less than four independent variables. However, the quality criterion of homoscedasity could not satisfactorily provide estimation for stem density at the RRNP sites. The results for the most structural attributes in the subtropical rainforest of the BRNP were less accurate than for the RRNP site; however combined sites data depicted acceptable high levels of accuracy.
Table 4.5 Summary of best subset regression models obtained from field measured structural attributes of vegetation (dependent variables), and different laser metrics (independent variables) for the RRNP, the BRNP, and combined (BRNP+RRNP)

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>RRNP (N=25) Adj. R² CV RMSE (%)</th>
<th>BRNP (N=25) Adj. R² CV RMSE (%)</th>
<th>Regional (BRNP+RRNP) Adj. R² CV RMSE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean tree height (m)</td>
<td>37.96 + 0.512 x P₇₀th - 27.31 x P₉</td>
<td>0.90 2.9</td>
<td>3.1 +0.72 x P₇₀th</td>
</tr>
<tr>
<td>Dominant tree height (m)</td>
<td>20.5 + 2.3x P₆ - 0.486 x Z_sd+0.1 x Z_med + 0.371 x P₈₀th</td>
<td>0.81 1.1</td>
<td>30.33+2.17 x P₈₀th - 1.82 x P₇₀th</td>
</tr>
<tr>
<td>Mean dbh (cm)</td>
<td>12.70+ 0.610 x P₄₀th + 0.60 x Z_sd</td>
<td>0.35 14.5</td>
<td>77.73+ 0.918 x P₉₀th - 405.2 x P₈</td>
</tr>
<tr>
<td>Dominant dbh (cm)</td>
<td>31.99+ 4.336 x Z_m - 0.837 x Z_rmed</td>
<td>0.70 9.6</td>
<td>42.46 - 6.40x P₆₀th + 8.02 x Z_m</td>
</tr>
<tr>
<td>Mean Basal Area (m² ha⁻¹)</td>
<td>45.14 + 0.035 x Fracov - 0.436 x P₅₀th - 50.05xP₂</td>
<td>0.65 9.4</td>
<td>33.88+1.442 x P₁₀₀th - 1.507 x P₉₀th + 4.393 x Z_sd - 1.595 x P₇₀th</td>
</tr>
<tr>
<td>Stem density (ha⁻¹)</td>
<td>877.77 -11.82 x Z_max</td>
<td>0.2 24.5</td>
<td>1255.7-1182 x PR_gl</td>
</tr>
</tbody>
</table>
4.3.2 Validation of the Regression Models Prediction

Table 4.6 summaries the cross-validation results of all candidate models. Validation results shows bias was relatively accurate for most of the models developed that indicated the least or no bias error. Regarding the combined site data (BRNP+RRNP), the CV was greater than for the individual sites. This clearly showed that the lowest CV was obtained only for the dominant height. The CV for mean height and dominant dbh was considerably lower, and ranged between 7 to 17 %. The highest CV values were depicted for the stem density, and mean dbh for combined site data.

The results for the RRNP site were more accurate than the BRNP site, and also for the combined sites. Most of the candidate models showed relatively low bias. For example the bias values for BA, mean tree height and dominant tree height were approximately zero. The CV values were relatively high however, the values were not as high as for the combined site data. The lowest CV was obtained for the estimation of the dominant canopy height and was only 2%. CV for estimation of mean height was 5.6%, dominant dbh (9.2 %), and mean basal area (15%). This clearly shows that CV were greater than 20% for all other parameters such as stem density and mean dbh.

For the BRNP, the calculated deviations from the observed means values were relatively high. The greatest deviation showed for estimation of stem density and was almost 30%. Some of the CV in this site was even smaller than for the RRNP. For instance CV was 14.8% for estimation of mean dbh in the BRNP while it was 22.5% for the RRNP. It showed that the lowest CV values were obtained for the dominant tree height, and mean tree height which was below 12%. However, the lowest CV was obtained for estimation of dominant height (9%).
Table 4.6 Summary of cross-validation results for the RRNP, the BRNP, and data combined (BRNP+RRNP); CV % - coefficient of variation

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>RRNP (N=25)</th>
<th>BRNP (N=25)</th>
<th>Combined (BRNP+RRNP)(N=50)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bias</td>
<td>CV</td>
<td>Bias</td>
</tr>
<tr>
<td>Mean tree height (m)</td>
<td>-0.03</td>
<td>5.6</td>
<td>-4.16</td>
</tr>
<tr>
<td>Dominant tree height (m)</td>
<td>-0.04</td>
<td>2</td>
<td>-2.02</td>
</tr>
<tr>
<td>Mean dbh (cm)</td>
<td>4</td>
<td>22.5</td>
<td>1.51</td>
</tr>
<tr>
<td>Dominant dbh (cm)</td>
<td>0.12</td>
<td>9.2</td>
<td>0.9</td>
</tr>
<tr>
<td>Mean Basal Area (m² ha⁻¹)</td>
<td>0.03</td>
<td>15</td>
<td>-0.8</td>
</tr>
<tr>
<td>Stem density (ha⁻¹)</td>
<td>7.8</td>
<td>22.9</td>
<td>15.61</td>
</tr>
</tbody>
</table>

4.4 Discussion

4.4.1 Comparison with Findings of other Studies

This chapter sought to investigate the potential application of height and density related LiDAR derived laser metrics to estimate selected structural parameters of two structurally different plant communities in hilly terrain. Thirty-one, height and density related laser metrics were used as independent variables in a linear regression framework to develop prediction models of structural parameters of vegetation. The findings of this study showed the feasibility of estimating most structural attributes of vegetation using this method, even in the dense canopy with complex forest structure and topography. However, the level of accuracy of each estimated parameter varied with the complexity of the structural components of the vegetation.

Estimation of dominant height and mean canopy height from laser metrics resulted in a high level of accuracy (error less than 3% CV RMSE), and explained over 0.80 of total variation in dominant height for the open-canopy eucalypts forest of the RRNP. The average bias was
negligible (< -1m) for these sample plots within these vegetation conditions. The overall accuracy for estimation of dominant canopy height in open canopy conditions concurs with the findings of previous studies carried out in eucalypt forested in Australia (Tickle et al., 2006, Haywood and Stone, 2011), and globally with structurally similar forests (Næsset, 2002, Næsset and Okland, 2002, Roberts et al., 2005, Heurich and Thoma, 2008). Haywood and Stone (2011) estimated canopy top height using laser metrics, and the error for determination of the canopy dominant height was quite similar to the open-canopy eucalypt dominant RRNP site (2 %).

Previous studies Næsset (1997), Magnussen and Boudewyn (1998), Næsset (2002), Næsset and Okland (2002), and Nord-Larsen and Riis-Nielsen (2010) demonstrated that for a given sampling site and canopy structure, a certain percentile in the height distribution exists that corresponds to the canopy height of interest. Several studies (Magnussen and Boudewyn, 1998, Naesset and Bjerknes, 2001) show a greater relationship between ground measured tree heights (dominant canopy heights or mean canopy height) and laser derived height was observed above the 70th percentile, however, the findings of this study is inconsistent with this relationship. However, this finding is consistent with Haywood and Stone (2011), who reported a similar relationship between eucalypt top height and laser derived reported 70th percentile. This is probably due to the density and complexity of spatial organization of broad leaf canopy, as LiDAR derived height percentiles may not correspond to the canopy height of interest. The accuracy of measures of dominant tree height, and mean tree height of the closed-canopy BRNP were not superior to that of the open-canopy RRNP. The accuracy of height models derived using laser metrics for the closed-canopy BRNP was rather similar to those found by Gatziolis et al. (2010) in a temperate rainforest characterized by complex terrain using a small footprint LiDAR. This study revealed incorporated laser metrics were disabled to account for a large amount of variations in mean and
dominant tree heights (Table 4.5), thus the magnitude of error for these predictions was considerably higher in the closed-canopy subtropical rainforest.

The diameter at breast height estimates of subtropical trees species and open-canopy eucalypt tree species based on laser metrics were found to be less accurate than the tree height estimation models. The best model had adjusted $R^2$ of 0.85 with 13.6 % for CV RMSE for mean dbh estimation in the combined site data, and the least accurate model was mean dbh estimation of the RRNP site. The findings of dbh estimation were similar to those of the investigation undertaken by Jensen et al. (2006) in forest with diverse vegetation structure and composition with topographically complex terrain in North America; and findings in similarly structurally rich natural European beech and Norway Spruce forests in Germany (Heurich and Thoma, 2008).

For the study, the estimation of mean basal area for RRNP and combined site data produced relatively more accurate results. Haywood and Stone (2011) reported similar results $R^2$ of 0.56 with an RMSE 14 m$^2$ when ground-measured basal area was regressed against laser metrics of vegetation on data from natural re-growth eucalypt forests in Australia. The mean basal area estimates of closed-canopy subtropical rainforest (BRNP) using LiDAR derived laser metrics gave less satisfactory results.

In the present study, the results for estimation of stem density were less satisfactory for all vegetation conditions compared to the other parameters investigated. The greatest error for estimation of number of tree stems was given for the BRNP, and combined sites data (~29%). Inconsistent with these results were those reported by Lim and Treitz (2004) who reported $R^2$ of 0.58 when stem density was regressed against mean laser height derived from all laser-scanning returns based on data from a mixed-species Canadian forest. Haywood and Stone (2011) found
an $R^2$ of 0.41 for regression against two height percentiles and measure of intensity from young Australian eucalypt forests and Heurich and Thoma (2008) reported $R^2$ of 0.69, 0.71 and 0.90 for all plots, coniferous forest, and deciduous forest respectively. The present study demonstrated that the laser metrics related to the penetration rate, LiDAR fractional cover, and maximum height explained 18-21% of variation in stem density of eucalypt forest, subtropical rainforest and of the combined site data. Penetration rate is the penetration of laser points into intermediate or ground strata, whereas fractional cover and maximum tree height describe the density of overstorey cover. Therefore, the variation of laser points penetration rate is a function of the stem density of sample sites.

4.4.2 Effect of Forest structure and Topography on the Accuracy of Estimates

The findings of this chapter demonstrated that the estimation of biophysical parameters of forest structure did not provide satisfactory level of precision in terms of correlation coefficient of RMSE (> 10%) for the BRNP, and for the combined sites. Based on these findings, it is suggested that forests with low diversity of vegetation structure and species composition, accuracy is likely to be superior as in the studies carried out in coniferous forests (Næsset and Okland, 2002, Næsset, 2004) than the results for the subtropical rainforest BRNP sites. For the BRNP sites a moderate relationship (adjusted $R^2$ of 0.40 and 0.61 for mean and dominant tree height) was found between ground-truth tree heights. In this study, LiDAR data with relatively high point spacing or point-to-point distance (~1 m) and low point density (~1.3/ m$^2$) with a high flying altitude (~2 km) are highly likely to affect the quality of DTM, and this may influence the accuracy of LiDAR derived laser metrics. As the complexity of a canopy structure increases, the probability that LiDAR pulses will penetrate below the canopy decrease by interference of middle and understorey strata. This causes a considerable impact on density of LiDAR points.
below the canopy which can affect the accuracy of laser metrics. Furthermore, a sufficient density of laser pulses of samples of the vegetation are required to allow a sufficient amount of reflecting material within each laser pulse footprint to cause a detectable return signal (Lefsky et al., 2002). This requirement was critical in the closed-canopy BRNP, as the laser energy was affected by the decreasing total amount of energy as laser pulses travel to lower strata through highly dense upper vertical tree structures. Therefore it creates some uncertainties for range measurements of such conditions. Further, a relatively large footprint (~50 cm) and continual varying topography within a sample plot creates uncertainty of the range measurements by considerably varying reflection characteristics within a footprint (Nilsson, 1996). Similarly, unavoidable error caused during the ground measurements also interfered with the accuracy of final products. In the highly dense canopy with tall trees, obtaining accurate tree height proved difficult due to interference from other tree crowns from the midstorey. In these conditions LiDAR range measurements may be more accurate than the field measurements. Obtaining accurate tree height in dense canopy is challenging because field estimates of tree height are obtained looking up, whilst LiDAR estimate range measurements are obtained looking downwards.

Additionally, due to the variation of light transmittance through the rainforest canopy, the rainforest tree species show a greater variance of leaf inclination and orientation than trees growing in an open-canopy forest. These modifications of leaf morphology may also affect the reflectance of laser energy throughout the forest profile. Thus, the high diversity of vertical and horizontal forest structures in the subtropical rainforest of the BRNP sites created a greater variation in laser pulse returns. Furthermore, due to the varying shapes of tree crowns, and the density of their stratification in different slopes and aspects of the topographically complex terrain (Bale et al., 1998), there was a greater potential in modification of the reflection behaviour
of laser points. All variations in laser reflectance were likely to increase uncertainty of the range measurements in the closed-canopy rainforest environment.

The regression analysis of mean dbh showed that accuracy was less satisfactory for estimation at individual sites (i.e. BRNP, RRNP) for than the combined sites. The ground measured mean dbh was found to be only positively correlated with the 40th height percentile and height standard deviation (Z_sd) for the RRNP. This is probably due to the young re-growth (~20 years) with the open-canopy RRNP largely containing small and medium size trees, as a consequence of logging. Additionally, most re-growth stems are heavily sprouted, and often damaged by fire, thus it showed a large standard deviation for mean dbh among the sampling plots. However, dominant dbh estimates based on LiDAR measurements showed an excellent agreement with laser metrics including medium tree height (Z_med), and relative medium height (Z_rmed). Incorporating height and density-related laser metrics enabled the estimates of mean, and dominant dbh at a reasonable level of accuracy for the BRNP data and the accuracy of the estimation of above variables were considerably higher for combined site data. This finding confirms that LiDAR-derived height metrics can account for a significant amount of the combined variance in stem diameter and height relationship.

The mean basal area is indicative of moderate or rather strong relationship between ground-based measurements and laser derived fractional cover (Fracov), and height percentiles and density related laser metrics for all data sets investigated. LiDAR fractional cover corresponds to the density of photosynthetic and non-photosynthetic components of the canopy (Weller et al., 2003). Armston et al. (2009) found a strong allometric relationship between the FPC and stand basal area for Australian woody plant communities. Inclusion of canopy attributes related to the LiDAR fractional cover with tree height for BA estimates prove that FPC is a key component for estimating basal area for Australian woody vegetation.
LiDAR assisted estimation of stem density was the least successful of the methods investigated in this study. The relationship between points density related laser metrics \( \text{PR}_{\text{tp}} \) with stem density, only poorly described the variation of stem density among sample plots for the BRNP, and combined sites data. Canopy die back in the RRNP, relatively young regrowth vegetation and presence of non eucalypt trees (mainly *Lantana camara*) likely influences the laser distribution throughout the forest profile. In the closed-canopy BRNP, the density of the overstorey layer that contains only a few trees controls considerably the laser penetration more than the influence of the density of stems. In principle, it is more difficult to employ laser data to estimate the stem density in closed-canopy subtropical and tropical rainforest.

### 4.5 Conclusions

Several key variables in forest planning are currently measured directly, or predicted indirectly using field data collection or stereoscopic aerial photointerpretation, but these can be estimated from LiDAR data. Forest structural parameters may be derived from small footprint LiDAR data with similar, or improved accuracy than that of conventional methods (Naesset, 2004). Interest in assessing biophysical structure of vegetation with LiDAR technology has grown tremendously over the past few years. The intention of this chapter was to investigate the potential application of height and density related laser metrics to quantify plot scale horizontal and vertical structural vegetation parameters in two structurally different plant communities in hilly terrain. The two plant communities tested represent a diverse assemblage of climatic conditions and topographic influences. This study demonstrated that airborne LiDAR data provides an alternative approach to estimate plot-scale structural parameters of vegetation for open canopy forest and subtropical rainforest in hilly landscapes. A key finding of this study is that the precision was reasonably high for the vegetation structural parameters of both plant communities; except for stem density.
The current study provides evidence that this can be achieved even in a subtropical rainforest in rugged terrain. However, the complexity of horizontal and vertical structural diversity and variation in topography degrade precision and are challenging for practical application. The findings demonstrate that predicting the accuracy of structural attributes by laser metrics in closed-canopy subtropical rainforest, with high species diversity is inferior to predicting the accuracy in sparse canopy with low species diversity. These findings reinforced that obtaining accurate LiDAR estimates of vegetation structure is a function of the complexity of horizontal and vertical structural diversity of vegetation. Due to the inadequate penetration of laser energy into the canopy in subtropical forest there is a high level of uncertainty in application of laser metrics to estimate structural parameters. For operational application of this technology in subtropical rainforests on topographically complex terrain, suitable methodologies need to be developed with levels of accuracy similar to those achievable in structurally simple forests on flat terrain. The incremental integration of laser generated attributes into the existing forest inventory will, over the short term, promote the increased use of LiDAR data for a range of forest applications, ultimately enabling time and cost savings for future operation activities.
Chapter–5
Impact of Different Topographic Corrections on Prediction Accuracy of Foliage Projective Cover (FPC) in Topographically Complex Terrain

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Please see the full article i.e. (Ediriweera et al., 2012) in Appendix-I

I would like to acknowledge the two reviewers for their constructive comments.

Declaration of Authorship

Components of this chapter relating to assessment of different topographic corrections were done in entirety by Sisira Ediriweera in partial fulfillment of his PhD. Sisira Ediriweera led the writing of the paper. S. Pathirana, T. Danaher, D. Nichols and T. Moffiet reviewed the manuscript prior to submission to the XXII ISPRS. The relative contributions of the five authors to the manuscript are indicated below.

Conception of the study: SE (50%), TD (40%), SP (10%)
Design of the study: SE (50%), TD (40%), SP (10%)
Collection of data: SE (70%), SP (20%), DN (10%)
Analysis of data: SE (70%), TD (20%), TM (10%)
Interpretation of data: SE (50%), TD (40%), SP (10%)
Conclusions: SE (60%), TD (30%), SP (10%)
Writing up manuscript: SE (100%)
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Declaration of Authorship

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Analysis of data: SE (60%), TD (30%), TM (10%)
Interpretation of data: SE (50%), TD (40%), SP (10%)
Conclusions: SE (60%), TD (30%), SP (5%), TM (5%)
Writing up manuscript: SE (100%)
5.1 Introduction

Operational mapping, monitoring of vegetation cover, and vegetation cover changes are important applications of remotely sensed data. The need for vegetation information over large areas has prompted investigation of the relationship between ground measurement of vegetation cover metrics and vegetation indices from spectral reflectance measured by remote sensors. The common approach has been to correlate a ground measured vegetation cover metric with the vegetation indices. Variation of reflectance by measured sensors caused by factors other than variations in vegetation cover modify this relationship, and reduces the accuracy of derived vegetation cover estimates. Change in atmospheric conditions alters the amount of light scattered and absorbed by the atmosphere. Furthermore, topography can substantially affect the radiometric quality of remotely sensed data. However, the estimation and monitoring of vegetation cover on hilly areas creates unique challenges compared to vegetation cover on flat terrain. Thus, it would seem that topographic correction is a necessary radiometric correction step when using remotely sensed data for vegetation mapping.

Several topographic correction methods including photometric techniques: cosine, Minnaert, C, and statistical empirical have been developed based on Sun-Terrain-Sensor geometry (STS) to minimise topographically induced illumination effects (Smith et al., 1980b, Justice et al., 1981, Teillet et al., 1982, Colby, 1991), and physically based topographic correction methods: Sun Canopy Sensor (SCS), a simple physical model, Processing Scheme for Standardised Surface Reflectance (PSSSR) (Gu and Gillespie, 1998, Shepherd and Dymond, 2003, Flood et al., 2012), and a semi-empirical method: Sun Canopy Sensor +C (SCS+C) Soenen et al. (2005) were developed to eliminate or minimize the topographic influences. These methods yield results with varying degrees of success for the respective investigated image. Thus, in order to improve
understanding of the influence of correction methods for minimising the topographically induced illumination of reflectances an appropriate method for accuracy assessment is required.

In general, proper accuracy assessment of corrected reflectance would require spectral information recorded by a spectroradiometer in the field during the time of a satellite overpass. The application of this method presents a number of difficulties due to strong anisotropic canopy reflectance, including a lack of an efficient method for accurate measurement of reflectance over forest canopy, physical accessibility, and costs of personnel and equipment. However, several feasible methods for accuracy assessments of topographic corrected reflectance have been reported in the literature. Land use landcover classification is one of the most commonly used methods to assess the performance of a topographic correction method (e.g. Hale and Rock, 2003, Riano et al., 2003, Shepherd and Dymond, 2003, Nichols et al., 2006). The method assumes that if topographically induced illumination has been effectively corrected, the image would contain spectral signatures with least variability for vegetation groups, hence greater distinction between groups. However, changing topography not only modifies the illumination of terrain, but also substantially modifies the biophysical properties of vegetation (i.e. tree height, foliage, stem density) in hilly terrain. Therefore, the variation in reflectance may be due to changing structure in addition to topographic effects of reflectance. A landcover classification approach seems to assess the accuracy of topographically corrected reflectance regardless of variations in canopy reflectance caused by biophysical properties of vegetation in hilly terrain. There are no clear separations between classification of forest types and the solar illumination changes caused by geomorphic variations of the terrain thereby the accuracy of the corrected image is unknown. Quantitative biophysical modelling is another approach to assessing the accuracy of topographically corrected images. This method relates to the data recorded by a remote sensing system to biophysical features and phenomena measured on a ground surface. Thus, the impact
of topographic correction methods on reflectance may be assessed by statistical comparison with ground surface measurements. Furthermore, subtle variation in apparent reflectance values related to the distribution of forest structure and composition may be accounted for in relation to the topography. Quantitative retrieval of biophysical parameters of vegetation for accuracy assessment of topographically corrected reflectance is scarce.

