CHAPTER 1: Introduction and Background

1.1 Introduction

A forest inventory provides quantitative and qualitative information on forest resources in an area, by sampling units or plots to generate estimates of the population (Wulder *et al.*, 2008). Forest inventories have often been used as starting points for the estimation of forest attributes, such as biomass and volume, of forests at local, regional and global scales. Due to the interest in bioenergy, carbon sequestration and ecosystems in response to climate change and anthropogenic disturbances, recent inventories have increasingly focused on biomass and carbon estimations (Edson and Wing, 2011).

Accurate estimation of biomass would improve the accuracy of carbon flux models, the estimation of forest productivity, the modeling of disturbances such as fire, the characterization of forest conditions and the modeling of energy production (e.g. Landsberg and Waring, 1997; Houghton, 2005; Wulder *et al.*, 2008). Biomass can be measured through direct and indirect methods; however, the most common method for estimating biomass (or volume) is the use of allometric equations, in which easily measurable tree variables such as Diameter at Breast Height (DBH) and height are related to standing biomass. Ketterings *et al.* (2001) have suggested that to develop a suitable allometric equation, the appropriate form of the equation should be selected, the input variables should be accurately measured and the trees should be selected to represent the range of forest types and tree species. Hence, an accurate representation of spatio-temporal variability of forest biophysical properties is essential for accurate forest predictions.

Large spatial variability has been reported in tropical forests (e.g. Brown, 1997; Chave *et al.*, 2003; de Castilho *et al.*, 2006), as well as in other forests with less heterogeneous structure and patterns. For example, Frelich (2002) reported a high degree of small-scale variation within the trees in the evergreen-deciduous forests due to environmental factors. Saatchi *et al.* (2011) showed that the biomass and volume variation of a forest stand were directly influenced by the complexity of forest structure in horizontal and vertical dimensions. The presence of spatial variability in forests can affect the levels of precision and bias when measuring total amount of biomass and volume across the landscape and it should be accounted for when evaluating forestry inventories.

Most of the current allometric equations that measure biomass and volume are developed mainly on DBH as it can be measured directly through intensive sampling (Jenkins *et al.*, 2003); however, it is not clear whether this factor alone can represent the variability of the species. Moreover, there is the question of whether the stratification process and the sampling design in the forests are able to provide an indication of the variability of forest attributes across the site. For example, in Australia, the recommended sampling intensity for inventory plots prescribed by radiata pine (*Pinus radiata* D. Don) plantation growers is 1 plot per 4 ha (Mike Sutton, Manager Forest Information & Planning, Forestry Corporation NSW, pers. comm., April 2014). However, can the selected plots adequately capture the variations and obtain accurate estimate of the whole stand? If the underlying spatial variability of the species is not assessed, prior to the tree sampling, uncertainties and bias will be created by using inaccurate equations.

Even though detailed information and understanding regarding the factors affecting the variability of trees is a prerequisite for accurate predictions, due to constraints on fund and survey time few attempts have been made to look at variations between the trees.

Until recently, knowledge of forest attributes and changes has been based on ground measurements and coarse or medium resolution satellite images (Kankare *et al.*, 2013). However, recent remote sensing methods such as Light Detection and Ranging (ALS or LiDAR), which deliver detailed three dimensional structural information, have been highly useful in various forest-monitoring tasks. The use of LiDAR as a rapid and efficient tool for forest inventories has offered the advantage of effective identification and delineation of forest over large-area coverage.

Previously, most forest studies have occurred mainly at a plantation-level or stand-level scale, as it was too labor-intensive and expensive to measure most of the attributes at microsite and individual tree scale. However, the availability of LiDAR technology has eliminated this limitation. In addition, the different surfaces derived from LiDAR, such as Digital Elevation Models (DEMs) with high spatial resolution, have provided accurate information about the ground surface such as elevation, aspect and slope, as well as improved solar radiation estimation compared with traditional methods (e.g. measurements from meteorological/climatological stations) (Turner, 2006).

Height and DBH are the most common variables recorded from sample trees, as they are widely used for forest inventory parameters such as stem volume, timber volume, biomass estimations and growth models, as well as local silvicultural and harvesting decisions (Castedo-Dorado *et al.*, 2009). In forest inventory designs, DBH is measured for all trees within sample plots, since it is cheaper to obtain, while height is measured for only some selected trees, as the measurement is time-consuming, costly and difficult. Recent improvements in LiDAR, however, have resulted in accurate measurement of tree height and other vegetation structure, such as crown dimensions, at the single tree-level (e.g. Hyyppä *et al.*, 2001; Edson and Wing, 2011). The detailed information extracted from LiDAR at tree-level can be helpful in monitoring the variation within tree structure. Since DBH and height are being extensively used in the allometric equations, the knowledge of spatial variability within these variables becomes increasingly important as they can influence the precision of different forestry estimates. Understanding the main factors causing variations in tree height and DBH could allow the detection of spatial auxiliary variables, and their possible inclusion in the models can improve the effectiveness of forest inventories.

It has long been recognized that the forest canopy has a complex structure that is significant for environmental interactions (Parker and Brown, 2000). Different factors such as climatic variables, soil type and fertility, forest types, genetics and stand age have been reported to affect the growth and canopy structure of radiata pine (Forrest, 1969; Álvarez *et al.*, 2013). However, while variability has been recognized within different forest stands, not many studies have looked at variability within even-aged forest compartments with relatively homogeneous environmental factors, and the potential causes of these variations. In Hanging Rock State Forest, despite the similar genetic, edaphic and climatic conditions as well as silvicultural practices, the trees display significant height and DBH variation within even-aged stands. It is not known what factors have caused these variations at the intra-compartment scale. The presence of variance in trees at microsite scales highlights the weakness of the current methodologies being used for forest inventories, and casts doubt on whether they meet their objectives to measure accurate forestry attributes.

1.2 Significance of this study

Despite attempts by many researchers to obtain an accurate estimation of forestry resources such as biomass and volume, the uncertainties remain high. Previous studies have developed many different equations, but because of the influence of environmental conditions they are only useful on a species- and site-specific basis and applying them generally can cause potential errors. Although the majority of equations and models employ DBH and height as input variables, several studies have increased the precision of *P. radiata* equations by adding site attributes as adjunct explanatory variables (e.g. Woollons *et al.*, 1997; Snowdon *et al.*, 2000). Nevertheless, few studies have attempted to use environmental and topographical variables in allometric equations due to the time and cost involved in measurement; as a result, few studies have considered these factors effective on forestry estimation accuracies.

The use of LiDAR as a tool for characterizing vertical forest structure can provide wider ranges of forest inventory information. The information regarding tree structure and ground surface can further be used to improve the precision of stand inventory estimates. This study will identify the environmental factors influencing variation in radiata trees and determine their interactions within single-aged compartments. Different LiDAR models such as DEM, Digital Surface Model (DSM) and Canopy Height Model (CHM) will be used to identify these relationships. While, there have been a number of studies using LiDAR to explore the relationships between spatial variations in tree attributes and environmental factors, none has explicitly looked at the relationships between LiDAR derived metrics such as height and topographic factors such as slope and aspect. In addition the outcome of these relationships will provide a guideline or direction towards improvements in sampling designs and accurate inventory measures.

1.3 Aims and objectives of the study

The principal aim of this study is to verify whether DBH and height of radiata pine trees within two even-aged compartments show any significant relationships with environmental factors by using LiDAR as a broad sampling tool for mapping both ground and tree characteristics. Further, this research will look at how this variability could affect the forestry estimate accuracies, and how topography can be used as a suitable spatially explicit attribute to improve forestry estimates as well as a sub-compartment stratification variable. The objectives of the present study are:

1. To document the use of LiDAR in forestry studies.
2. To investigate the presence of variation in DBH and height of *P. radiata* in even-aged forest compartments and the environmental factors causing this.
3. To address the issues of intra-compartment variations in DBH and height and how they can challenge the acceptable levels of forestry precision.
4. To suggest methods to improve sampling designs and inventory estimates.