The topographic correction is challenging due to a lack of a standard accepted correction method (Riano et al., 2003), and identifying a suitable topographic correction method remains contentious. Moreover, Gu and Gillespie (1998) reported that influence of topography on reflectance is image dependent, and a single model would not account for such effects equally for different images. In fact the impact of different topographic normalization methods on Landsat images collected over structurally complex tropical or subtropical forest conditions have been poorly examined. Therefore, this study considered five commonly used topographic correction methods and assessed their accuracy by comparing prediction accuracy of a biophysical variable, FPC using Landsat5 TM (TM5) in a topographically complex landscape. The FPC is defined as the vertically projected percentage cover of photosynthetic foliage of all strata (Specht and Specht, 1999) and has a logarithmic relationship with LAI (Chen and Cihlar, 1995). FPC measures the interception of canopy elements in a series of vertical transects throughout the sampling plot, and yields percentages of horizontal and vertical distribution of elements in the canopy. Since Australian plant communities are dominated by trees and shrubs with sparse foliage and irregular crown shapes, overstorey FPC is a more suitable indicator of a plant community’s radiation interception and transpiration than crown cover (Specht and Specht, 1999). FPC is a widely adopted metric system of measurement of vegetation cover in vegetation classification frameworks in Australia (Sun et al., 1997). Since 1988, the Queensland Remote Sensing Centre (QRSC) has been monitoring vegetation cover and vegetation cover change over large areas in
Australia by automated prediction of FPC from Landsat data. Leaf Area Index (LAI) is another type of vegetation metric that could be used to estimate the foliage cover of plant communities. LAI is defined as the one-sided green leaf area per unit ground surface area, thus, it can overestimate the value of LAI in sparse foliage and irregular crown shapes. Additionally, LAI is merely the projected area of foliage on the horizontal plane providing no information on the vertical distribution of leaf area through the canopy (Coops et al., 2004).

In this study for the evaluation of the impact of topographic correction methods on reflectance, a ground measured FPC collected from different slopes and aspects across the landscape provides highly accurate information. However, it is difficult to adequately represent all combinations of slope, aspect, and FPC using site data alone due to the time involved in recording field measurements, and the difficulty in accessing steep terrain. Small footprint LiDAR has been shown to have potential for generating FPC estimates that are equivalent to ground-measurements over a range of vegetation types in Australia (Weller et al., 2003, Armston et al., 2009). Therefore, LiDAR derived overstorey FPC surrogates could be used to assess the impact of topographic correction on assessing the accuracy of TM5 reflectance. Using LiDAR surrogates it is possible to sample many more areas than using site data including steep slopes extracted across the landscape.

5. 2 Materials and methods

5.2.1 Field Data

Information on existing land cover types was gathered from a comprehensive survey of field data collection and CRAFTI data (Comprehensive Regional Assessment Aerial Photograph Interpretation). CRAFTI includes all refined broad floristic maps from NE NSW compiled by the Resource and Conservation Division in 1997.
A random sampling method was adopted to ensure that sampling measurements acquired all possible variability of forest cover. The Queensland Remote Sensing Centre (QRSC) methodology on ground cover measurement (Armston et al., 2009) was used to estimate field FPC. The QRSC methodology requires three transects radiating in N-S, NE-SW and NW-SW directions and the length of each transect is 100 m. In order to select sample plots in uniform slopes and aspects, a modification was made for the length of transect of QRSC methodology. In this study, FPC was estimated from three 50 m point intercept transects laid in the same orientation using a compass, and the area of each sampling plot was approximately 0.25 ha (see Figure 5.1). A total of 50 sampling plots representing 25 plots for each study site were used. There is no significant seasonal variation in the region.

At 1 m intervals along each transect, overstorey (woody plants greater than or equal to 2 m height) and understorey (woody or shrubs < 2 m height) were recorded. The overstorey woody plant intercepts were recorded using a GRS Densitometer with intercepts classified as green leaf, dead leaf, branch or sky by the observer as described by Johansson (1985). The understorey ferns, herbs and grass measurements were made with a laser pointer aimed downwards, with intercepts classified as green leaf, dead leaf, rock, cryptogam, or litter by the observer. The centre of each plot was located at the intersection of the three transects and was determined by using a GPS unit (GARMIN GPSMAP (R) 62stc). Five GPS points were recorded at the centre of each sampling plot over a 20 minute period and then averaged. The accuracy of the GPS under the trees varied with the density of overstorey canopy with a standard deviation of the five measurements ranging from 5 m to 8 m in the closed-canopy BRNP and from 3 m to 6 m in the open-canopy RRNP.
5.2.2 Remotely Sensed Data

5.2.2 (a) Data Acquisition

Cloud and haze free TM5 (Level 1 G) calibrated and rectified imagery (path/row- 89/ 80) were obtained on 15\textsuperscript{th} October 2011, and the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) with 25 m resolution were acquired from the United States Geological Survey (USGS). The acquired TM5 image comprised a high sun elevation angle image (54.6°) with a sun azimuth angle of 61.2°.

5.2.2 (b) Image Pre-processing

Radiometric calibration of the TM5 image was a procedure containing multiple steps. Firstly, the 8- bit satellite digital numbers (DN) in TM5 image were converted to at-satellite radiance using the most recent calibration coefficients (Markham and Helder, 2012). Next the top-of-atmosphere radiance was converted to surface reflectance. The Second Simulation of the Satellite Single in the Solar Spectrum atmospheric radiative transfer modelling (6S), a generic model (Vermote et al.,...
was used to predict the direct and diffuse irradiance from clear sky onto horizontal surfaces with an Aerosol Optical Depth (AOD) of 0.05 for this study. A bi-directional reflectance model correction was applied to remove the effects of angular variation in reflectance due to varying sun and view angles (Flood et al., 2012). The Landsat TM images were obtained from the USGS as rectified data in universal transverse mercator projection at 30m resolution. A subset of 25 m resolution SRTM DEM was re-sampled into 30 m x 30 m pixels using nearest neighbour technique to match the base image, and to be equivalent to the pixel size of TM5.

5.2.2 (c) Summary of Topographic Corrections Applied

Five non-Lambertian topographic correction models that have been widely used in vegetation studies were assessed. These included the two empirical models: C, Minnaert (Teillet et al., 1982), one semi-empirical model: SCS+C (Soenen et al., 2005), and two physically based correction models including the SCS (Gu and Gillespie, 1998) and the recently developed PSSSR (Flood et al., 2012). PSSSR corrected TM5 data was provided by the QRSC. Apart from PSSSR the topographic corrections were tested separately based on an illumination map [equation 1] derived from DEM data. All the following topographic correction methods were applied separately for the different landcover types in the BRNP and the RRNP images. A summary of all the topographic corrections applied are given in the following subsection.

If $\theta_o$, $\phi_o$, $\theta_n$, $\phi_n$ denote solar zenith angle, solar azimuth angle, surface slope angle, surface aspect angles respectively, the local incidence angle $\cos (i)$ can be computed from the terrain slope and aspect and solar geometry:

$$\cos (i) = \cos \theta_o \cos \theta_n + \sin \theta_o \sin \theta_n \cos (\phi_o - \phi_n)$$  \hspace{1cm} (1)

$\cos (i)$- solar illumination angle between solar incident angle and the local surface normal [varies from -1 (minimum) to +1 (maximum)]
If $L$ and $L_n$ denote the reflectance of and horizontal and inclined terrain respectively then the cosine correction (Lambertian correction) for topographic correction is obtained as:

$$\ln = L(\cos \theta_o/\cos (i)) \quad (2)$$

However, it is well known that this correction method overcorrects the images, mainly in areas of low incidence angle (Teillet et al., 1982, Duguay and Ledrew, 1992, Meyer et al., 1993). Hence, the Lambertian method was not evaluated in this study.

The Minnaert correction (Smith et al., 1980, Teillet et al., 1982) approach developed to minimise overcorrection of cosine correction and is widely applied for topographic correction in vegetation studies.

$$\ln = (L \cos \theta_o)/(\cos^k(i) \cos^k \theta_o) \quad (3)$$

The Minnaert parameter $k$ models the extent to which a surface has non Lambertian reflectance properties. Since $k$ is wavelength dependent, separate parameters need to be computed for each band.

Teillet et al. (1982) suggested the $C$ correction is based on a semi empirical approach similar to Minnaert correction. This correction introduces $C$ parameter to counterbalance and prevent the overcorrection of images. $C$ parameter is wavelength dependent, and that is the quotient between the slope ($b_k$) and intercept ($a_k$) of the regression $L = a \cdot \cos(i) + b$ so $C = a/b$

$$\ln = L((\cos \theta_o + C)/\cos (i) + C)) \quad (4)$$

In the study $k$ and $c$ parameters were separately calculated for each vegetation group (i.e. eucalypt forest, grassland, rainforest) in both study areas.
The SCS correction was introduced (Gu and Gillespie, 1998) as an improved version of cosine correction for all wavelengths. This correction is more appropriate for topographic correction in forested areas since it preserves sun canopy sensor geometry (Gu and Gillespie, 1998). This also assumes that radiation from the sunlight canopy is largely dependent of topography due to the geotropic nature of tree growth.

\[ \ln = L((\cos \theta \cos \alpha)/(\cos (i))) \]  

(5)

where \( \alpha \) is the terrain slope.

Soenen et al. (2005) introduced SCS+C, adding the C parameter to the SCS correction to moderate the overcorrection in areas of low \( \cos (i) \). This assumes the improvement of SCS correction occurs in a similar ways as the C correction improves on the cosine correction.

\[ \ln = L((\cos \theta \cos \alpha + C)/(\cos (i) + C)) \]  

(6)

The PSSSR is an application of bi-directional reflectance modelling to remove the effect of topography and bi-directional reflectance (Flood et al. 2012). The result is surface reflectance standardised to a fixed view and illumination geometry (an incidence angle of 45 degrees and exitance angle of 0 degrees). Standardised surface reflectance was obtained by PSSSR applying a sequence of steps using Equation 7 as described by Flood et al. (2012)

\[ \rho^\text{dir}_p = \frac{\gamma_m L_m \pi}{E^\text{dir}_m + \rho^\text{dir}_m E^\text{diff}_m} \]  

(7)

Where \( \rho^\text{dir}_p \) standardised direct reflectance, \( L_m \) is surface radiance, \( E^\text{dir}_m \) is measured direct irradiance, and \( E^\text{diff}_m \) is measured diffuse irradiance. The quantities of \( L_m, E^\text{dir}_m \) and \( E^\text{diff}_m \) computed from the atmospheric transfer modelling software, 6S (Vermote et al., 1997). \( \beta_m \) is the ratio of bi-directional reflectance factor to reflectance factor illumination by diffuse light only and \( \gamma_m \) is
correction factor that transforms a measured direct reflectance to $p_p^{dir}$. The $Y_{mp}$ was estimated using Equation 8

$$Y_{mp} = \frac{f_{iso} + f_{vol}K_{vol}(i_p, e_p, \omega_p) + f_{geo}K_{geo}(i_p, e_p, \omega_p)}{f_{iso} + f_{vol}K_{vol}(i_m, e_m, \omega_m) + f_{geo}K_{geo}(i_m, e_m, \omega_m)} \tag{8}$$

Where the subscripts $m$ and $p$ refer to the measured and standardised angle respectively, $i$ is incidence, $e$, is exitance angle, $\omega$ is the relative azimuth angle. $f_{iso}$ is isotropic scattering, $K_{vol}$ is volume scattering were modelled using the kernel $K_{vol}$ of Ross (1981) and $K_{geo}(i_p, e_p, \omega_p)$ is geometric scattering that was modelled using the geometric shadow casting kernel of Li and Strahler (1992).

The ratio of bi-directional reflectance factor to reflectance factor illumination by diffuse light only, $\beta_{im}$ was calculated by Equation 9

$$\beta(i, e, \omega) = \frac{\rho^{diff}(i, e, \omega)}{\rho^{dir}(i, e, \omega)} \tag{9}$$

Where $\rho^{diff}$ is reflectance factor illumination by diffuse light only, $\rho^{dir}$ is bi-directional reflectance factor. Diffuse reflectance factor, $\rho^{diff}$ for a fixed exitance angle was determined numerically from the BRDF model using Equation 10

$$\rho^{diff}(i, e, \omega) = \frac{1}{jk} \sum_{i=0}^{\gamma_{1/2}} \sum_{\omega_{\gamma=0}}^{\gamma_{2\gamma}} \rho^{dir}(i, e, \omega) \tag{10}$$

where $j$ and $k$ are the number of incidence and relative azimuth angles respectively for which the integral is to be evaluated. Direct reflectance from a surface, $\rho^{dir}(i, e, \omega)$ was calculated by Equation 11

$$\rho^{dir}(i, e, \omega) = f_{iso} + f_{vol}K_{vol}(i, e, \omega) + f_{geo}K_{geo}(i, e, \omega) \tag{11}$$
Recall $f_{\text{iso}}$ is isotropic scattering, $K_{\text{vol}}$ is volume scattering and $K_{\text{geo}}$ is geometric scattering that was modelled using the geometric shadow casting kernel of Li and Strahler (1992). This method was specifically chosen for evaluation as it has been used for vegetation mapping in Queensland and New South Wales.

5.2.2 (d) LiDAR Data Acquisition

Leica ALS 50-II LiDAR system was employed to acquire LiDAR data over the study areas during 19–20 August 2010. Parameters of LiDAR acquisition and data specification were summarised in the section 4.2.2.

5.2.3 Linking the Field, the LiDAR and Image Data

LiDAR fractional cover is defined here as one minus the gap fraction probability $P_{\text{gap}}$ at a zenith of zero. It was calculated from the proportion of first return counts by the following equation (12)

$$1 - P_{\text{gap}} = \frac{C_v(z)}{C_v(0) + C_G}$$

(12)

where $C_v(z)$ is the number of first returns higher than $Z$ m above the ground and $C_G$ is the number of first return points from ground level (Lovell et al., 2003). $Z$ was set to 0.5 m for both study areas with the objective of reducing the impact of understorey and other ground objects.

LiDAR fractional cover estimates were calculated by aggregating all points into 30 m spatial bins using equation (10). Calibration of LiDAR fractional cover to estimate overstorey FPC was performed using ground measured FPC estimates from both the RRNP and the BRNP sites. As both data sets were acquired using the same sensor and had a similar footprint diameter (~0.5 m) with off-nadir angle (15°), a common calibration of LiDAR fractional cover was conducted. It is important to note that other differences in the survey configurations (i.e. time and day of data
acquisition) were not accounted for in the estimation of LiDAR fractional cover. LiDAR analysis was carried out using a LiDAR processing tool developed by Armston et al. (2009).

Each topographically corrected TM5 was used to extract co-located 2 x 2 pixels surrounding the locations where the field sampling plots were located. Potential sample points for further LiDAR FPC based accuracy assessment for both study areas were randomly selected using Hawth’s Analysis Tools (version 3.27) in the ArcGIS Spatial Analyst Extension: ESRI Inc. Overall, there were 170 potential sample sites representing different slopes, aspects of the terrain, and various tree species with different density of foliage cover randomly selected from both study areas. Values of TM5 bands 2 to 7 were extracted for the 2 x 2 pixel mean surrounding the locations where the LiDAR were sampled. The 2 x 2 block average provided the best match to 2 x 2 LiDAR bins of 30 m spatial resolution and also minimized the effects of geometric misregistration between the imagery and LiDAR data. As the sites were generally located in mature vegetation, it was assumed that any increase in FPC between the date of site measurement and the image acquisition date were less than measurement error. The Multiple Linear Regression model for predicting woody FPC developed by the QRSC (Armston et al., 2009) was used to estimate FPC from topographically corrected images. This is an automated FPC prediction method that has been developed using an extensive set of over 2000 field observations from different plant communities in Queensland.

Sampled LiDAR fractional cover data and TM5 were used to compute FPC using a LiDAR calibrated equation for FPC estimates, and the QRSC developed a multiple linear regression model for estimates of FPC from TM5 respectively. To achieve better representation through the FPC range, computed FPC from all sample plots from both study areas were pooled and sorted into sets of plots by FPC classes. Subsequently, an even amount of sample plots were taken from
each FPC class (i.e. 30-50, 51-71, 71-91, 91-100%) together with 112 plots without bias using the random number generation function of Microsoft Excel.

5.2.3 Accuracy Assessment

![Flowchart of the applied methodology](image_url)
The performance of topographic normalization methods on TM5 reflectance was assessed by visual analysis and comparing topographic corrected/non-topographic corrected TM5 predicted FPC values with (i) ground measured FPC, and (ii) LiDAR derived FPC surrogates. A simple linear regression between each topographically corrected TM5 predicted FPC, with ground measured FPC, and LiDAR FPC was employed. Two parameters were used to quantitatively assess the accuracy of topographically corrected TM5 predicted FPC. The coefficient of determination ($R^2$) indicates the variance of topographic normalized TM5 predicted values for each correction model; the higher the correlation, the better the match with ground measured FPC and LiDAR FPC values. The root mean squared error (RMSE) measures the residuals of the fit (smaller RMSE - better fit), thus comparing RMSE indicates the accuracy of the predictions from topographic corrected data.

Repeated measures analysis of variance (ANOVA) was further employed to compare the mean residuals for observed FPC (i.e. ground measured FPC and LiDAR predicted FPC) and TM5 predicted FPC (ground FPC – topographically corrected TM5 FPC and LiDAR FPC – topographically corrected TM5 FPC) based on each topographic correction model. The repeated measures variable was ‘correction type’. The between group factor was ‘National Park’. Means and standard errors for residuals were used to evaluate the effect of topographic correction and the structure of vegetation against the predicted FPC. The mean differences of FPC should have been approximated to zero by minimising the variation in measured radiance caused by the different solar illumination on both vegetation types. Figure 5.2 shows a summary of the complete methodology that was adopted for the study.
5.3 Results

5.3.1 Visual Analysis

Figure 5.3 shows the false colour composite TM bands 5, 4, and 2 as red, green, and blue for the BRNP and the RRNP to highlight the non-topographic corrected and topographically corrected images obtained by the different topographic correction methods. Additionally, computed FPC using the same subset of images in the same study areas is shown as greyscale subsets, with bright for higher and dark for lower FPC values. The topographic variability in three-dimensional relief effects with dark shades was prominent in both the non-topographic corrected BRNP and RRNP images. The comparison between the non-topographic corrected and corrected images showed all applied topographic correction methods minimised different degrees of topographic effect by minimizing the three dimensional impressions in the topographic normalised images. However, the PSSSR and SCS corrections applied to scenes markedly showed a loss of the three-dimensional relief effect, and the scenes look flat in the closed-canopy of the BRNP. Furthermore, bright and dark areas on the greyscale images correspond to different densities of FPC, and were inseparable from homogenous evergreen canopy conditions even in steep slopes and gully areas, where dark shady areas were prominent in the non-topographic corrected images. In contrast, in the three dimensional impressions and dark shade areas was still evident particularly in Minnaert, SCS+C and C corrections applied to the BRNP scenes. Patterns with bright pixels due to poor correction were visible on areas of low illumination in the steep slopes and gullies of the BRNP greyscale scenes. Additionally, the topographic variability (i.e. three-dimensional relief effects) remained visible in the open-canopy RRNP scenes, when compared to the non-topographic corrected scene. Thus, none of the topographic normalization methods resulted in better visual renditions in terms of the removal of three-dimensional relief effects.
<table>
<thead>
<tr>
<th></th>
<th>BRNP</th>
<th>RRNP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-topographically corrected</td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
</tr>
<tr>
<td>PSSSR</td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
</tr>
<tr>
<td>SCS+C</td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
</tr>
<tr>
<td>Minnaert</td>
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<td><img src="image8.png" alt="Image" /></td>
</tr>
<tr>
<td>SCS</td>
<td><img src="image9.png" alt="Image" /></td>
<td><img src="image10.png" alt="Image" /></td>
</tr>
<tr>
<td>C</td>
<td><img src="image11.png" alt="Image" /></td>
<td><img src="image12.png" alt="Image" /></td>
</tr>
</tbody>
</table>

Figure 5.3 False colour image (band 5,4,2 shown as red, green and blue respectively) extract of the BRNP and the RRNP showing non-topographic corrected and topographic corrected images and greyscale images showing computed FPC (bright and dark represent higher and lower FPC values)
5.3.1 Linking LiDAR Data with Ground Measured FPC Estimates

For this study, LiDAR fractional cover was utilised to estimate overstorey FPC in order to assess the prediction accuracy of different topographic corrections applied to TM5 data. Figure 5.4 shows the correlation of LiDAR fractional cover (%), and ground-measured FPC (%). The results depicted a strong correlation between the LiDAR fractional cover with field estimates of FPC ($R^2$ 0.83 and RMSE of 5.5% FPC). The equation for the regression line is:

\[
\text{FPC} (%) = 1.1236 \times \text{LiDAR fractional cover} (%) - 16.307
\]

(13)

with slope (1.12, SE 0.08) and intercept (-16.3, SE 0.08).

Figure 5.4 The relationship between ground measured FPC and LiDAR fractional cover
5.3.2 Comparison of TM5 Predicted FPC with Ground Measured and LiDAR FPC

5.3.2 (a) Comparison with Ground Measured FPC

Note that, Non-topographic normalised TM5 predicted FPC (herein non-normalised FPC), PSSSR corrected TM5 predicted FPC (herein PSSSR FPC), SCS corrected TM5 predicted FPC, Minnaert corrected TM5 predicted FPC (herein Minnaert FPC), C corrected TM5 predicted FPC (herein C FPC), and SCS+C corrected TM5 predicted FPC (herein SCS+C FPC) are used in the results and the discussion.

Figure 5.5 illustrates the relationship between field measured overstorey FPC estimates and TM5 data predicted overstorey FPC estimates, before and after the topographic corrections. There was slight variation between $R^2$ and RMSE obtained for the correlations between TM5 predicted FPC and ground measured FPC. The $R^2$ ranged between 0.57 and 0.66, and the RMSE varied from 8 to 12.5% of FPC. Nevertheless, the PSSSR FPC showed a higher correlation ($R^2$ 0.66) between ground measured FPC with the lowest RMSE (8% of FPC) compared to the other TM5 predicted FPC. The SCS corrected TM5 showed similar results to PSSSR corrected TM5 in terms of predicting FPC by depicting a higher relationship ($R^2$ 0.62) between field measured FPC estimates. The corresponding RMSE was (8.5% of FPC). SCS+C FPC and Minnaert FPC had high correlations with ground measured FPC by yielding greater $R^2$ values compared to the $R^2$ obtained by the SCS FPC. However, respective RMSE for SCS+C FPC and Minnaert FPC were greater compared to the RMSE values obtained by SCS FPC. Results of this comparison showed a low correlation ($R^2$0.57), with RMSE of 12.5% FPC for C FPC compared to all other topographic corrections and non-normalised FPC.
Figure 5.5 The relationship between ground measured FPC and Landsat5 TM predicted overstorey showing regression and 1:1 lines
5.3.2 (b) Comparison with LiDAR FPC

Figure 5.6 shows the comparison results of LiDAR FPC and FPC predicted models using topographically corrected and non-topographic corrected TM5. Both $R^2$ and RMSE show no remarkable differences in terms of depicting a greater variation in $R^2$ and RMSE between the five topographic correction methods applied TM5 FPC. Figure 5.6 shows PSSSR FPC with a high correlation, and this prediction was more closely matched with LiDAR FPC compared to other topographic corrections. The $R^2$ between LiDAR FPC and PSSSR FPC is 0.75. RMSE varied from 10 to 12.4%. PSSSR FPC reported relatively low RMSE (10%) which was the lowest of all other correction applied FPC predictions. The linear regression results showed that the second highest accurate FPC predictions were obtained from SCS FPC. Figure 5.6 shows an improvement of FPC, predictions through reduction of topographically induced illumination. The $R^2$ of SCS FPC was 0.69 and the RMSE was 11.6%.

In contrast, empirical and semi-empirical based topographic corrected data produced the least accurate prediction of FPC, while the C correction showed the poorest results of all corrections that were evaluated. Instead of reducing the effect of topography on reflectance, the C correction seemed to have increased it (see Figure 5.6) compared to the topographic non-normalized data. The coefficient determination for C FPC was 0.61 and the RMSE of the prediction was 12.4%. Figure 5.6, FPC shows predictions from the Minnaert and SCS+C corrected TM5 produced results were no better than non-normalised FPC.
Figure 5.6 The relationship between LiDAR predicted FPC and Landsat5 TM predicted overstorey showing regression and 1:1 lines.
5.3.3 Comparison of TM5 Predicted FPC between Vegetation Types

To test the influence of topographic correction methods on image reflectance, repeated measures ANOVA was employed to compare the mean residuals for (ground FPC–Landsat FPC) and (LiDAR FPC–Landsat FPC) between the national parks study areas which represent the different vegetation types. Table 5.1 ANOVA shows a significant difference for the mean ground FPC residuals FPC ($F = 46.03$, $P < 0.000$) and interaction of mean difference of the ground measured and TM5 predicted FPC and vegetation types ($F=9.732$, $P=0.034$).

There was a significant difference in the interaction of mean ground FPC residuals and vegetation types (Table 5.1), greater mean ground FPC residuals were noted for C FPC (12.1) for the open-forest in the RRNP (Table 5.2). The mean ground FPC residuals of PSSSR FPC showed the lowest value (6.5) and the respective SE was 1.27 for the same vegetation conditions. In the closed-canopy of the BRNP, the lowest mean ground FPC residuals were recorded for the non-normalised FPC (4.098), and SE was higher (1.38). The second lowest mean ground FPC residuals (4.243) and the lowest SE (1.048) were observed for the PSSSR FPC. The mean ground FPC residuals of the Minnaert FPC showed 7.587 and this was the largest mean ground FPC residual observed for the BRNP and the corresponding SE was 1.345. The second and third largest mean ground FPC residuals were reported by C FPC and SCS+CFPC respectively.

ANOVA test showed significant differences in mean residuals between LiDAR FPC and TM5 predicted FPC ($F = 95.85$, $P < 0.000$) between vegetation types ($F = 59.43$, $P < 0.000$) and interaction ($F = 17.74$, $P < 0.000$) as shown in table 5.1. There was a significant difference in the mean LiDAR FPC residuals and vegetation type, while the highest difference in estimated means for FPC were observed in the BRNP. The lowest estimated means (9.816) with the lowest SE (1.873) were obtained by the PSSSR FPC, and this is followed by the non-normalised FPC, Minnaert FPC, and SCS+C FPC which rank third with fourth respectively (Table 5.2). The SCS FPC (17.374) and C
FPC (17.625) produced the highest mean residuals and deviated from the mean LiDAR FPC of the BRNP. Nevertheless, the SE for mean residual of SCS FPC was 1.96 and this was lower than SE reported for CFPC, SCS+CFPC, Minnaert FPC and non-normalised FPC. In contrast, the lower mean LiDAR FPC residuals for all topographic normalized and non-topographic normalised TM5 predicted FPC were observed in the RRNP. The mean LiDAR FPC residuals for PSSSR FPC showed the lowest difference (4.133) with the lowest SE. The estimated mean residuals for C FPC was significantly higher (8.597) and produced the highest SE (1.211) which was greater compared to the non-topographic corrected TM5 predictions for the RRNP.

Table 5.1 One-way repeated ANOVA on mean difference of FPC (ground measured FPC- five different topographic corrections and non-topographic correction applied TM5 FPC) and (LiDAR FPC- five different topographic corrections and non-topographic correction applied TM5 FPC) between vegetation types (open-canopy forest and subtropical rainforest)

<table>
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<th>P</th>
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<td>0.099</td>
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<td>mean of difference predicted FPC x vegetation</td>
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Table 5.2 Summary of estimated means and standard error (SE) in parentheses, parameter estimates modelled as one-way repeated measures with interactions between topographic corrections and vegetation types

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<thead>
<tr>
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<th>Ground measured FPC–TM5FPC</th>
<th>LiDAR FPC– TM5FPC</th>
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<tr>
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<td>5.014 (1.346)</td>
<td>8.566 (1.346)</td>
</tr>
<tr>
<td>C</td>
<td>7.492 (1.389)</td>
<td>12.118 (1.389)</td>
</tr>
</tbody>
</table>

5.4 Discussion

5.4.1 Overall Accuracy of FPC Prediction by Topographic Corrected Images

Quantitative retrieval of vegetation parameters and vegetation mapping are key operations in application of remotely sensed data. However, implementation of such operational activities in hilly terrain has proved to be difficult due to the modification of illumination of the surface, and the variations in the proportion of light reflection toward the satellites as the geometry of sun, target, and viewer vary (Teillet et al., 1982). Thus, topographic correction is a necessary pre-processing step in the remote sensing application of the data for topographically complex terrain.

The impact of topographic corrections on the accurate estimation of biophysical parameters using multispectral data in different plant communities has been poorly investigated. This study sought to evaluate the correction accuracy of five different topographic correction methods on TM5 reflectances by visual comparison and by statistically comparing the prediction accuracy of TM5 estimated FPC with ground measured FPC and LiDAR FPC of structurally different plant communities. The results for the visual comparison test of topographically corrected images showed that topographic variability in the non-topographically corrected image was minimised.
by different degrees for all topographic correction methods in both study areas (Figure 5.3). Topographic influence on TM reflectance was effectively minimised by the application of PSSSR and SCS compared to the other topographic correction methods. It is expected that cleaner or less variability in TM5 spectral signatures will be produced for areas with similar plant groups, with reduced or complete elimination of three dimensional relief effects in images (Shepherd and Dymond, 2003). The results for comparisons tests showed that PSSSR, and SCS corrections applied images were only able to enhance the accuracy of FPC estimates compared to the other corrections applied to TM5 images. The findings in this chapter have demonstrated that topographic variation exhibited in satellite data can be improved, producing a reduction in the topographic illuminated variation of spectral data using physically based topographic correction methods (Gu and Gillespie, 1998, Shepherd and Dymond, 2003), especially PSSSR (Ediriweera et al. 2012). Nonetheless, both these correction methods performed comparatively better than other topographic corrections; the PSSSR corrected images achieved the best results which indicated the highest determination of coefficient and the lowest RMSE for PSSSR FPC. This is probably because PSSSR removes the effect of topography and bi-directional reflectance together with one model, thereby resulting in surface reflectance standardised to a fixed viewing and illumination geometry (Gill et al., 2010, Flood et al., 2012).

The SCS physically based correction method yielded better results for prediction of FPC estimates by minimising topographic variations exhibited in the TM5 scene, though the accuracy of the prediction was not as high as PSSSR applied to TM5. This is probably, due to the negligence of correction of diffuse sky radiation and multiple reflections by the SCS (Huang et al. 2008) the topographic effect has not effectively been removed. Generally, forest canopies consisted of a large amount of diffuse sky radiation, the radiation from multiple reflectances in the areas of shade and shadows cast by large tree crowns, adjacent hills, and in valleys. Therefore, taking into
account of the diffuse sky radiation, a terrain radiation of an image may provide additional refinement of data in the process of topographic correction. However, the SCS has proven to have the potential to improve vegetation classification by removing the topographic effect of topographically complex terrain using Landsat images (Dorren et al., 2003, Koukal et al., 2004, Huang et al., 2008).

In contrast, there were no improvements of accuracy for predictions of FPC after applying C, Minnaert, and SCS+C when comparing both ground and LiDAR FPC for both forested TM images. The results for comparison of ground measured FPC with C, Minnaert and SCS+C corrections based topographic normalised TM images prediction of FPC showed higher determination of coefficients compared to the non-normalised FPC however, the corresponding RMSE values were greater than the RMSE of non-normalised FPC. The comparison of ground measured FPC and LiDAR FPC with the C FPC using simple linear regression clearly showed lower correlations in terms of the lowest $R^2$ values, and the largest RMSE when compared to the other corrections applied to TM5 data and non-topographic corrected TM5. Although several studies have adopted C correction and obtained promising results (Meyer et al., 1993, Riano et al., 2003, Richter et al., 2009), this study noted that the C correction has performed poorly in the correction of reflectance of TM5. C parameter is scene dependent which is not suitable for quantitative forest parameters retrieval and forest mapping operations, particularly as multi-sensor and multitemporal reflectance images are required in image comparison for change analysis (Huang et al. 2008). Thus results indicated that C correction is not particularly suited for forest canopy surfaces as the correction assumes the Lambertian surface despite it allowing for diffuse sky radiation (Koukal et al. 2004).

Meanwhile, the comparison for FPC estimates of SCS+C and Minnaert corrected TM5 data with ground and LiDAR FPC appear to provide no improvement compared to the non-normalised
FPC thus prediction FPC estimates were not closely matched with ground measured FPC and LiDAR FPC. The $c$ parameter was introduced (Soenen et al., 2005) to the SCS to moderate the overcorrection in images where pixels were faintly illuminated. However, the findings of this study noted that the aim of adding $c$ parameter to SCS correction was not accomplished. The image data incurred deterioration in biophysical properties for spectral data through poor corrections that proved to be even greater than before the correction. The findings were consistent with Riano et al., (2003), Gao and Zhang, (2009), who demonstrated that Minnaert correction applied Landsat data produce unsatisfactory results for vegetation classification. In contrast, Colby (1991), Ekstrand (1996), Hale and Rock (2003), Itten and Meyer (1993), and Tokola et al. (2001) recommended the Minnaert correction to eliminate topographic effects of forested scenes.

The results indicated that the variations in vegetation structure and composition may have greater influence on calculation of empirical parameters which are used in empirically, and semi-empirically based topographic corrections. The empirical parameters (i.e. $k$, $c$) are derived each TM5 band from the relationship between the terrain reflectance and the illumination angle of the image. As the Minnaert method is object dependent (Koukal et al., 2004) accurate calculation of Minnaert $k$ parameter is a prerequisite before the application of the correction. For this study $k$ and $c$ empirical parameters were derived for each plant community including grassland, rainforest, and eucalyptus forest etc for each study area. However, in most cases the calculated $c$ parameters were considerably large and the estimated Minnaert $k$ parameter from different vegetation groups of the open-canopy RRNP sites produced unusable negative value for this study. This is probably due to the sparse canopy with mesic understory (Lantana camara shrubs and tall grass species) particularly in the RRNP and some areas of the BRNP. Delineation of TM5 pixels representing homogeneous vegetation cover type was impractical and may have caused
weak correlations (but significant) between the spectral data of an image and illumination angles. These issues may have influenced the accuracy of $c$ and $k$, and ultimately overall performance for the removal of topographic effects by both empirical and semi-empirical topographic corrections. This issue may have implications for the accurate derivation of empirical parameters particularly for open-canopy forested areas such as woodlands or savannah etc. The object dependent empirical topographic correction methods could limit accurate application for forested images as accurate determination of this information is unfeasible over a wide range of natural environmental variations in extensive landscapes (Gao and Zhang, 2009).

5.4.2 Comparison of TM5 Predicted FPC between Vegetation Types

To investigate the influence of normalization methods on the TM spectral signatures of each plant community, a repeated measures ANOVA was employed to compare the mean residuals of TM5 predicted FPC in relation to ground measured FPC, and LiDAR FPC. On the basis of the results of the ANOVA test, the mean residual (ground measured FPC−TM5FPC) for topographic corrected and non-topographic corrected TM images based estimated FPC demonstrated no significant differences between the plant communities investigated (i.e. open-canopy and closed-canopy forest). However, the greatest mean differences were observed for both the topographic corrected and non-topographic corrected open-canopy RRNP TM images to estimate FPC compared to the closed-canopy BRNP. In contrast, the comparison of mean residuals (LiDAR FPC−TMFPC) for topographic corrected, non-topographic corrected TM scene estimations of FPC revealed significant differences between residuals of topographic corrected, and non-topographic corrected TM scene estimated FPC as well as between vegetation types including vegetation interactions. Based on the tests comparing TM5 estimated FPC with ground measured FPC, and LiDAR FPC, the best overall results were achieved with the PSSSR FPC estimations, with relatively lower mean residuals than all other topographic corrections applied scenes. The
SCS based corrected TM5 estimations of FPC yielded satisfactory results particularly for the closed-canopy forest. However, none of other correction methods applied TM5 produced FPC with lower mean residuals when compared to the mean residuals of the non-topographic corrected TM5 estimations of FPC in both forested areas.

On the other hand, the results showed higher mean residuals between all topographic corrected, non-topographic corrected TM scenes estimated FPC, and LiDAR FPC for the closed-canopy subtropical BRNP data. This residual variation was considerably greater than the residuals observed in the comparison test of mean ground FPC residuals for ground measured FPC and topographic corrected, non-topographic corrected TM scene estimated FPC. This is likely as LiDAR fractional cover is estimated using both photosynthetic and non photosynthetic components of the canopy, hence the resultant LiDAR based estimated FPC is greater than field observed FPC estimates (Weller et al., 2003). Further, in the study it was noted that LiDAR fractional cover values were always greater (> 90%) in the closed-canopy BRNP compared with values for the open-canopy RRNP conditions. This occurs as the laser pulses of a small footprint discrete LiDAR system are incapable of discriminating small holes in clumps of leaves in the closed-canopy (70-100% FPC), subtropical forested BRNP, consequently the laser pulses are blind to the small holes in clumps of leaves detected using the point intercept field technique. These may have caused the overestimation of LiDAR FPC in both study areas and particularly the closed-canopy BRNP.

5.5 Conclusions

Topography affects the illumination of slopes, and significantly changes the reflectance of vegetation as a function of geometry of the sun, and target and viewer relative to the slope. For convenience, the correction for reflectance by a topographic correction method should not have parameters, and may be applied to any vegetation type, especially in inaccessible topographically
complex terrain (Shepherd and Dymond, 2003). The results outlined in this chapter have shown PSSSR and SCS corrected TM images revealed more effective reduction of topographic variability by better minimising of three dimensional relief effects of scenes compared to all other correction types. This is due to the independence of the PSSSR and SCS methods from the canopy characteristics. Furthermore, the results for the biophysical modelling of FPC indicated PSSSR and SCS perform better than the other correction methods by better correction of topographically induced illumination, and better preservation of the biological properties of spectral data of vegetation. The PSSSR correction approach yielded the most satisfactory improvement of the prediction of FPC of the two structurally different plant communities. The success of the PSSSR is due to the combination of illumination and reflectance correction. These results obtained by PSSSR are due to the fact that in addition to correcting for illumination, this correction method corrects for the dependence of vegetation reflectance on slopes. This reduction means that automated classification of features, and operation mapping and monitoring of vegetation cover on rugged terrain becomes a realistic proposition. The empirically based C correction showed the poorest performance; instead of reducing the effect of topography on reflectance the C correction actually increased the degree of variation of Landsat5 TM reflectance. This study also highlighted that variations in vegetation structure and composition may have influenced Minnaert \( k \), and \( c \) under sparse canopy heterogeneous conditions. Finally, despite some issues in overestimation, LiDAR measured FPC estimations can be used as proxy to field measurements for quantitatively assessing the accuracy of topographic correction images.
Chapter–6
The Influence of Topographic Variation on Forest Structure in Two Woody Plant Communities: A Remote Sensing Approach

6.1 Introduction

Topography has important influence on forest structure and composition. Variation in topography (slope angle, aspect, or elevation) creates resources heterogeneity across the landscape. Topography generally influences changes in soil depth and soil composition, in water content and soil drainage, and in light availability (Bale and Charley, 1994, Chen et al., 1997, Bale et al., 1998, Oliveira-Filho et al., 1998, Galicia et al., 1999, Tokuchi et al., 1999, Yanagisawa and Fujita, 1999). This patchy distribution of environmental resources often leads to complexity of forest structure and composition across a landscape. Understanding of forest structure over a landscape is required for sustainable management of forest landscapes for multiple purposes including the provision of wildlife habitats, timber production, and fire hazard reduction. In recent years, emerging literature reveals that the understanding of relationships between variations in topography, and forest structure and composition in Australian plant communities has substantially advanced (Kirkpatrick and Nunez, 1980, Kirkpatrick et al., 1988, Bale et al., 1998, Specht and Specht, 1999, Specht et al., 2001).

Though much is known about how changes occur in forest structure in a dissected topography, there is scant information available about the potential of predicting such variations using remote sensing over extensive rugged terrain. However, empirical studies across large areas are rare due to limited resources and other difficulties inherent in collecting information on these scales. Therefore, traditional field sampling inevitably encompasses a very small fraction of the
landscape, raising the question of how representative the resulting models are for the area not sampled. Remote sensing technology has produced alternatives for investigating variation in forest structure beyond traditional field surveys of landscape. Remotely sensed data is commonly used to obtain quantitative information on biophysical characteristics of vegetation of topographically extensive landscapes (Wu and Strahler, 1994). This technology may be used to generate a wide range of estimates that are valuable to ecologists including information on landcover, forest structure, habitat, and forest function (Kerr and Ostrovsky, 2003).

Recent advancements in remote sensors have resulted in new capabilities for data capture at high resolution. High resolution remotely sensed data, corresponding well to the size of individual tree crowns, are now seen to have much greater potential for investigating forest structure and composition. Among the remote sensing sensors, LiDAR has emerged as a robust means to collect and subsequently characterize vertically distributed objects (Wulder et al., 2012). This has been shown to have potential for generating information that is equivalent to the field measurements for instance of foliage cover (Weller et al., 2003, Armston et al., 2009), tree height (Nilsson, 1996, Magnussen and Boudewyn, 1998, Popescu et al., 2002, Holmgren et al., 2003), and forest volume and biomass (Nelson et al., 1988, Næsset, 1997, Holmgren et al., 2003, van Aardt et al., 2006) over much larger geographical areas that can be surveyed on the ground. Additionally, Armston et al. (2009) and Moffiet et al. (2010) described the use of LiDAR data in a sample-based approach to validating Landsat-based vegetation indices using sampled field plots and LiDAR transects in Queensland, Australia. Continuous technological advancements and intense competition among vendors has resulted in substantial reduction in the cost of acquiring LiDAR data (Gatziolis et al., 2010), which provides an opportunity to actively integrate this technology in forestry and ecological studies. Similarly, optical remotely sensed data source with an appropriate spatial resolution, such as Landsat could be used to characterise forest structure in...
large scale landscapes (Warren and Spies, 1992, Trotter et al., 1997, Turner et al., 1999, Lu et al., 2004, Pocewicz et al., 2004, Zheng et al., 2004, Gillespie et al., 2006, Hall et al., 2006, Armston et al., 2009). Landsat5 TM derived FPC is a good indicator of the density of vegetation cover and vegetation cover changes across a landscape (Armston et al., 2009). These two sources of data provide vertical and horizontal structural information of vegetation, and the spectral information of vegetation. Thus, if structural configuration of vegetation in relation to the variation of topography can be modelled using remotely sensed data, then spatial and temporal parameterisation of forest structure, understanding of response to climate change, or application of these ecological and forest dynamics models could be improved.

The objective of this chapter is to characterise variation in structural attributes of forest including maximum overstorey height, average crown area, FPC, and LiDAR fractional cover in relation to variations in topographic position using airborne discrete return LiDAR, and multispectral satellite data over landscapes. In the literature for field based ecological studies these structural elements have shown strong relationships in relation to the topography and environmental gradients, thus, they were considered for this investigation. Furthermore, these parameters represent vertical (maximum overstorey height), and horizontal (average crown area) as well as species richness (FPC and LiDAR fractional cover) of distributed vegetation over the landscape. In regard to changing conditions of environmental gradients with topography in complex terrains, it can be assumed that such changes in overstorey height, FPC, LiDAR fractional cover, and crown area caused by variation of topography could be discernible using remotely sensed data.
6.2 Material and Methods

6.2.1 LiDAR data and Processing

Leica ALS 50-II LiDAR system was employed to acquire LiDAR data over the study areas during 19–20 August 2010. Parameters of LiDAR acquisition and data specification were described in the section 4.2.2.

For the LiDAR data analysis, non-commercial LiDAR processing code developed by Armston et al. (2009) in IDL 8.0 and ESRI Inc. ArcGIS 9.3 were employed. All returns were used for analysis to maximise utilization of data acquired by the sensor. Ground and non ground returns were separated. A 1 m Digital Elevation Model (DEM) was produced using filtered returns classified as representing the ground via Kriging interpolation. For each cell in the DEM, the 6 closest points were used for the interpolation. To evaluate the accuracy of the LiDAR DEM, post-processed differential GPS points (dGPS) were collected using a Mobile Mapper from Thales Navigation Systems™ in different locations which were distributed over LiDAR transects of BRNP and RRNP. There were 70 GPS points for the BRNP and 55 for the RRNP, and these points included 4 transects for the BRNP and 3 for the RRNP, which were collected from flat to slope terrain in open ground (park roads), and under forest canopy with different densities. In order to assess the accuracy of the LiDAR DEM, ground collected dGPS points were overlaid on the LiDAR DEM. To evaluate the quality of LiDAR-derived DEMs, root mean square error (RMSE) were calculated. The calculated RMSE for the BRNP was 5.7 m and 1.9 m for the RRNP.

6.2.1 (a) Terrain Analysis and Remote Sensing Sampling Design

All LiDAR derived DEMs were Bicubic Spline resampled into 10 m x 10 m pixels resolution. Characterization of vegetation structure by potential insolation, topographic wetness index (TWI), and the slope and elevation of terrain were used as proxies for energy, soil water distribution, and topographic variations. LiDAR derived 10 m resolution DEMs were used as
input for the area solar radiation analysis (ArcGIS Spatial Analyst Extension: ESRI Inc) to calculate total insolation (direct and diffuse) at monthly intervals for the whole year 2011 and were then averaged for a month period. Zhang and Montgomery (1994) demonstrated that 10 m DEM resolution is sufficient for estimating geomorphic, and hydrological processes. The TWI describes the effect of topography on the location and size of saturated source areas of runoff generation. The TWI, given by Equation (1), define areas of saturated soil typically found in geomorphologically convergent segments, where $a$ is the area of specific contribution based on flow-direction (summed over the area upstream of the cell) and $\beta$ is surface slope. It is determined from the flow direction and accumulated runoff.

$$\ln \left(\frac{a}{\tan \beta}\right)$$

(1)

The specific contributing area is related to the concept of accumulated runoff and takes into account the complexities of hill-slope form. The curvature of slopes both in the plane and in profile effectively determined the hydro-sedimentological behaviour of erosive process. It is defined as accumulated drainage area ($m^2, m^3$). In the case of convex slopes, the specific contributing area tends to diminish. For concave slopes, the specific contributing area tends to increase, giving rise to a rapid increase in accumulated downstream flow, defined as a specific contributing area (Wilson and Gallant, 2000). Spatial Analyst: ESRI Inc was employed for TWI calculation of both study areas.

The insolation and TWI surfaces were stratified into low and high solar insolation, and two classes of TWI (low and high) were identified. Stratification into intermediate or transitional class (i.e. medium) for insolation and TWI was complicated, thus, intermediate (i.e. medium) TWI and insolation were not classified. Classification of insolation and TWI was effectively distinguished in valley or gully areas, and upper slopes of the terrain. A total of 150 sampling plots representing 75 plots for each study site were randomly and remotely selected using Hawth’s
Analysis Tools (version 3.27). In order to maintain the heterogeneity of the topography (i.e. to select uniform slope angle and aspect) the area of a sample plot was restricted to 50 m x 50 m. Selected plots were located throughout the topographic positions crossing two classes of solar insolation (low and high) and two classes of TWI (low and high) in different topographic positions. The insolation and TWI classification thresholds for BRNP and RRNP are summarised in Table 6.1. During the remote sensing based sampling plot selection, field knowledge and existing topographic maps were used to exclude plots which were located near roads, camping areas or other anthropogenic disturbance areas. Furthermore, average slope of the sampling plots was computed using the ArcGIS Spatial Analyst Extension: ESRI Inc. while average elevation of each sampling plot was extracted from LiDAR derived DEMs.

Table 6.1 Classification of insolation and TWI classes in the BRNP and RRNP study areas

<table>
<thead>
<tr>
<th>Study area</th>
<th>Topographic position</th>
<th>Insolation (MJ/m²/hour)</th>
<th>TWI</th>
</tr>
</thead>
<tbody>
<tr>
<td>BRNP</td>
<td>valley</td>
<td>3813-5283 (low)</td>
<td>&gt; 5.5 (high)</td>
</tr>
<tr>
<td></td>
<td>upper slope</td>
<td>5283-5950 (high)</td>
<td>4.5-5.5 (low)</td>
</tr>
<tr>
<td>RRNP</td>
<td>valley</td>
<td>4041-5283 (low)</td>
<td>&gt; 5 (high)</td>
</tr>
<tr>
<td></td>
<td>upper slope</td>
<td>5283-6211 (high)</td>
<td>3-5 (low)</td>
</tr>
</tbody>
</table>

6.2.2 Derivation of Structural Variables of Forest using LiDAR

6.2.2 (a) Maximum Overstorey Height

The separated non-ground LiDAR point clouds were used to construct Canopy Surface Models (CSM) using natural neighbour interpolation at 1 m resolution. Potential CSM interpolation artefacts—a consequence of data gaps in the open-canopy RRNP study area were reduced by incorporating spatially selected ground points that fell closer to non-ground points than the nominal point spacing (1 m) to fill the gaps. Canopy Height Models (CHMs) were derived by
subtracting the DEM from CSM. A 3 x 3 median filter was applied to the CHM to preserve edges while reducing the effect of inter-canopy variation (Popescu et al., 2003), which should enhance canopy-open-canopy discrimination. Vegetation metrics require local height of non-ground points, rather than height above sea level. This was derived by subtracting of DEM height from the discrete non-ground data points. Two classes of solar insolation and two classes of TWI representing 50 m x 50 m sample plots were separated from CHMs. Maximum overstorey height was calculated of selected sampling plots. Maximum overstorey height was based on the 99th height percentile, to reduce outlier effects (Riaño et al., 2003).

6.2.2 (b) LiDAR Vertical Foliage Profiles

LiDAR vertical foliage profiles have shown promise in assessing vertical structure of forests, and conditions such as growth stage and understorey recovery since disturbance (Lovell et al., 2003). Apparent foliage profiles are the sum of non-ground LiDAR returns per arbitrary height interval. Foliage profiles of understorey and overstorey strata were termed “apparent” as the literature identified that they may not be entirely representative of the full vertical forest structure (Ni-Meister et al., 2001, Lovell et al., 2003). Most LiDAR profiles reported in the literature (Ni-Meister et al., 2001, Lovell et al., 2003) used 1 m as height bins, and are an efficient compromise between details of vertical forest structure and the number of LiDAR returns collected. Height bins with a small height range would only record a few returns and show little information. Thus, in this study, apparent foliage profiles were generated for selected sample plots with 1 m height bins representing different topographic positions (valley and upper slope) in both study areas. Derivation of the apparent foliage profile from LiDAR data has been described in the literature (Lovell et al., 2003, Riaño et al., 2003) and the probability of a gap from the canopy to given height, z, can be estimated by summing the total number of LiDAR points down to z, and comparing these to the total number of independent LiDAR points (N) see equation (2):
where \( z \) is the number of hits down to a height \( z \) above the ground. The cumulative projected foliage area index from the top of the canopy down to a height \( z \) is then given by equation (3),

\[
P_{\text{gap}}(z) = 1 - \frac{\{#zj | zj > z\}}{N} \tag{2}
\]

where the first derivative of \( L(z) \) is the apparent foliage density profile (Lovell et al., 2003).

### 6.2.2 (c) LiDAR Fractional Cover of Overstorey

LiDAR fractional cover corresponds to the density of photosynthetic and non-photosynthetic components of the canopy and defines one minus the gap fraction probability at a zenith of zero (Lovell et al., 2003). Computation of LiDAR fractional cover was described in the section 5.2.3.

### 6.2.2 (d) Estimation of Plot Scale Average Crown Diameter

Tree crown diameter was measured on the LiDAR derived 1 m resolution CHM by automated processing using non-commercial TreeVaw 1.1 software (Popescu et al., 2003), with the algorithm described in (Popescu et al., 2003, Popescu, 2007). TreeVaw computes crown area based on a local maximum technique, which assumes that high laser values in a spatial neighbourhood represent the top of a tree crown. The derivation of the appropriate window size to search for tree tops is based on the relationship between the height of the trees and their crown area. Basically, higher trees tend to have larger crown areas. Thus, collecting measurements of height and crown widths for an appropriate number of trees is crucial to derive an accurate relationship.

Measurements of tree height and crown width were restricted to trees that were larger than 10 cm dbh for plot in each study area (85 and 70 trees per RRNP and BRNP plot respectively). Accurate measurement of overstorey tree height in the BRNP plot was dependent on clear visibility of overstorey tree crowns from the ground. Hence, height measurements recorded were
to the furthest visible point of the crown from ground level in the BRNP plots. In each sample plot, tree heights were measured using a Nikon Forestry 550 Laser Rangefinder/Heightmeter.

There is no standard method of measuring crown width or calculating mean crown diameter. However, a wide variety of instruments have been developed and used to measure the widths of tree crowns. For this study crown width was measured using a SUUNTO clinometer and a distance tape. The use of a clinometer ensured that the operator was positioned directly below the edge of the crown being measured. This has the advantage that the whole crown can be viewed whilst looking through the instrument, and thus the perimeter can be clearly determined.

The use of a clinometer ensured that the operator was positioned directly below the edge of the crown being measured. An average of four perpendicular crown radii were measured with a distance tape from the tree trunk towards the plot centre.

For each study area, measured height and crown data were used to derive a biometric relationship between tree height and crown areas. The developed biometric relationships showed excellent agreement between ground measured tree height and crown diameters for both study areas, for example, the $R^2$ values for the RRNP and the BRNP were 0.82 and 0.74 respectively (Figure 6.1 A and B). As Popescu et al. (2003) explained, CHM based tree crown diameter estimation is more appropriate for measuring crown diameter for dominant and co-dominant trees that have individualized crowns on the CHM surface. Average crown radii estimation was limited to tree height at 30 m for the BRNP and 25 m for the RRNP in each sample plot. Once crown radiiues were estimated, the values were converted to crown area, assuming all crowns are approximately circular.
Figure 6.1 Relationships between ground measured crown diameter and tree height A- RRNP and B-BRNP

6.2.3 Landsat5 Thematic Mapper and Image Processing

Cloud and haze free data was captured on 15 October 2011 under high sun angle conditions (54.6°). Landsat5 TM (Level 1 G), product (Path/Raw- 89/80) was acquired from the United States Geological Survey (USGS). Radiometric calibration and atmospheric correction procedure of the TM5 image were outlined in the 5.2.2b. The image was Bicubic Spline re-sampled into 25 m x 25 m pixels to match the base image and to be equivalent to the size of the sampled sites. The PSSSR topographic correction method (Flood et al., 2012) was employed to minimise the topographically induced illumination.

Reflectance of all Landsat TM5 bands was included in the analysis. Signatures for TM5 bands 1 to 5, and 7 were extracted for the 2 x 2 pixel mean surrounding the field plot location. The 2 x 2 block average provided the best match to the spatial extent of field measurements. The Queensland Remote Sensing Centre (QRSC) of the Department of Natural Resources and Water (NRW) developed the regression model for predicting woody FPC (Armston et al., 2009), which
was used to estimate FPC from Landsat TM5. The estimation of FPC was carried out for both study areas separately.

6.2.4 Statistical Analysis

Figure 6.2 Flowchart of data processing and analysis
Figure 6.2 provides a summary of the remotely sensed data processing and analysis. The BRNP and RRNP study area data were analysed separately within the General Linear Models (GLM). SPSS software (IBM SPSS Statistic version 20) was employed to establish how plot scale average maximum overstorey height, crown diameter, and FPC vary with TWI, potential insolation, slope of the terrain, and elevation in different topographic positions. Mean comparison of insolation, TWI, elevation, and slope of the terrain effect on maximum overstorey height, crown diameter, and FPC were performed using Analysis of Variance (ANOVA) and type-I sums of squares where results were considered significant at $P < 0.05$. In each case, residual plots were assessed to ensure that the models satisfied the standard GLM assumptions.

### 6.3 Results

#### 6.3.1 Investigation of Vegetation Structure Using Plot Scale LiDAR Derived Apparent Vertical Profile

With apparent vertical profile, larger percentage values indicate where the foliage is most dense and/or the crowns most wide. Strata breaks (i.e. between over and understorey) are most likely to be where there are the lowest percentage values. Both these statements assume a representative sample of the actual vertical foliage distribution. For the apparent vertical profiles for representative plots the X-axis represents percentage vegetation returns, and the Y-axis represents height interval (m). Taller trees are associated with the upper bulge in apparent vertical profiles. Figure 6.3 (E) - (e) and 6.4 (E) - (e) illustrate apparent vertical profiles for selected sample plots; representing valley and upper slope plots in both study areas. The apparent vertical profiles for both study areas show good correspondence with raw points profiles and photographs.

The utilization of LiDAR analysis for creating apparent vertical profile for the BRNP data is illustrated in Figure 6.3 (E) for upper slope and (e) for valley sample plots. It can be seen that
vertical profiles in Figure 6.3 (E) and (e) are quite different. Where trees are sparsely distributed, the apparent vertical profiles of sample plots in both valley, and upper slopes detect tall trees that are representative of the overstorey. The average maximum overstorey height of upper slope BRNP plots show approximately 31 m and valley plots show approximately 40 m; evident as the large bulge in the vertical profiles. Two distinct strata are not clearly evident in the upper slope sample plot profile, however, large peaks at the bottom section of the profile are likely related to the understorey. Figure 6.3 (e) shows the vertical profile for the 50 m x 50 m valley sample plot of the BRNP. In the valley sample plot of the BRNP with mature and large trees, there is marked vertical complexity with well distinguishable overstorey greater than 20 m, and another middle and understorey layer below 16 m. This qualitative assessment shows that due to the lack of intact overstorey layer in the upper slope, the intensity of the returns from middle layer and understorey (1-16 m above) was high. These qualitative assessments that are evident in photographs can also be inferred from the LiDAR vertical profiles, in terms of presence of LiDAR returns from understorey strata.

The vertical profiles derived for valley, and upper slope sample plots of the RRNP clearly demonstrate the horizontal variation in the spatial arrangement of the elements within the vertical forest structure [see Figure 6.4 (E) and (e)]. The maximum overstorey height of 31 m for upper slope, and 36 m for valley are shown in the vertical profiles. There is a clear variation of foliage distribution in the two sample plots with the majority of foliage concentrated in the overstorey in the upper slope plots, and a nearly uniform foliage distribution shown across the vertical structure of the sample of the valley plots. However, on examination of the vertical profile Figure 6.4 (e) it can be seen that a larger proportion of the LiDAR has interacted with understorey layer vegetation below 5 m in the valley sample plot, compared to the vertical
profiles of upper slope sample plots. This implies that the density of understorey vegetation is higher in valley sample plots than upper slope sample plots.

This qualitative assessment provides information about how elements of vegetation structure such as vertical distributed foliage, stratification of tree layers, and tree density are distributed across sample plots. Coops et al. (2007) demonstrated the suitability of vertical profiles derived from discrete return LiDAR for extracting quantitative information on forest stands such as tree height, as well as information on foliage profiles. However, the limitations of this method become clear as the complexity of overstorey canopy structure increases, leading to the probability that LiDAR pulse penetration below the rainforest canopy in areas such as the BRNP decreases and leads to occlusion of middle and understorey strata. This may have a significant impact on density of LiDAR points below the upper storey which can affect the information of vertical profiles.
Figure 6.3 LiDAR apparent vertical profile showing the potential differences in vegetation structure in different topographic positions in the BRNP (A)- (a) raw points profile in upper slope (B)- (b) Field photo (E)-(e) apparent vertical profile in upper slope
Figure 6.4 LiDAR apparent vertical profile showing the potential differences in vegetation structure in different topographic positions in the RRNP (A)- (a) raw points profile in upper slope (B)- (b) Field photo (E)-(e) apparent vertical profile in upper slope
6.3.2 Effect of Insolation, TWI and Topography on Forest Structure

A General Linear Model was employed to examine the forest structure-environment relationship by comparing structural attributes of vegetation; average maximum overstorey height, average crown area, LiDAR fractional cover, and FPC in valley and upper slope plots of both study areas. Low insolation and high TWI was observed in the selected sample plots of the valley area, whereas high insolation and low TWI were observed in the upper slopes in the BRNP and the RRNP study areas. Tables 6.2 and 7.3 show a statistical summary for the effect of insolation, TWI and other topographic variables on average maximum overstorey height, average crown area, LiDAR fractional cover, and FPC in both study areas.

Average maximum overstorey height reflects the potential insolation and TWI along topographic gradients. The average maximum overstorey height of both study areas was found to be the greatest in the sample plots with high TWI and low insolation in valleys. The average maximum overstorey height decreased from valley to upper slope, and varied between 50.8 m in valley plots to 48.1 m on upper slope plots in the BRNP while height ranged from 47.1 m in valley plots to 42.4 m on upper slope plots in the RRNP (Table 6.4). However, no relationship was found between maximum overstorey height and insolation gradient in the BRNP. In contrast, a negative trend ($R^2$ 0.45) was shown between maximum overstorey height and insolation in the RRNP (Figure 6.6 A). As would be expected in the BRNP, maximum overstorey height showed significant change with elevation. Regressions for this variable depicted a decreasing trend with increases in elevation from 400 m to 1200 m amsl (Figure 6.5 B). In addition Table 6.3 and Figure 6.6 E show that average maximum overstorey height increased with increasing TWI in the RRNP study area.

In general, it is expected that taller trees have a larger crown area, thus, average crown area can vary with the average height of trees. The greatest average crown areas were recorded in valley
plots; 44.8 m² and 36.3 m² in the BRNP and RRNP respectively. In this study, average crown area decreased with an increase in insolation in both study areas (see Figures 6.5 A and 6.6 B). However, the average crown area of both plant communities did not show a clear relationship with TWI, which is a surrogate for variation in soil water accumulation.

Estimates of LiDAR fractional cover of sample plots characterized vertical and horizontal distribution of density of photosynthetic and non-photosynthetic overstorey components across the landscape. No significant trends were shown for LiDAR fractional cover with insolation or TWI in the BRNP (Table 6.2). Significant trends were shown (Table 6.3) with insolation and TWI for LiDAR fractional cover in the RRNP. Interestingly, LiDAR fractional cover decreased with increased insolation, and increased with increasing TWI (Figure 6.6 D and G). The differences in LiDAR fractional cover which were shown across TWI gradient could be related to changes in underlying soil water content.

FPC is used to characterize the architecture of foliage in all strata in a plant community (Specht and Specht, 1999) and it has a logarithmic relationship with LAI (Chen and Cihlar, 1995). In this study FPC was estimated using the regression model developed by Armston et al. (2009) for predicting woody FPC from Landsat TM5. Results of GLM analysis (Table 6.2) showed no significant trends for TWI, elevation, and slope of the terrain with Landsat derived FPC in the BRNP. However, a significant trend was shown with insolation for FPC in the same study area. In contrast, in the open-canopy RRNP, FPC showed significant change with insolation, TWI, and elevation. Regressions for FPC depicted weak decreasing trends with an increase in insolation (Figure 6.6 C) and a weak increment with an increase in TWI (Figure 6.6 F). The trend for FPC to decrease with elevation was significant. Values changed from 85% to nearly 50% FPC with increasing elevation (Figure 6.6 H). However, no relationship showed between FPC and the slope of the terrain.
Table 6.2 Results of GLM analysis on average maximum overstorey height (m), Average crown area (m²), LiDAR fractional cover and FPC (%) with abiotic factors (insolation, TWI, elevation, and slope of the terrain) of the BRNP subtropical rainforest. Degree of significance: **** P<0.0001, ***P<0.001, **P<0.01, *P<0.05.

<table>
<thead>
<tr>
<th></th>
<th>Average maximum overstorey height (m)</th>
<th>Average crown area (m²)</th>
<th>FPC (%)</th>
<th>LiDAR fractional cover</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>df</td>
<td>F</td>
<td>P</td>
<td>df</td>
</tr>
<tr>
<td>Elevation</td>
<td>1</td>
<td>26.36</td>
<td>****</td>
<td>1</td>
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<tr>
<td>TWI</td>
<td>1</td>
<td>1.80</td>
<td>ns</td>
<td>1</td>
</tr>
<tr>
<td>Insolation</td>
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<td>0.14</td>
<td>ns</td>
<td>1</td>
</tr>
<tr>
<td>Slope</td>
<td>1</td>
<td>2.22</td>
<td>ns</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6.3 Results of GLM analysis on average maximum overstorey height (m), Average crown area (m²), LiDAR fractional cover and FPC (%) with abiotic factors (insolation, TWI, elevation, and slope of the terrain) of eucalypt dominated open-canopy RRNP. Degree of significance: **** P<0.0001, ***P<0.001, **P<0.01, *P<0.05.

<table>
<thead>
<tr>
<th></th>
<th>Average maximum overstorey height (m)</th>
<th>Average crown area (m²)</th>
<th>FPC (%)</th>
<th>LiDAR fractional cover</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>df</td>
<td>F</td>
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<tr>
<td>Elevation</td>
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<tr>
<td>TWI</td>
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<td>****</td>
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</tr>
<tr>
<td>Insolation</td>
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<td>78.75</td>
<td>****</td>
<td>1</td>
</tr>
<tr>
<td>Slope</td>
<td>1</td>
<td>0.69</td>
<td>ns</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 6.4 Comparisons of the various measures of DEM derived potential insolation and TWI across topographic positions (valley and upper slope plots). Plot means, standard error and for a given mean sharing the same letter are not significantly different at ($P<0.05$).

<table>
<thead>
<tr>
<th>Topographic position</th>
<th>Average maximum overstorey height (m)</th>
<th>Average crown area ($m^2$)</th>
<th>LiDAR fractional cover (%)</th>
<th>Landsat FPC (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BRNP</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Valley</td>
<td>50.8±1.2a</td>
<td>44.8±2a</td>
<td>96.5±0.4a</td>
<td>71.8±0.87a</td>
</tr>
<tr>
<td>Upper slope</td>
<td>48.1±0.8a</td>
<td>38.8±0.9b</td>
<td>95.3±0.6a</td>
<td>70.6±0.82a</td>
</tr>
<tr>
<td>RRNP</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Valley</td>
<td>47.1±1.2a</td>
<td>36.3±1.5a</td>
<td>75.1±1.9a</td>
<td>72.2±0.9a</td>
</tr>
<tr>
<td>Upper slope</td>
<td>42.4±1.3b</td>
<td>18.5±1.6b</td>
<td>69.4±1.5b</td>
<td>67.3±1b</td>
</tr>
</tbody>
</table>

Figure 6.5 Closed-canopy BRNP study area regressions depicting (A) average crown area against insolation and (B) average maximum overstorey height against elevation.
In conclusion, the average maximum tree heights estimated from LiDAR for the RRNP study showed significant trends with variation in DEM derived potential insolation and with TWI (Table 6.3). The greatest average tree heights were observed in low sunlight and wet (i.e. high TWI) valley plots, compared to high sunlight and dry (low TWI) upper slope plots. In contrast, average maximum overstorey heights of the BRNP did not show significant trends with changing insolation and TWI, however, average maximum overstorey heights of the BRNP varied with elevation. Average crown areas varied with intensity of insolation and no trends were observed with TWI in both plant communities. Variation of LiDAR fractional cover showed good correlations with insolation and TWI in the RRNP, however, there was no significant trend observed for LiDAR fractional cover in relation to insolation and TWI in the BRNP. A significant trend was noted for variation in FPC with TWI and insolation in RRNP. In contrast, FPC of BRNP did not vary with insolation, TWI or elevation. The results for most structural attributes in the BRNP showed less variation with environmental and topographic variables compared to the RRNP.
6.4 Discussion

6.4.1 Studying Relationships between Vegetation Structure-environment, Topography

Variation in insolation and soil moisture over topographic gradients have proven to be the most important factors controlling forest structure, composition, and ecosystem function. This study investigated the potential application of remotely derived (i.e. using LiDAR, Landsat TM5) plot scale structural vegetation variables; maximum overstorey height, average crown area, LiDAR fractional cover, and FPC to understand the variation of forest structure on a large scale. Several other studies in Australia have investigated forest structure in low-rainfall woodland ecosystems (Lee and Lucas, 2007) and higher-rainfall woodland with scrubby understorey (Jenkins and Coops, 2011), however, scant information is available regarding remotely examined forest structure-environmental relationships in subtropical rainforest, and eucalypt dominated open-canopy forest landscapes.

In this chapter, DEM based calculation of potential insolation increased from valley to upper slopes of the topography in both study areas. The average maximum overstorey height of canopy trees trended downward with an increase in insolation in the open-canopy eucalypts forest in the RRNP study area. This is likely to be the variation of incoming surface solar radiation which in turn determines the dynamics of many landscape processes, such as surface heating, moistening evapotranspiration, and photosynthesis (Specht and Specht, 1999, Chen et al., 2006), which in turn indirectly determines plant growth in forest structure across radiation gradients (Tanner, 1980b, Tanner, 1980a, Webb et al., 1999, Takyu et al., 2002). The average maximum overstorey height of the RRNP study area was found to be the greatest in the valley sample plots with high TWI. This finding is consistent with (Ashton and Hall, 1992; Aiba and Kitayama, 1999), who demonstrated changes in canopy height in response to water availability; in general, the forest canopy height is lower in dry than in wet environments. In this study, the average maximum
overstorey height decreased with increased elevation in the BRNP; as would be expected, and as is reported by many studies that have measured forest structure across elevation gradients elsewhere (Weaver and Murphy, 1990, Singh et al., 1994, Kitayama and Aiba, 2002, Ediriweera et al., 2008). Due to dramatic changes in the processes causing hillslope erosion especially in areas such as the BRNP (high rainfall compared to the RRNP), soil and soil nutrients tend to accumulate to considerable depths in valleys, which have contributed to the spatial distribution of the nutrient pool and subsequently changes in vegetation structure. Additionally, slow growth of high elevation forests may be influenced by cool temperatures, with persistent cloud cover and fog, and exposure to wind (Bruijnzeel & Veneklaas 1998, Bellingham & Tanner 2000). No difference in variation of maximum overstorey height was detected with potential insolation in the BRNP. This indicates the variation in insolation in relation to the topography probably does not have a marked influence on tree height of subtropical rainforest compared to the eucalypt dominated open-canopy.

LiDAR fractional cover corresponds to the foliage and non-foliage components of the canopy, which decreased with increased insolation in the RRNP. The greatest LiDAR fractional cover was recorded in valleys and was approximately 75%. This suggests that as potential insolation increases across the landscape, evapotranspiration will increase, thus it can be expected the density of the foliage of the overstorey will decrease (Specht and Morgan, 1981, Specht and Specht, 1999, Ackerly et al., 2002). The components of the water balance of forested areas (i.e. evapotranspiration) are determined by the availability of solar radiation. Since the amount of energy available depends strongly on insolation, insolation of upper slopes and ridges are critical to the water balance of vegetation on an inclined surface. Similarly, in the present study, TWI increased at lower topography where there is a high potential for water accumulation, in turn the greatest value of LiDAR fractional cover was observed in sample plots in gullies in the RRNP.
This suggests that the variation in density of foliage and other non-photosynthetic components as captured by LiDAR fractional cover in the open-canopy RRNP study area was caused by insolation and soil water gradients. Since solar radiation and the slope are directly related to water availability in plant communities and soil properties, there may consequently be a noticeable variation of structure and composition among plant communities (Specht, 1988). However, neither insolation nor TWI showed a significant trend with LiDAR fractional cover in the closed-canopy BRNP study area.

The environment varies in terms of the availability of insolation, soil chemical and physical properties and water that determine plant growth and vegetation structure. In this study, eucalypt trees with the largest crowns were found in gullies, as opposed to the upper slopes or ridges of the RRNP and BRNP. The spatial variation in LiDAR estimated crown area is influenced by the local landscape topography, hydrology, soil type and potential insolation. Additionally a weak relationship was observed between average crown area with insolation in the closed-canopy BRNP study area. A similar trend for the variation in tree crowns has been reported through field investigation in dipterocarp dominated tropical rainforest in Sri Lanka (Ashton, 1992, Ediriweera et al., 2008). In this study the greatest average maximum overstorey height was observed on lower slopes in both study areas and thus the variation of crown area appear be related to decrease in tree stature. The weak correlation for crown area with insolation in BRNP is likely a failure to accurately delineate the tree crowns due to the complexity of the irregular shaped overlapped tree crowns, and the spatial organization of tree crowns within the canopy.

The architecture of the foliage of all strata in a plant community provides an estimate of the photosynthetic potential of the landscape (Specht, 1970, Specht, 1983). FPC is the percentage of land covered by a vertical foliage component, and provides a better indication of photosynthetic potential of Australian plant communities (Specht and Specht, 1999). The current study
demonstrated a weak correlation between LandsatTM5 estimated FPC and insolation for the open-canopy RRNP and a similar trend was observed with TWI. The impact of previous logging activities has damaged vegetation and encouraged the establishment of weeds, particularly lantana (*Lantana camara*) in the understorey and thus more background reflectance may have originated from the understorey. In contrast to open-canopy RRNP, the subtropical rainforest BRNP shows no obvious relationship between Landsat predicted FPC with environmental and topographic variables.

Overall, the subtropical rainforest of the BRNP study area did not display strong regional gradients, and these were not affected by TWI and mean insolation. Presumably, potential insolation or TWI was not able to describe the variation in forest structure in the hilly subtropical rainforests compared to the open-canopy eucalypt forests. This indicates that forest structure of subtropical rainforest of the BRNP can be expected to vary with the geology. Where soils have developed *in situ*, the chemical composition of the substrate geology has been shown to be an effective indicator of nutrient availability for the vegetation (Ridley, 1962). In gully areas of the BRNP, deep fertile red soils derived from Tertiary basalt imposes edaphic conditions that are unique, including high nutrient availability, good infiltration and clay content generally more than 50% in the surface soil which support to holds high soil moisture content (Stevens, 1977). In contrast to valley areas, (Stevens, 1977) described that free-draining, and low-nutrient soils which are formed from the rhyolite are common in upper slopes or high elevation. These contrasting geology and soil types are appeared to be influenced on forest structure, species composition and the distribution of tree species across topographic catena. Thus results suggest that physical, and chemical properties of soil, and geology may have significant influences on forest structure potentially more than the TWI, and insolation in subtropical forest BRNP. Conversely, due to the density and complexity of the spatial organization of the canopy of the BRNP which could be
affected the accuracy of structural elements of vegetation derived from small footprint LiDAR and multispectral satellite data. This may have a significant impact on the derived relationships between vegetation structure and environmental, topographic variables of the BRNP. Other most striking outcomes of the study are the greater variations of vegetation structure in relation to the environmental (TWI and insolation) and topographic variables which were discerned in the open-canopy eucalypt plant community. This suggests the characterisation of forest structure in relation to topography using remotely sensed data is determined by the strength of the correlation of vegetation with topographic and environmental variations.

6.4.2 Overall Assessment of the Methodology

The characterisation of vegetation structure and its development in space and time are labour intensive and expensive activities. Consequently there are many gaps in our ecological knowledge due to a paucity of investigations. This study using remote sensing technology assessed how complex terrain, soil water availability, solar insolation, and topographic variables influence the relationship with vegetation structure of two structurally different plant communities including subtropical rainforest and eucalypt dominated forest. Structural components of vegetation including plot scale average maximum overstorey height, average crown area, fractional cover of photosynthetic and non-photosynthetic canopy components using the small footprint discrete LiDAR and FPC from the Landsat TM5 were derived in both plant communities. LiDAR derived DEMs were used to calculate spatial distribution of insolation, soil water (TWI), and topographic variables (i.e. slope and elevation) across the landscape. The characterizing of remotely derived forest structure in two plant communities via insolation, TWI, and topography confirms the potential to discern, to some extent, the vegetation structure-environmental relationship at a landscape scale. The method indicates important practical and technical consequences related to the assessment of forest structure with environmental and
Characterizing forest structure from remotely field sampled data is prone to error. The method used included the selection of randomly remote-sensing sample plots using Hawth’s Analysis Tools (version 3.27) in ArcGIS and the selection of suitable plots from potential sample plots in each study area. Thus, prior field knowledge, and current vegetation and topographic maps proved to be important for the selection of sample plots free of disturbance and away from roads or other developed areas. These are critical considerations for the use of this methodology to characterise vegetation over extensive landscapes.

The environmental variables (TWI and potential insolation) used were of particular interest, since these only requires DEM, (a product of LiDAR) with other predictors (slope angle, slope aspect). The DEM not only provides environmental data for improving the sampling strategy of the area under study, but also facilitates the characterizing of the vegetation structure in relation to the topography. TWI was designed to model soil moisture determined by terrain topography and therefore performance is related to the relief of the study area. While this is not a problem in regions with highly dynamic relief, it could cause serious limitations in lowland regions with small variations in terrain (Grabs et al., 2009). This may have severely affected sample plots that were located in the lower region with small terrain variability in the BRNP. Moreover, several studies such as Zhang and Montgomery (1994), Hancock (2005), and Sorensen and Seibert (2007) have explained that the resolution and information content of a DEM influences the resultant topographic indices. Identifying a suitable resolution for the DEM was challenging as it can affect the accuracy of the computed topographic indices. Similarly, the landscape pattern of soil water
availability is affected by site accumulation potential, and by evaporation, which is in turn largely controlled by site exposure (Lookingbill and Urban, 2004, Dyer, 2009). However, site exposure does not affect the values of TWI as this pattern is unrealistic. Further investigation is required to explore the possibility of combining TWI with proxies of evaporative demand such as solar insolation. Furthermore, the degree of information assumed by TWI and potential insolation is correlated with topographic predictors (i.e. slope angle, aspect angle), and since they were built as spatially explicit functions of such variables this can lead to misinformation about a study area.

It is not feasible to derive vegetation structural dimensions of maximum overstorey height, average crown area, and LiDAR fractional cover with small footprint LiDAR data in closed-canopy subtropical rainforest, due to the subtle variation of forest structure in relation to the topography. The complexity of forest structure especially in the closed-canopy BRNP study area influenced the accuracy of the DEM and derived structural parameters of vegetation. As the complexity of a canopy structure increases (especially in the subtropical rainforest BRNP condition), the probability that LiDAR pulse penetrates below the canopy decreases and leads to occlusion of middle and understorey strata. This may have a significant impact on density of LiDAR points below the canopy, which can affect the accuracy of LiDAR derived metrics. Furthermore, with increased topographic variation, the variability in laser pulse ranges tends to increase. This may be due to the relatively large footprint differing from one plot to another. It is well known that footprint diameter affects tree height estimation from LiDAR data (Nilsson, 1996). This is probably why most derived structural parameters did not show any significant trends with environmental and topographic variables of the study area.

In the present study, high sun elevation angle Landsat TM5 data was used as a source of multispectral data. As both study areas are located in topographically complex terrain, a considerable proportion of topographic distortion resulted especially for steep sloping and valley
areas. Thus topographic effect can greatly influence the empirical relationship between satellite recorded reflectance and forest biophysical properties of vegetation (Sader et al., 1989). The topographically induced illumination was minimized by using an appropriate correction algorithm developed by Flood et al. (2012), however, it is likely that the topographic effects still remain in the corrected images as residual topography (over corrected or under corrected), however, this is not the subject of discussion here. Furthermore, it has been recognized that moderate resolution images like Landsat TM with broad wavelength data encourage digital number (DN values) saturation due to intact large rainforest crowns and the impact of shadowing (Lu, 2006). This can be a limitation in employing lower radiometric resolution multispectral images (e.g. Landsat) to characterise structural attributes of subtropical and tropical rainforests in topographically complex terrain.

6.5 Conclusions

Quantitative vegetative metrics derived from LiDAR and multispectral data can complement and extend field-based structural assessment, and can distinguish vegetation pattern variation at landscape scale, even where relatively subtle structural variation occurs (Su and Bork, 2007, Jenkins and Coops, 2011). This chapter sought to investigate the environmental-forest structure relationships using a remote sensing approach in two structurally different plant communities in topographically complex terrain. The study used DEM based derived insolation, TWI and topographic variables to characterize the variation in the complex terrains and understand functional relationships among selected structural attributes of the two plant communities. The results presented here demonstrated how remote sensing investigations of vegetation can contribute to the analysis of regional structural patterns of vegetation, and the association of the forest structure with environmental and topographic variables. In fact, plot scale average maximum overstorey height, average crown area, the fraction of photosynthetic and non-
photosynthetic component of canopy showed a significant negative trend with solar insolation in the eucalypt dominated open-canopy forest RRNP study area. Only the variation of elevation markedly affected the plot scale average maximum overstorey height, and tree height decreased with increased elevation in the closed-canopy of the subtropical rainforest in the BRNP. Average crown area of the BRNP showed a weak relationship with solar insolation and no other variables showed trends with environmental and topographic variables in the BRNP. Thus results revealed that physical and chemical properties of soil and geology appeared to have significant influences on tree size, crown area, and FPC potentially more than the TWI and insolation in subtropical forest BRNP. This method of characterising forest structure in relation to the environmental and topographic variation is more feasible in eucalypt dominated open-canopy forest than the closed-canopy subtropical rainforest. The key finding of this chapter revealed that if environmental variables show higher level of gradients with variation of topography in the landscape, such variations could be discernible through structural and compositional variation of the plant community. The potential applications for this adopted method include interpretation of ecological variation and gradients within a landscape based context, understanding responses to climate change, monitoring the vigour of vegetation using quantitative assessment, and incorporation of structural assessment for biodiversity related studies. Pattern analysis in landscape ecology is one of the fundamental requirements of landscape ecology, and the methods described here offer statistically significant, quantifiable and repeatable means to realise that goal at a fine spatial scale. These results add to a growing literature attempting to understand how to better investigate variation of forest structure in relation to environmental and topographic variables over extensive landscapes.
Chapter 7
Fusion of Airborne LiDAR and Multispectral Data to Estimate Above Ground Biomass in Eucalypt and Subtropical Rainforest in Topographically Complex Terrain

This chapter has been submitted to the Forest Systems as: EDIRIWEERA, S., PATHIRANA, S., DANAHER, T. & NICHOLS, D., ‘Estimating above-ground biomass by fusion of LiDAR and multispectral data in subtropical woody plant communities in topographically complex terrain in North-eastern Australia’ Forest Systems, under review

Declaration of Authorship

Components of this chapter relating to assessment of different topographic corrections were done in entirety by Sisira Ediriweera in partial fulfillment of his PhD. Sisira Ediriweera led the writing of the paper. S. Pathirana, T. Danaher, and D. Nichols reviewed the manuscript prior to submission to the journal Forest Systems. The relative contributions of the four authors to the manuscript are indicated below.

Conception of the study: SE (60%), SP (20%), TD (20%)
Design of the study: SE (60%), SP (30%), TP (10%)
Collection of data: SE (70%), SP (20%), DN (10%)
Analysis of data: SE (70%), TD (30%)
Interpretation of data: SE (60%), TD (15%), SP (15%), DN (10%)
Conclusions: SE (60%), TD (20%), SP (20%)
Writing up manuscript: SE (100%)
7.1 Introduction

Forest ecosystems exert considerable influence on global carbon cycles through the flux and storage of carbon in plant biomass (Chave et al., 2005). Plant biomass in forest ecosystems is distributed above and below ground, and is the total amount of biological material present above the soil surface in a specified area. Tree biomass is useful, for example, in assessing forest structure and condition (Westman and Rogers, 1977, Specht and Specht, 1999), to estimate forest productivity and carbon fluxes based on sequential changes in biomass (Chambers et al., 2001), to provide a means of assessing sequestration of carbon in wood, leaves, and roots (Specht and West, 2003), and also as an indicator of both the biological and economic value of a forest ecosystem. Additionally, Berard (1996) explained that estimation of biomass is an alternative way to measure the potential energy of a forest as plant material stores the solar energy needed for photosynthesis. Thus, estimation of forest biomass at different geographical scales (from local to global) becomes significant in reducing uncertainty of carbon emission and sequestration, understanding its role in influencing soil fertility, measures of land degradation or restoration, and understanding the roles a forest plays in environmental processes and sustainability (Foody et al., 2003).

Generally, estimation of forest biomass can be categorised into two methods, one is a field based method that provides a consistent means of estimation of forest biomass, however, usually at a high cost and often involving destructive sampling. An alternative method is the acquisition of data using remote sensing. Remotely sensed data such as LiDAR and multispectral satellite data can be effectively used to estimate above ground biomass (AGB) of forested landscapes. Advantages of estimating biomass using remote sensing include the ability to obtain measurements from any location in a forested area, the speed with which remotely sensed data
can be collected and processed, the relatively low cost of various remote sensing data, and the ability to collect data easily in extensive areas containing diverse topography.

LiDAR is an active remote sensing system that has proved to have potential to accurately measure vertical and horizontal structural elements of forests. This technology allows extraction of data regarding highly accumulated biomass structural elements of forests (i.e. tree heights, dimensions of crown number of stems), which are important measures for estimation of AGB in forests. Several studies have demonstrated the potential of accurate estimation of tree height using LiDAR for a single tree or on a plot scale (Nilsson, 1996, Means et al., 2000, Næsset and Okland, 2002, Popescu et al., 2002). Similarly, LiDAR has proven its potential to characterize horizontal structure of vegetation such as forest biomass (Nelson et al., 1984, Drake et al., 2002, Popescu et al., 2003, van Aardt et al., 2006, Popescu, 2007, Riggins et al., 2009, Latifi et al., 2010), forest volume (Nelson et al., 1984, Nelson et al., 1988, Popescu et al., 2004), and canopy attributes (Lefsky et al., 1999, Popescu et al., 2003, Weller et al., 2003, Koukoulas and Blackburn, 2004, Riaño et al., 2004, Andersen et al., 2005, Coops et al., 2007, Lee and Lucas, 2007). Whilst current small footprint LiDAR systems are able to record data over 10 points per m² with a higher pulse repetition rate, the accurate quantifying of vertical and horizontal structural properties of vegetation continues to depend on the complexity of the target vegetation and the topography (Gatziolis et al., 2010). Therefore, LiDAR employed on tropical and subtropical forest is unlikely to extract the same level of accuracy as when it is employed in temperate forests.

In addition, Landsat Thematic Mapper (Landsat TM) data with suitable spectral and spatial resolution and a relatively long history of availability have made it a primary data source for biomass estimations. Application of Landsat TM data to estimate forest biomass has been well used among researchers for small scale to large scale investigations (Roy and Ravan, 1996, Foody et al., 2001, Phua and Saito, 2003, Lu and Batistella, 2005). The data are much less expensive (or
no cost i.e. Landsat5 data TM or Multispectral Scanner) than LiDAR, covers a vast geographical area, and provides a great deal of spectral information. Landsat TM derived variables for AGB estimation such as spectral signatures, vegetation indices, and texture are commonly used to develop suitable AGB estimation models. In order to select suitable spectral variables for the model development, multiple regression analysis, neural networks, and K-nearest neighbour (KNN) have been widely used in the literature (Lu, 2006). In the regression approach, spectral signatures or vegetation indices derived from multispectral data are often used as independent variables. Several studies have demonstrated the potential of application of visible bands (i.e. red reflectance) in multispectral data as independent variables to estimate AGB by regression (Franklin, 1986, Jakubauskas and Price, 1997). Similarly, several vegetation indices have also been developed and applied to estimate structural parameters of forests (Anderson et al., 1993, Lu et al., 2004). Lu et al. (2004) used simple band ratio, Normalized Difference Vegetation Index (NDVI), complex vegetation indices, image transform and non transformed image bands derived from Landsat TM data to estimate AGB, and other forest structural parameters including basal area, stand diameter, and stand height in tropical rainforest in Brazil. In general, vegetation indices have been recommended for dealing with variation caused by canopy geometry, soil background, sun view angles, and atmospheric conditions when estimating structural parameters of vegetation (Elvidge and Chen, 1995, Treitz and Howarth, 1999). However, application of multispectral data such as Landsat to estimate AGB is recognised as being limited in its inability to compensate for canopy reflectance being saturated in highly complex conditions (particularly in tropical rainforests) (Steininger, 2000, Lu and Batistella, 2005), the impact of shadows caused by canopy, and the variations in complex topography (Steininger, 2000, Lu and Batistella, 2005).

This study is focused on combined application of LiDAR and Landsat5 TM (TM5). As indicated above, LiDAR represents one of the best sources of information for investigating vegetation
structural parameters (e.g. tree height, crown area, foliage cover) and provides detailed information on vertical profiles of vegetation. Landsat data is a powerful source of data on spectral information of land use cover that allow the investigation of vegetation structure, and structural changes in forest ecosystems. These two sources of data can be considered complementary as one provides vertical and horizontal structural information of vegetation, and the other provides spectral information of vegetation. A combined application of active and passive remotely sensed data could be a powerful technique that exploits the strengths of both data sources to optimize the estimation of plot scale AGB. A combination of data from multiple sources attempts to acquire more knowledge about observed phenomenon than can be gained from a single data source (Hall, 1997). Several studies demonstrated that the fusion of LiDAR derived structural variables of vegetation with multispectral data (spectral bands or derived vegetation indices) improved prediction capacity of different vegetation structural parameters by statistically integrating both variables. This technique has been successfully used by Popescu et al. (2004) to estimate plot scale forest volume and biomass, by integrating small footprint LIDAR with multispectral satellite data of deciduous and pine forests. Similarly, Latifi et al. (2010) estimated timber volume and biomass using a nonparametric method in a temperate forest combining LiDAR and Landsat data. Combined LiDAR with IRS 1C LISS III derived biophysical variables was also used by Tonolli et al. (2011) to estimate plot scale timber volume in the Southern Alps in Italy. Hudak et al. (2006) integrated LiDAR and multispectral data to model and map basal area and tree density across two diverse coniferous forests. Additionally, Jensen et al. (2008) improved LiDAR based plot scale LAI quantifying capacity by adding SPOT derived vegetation indices.

In general, estimation of the plot scale AGB of tropical and subtropical forests in topographically complex terrain is limited. Despite much information on estimation techniques of plot scale AGB
in structurally complex tropical and subtropical forests, much uncertainty remains regarding estimation accuracy (Lu et al., 2012). The current investigation is potentially useful to quantify plot scale AGB as it comprises vertical and horizontal information of vegetation structure (i.e. canopy heights, canopy photosynthetic and non photosynthetic components) derived from LiDAR and spectral responses of vegetation provided by multispectral data in areas with structurally complex vegetation and diverse topography. It is anticipated that fusing LiDAR derived large biomass partitioning structural components (e.g. tree height, dbh, crown area) with TM5 derived spectral information data will improve AGB estimation in closed-canopy subtropical rainforest in topographically complex terrain. The main objective of this study is to improve the capacity of estimating plot scale AGB for eucalypt dominated forest and subtropical rainforest by fusion of small footprint LiDAR and Landsat5 TM multispectral data. The main objective of this chapter translates into two more targeted sub-objectives: 1) the capability of LiDAR derived laser metrics, other structural parameters of vegetation and TM5 variables to estimate measured plot scale AGB, and 2) the extent to which combining of TM5 and LiDAR derived variables may improve estimates of AGB to quantify AGB in a topographically dissected landscape in NSW. A unique characteristic of the targeted vegetation is the variation of vegetation in relation to changes in the topography and the distribution of sclerophyll forests particularly on the ridges or upper slopes, while the subtropical rainforests are restricted to the gullies or lower slopes of the topography (Florence, 1996). Therefore, data will be analysed separately for both plant communities, and again as a combination of the data of both sites.

7.2 Material and Methods

7.2.1 Field Data Collection and Processing

Field sampling was conducted between July and December 2010. A random sampling method was adopted in order to obtain a structurally significant representation of vegetation in relation
to the slope and aspect in the study areas. There were 50 sample plots representing 25 sample plots for each study area randomly distributed within each LiDAR transect across the two forested areas. Each sample plot area was approximately 0.25 ha. Selected sample plots were largely undisturbed mature vegetation covering a range of species on uniform slopes and aspects. The centre of each plot was determined by using a GPS unit (GARMIN GPSMAP (R) 62stc). Five GPS points were recorded in the centre of each plot over a 20 minute period and then averaged. The accuracy of the GPS varied with the density of overstorey with standard deviation of the five measurements ranging from 5 m to 8 m in the closed-canopy BRNP and from 3 m to 6 m in the open-canopy RRNP.

7.2.1 (a) Above Ground Biomass Estimation using Ground Measured Data

For this study AGB was estimated based on previously developed allometric equations of plant communities within Australia. Allometric equations are used as a means of estimating tree biomass from the relationship between component biomass and tree dimensions (Keith et al., 2000). Unfortunately, allometric equations at fine taxonomic resolution were not available for Australian tree species. Therefore, to estimate plot scale AGB, two specific vegetation types (rainforest and sclerophyll forest) with published general allometric equations were considered (Keith et al., 2000) (Table 7.1).

Table 7.1 Allometric equations used for deriving above ground biomass of study areas

<table>
<thead>
<tr>
<th></th>
<th>Closed-canopy subtropical rainforest</th>
<th>Open-canopy sclerophyll forests</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnY =</td>
<td>-1.8957 + 2.3698 lnX</td>
<td>lnY = -2.3267 + 2.4855 lnX</td>
</tr>
</tbody>
</table>

where Y = AGB (kg), X = dbh (cm)

Many variables (e.g. tree height, volume) have been used in allometric equations, however, dbh is the most widely available variable and was recommended by Parde (1980) in a review of forest
biomass and which has been often used Crow and Schlaegel (1988) and Burrows et al. (2003). In this study, field measured plot scale dbh measurements were used to estimate total AGB of each plot. All trees with dbh greater than 10 cm in each plot in both study areas were marked, and diameters at 1.3 m height were measured using a diameter tape. Diameters for buttressed trees were measured immediately above the buttress.

Table 7.2 shows a summary of the statistics of the estimated AGB of both study areas measured using allometric equations. Application of two equations for each study area allowed comparison to be made between AGB estimates derived by different allometric equations with LiDAR derived laser metrics, other structural parameters of vegetation and multispectral data. Trees must be felled in order to ground truth biomass. This study was conducted in National Parks, and destructive sampling was not permitted.

Table 7.2 Estimated AGB (t/ha) of both study areas

<table>
<thead>
<tr>
<th>Study area</th>
<th>Mean AGB</th>
<th>SD AGB</th>
<th>Min AGB</th>
<th>Max AGB</th>
</tr>
</thead>
<tbody>
<tr>
<td>BRNP</td>
<td>340</td>
<td>72</td>
<td>223</td>
<td>478</td>
</tr>
<tr>
<td>RRNP</td>
<td>171</td>
<td>57</td>
<td>98</td>
<td>353</td>
</tr>
<tr>
<td>Combined sites</td>
<td>255</td>
<td>107</td>
<td>98</td>
<td>478</td>
</tr>
</tbody>
</table>

7.2.2 LiDAR and Multispectral Data

A Leica ALS 50-II LiDAR system was employed to acquire LiDAR data over the study areas during 19–20 August 2010. Parameters of LiDAR acquisition and data specification were described in the section 4.2.2.

Landsat5 TM (Level 1 G), product (Path/Raw- 89/80) was acquired from the United States Geological Survey (USGS). Cloud and haze free data was captured on 15 October 2011 under high sun angle conditions (54.6°). Radiometric calibration and atmospheric correction procedure of the TM5 image were outlined in section 5.2.2b. The image was Bicubic Spline re-sampled into
25 m x 25 m pixels to match the base image and to be equivalent to the size of the sampled sites. The PSSSR topographic correction method (Flood et al., 2012) was employed to minimise the topographically induced illumination.

7.2.2 (a) Extraction of Laser Metrics, other LiDAR Based Structural Parameters

The LiDAR data analysis was performed using a non-commercial LiDAR processing code developed by Armston et al. (2009), TreeVaw 1.1 software Popescu et al. (2003) in IDL 8.0, and ESRI Inc. ArcGIS 9.3. All returns were used for analysis to maximise utilization of data acquired by the sensor. Firstly, ground and non-ground returns were separated. A 1 m DEM was produced using filtered returns classified as representing the ground via Kriging interpolation. For each cell in the DEM, the six closest points were used for the interpolation. To evaluate the accuracy of the LiDAR DEM, post-processed differential GPS points (dGPS) were collected using MobileMapper from Thales Navigation Systems™ in different locations. GPS points were distributed over LiDAR transects. There were 70 GPS points (4 transects) for the BRNP, and 55 points (3 transects) for the RRNP collected from flat to slope terrain in open ground (park roads) and under different forest canopies. In order to assess the accuracy of the LiDAR DEM, ground collected dGPS points were overlaid on the LiDAR DEM. To evaluate the quality of LiDAR-derived DEMs, root mean square error (RMSE) were calculated. The calculated RMSE for the BRNP was 5.7 m and 1.9 m for the RRNP.

Secondly, LiDAR derived laser metrics and other structural parameters of vegetation were calculated from separated non-ground laser returns. Observations with height values less than 2 m for the RRNP and 0.5 m for the BRNP were discarded from existing non ground data. These threshold values were appropriate to remove undulation of the terrain and other objects including herbaceous vegetation, litter, fallen logs, and boulders. Thus, most reflectance represented only understorey and overstorey vegetation. The lower threshold heights were
appropriate for the BRNP, as the closed-canopy overstorey vegetation leads to suppressions of the understorey layer, and consequently weak penetration of laser pulses through the closed canopy to the ground. Whilst sparse overstorey trees with dense shrubs (*Lantana camara*), fallen trees, and logs were common in the RRNP, to eliminate laser returns from vegetation and non-ground objects a 2 m height threshold was applied. Thirdly, the non-ground returns were used to extract co-located 50 m x 50 m plots of each study area, and subsequently LiDAR derived variables including LiDAR derived laser metrics, other structural parameters of vegetation (i.e. crown diameter, LiDAR fractional cover) were computed. The calculated height related laser metrics comprise maximum, mean, median, and relative median canopy heights, from 10th to 90th height percentiles.

**7.2.2 (b) LiDAR Fractional Cover**

LiDAR fractional cover (Fraccov) is defined as one minus the gap fraction probability at a zenith of zero (Lovell et al., 2003) and corresponds to the photosynthetic and non-photosynthetic components of canopy (Weller et al., 2003). LiDAR fractional cover estimates were calculated by aggregating all points into 50 m spatial bins using equation

\[ 1 - p_{gap} = \frac{C_v(z)}{C_v(0) + C_G} \]  

(3)

where \( C_v(z) \) is the number of first returns higher than \( Z \) m above the ground (2 m for the RRNP and 0.5 m for the BRNP) and \( C_G \) is the number of first return points from the ground level.

**7.2.2 (c) Plot Scale Average Crown Diameter**

Tree crown diameters were measured on the LiDAR derived 1 m resolution CHM by automated processing using the non-commercial TreeVaw 1.1 software (Popescu et al., 2003). The estimation procedure of plot scale average crown diameter was described in the 6.2.2(d). As Popescu et al.
(2003) explained, CHM based tree crown diameter estimation is more appropriate for measuring crown diameter for dominant and co-dominant trees that have individualized crowns on the CHM surface. In this study, average crown diameters were estimated at canopy heights of 15 m, 20 m, and 30 m for RRNP and 15 m, 20 m, and 35 m for the BRNP for each plot. LiDAR derived heights, fractional cover, and crown diameter variables corresponding to the sampling sites are summarised in Table 7.3

Table 7.3 Variables calculated from LiDAR returns in each study sites

<table>
<thead>
<tr>
<th>Variable ID</th>
<th>Description of variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>ht_m</td>
<td>Mean height values</td>
</tr>
<tr>
<td>ht_mx</td>
<td>Maximum height values</td>
</tr>
<tr>
<td>ht_med</td>
<td>Median height values</td>
</tr>
<tr>
<td>ht_rmed</td>
<td>ht_rmed (%) = ( \frac{ht_{median}}{ht_{max}} \times 100 )</td>
</tr>
<tr>
<td></td>
<td>The median height is expressed in per cent, is derived by maximum laser heights (ht_max) multiplied by 100</td>
</tr>
<tr>
<td>hp_10th - hp_90th</td>
<td>height percentiles from 10th to 90th</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Canopy height related variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canopy structure related variables</td>
</tr>
</tbody>
</table>

7.2.2 (d) Landsat 5 TM Variables

Signatures for TM5 bands 1-5 and band 7 were extracted from the 2 x 2 pixel mean surrounding the field site location. The 2 x 2 block average provided the best match to the spatial extent of field measurements. It was assumed that any increase in vegetation structure between the date of site measurement and the image acquisition date was less than measurement error, as the sites were generally located in mature vegetation. Proposed TM5 variables included: (i) normal band values, natural logarithm, reciprocal, and square root transformed band values, (ii) simple band ratios, (iii) normalized band ratios, and (iv) high order transformed greenness indices (Table 7.4). Calculation of the MIR-corrected normalised difference vegetation index (NDVIc) required that
minimum (min) and maximum (max) MIR values (TM5 band 5) be derived from the scene of the study area. MIR min corresponds to MIR reflectance of the completely closed canopy, and MIR max corresponds to the reflectance of the completely open canopy environment of the study area (Nemani et al., 1993). In this study, water body and exposed rock were not available to determine MIR min and MIR max MIR reflectance, therefore minimum and maximum MIR reflectance of the study sites were used for computation of MIR-corrected NDVI and SR indices.

Table 7.4 Summary of Landsat5 TM derived variables

<table>
<thead>
<tr>
<th>Variable ID</th>
<th>Formula / description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Landsat5 TM bands</strong></td>
<td></td>
</tr>
<tr>
<td>Band1-7</td>
<td>Normal TM bands</td>
</tr>
<tr>
<td>In Band1-7</td>
<td>Natural logarithm transferred TM bands</td>
</tr>
<tr>
<td>Sqrt Band1-7</td>
<td>Square root transferred TM bands</td>
</tr>
<tr>
<td>Inv Band1-7</td>
<td>Reciprocal transferred TM bands</td>
</tr>
<tr>
<td><strong>Simple band ratios</strong></td>
<td></td>
</tr>
<tr>
<td>SR$^1$</td>
<td>$\frac{NIR}{Red}$ (Birth, 1968)</td>
</tr>
<tr>
<td>SRc$^2$</td>
<td>$\frac{NIR}{Red} \times \left[1 - \frac{(MIR - MIR_{\text{min}})}{(MIR_{\text{max}} - MIR_{\text{min}})}\right]$ (Brown, 2000)</td>
</tr>
<tr>
<td>MSI$^3$</td>
<td>$\frac{SWIR}{NIR}$ (Vogelmann, 1990)</td>
</tr>
<tr>
<td>MSR$^4$</td>
<td>$\frac{(NIR/Red) - 1}{\sqrt{(NIR/Red) + 1}}$ (Chen, 1996)</td>
</tr>
<tr>
<td><strong>Normalized band ratios</strong></td>
<td></td>
</tr>
<tr>
<td>NDVI$^5$</td>
<td>$\frac{(NIR - Red)}{(NIR + Red)}$ (Rouse, 1974)</td>
</tr>
<tr>
<td>NDVI$^c_6$</td>
<td>$\frac{(NIR - Red/NIR + Red)}{\left[1 - \frac{(MIR - MIR_{\text{min}})}{(MIR_{\text{max}} - MIR_{\text{min}})}\right]}$ (Nemani, 1993)</td>
</tr>
<tr>
<td>SLAVI$^7$</td>
<td>$\frac{NIR}{(Red + MIR2)}$ (Lymburner, 2000)</td>
</tr>
<tr>
<td><strong>High order transformed greenness indices</strong></td>
<td></td>
</tr>
<tr>
<td>PPSG$^8$</td>
<td>$PPSG = \tan^{-1}\left(\frac{(PC_2 - SF_2)}{(PC_1 - SF_1)}\right)$</td>
</tr>
<tr>
<td></td>
<td>PC1 and PC2 are the first two principal components scores</td>
</tr>
<tr>
<td></td>
<td>SF1, SF2 = -0.25, -0.25 (Moffiet, 2010)</td>
</tr>
</tbody>
</table>

$^1$ Simple Ratio, $^2$Mid-Infrared corrected Simple Ratio, $^3$short-wave infrared/near infrared index , $^4$ Modified Simple Ratio, $^5$Normalised Difference Vegetation Index, $^6$Mid-Infrared corrected NDVI index (NDVIc), $^7$Specific Leaf Area Vegetation Index, $^8$Principal Polar Spectral Greenness
7.2.3 Statistical Analysis

Figure 7.1 Flowchart of the model building method

Most allometric equations for calculating field-based AGB are power models (Zianis and Mencuccini, 2004), hence AGB and LiDAR derived laser metrics, other structural parameters of
vegetation (herein LiDAR derived variables) are generally log transformed when developing regression models (Lim et al., 2003, Patenaude et al., 2004, Lu et al., 2012). In the study, the ground measured AGB, LiDAR derived variables and Landsat derived variables were log transformed. The BRNP and the RRNP sites were analysed separately, and then again as a combined data set within a Multiple Linear Regression (MLR) framework. The statistical software (IBM SPSS-20) was employed to model average AGB using the best subsets regression procedure. Stepwise multiple linear regression models, each with a 0.1 significance level, were developed separately for each of the study areas and the combined site data. The independent variables (Tables 7.3 and 7.4) were LiDAR derived different laser metrics, LiDAR fractional cover, LiDAR derived crown diameter, transformed and non-transformed TM5 bands, and TM5 derived different vegetation indices. The variance inflation factors (VIF) greater than 10 was used to detect the multicollinearity of independent variables.

Several criteria were employed to examine potential models including adjusted $R^2$ and root mean square error (RMSE) and residual plots. RMSE were computed as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{N}}$$

(4)

where $O$ is observed value, $P$ is predicted values and $N$ is number of observations.

All above criteria were considered for the final model selection. Since the ground measured data of all sample plots were used for model development, there was no data available for a validation process. Therefore, Predicted Residual Sum of Squares (PRESS) statistics was used as a form of cross validation (Myers, 1990). The PRESS statistic is defined as:

$$\text{PRESS} = \sum_{i=1}^{n} (e_{i-i})^2$$

(5)

where $e_{i-i}$, $i=1,\ldots,n$, are prediction error or PRESS residuals.
The PRESS statistics is effectively a leave one out cross validation approach, where the model is re-parameterised with n-1 observations and the n-1 models is used to predict the excluded sample plot. For the choice of the best model, one favours the model with the lowest PRESS. The applied methodology for data processing and model development is summarised in Figure 7.1.

7.3 Results

Results for each study area and the combined dataset of each study area (denoted ‘combined’) were summarised for AGB estimates and the regression-based analysis (i.e. LiDAR, Landsat5 TM, and LiDAR+Landsat5 TM estimates models).

7.3.1 LiDAR Based AGB Estimates

The AGB estimates models obtained using LiDAR derived variables of the two study areas and combined data are summarised in Table 7.5. The LiDAR derived four height related variables (i.e. ht_m, ht_med, ht_60th and ht_rmed), and fractional cover for canopy components were most significant for all predictive models of the three data sets investigated. These variables performed well with models significant at \( p<0.0001 \). In terms of AGB estimates, the LiDAR based prediction model for the combined data set was high, explaining 79% (0.79 adjusted \( R^2 \)) variation in measured values. Given the similar number of plots for the different plant communities, the RRNP AGB prediction models accounted for 31% more variation than for the BRNP. RMSE among the selected LiDAR based prediction models were lower for the RRNP at almost 30 t/ha. The highest RMSE (47 t/ha) was observed for ground estimated AGB from the combined data, however, a large proportion of variation in ground estimated AGB was explained by LiDAR.
Table 7.5 Results for LiDAR based regression analysis of AGB estimates of the BRNP, the RRNP, and combined data

<table>
<thead>
<tr>
<th>Dataset</th>
<th>LiDAR model</th>
<th>$R^2$</th>
<th>Adj. $R^2$</th>
<th>RMSE (t/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BRNP</td>
<td>-0.908 + 2.24x log Fraccov + 0.920 x log ht$<em>{rmed}$ + 0.531x log CD$</em>{m20}$</td>
<td>0.53</td>
<td>0.45</td>
<td>41</td>
</tr>
<tr>
<td>RRNP</td>
<td>2.505 + 1.062 x log Fraccov + 1.224x log ht$<em>{m}$ - 0.808 x log ht$</em>{rmed}$</td>
<td>0.79</td>
<td>0.76</td>
<td>30</td>
</tr>
<tr>
<td>Combined</td>
<td>5.027 + 11.819 x log ht$<em>{m}$ - 2.831x log hp$</em>{60^th}$ - 8.44 x log ht$_{med}$</td>
<td>0.83</td>
<td>0.79</td>
<td>47</td>
</tr>
</tbody>
</table>

7.3.2 Landsat5 TM Based AGB Estimates

Regression of individual Landsat5 TM model covariates resulted in the most acceptable model performance for individual sites rather than the combined sites, however, the overall performance was not as high as the LiDAR based AGB estimates models (Table 7.6). The best model fits were obtained from selection of the SR and SLAVI for the combined site data and these covariates explained 75% of variation in the ground measured AGB. For the estimation model of AGB in the RRNP, the SR and NDVIc, covariates were selected and the adjusted $R^2$ of overall predictive models was 0.59. It was found that the regression of Landsat5 TM model covariates for the BRNP sites performed poorly; SLAVI and PPSG were enabled to account for 31% of variation of response data. The lowest RMSE (38 t/ha) was found for the RRNP, and the least accurate results were produced for the BRNP (54 t/ha).

Table 7.6 Results for Landsat5 TM based regression analysis of AGB estimates of the BRNP, the RRNP, and combined data

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Landsat5 TM model</th>
<th>$R^2$</th>
<th>Adj. $R^2$</th>
<th>RMSE (t/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BRNP</td>
<td>23.632+ 4.595x log SLAVI - 10.445 x log PPSG</td>
<td>0.38</td>
<td>0.31</td>
<td>54</td>
</tr>
<tr>
<td>RRNP</td>
<td>2.882 + 2.237 x log SR - 1.789x log NDVIc</td>
<td>0.64</td>
<td>0.59</td>
<td>38</td>
</tr>
<tr>
<td>Combined</td>
<td>3.079+ 1.247 x log SR + 3.650 x log SLAVI</td>
<td>0.77</td>
<td>0.75</td>
<td>48</td>
</tr>
</tbody>
</table>
7.3.3 LiDAR+Landsat Based AGB Estimates

Table 7.7 shows the results of AGB estimate models by combining both LiDAR and Landsat5 TM derived variables. The RRNP and combined sites models using both sensors derived variables showed an enhancement of accuracy of prediction of AGB. The best model in terms of adjusted $R^2$ (0.81) was obtained from selection of both LiDAR and TM5 derived variables for the combined site data; respective RMSE (43 t/ha) was greater than the RMSE obtained for RRNP (25 t/ha). However, no improvement was observed for the AGB prediction model for the BRNP using a combination of variables of both sensors.

Overall, the fusion of Landsat5 TM and LiDAR derived variables increased adjusted $R^2$ and decreased RMSE for the RRNP, and combined sites (Table 7.8), and the improvement for both cases was not much higher. For example, the RRNP integrated AGB prediction model improved adjusted $R^2$ from 0.76 to 0.79 and decreased RMSE by from 30 t/ha to 25 t/ha. For all cases, the BRNP, the RRNP, and the combined AGB were free from multicollinearity (i.e. $VIF < 10$), and all developed equations were parsimonious models containing four or less than four independent variables. Figure 7.2 provides scatter plots for the observation, and each prediction model predicted AGB for the BRNP, the RRNP, and the combined sites data.
Table 7.7 Results for LiDAR+ Landsat5 TM based regression analysis of AGB estimates of the BRNP, the RRNP, and the combined data

<table>
<thead>
<tr>
<th>Dataset</th>
<th>LiDAR+LandsatTM5 model</th>
<th>$R^2$</th>
<th>Adj. $R^2$</th>
<th>RMSE t/ha</th>
</tr>
</thead>
<tbody>
<tr>
<td>BRNP</td>
<td>$-0.908 + 2.24x \log \text{Fraccov} + 0.920 x \log \text{ht}<em>{rmed} + 0.531x \log \text{CD}</em>{m20}$</td>
<td>0.53</td>
<td>0.45</td>
<td>41</td>
</tr>
<tr>
<td>RRNP</td>
<td>$2.412 + 1.087 x \log \text{Fraccov} + 0.431 x \log \text{ht}_m + 1.365x \log \text{NDVI}_c$</td>
<td>0.83</td>
<td>0.79</td>
<td>25</td>
</tr>
<tr>
<td>Combined</td>
<td>$3.153 + 5.526 x \log \text{ht}<em>m - 5.089 x \text{ht}</em>{med} - 2.45 x \log \text{SR}$</td>
<td>0.83</td>
<td>0.81</td>
<td>43</td>
</tr>
</tbody>
</table>

Table 7.8 The variation of adjusted $R^2$ and RMSE among prediction models developed using LiDAR and Landsat5 TM derived variables separately and LiDAR+ Landsat5 TM for the BRNP, the RRNP, and the combined data

<table>
<thead>
<tr>
<th>Dataset</th>
<th>LiDAR</th>
<th>Landsat5 TM</th>
<th>LiDAR+Landsat5 TM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adj. $R^2$</td>
<td>RMSE</td>
<td>Adj. $R^2$</td>
</tr>
<tr>
<td>BRNP</td>
<td>0.45</td>
<td>41</td>
<td>0.31</td>
</tr>
<tr>
<td>RRNP</td>
<td>0.76</td>
<td>30</td>
<td>0.59</td>
</tr>
<tr>
<td>Combined</td>
<td>0.79</td>
<td>47</td>
<td>0.75</td>
</tr>
</tbody>
</table>
Figure 7.2 Ground measured (X axis) versus predicted (Y axis) AGB for the models based on study sites division: The solid lines show 1:1 relationship.

No significant improvement observed.
7.3.4 Validation of the Regression Models Prediction

Table 7.9 shows the cross-validation results of all candidate models. For the RRNP, and combined sites data, the cross-validation showed that integration of LiDAR and Landsat5 TM derived variables improved the prediction of AGB, revealing overall smaller PRESS statistics and standard deviation of PRESS residuals. The LiDAR derived variables based prediction models consistently gave satisfactory results for each data set as indicated by PRESS statistics. For each data set, the highest overall PRESS statistics and standard deviation of PRESS residuals were observed for Landsat5 TM derived variables based AGB prediction models.

In conclusion, the most accurate estimation results were obtained for LiDAR and Landsat5 TM derived variables integrated AGB prediction models for the RRNP, and this is followed by the combined sites data sets. The AGB estimation in the BRNP was less accurate, and the combination of LiDAR and Landsat5 TM covariates did not improve model performance.

Table 7.9 PRESS statistics for predicting AGB for the BRNP, the RRNP, and the combined sites data

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Method</th>
<th>PRESS</th>
<th>Range of PRESS residuals</th>
<th>Mean of PRESS residuals</th>
<th>SD of PRESS residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>BRNP</td>
<td>LiDAR</td>
<td>62080.7</td>
<td>-118.54 - 103.25</td>
<td>-5.15</td>
<td>56.92</td>
</tr>
<tr>
<td>BRNP</td>
<td>Landsat5 TM</td>
<td>77788.25</td>
<td>-112.57 - 87.25</td>
<td>-8.83</td>
<td>63.34</td>
</tr>
<tr>
<td>RRNP</td>
<td>LiDAR</td>
<td>52863.89</td>
<td>-131.63 - 74.19</td>
<td>-5.57</td>
<td>52.44</td>
</tr>
<tr>
<td>RRNP</td>
<td>Landsat5 TM</td>
<td>60950.56</td>
<td>-129.52 - 80.66</td>
<td>5.34</td>
<td>56.36</td>
</tr>
<tr>
<td>RRNP</td>
<td>LiDAR+ Landsat5 TM</td>
<td>33003.45</td>
<td>-111.4 - 56.62</td>
<td>4.41</td>
<td>41.43</td>
</tr>
<tr>
<td>Combined</td>
<td>LiDAR</td>
<td>102340.81</td>
<td>-102.69 - 105.45</td>
<td>-0.01</td>
<td>51.23</td>
</tr>
<tr>
<td>Combined</td>
<td>Landsat5 TM</td>
<td>122745.94</td>
<td>-102.63 - 108.64</td>
<td>-0.19</td>
<td>56.1</td>
</tr>
<tr>
<td>Combined</td>
<td>LiDAR+ Landsat5 TM</td>
<td>83277.63</td>
<td>-107.36 - 82.17</td>
<td>1.76</td>
<td>46.18</td>
</tr>
</tbody>
</table>
7.4 Discussion

7.4.1 Influence of Fusing LiDAR and Landsat 5 TM for AGB Estimates

This study sought to improve the predicting capacity of plot scale AGB estimation by combining LiDAR and Landsat5 TM derived variables for eucalypt dominated forest and subtropical rainforest. The study was anticipated that combining LiDAR derived variables with various Landsat5 TM derived vegetation indices would significantly improve accuracy of plot scale AGB in the subtropical rainforest with complex terrain of the BRNP site. However, the findings revealed that fusing LiDAR and Landsat5 TM derived variables did not improve estimation of plot scale AGB in the BRNP. Estimation of plot scale AGB by fusing LiDAR and Landsat5 TM enhanced the accuracy of prediction by improving adjusted $R^2$ and decreasing the RMSE for the open-canopy RRNP, and combined sites data. This results conforms with the expected findings as presented in the literature for estimation of forest biomass (Popescu et al., 2004, Latifi et al., 2010) and other structural parameters of vegetation (McCombs et al., 2003, Hudak et al., 2006, Tonolli et al., 2011). The most important and informative variables (e.g. tree height, LiDAR fractional cover, crown diameter) derived by LiDAR explained the largest proportion of variation in plot scale AGB estimates among the three datasets. The accuracy of LiDAR based models improved the AGB estimation by 3% in the RRNP and 2% in the combined sites after the Landsat5 TM derived variables were included. Although the accuracy of AGB prediction models for combined sites improved, its RMSE values were higher compared to all AGB prediction models developed by LiDAR, Landsat5 TM, and fusing both data. This is probably due to the increase in standard deviation of plot scale ground measured AGB after combining individual sites data (Table 7.2). This study fitted LiDAR derived variables in AGB estimation models that differed due to the number of variables and the structural component of vegetation between the study data sets. The results showed that that LiDAR derived overstorey height related variables tend to be those
which have incorporated LiDAR based AGB estimation model for each data set investigated. The LiDAR metrics comprised of vertical and horizontal information about vegetation structure (i.e. tree height and canopy structure) are more likely to detect the structural components which are contained in the high biomass. For most forest types the bulk of AGB is located in tree stems, therefore, inclusion of LiDAR derived height variables to estimate AGB results in more accurate predictions are similar to the findings by Bortolot and Wynne (2005) and Popescu (2007) who estimated AGB at individual tree scale, and Drake et al. (2002), Drake et al. (2003), Popescu et al. (2003) and Popescu and Zhao (2008) who estimated AGB at plot scale. LiDAR fractional cover was also instrumental in predicting significant amounts of plot scale AGB in both plant communities. LiDAR fractional cover measures total photosynthetic and non photosynthetic components (i.e. twigs, branches, and other canopy materials) (Weller et al., 2003) of forest canopy, thus, it is possible to consider it as the second largest pool of accumulated AGB in vegetation. This is consistent with findings of previous studies (Li et al., 2008, Krasnow et al., 2009, Erdody and Moskal, 2010) which have used similar information about canopy cover density, and found this to be a key predictor of AGB. Estimating individual tree, or plot scale AGB using LiDAR derived height variable is not new, however, this study is unique in its improvement of AGB estimation by incorporating a canopy component related variable such as LiDAR fractional cover. LiDAR fractional cover used for estimating plot scale AGB of forests in hilly terrain can improve the prediction ability of models as it lowers the vulnerability to errors created by variations in topography. The LiDAR estimated crown diameter (above 20 m and 25 m overstorey) moderately correlated with AGB estimates, however, the relationship was not as high as the height and LiDAR fractional cover parameters in all sites. This finding is inconsistent with Popescu et al. (2003) and Popescu (2007) who showed that plot level tree crown diameter calculated from individual trees LiDAR measurements were particularly important in prediction of forest biomass in temperate forests. This is likely a failure to accurately delineate the tree
crowns of broad leaf trees due to the complexity of the irregular shaped overlapped tree crowns, and the spatial organization of tree crowns within the canopy.

Landsat TM visible bands, and Landsat derived vegetation indices have potential to estimate AGB in different forest areas in the literature. However, this study did not show any strong relationships for Landsat5 TM spectral signatures with ground measured AGB for either plant community. This finding is inconsistent with previous studies that have shown spectral signatures are highly related to biomass (Franklin, 1986, Jakubauskas and Price, 1997). This is probably may also be due to different species and community types between plots being located on different slopes and aspects in both study areas, thus, this seems to be a topographic effect which has not been effectively compensated for at the pixel and sub-pixel scale. Additionally, the utilised band ratios and vegetation indices showed varying degrees of success in estimating AGB of the testing data for both study areas. Vegetation indices are sensitive to internal factors (i.e. canopy geometry, terrain factors, species composition, topographic influence), and external factors (i.e. sun elevation angle effect, atmospheric condition) that influence vegetation reflectance (Treitz and Howarth, 1999) in a topographically complex landscape. It was noted that SLAVI (uses Landsat5 TM band 3, 4, and 7), and high order (6) dimensional set of Landsat5 TM derived principal polar spectral greenness (PPSG) only correlated with ground estimated AGB of the structurally complex BRNP. SLAVI estimates the important ecophysiological characteristics of foliage such as specific leaf area, which has a direct relationship with net photosynthesis (Reich et al., 1988, Reich et al., 1997) and above ground net primary productivity (Fassnacht and Gower, 1997). PPSG is assumed to be associated with spectral profile variations related to the projected aerial proportions of green photosynthetic material and substrate (Moffiet et al., 2010).

For open forest in a dissected topography, the relationship between AGB and Landsat derived variables can be affected by pixel heterogeneity, and site factors such as topography and aspect.
The relationship is sensitive to background, atmosphere, and bidirectional effects (Myneni and Williams, 1994). However, for the open-canopy RRNP, NDVIc together with SR proved to be good predictors in estimating the AGB. The NDVIc is derived from multispectral remotely sensed data including red, NIR, and MIR bands (Nemani et al., 1993), and may be useful in accounting for understory effects in more open-canopy forest and woodlands (Badhwar et al., 1986, Spanner et al., 1990, Nemani et al., 1993, Zheng et al., 2004). The RRNP study area was classified as eucalypts dominated open-canopy forest with mesic understory (i.e. mixed grass, shrubs), which is more likely to be disturbed by tree felling and canopy dieback.

### 7.4.2 Sources of Error

Several sources of error are associated with estimating AGB using LiDAR and multispectral data for the two study areas. These error sources can be divided into three groups: (i) the field data collection and AGB estimation, (ii) remote sensing data processing, and (iii) the influence of vegetation structure and topography.

A random sampling method was adopted to collect field data. For practicality, all trees with dbh > 10 cm dbh were measured in each 0.25 ha (50 m x 50 m) plot. Adoption of the 10 cm threshold for dbh measurements was crucial in the RRNP site due to young re-growth (approximately 20 years) and largely contained small and medium size trees, and conditions may have changed considerably as a result of logging activities. Additionally, most re-growth stems were damaged by fire and heavily sprouted. Standing dead trees (standing stems without branches or leaves) were found in most of the sample plots in the RRNP, and were included in the dbh measurement. These factors may influence the accuracy of LiDAR information. This is due to the lack of crown or branches in the sampled area composed of dead trees, and the distribution of laser measurements differed from those in sample areas with living trees. Heurich and Thoma (2008) described that dead trees alter the distribution of laser readings, and can influence the accuracy of
results. Additionally, dbh measurements for trees along the plot borderlines were problematic, particularly for groups of large trees in the BRNP.

Most previous studies related to biomass estimation employed allometric equations for prompt estimation of biomass without using a destructive harvesting approach. In this study, due to the lack of allometric equations at the finest taxonomic resolution for the targeted plant communities, two published general allometric equations (specific to rainforest, and sclerophyll forest) were used. Generally, utilizing these equations adds to the presence of error as the allometric relationships vary in response to climatic conditions, nutrient availability, genotype, age, and growth form of trees (Keith et al., 2000).

High sun elevation angle Landsat5 TM data was used as a source of multispectral data. As both study areas are located in topographically complex terrain, a considerable proportion of topographic distortion resulted, especially for steep slopes and gully areas. Furthermore, the images have been severely distorted as a result of vertical structure of vegetation (tall stems and crowns), likely creating more self shadowing by overstorey trees in the BRNP than for the RRNP, thus decreasing the amount of visible reflectance. Treitz and Howarth (1999) showed that in such conditions near-infrared light should increase, however, they concluded that increased shadow in a complex canopy acts to suppress near-infrared reflectance. Thus, topographic effect can greatly influence the empirical relationship between satellite recorded reflectance and the biophysical properties of forest vegetation (Sader et al., 1989). In this study, models to estimate AGB were developed using spectral information, thus, effectively reducing variance created by topography is required in order to extract true biophysical information of data recorded by the sensor. The topographically induced illumination was minimized by using an appropriate correction method developed by Flood et al. (2012), however, it is likely that the topographic effects remain in the corrected images as residual topography; which is not discussed here. Furthermore, it has been
recognized that moderate resolution images like Landsat TM with broad wavelength data are susceptible to saturation due to similar canopy structure (intact large rainforest crowns), and the impact of shadowing (Lu, 2006).

The LiDAR data employed for this study was acquired at approximately 2 km flight altitude with a resulting footprint of 50 cm. With increased topographic variation, the variability in laser pulse ranges will tend to increase. This may be due to the relatively large footprint on the ground differing from one to another within a site. It is recognized that footprint diameter affects, for instance, LiDAR based tree height estimation (Nilsson, 1996). Additionally, insufficient density of LiDAR pulses (1.3 per m$^2$) causes increasing error and a bias of range measurements (Lefsky et al., 2002), particularly in closed canopy conditions. Furthermore, the BRNP site consists of highly intact and overlapping large tree crowns in overstorey layers with over 70% of overstorey FPC (Specht and Specht, 1999), hence, there was a tendency to cause more first returns from the upper level of canopy recorded by the LiDAR system (Magnussen and Boudewyn, 1998). In other words, large tree crowns with planar outer surfaces were distinguishable in the subtropical rainforest of the BRNP, therefore, the return energy may have decreased due to occlusion in a horizontally uniform way. These conditions prohibited exploiting necessary LiDAR derived height information of other lower strata at a high level of accuracy.

The complexity of the vegetation structure particularly in the closed-canopy BRNP sites influenced the accuracy of the models and is another potential error in this study. As the complexity of canopy structure increases, the probability that LiDAR pulse penetrates below the canopy decreases, and leads to occlusion of middle and understorey strata. This may have a significant impact on density of LiDAR points below the canopy, which can affect the accuracy of LiDAR metrics. Similarly, laser pulses of discrete LiDAR systems are incapable of discriminating small canopy holes from canopy attributes in structurally complex dense canopy subtropical
forest, consequently over estimating LiDAR fractional cover by measuring the collective mean of canopy components, and small holes in clumps of leaves. Additionally, in a closed-canopy forest, large overstorey trees on a sloping terrain tend to extend their branches or whole tree crown down slope. This was a critical issue with borderline trees which were found on sloping terrain in sample plots, as it influenced the extraction of LiDAR fractional cover that contained unnecessary information from outside the plot.

7.5 Conclusions

Fusion of LiDAR data with other optical sensors assists in improving vegetation structural parameters including above ground biomass (AGB) (Popescu et al. 2004, Hudak et al. 2006, Jensen et al. 2008, Latifi et al. 2010, Tonolli et al. 2011). The chapter presented an analysis to estimates AGB on the combined use of two sensors (LiDAR and Landsat5 TM) in areas that comprise three characteristics, (i) large extension; (ii) large species variability and (iii) topographically complex terrain. The findings show that LiDAR derived structural variables of vegetation were able to describe significant amounts of variation on plot scale AGB. They were most accurate for the open-canopy RRNP, followed by the combined sites, and were least able to account for plot scale AGB in the closed-canopy BRNP. Several studies demonstrated that fusion of sensors have improved the accuracy of estimating AGB as well as timber volume, tree height, species identification, and fuel mapping (McCombs et al., 2003, Popescu et al., 2004, Mutlu et al., 2008, Erdody and Moskal, 2010, Tonolli et al., 2011). A significant finding of the investigation is the potential usefulness of this analysis to estimate AGB of subtropical plant communities, as it includes the application of standard techniques with potential advances in data managing (e.g. data fusion) in topographically complex landscapes. The results illustrate the value of integrating multiple types of remote sensing data with field data to objectively and accurately characterise AGB to support forest science and management. This study reinforced that Landsat5 TM derived
variables fused with LiDAR derived models increased overall performance for open-canopy forest by accounting for extra variation of field estimated plot scale AGB. Additionally, significant minor improvements were made within the model when LiDAR and Landsat derived variables for regional estimation of AGB were utilised. Despite improvements gained by fusion of the two sensors, the degree of improvement in estimating plot scale AGB of hilly plant communities was not considerable given the cost of data processing. An interesting conclusion of this study is that fusing LiDAR derived large biomass partitioning structural components with Landsat TM derived spectral information data did not improve AGB estimation in closed-canopy subtropical rainforest in topographically complex terrain. Thus, remote sensing-based AGB estimation is a complex procedure in which many factors, such as atmospheric conditions, mixed pixels, data saturation, complex biophysical environment, insufficient sample data and extracted remote sensing variables may interactively affect AGB performance (Lu, 2006). This study reinforces that identifying major uncertainties during the development of the AGB estimation models is critical for improving the estimation performance.
Chapter–8 Synopsis and Recommendations

This chapter provides a synopsis of the research, including a review of relevant background information related to the study, a synopsis of the study area, the methodology, key findings, and recommendations for future investigation of the use of remote sensing to explore forest structure in topographically complex terrain.

The literature review presented in Chapter-1 and Chapter-2 showed that in recent years knowledge of fundamental forest structure, composition, and ecophysiological functions of Australian woody plant communities has advanced substantially. However, literature showed that very little work has been carried out to investigate structural variations of woody plant communities using remotely sensed data in topographically complex terrain. This study was conducted to address this issue by application of remotely sensed data to enhance the knowledge of forest structure and AGB of two structurally different plant communities in topographically complex landscapes in north-eastern New South Wales, Australia. The objectives of the study were: (1) to predict plot scale biophysical attributes of vegetation using airborne LiDAR, (2) to assess the impact of topographic corrections on estimation accuracy of FPC, (3) to investigate the influence of topographic variation on forest structure using a remote sensing approach and (4) to predict above ground biomass using airborne LiDAR and multispectral data.

Two distinct forested areas were selected, the RRNP (28.69° S, 152.72° E) and the BRNP (28.36°S, 153.86°E) to represent the broad range of vegetation characteristics found throughout north-eastern NSW. The study area varies from rolling hills to rugged terrain with elevation in the RRNP varies between 150 m – 750 m, and average slope 27°. The elevation in the BRNP varies between 600 m to 1200 m with average slope 36°. Closed-canopy subtropical rainforest species
comprise the overstorey in the BRNP, and vegetation in the RRNP is characterised as open-canopy eucalypt dominated overstorey with mesic understory.

**Objective 1: To predict plot scale biophysical attributes of vegetation using airborne LiDAR over a eucalypt-dominated open-canopy forest and a closed-canopy subtropical rainforest**

Chapter-4 investigated the application of height and density related LiDAR derived laser metrics to estimate selected structural parameters such as mean height, dominant height, mean dbh, dominant dbh, mean basal area (BA), and stem density of two structurally different plant communities. This investigation was an extreme application of LiDAR technology on structurally complex subtropical rainforest in highly topographically complex environments with steep slopes and gullies, compared to applications in open canopy vegetation (eucalypt dominated open-canopy forest) in similar topography. The use of LiDAR derived metrics in conjunction with regression equations to estimates structural parameters of vegetation offers the advantage that is quite straightforward in terms of computationally inexpensive and it can be applied to larger areas without much effort. The developed prediction models of this study demonstrated that important structural parameters of vegetation in the test area of the subtropical rainforest of the BRNP yielded satisfactory results albeit with a number of limitations. Linear regression models were able to explain 62% of the variability associated with basal area, 66% for mean dbh, and 61% for dominant height in subtropical rainforest. Findings of the BRNP indicate that where LiDAR penetration is poor due to a closed canopy, substantial over estimation of ground elevation, an attribute that nearly defies prediction, results in relatively high error in structural parameters especially in tree height estimates. A major obstacle in the LiDAR based assessment of tree height and other structural parameters of closed canopy forest is the generation of accurate digital terrain models. Experimentation with different algorithms that process the laser data to identify ground returns and subsequently generate the terrain models used in tree height assessment
suggests that although trial and error-based adjustment of algorithmic components yield accurate DTMs elsewhere, such efforts often fail in forest and terrain conditions prevalent in the BRNP subtropical rainforests. In contrast, the eucalypt dominated the RRNP study area with sparse canopy, represented similar conditions to where LiDAR applications have been widely used, producing results with a relatively high level of accuracy for most of the parameters investigated. For example, mean height (adjusted $R^2$ 90) and dominant height (adjusted $R^2$ 81) was predicted with highest accuracy in open-canopy study area. These findings reinforced that obtaining accurate LiDAR estimates of vegetation structure is a function of the complexity of horizontal and vertical structural diversity of vegetation. Furthermore, this study demonstrated that combined data set of each study area provide an alternative operational approach to estimating plot-scale structural elements of forests over landscape scale. Despite these limitations, applied LiDAR derived metrics of vegetation were found to be more effective in characterising the vertical and horizontal forest structure of the areas examined. Generally the lesser point density of the higher flying altitude, and lower point density could also be influenced accurate estimation of vegetation structure. Therefore, careful consideration is required when planning LiDAR data acquisitions; especially for vegetation application in structurally complex forests in hilly terrain, since many LiDAR derived laser metrics may have affected by flying altitude, point spacing density and footprint size. Optimizing the laser data acquisition specifications to ensure maximum pulse penetration to the ground would probably improve DTM, and ultimately vegetation structure estimation accuracy. LiDAR data discretazation with both leadingedge and generic algorithms offers potential for improving estimates of vegetation structure. To estimate laser-derived structural parameters of subtropical rainforests growing on steep slopes with an accuracy and precision comparable to what is attainable in more conducive vegetation and terrain, techniques would need to be developed to
assess vegetation structure, and specifications for operating the laser instrument would need to be modified with the aim of improving canopy penetration rates.

**Objective 2: To assess the impact of topographic corrections on estimation accuracy of FPC in a topographically complex landscape**

The impact of topographic corrections on the prediction of FPC in hilly terrain using an established regression model was assessed in Chapter-5. Five established topographic corrections (C, Minnaert, SCS, SCS+C, and PSSSR) were evaluated on Landsat5 TM data acquired under a high sun angle. The effectiveness of the methods to normalize topographic influence, while preserving biophysical spectral information and internal data variability, were assessed by visual comparison of topographically corrected images, and statistically comparing ground measured and LiDAR derived FPC data. Visual comparison of the corrected images showed that topographic variability in the non-topographically corrected images were best minimised by the application of PSSSR and SCS compared to the other topographic correction methods. Furthermore, a relatively high relationship was found with PSSSR corrected Landsat5 TM predicted FPC with ground measured FPC and LiDAR derived FPC. This suggests that the PSSSR model performed significantly better in terms of yielding a markedly improved FPC prediction from Landsat5 TM, compared to other correction models. Moreover PSSSR produced less overcorrected or under corrected Landsat5 TM data under the sun angle investigated. PSSSR significantly enhances the accuracy of the assessment of forest parameters in topographically complex terrain, and this method is easily implemented and considered suitable for operational application. The results obtained by PSSSR is due to the fact that in addition to correcting for illumination, this correction method corrects for the dependence of vegetation reflectance on slopes. This reduction means that automated classification of features, and operational mapping and monitoring of vegetation cover on rugged terrain becomes a realistic proposition. The
empirically based C correction showed the poorest performance, instead of reducing the effect of topography on reflectance, the C correction actually increased the degree of variation of Landsat5 TM reflectance. However, none of the correction methods were performed outstandingly in completely eliminating topography induced illumination of both forested areas in order to improve the accuracy of FPC predictions.

It is important to mention that terrain effects are image-dependent and that any single model will not describe such effects equally well for different images. The PSSSR method may work better for forested images, but other SCT (Sun, Canopy Terrain models) will be more appropriate for less-structured surfaces. How to correct terrain effects in a complicated image is an interesting future research topic. A possible strategy could be to apply different models to forested and non-forested areas, which usually have distinct spectra and well separable. Initially, it is important to assess whether such efforts are useful considering data errors and natural image variability.

The results revealed that LiDAR derived overstorey FPC surrogates are an important source of data to assess the impact of topographic correction on the TM5 reflectance over topographically complex landscape. However, it was quantified that LiDAR fractional cover overestimated FPC in closed-canopy subtropical rainforest. This is due to the LiDAR pulses are measured the collective mean of canopy components without taking non-photosynthetic components and small holes into account, and this issue cannot be neglected. Nonetheless, the findings of this investigation showed the feasibility of LiDAR derived vegetation metrics relative assessment of the impact of topographic corrections on the predictions of FPC in hilly terrain.

**Objective 3: To investigate the influence of topographic variation on forest structure in two woody plant communities using a remote sensing approach**

Characterisation of landscape-based structural variation of vegetation and pattern is a significant goal for a variety of ecological, monitoring and biodiversity studies. Forest structural metrics,
derived from LiDAR and multispectral satellite data were used to characterise the forest structure in relation to topographic variations of two structurally different plant communities. This study assumed that if structurally different species occupy different topographic niches, then multispectral data signature and spatial distribution of LiDAR point density may differ by vegetation structure as well as slope and aspect of the landscape. Spatial distribution of environmental variables such as insolation, TWI and topographic variables (i.e. slope, elevation) were computed within GIS by employing LiDAR derived Digital Elevation Models (DEMs). Chapter-6 reported that the characterization of forest structural parameters (i.e. average maximum tree heights, average crown area, the fraction of canopy cover) in relation to variation in topography was possible in the eucalypt dominated open-canopy forest. In comparison, wet and dry plots in relation to the topographic position (i.e. up slope and valley) have high levels of variance in forest structure, suggesting greater structural heterogeneity in the open-canopy eucalypt forest. The presence of valley sampling plots in wet-sclerophyll patches, which have tall trees with substantially higher canopy cover (as shown in the apparent vertical profiles) contribute to landscape heterogeneity. This suggests that if environmental variables show higher level of gradients with variation of topography in the landscape, such variations could be discernible through structural and compositional variation of the plant community. The study revealed that spatial variability of forest structural parameters of subtropical rainforest nor the insolation nor soil water availability seem to have an important effect. This indicates that spatial distribution of forest structure of subtropical rainforest can be expected to vary with underlying geology and soil nutrients. Consequently, these findings create a new research hypothesis that spatial distribution of geology and soil nutrients will shape spatial pattern of structural parameters of closed canopy subtropical rainforest plant communities. Therefore, further studies are needed to identify which are the primary underlying factors (e.g. soil nutrients, geology) defining change in forest structure across elevation. By combination of remotely sensed data
including LiDAR data with available fine scale geology and soil data, and different environmental data (e.g. evapotranspiration data, rainfall data, insolation, soil water) could be employed in order to improve characterisation of structural patterns of vegetation over the landscape scale. These findings support the necessity for further remote sensing based investigation of north-eastern NSW, particularly in the hilly subtropical rainforests, as this study revealed less predictability with the greater height and complex canopy structure compared to the open-canopy eucalypt forests. This was also noted in the local literature (Weller et al., 2003, Goodwin et al., 2007, Lee and Lucas, 2007, Arroyo et al., 2010). It can be concluded that the potential applications for this adopted method include interpretation of ecological variation and gradients within a landscape based context, understanding responses to climate change, monitoring the vigour of vegetation using quantitative assessment, and incorporation of structural assessment for biodiversity related studies.

**Objective 4: To predict above ground biomass in a eucalypt dominated open canopy-forest and a closed-canopy subtropical rainforest using airborne LiDAR and multispectral data**

In the Chapter 7, an analysis on the fusion of LiDAR and Landsat5 TM data for the estimation of AGB has been presented. The analysis indicates that: i) the combination of LiDAR and multispectral data can be useful as it provides a slight increase in estimation accuracy by 3% for eucalypt forest and 2% for combined sites (subtropical rain forest + eucalypt forest); ii) models derived only Landsat5 TM data do not provide high level results for estimation of AGB in open-canopy eucalypts forest and combined sites; iii) LiDAR variables alone provide the majority of the explanatory contribution. However, there was no noticeable improvement regarding the estimation of AGB by integrating LiDAR and Landsat5 TM for the subtropical rainforest. Unlike the Landsat5 TM (adjusted R² 0.31), variables derived from LiDAR related to the forest structure demonstrated a moderate relationship (adjusted R² 0.45) with ABG of the closed-canopy forest.
As canopy density increases, the likelihood that laser pulse penetrate below the canopy decreases and leads to occlusion of areas below the canopy. This issue, lower point density and highflying altitude may have influenced on the accuracy of laser metrics and subsequently AGB estimates. The lack of structural information beneath the canopy is major reason why multispectral data is not a good estimator of three dimensional structural variables of vegetation including AGB. Additionally shadowing imagery due to the self-shading created by adjacent trees, impact of topographic on radiometric quality of data, impact of understorey vegetation on reflectance and bands saturation due to similar canopy structure (Lu, 2006), can have a significant influence for the least accurate estimation of AGB. Since our understanding of the interaction of radiation at sub-pixel scale is limited, the findings suggest more investigations are required in order to improve the relationship between structural elements of forest including AGB with radiation at sub-pixel scale by minimising influence from the background environment, and be free of influence of topography induced illumination and self-shadowing.

The fusion of spectral data with LiDAR data shows promise for improving estimation of AGB from remotely sensed data. The data fusion processed used in this study could be improved, however, geographic registration errors between the spectral and LiDAR need to be reduced through the orthorectification of the spectral data using the LiDAR canopy surface as an elevation model. Another issue to be considered is the different spatial resolutions of two data sets. There are three options that could be performed with the different spatial resolution: (1) keep them as they are, (2) resample to coarsest resolution, or (3) resample to the finest resolution. However, the deterioration of data quality during the process of changing resolution of data resampling will be a major issue. For this study to avoid the resampling issue, the current resolution of Landsat 5TM data (30m) was used. Despite an improvement gained by the fusion of the two sensors, it is worth mentioning that the degree of improvement gained by this technique
to estimate plot scale aboveground biomass of hilly plant communities was not significant given the cost of data processing.

In summary, the research presented in this thesis contributes to the refinement of the predictions of forest structure and biomass of two structurally different plant communities in topographically complex landscapes using remote sensing and modelling techniques in order to enhance the sustainable utilization and conservation of such areas.

8.1 Limitations and recommendations for future investigation

In the course of this investigation a number of research limitations were identified. These can be categorised into two general areas: (1) field data limitations, and (2) remotely sensed data and data processing limitations. Overall, rather than detracting from the research findings, the limitations identified here represent opportunities for future research avenues.

Field data limitations refer to measurements taken in the field that cannot be validated fully due to the measurement methods utilised, recording devices and/or operator error. When the observed data has uncertainty greater than expected, it is difficult to identify where or why error has occurred in the data sources. The complexity of vegetation structure of the closed-canopy BRNP interfered with the accurate collation of field measured structural elements of vegetation which was the main issue encountered with regard to field collection, and the effect intensified on inclined terrain. In the rainforest plots with tall trees, obtaining accurate tree heights proved to be difficult due to occlusion of tree tops by dense middle and understorey strata, ultimately this influenced the accuracy of estimates. Similarly, due to the overlapping tree crowns, and low light penetration to the forest floor, accurate measurements of crown radii were impractical. However, taking several measurements from multiple viewing locations of a targeted tree height can minimise the uncertainty of field measurements, even so, it is more difficult to minimise these issues than acknowledge them. Finally, uncertainty in field estimates was noted in the collection
of differential GPS points for evaluation of the LiDAR derived DEMs and sample plot locations, due to issues associated with poor GPS signals under rainforest canopy in steep terrain. This was unavoidable under the rainforest canopy, however, it was possible to partially minimise by taking several GPS points over extended time period and averaging.

The LiDAR data employed in this study was of rather a low density (approximately 1.3 points/m$^2$), and due to the high variation of the topography the data was also affected by aircraft altitude variability, which resulted in variations in LiDAR point density within a short distance across the sample plots. LiDAR data limitations are those related to the data itself and data acquisition. Whilst it may not be always practical or affordable, acquisition of data at high sampling densities would overcome some of the issues identified. Optimising the LiDAR data acquisition specifications is suggested to ensure maximum pulse penetration to the ground. When higher sampling densities are collected there is high probability for LiDAR points to penetrate to the forest floor, particularly in closed canopy conditions and the possibility of extraction of structural information of sub-canopy and understorey components of the target vegetation (and less evidence of sensor lag issues e.g. (Lovell et al., 2003)).

Further LiDAR based studies are needed to improve estimation of structural elements of subtropical and tropical forest structures especially in topographically complex landscape through collection of data with higher point densities than used in this study. Also, it would be informative to use full-waveform LiDAR data as these sensors make it possible to acquire more information on forest structure than can be obtained from discrete return LiDAR. This additional information could also contribute to a refinement in estimation of predictions. Full-waveform LiDAR could improve the prediction accuracy of forest structures of subtropical and tropical rainforests in topographically extensive terrain. Subsequent investigation using more detailed
full-waveform LiDAR data on the effects of structural differences for species discrimination in the vegetation stratification process is worthwhile.

The effect of topographic induced illumination on multispectral satellite data was one of the major limitations in effective utilisation of satellite data for vegetation studies in the topographically extensive terrain. Thus, further investigations are necessary to better understand corrections of topographic effects by PSSSR with different structural types of plant communities (i.e. heath lands, shrub lands, meadow and grasslands) located on different slopes and aspects, and with different densities of ground cover. Additionally, investigation is required to improve the normalisation of topographic effects of low sun angle images, as these images are important in long-term monitoring of vegetation cover and vegetation cover changes. Low sun angles that exist for a few months at a time are common in many subtropical and temperate regions of the world, thus, correcting for low sun angle would also enable to investigate the influence of seasonal variation in vegetation.
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