1.4 Structure of the thesis

The thesis starts with a review of literature related to the potential use of LiDAR in forestry applications (Chapter Two) and how it can overcome some of the limitations of extracting forestry information. Chapter Three provides detailed information about the effect of LiDAR-derived topography aspect and slope on tree height variation. In addition, by comparing LiDAR heights with field measured height, this chapter confirms the reliability and accuracy of LiDAR-derived heights. This chapter has been published in *Trees - Structure and Function.*

The aim of Chapter Four is to determine the relationship between the DBH variation in radiata trees and the local topography derived from LiDAR. In addition, the effect of topography on DBHs of similar height trees is examined. This chapter has been published in *Annals of Forest Science.*

Chapter Five looks at the relationships between tree height and DBH variation with LiDAR-derived DEM estimates of summer and winter radiation. This chapter has been published in *GIScience & Remote Sensing.*

Chapter Six investigates the interrelationship between DBH, height and stocking with the use of LiDAR. Moreover, LiDAR is used to estimate stem counts in fixed plots (stocking) based on the accurate detection of tree crown maximas. This chapter has been published in *Remote Sensing.*

The final chapter, Chapter Seven, looks at the current operational practices, highlights the main deficiencies and gaps of the forestry planning system in Australia, illustrates the findings of this research and provides recommendations to improve inventory estimates for softwood plantations, as well as clarifying areas deemed necessary for further research.

CHAPTER 2: The potential use of airborne LiDAR in acquiring variables for forestry estimations

2.1 Accurate forest inventories

Forests are one of the major sources and sinks of carbon (Vashum and Jayakumar, 2012). They either reduce the CO_2 concentration by absorbing carbon from the atmosphere or increase levels of atmospheric CO_2 by human and natural disturbance such as logging and burning. The importance of the amount of carbon stored in biomass has led to the Kyoto protocol, which recommends that countries report any carbon changes in the forests (UNFCCC, 1997). Estimation of carbon pools relies on the accurate estimation of forest biomass (Banaticla *et al.*, 2004). Biomass can determine the potential carbon emission that is released due to deforestation and conversion of forests to non-forest land use; therefore, its accurate estimation is significant for better understanding of deforestation impacts on global warming.

Moreover, accurate estimations of other forestry inventories, such as forest volumes, are essential for forest management planning. Detailed inventories can play a significant role in providing accurate information on forest timber and environmental benefits, such as round wood production and biodiversity (Kinnunen *et al.*, 2007). Accurate data from forest inventories provide valuable information for the development of nationwide forest policies, as well as strategies for protection, management and utilization of forest resources (Fang *et al.*, 2001). For example, accurate stand age and height information can be used as surrogates for site quality and therefore are useful as an index for wood and biomass estimation as well as economic value assessment or commercial potential.

Depending on the objective of the forest inventory and the intended use, measurements or predictions of forest attributes can vary. However, since the changes in biomass are associated with components of climate change, more studies have been undertaken to improve these estimations. In this section I will: (1) look at how most inventories, in particular biomass, are calculated and what common variables are used in allometric equations, (2) discuss the major factors affecting these equations, (3) determine some of the allometric equation drawbacks and (4) discuss how LiDAR can overcome some of these limitations.

2.2 Biomass estimation

Biomass can be calculated at tree-, plot- or stand-level. For plot-level samples, researchers determine the biomass by measuring every tree and summing estimates within each plot (Jenkins *et al.*, 2003). Generally, two methods are available for biomass estimation, destructive (cutting down and weighing) and non-destructive (use of allometric equations). Allometric equations are usually preferable over other methods of biomass measurement (Gehring *et al.*, 2004). These equations require easily collected input attributes such as Diameter at Breast Height (DBH), height and basal area, which can be directly measured in the field or indirectly estimated by remotely-sensed data. A number of allometric equations have also been developed by combining measured data with existing equations from the literature or by using several different equations to obtain the range of biomass (Schmitt and Grigal, 1981; Jenkins *et al.*, 2003). To develop allometric equations, the choice of model and method of fitting the parameters are important factors that must be considered (Woods *et al.*, 1991). The selection of the most appropriate allometric equation largely depends on the intended use and available independent variables (Cienciala *et al.*, 2006).

Over the years, allometric equations have been created as generalized and site-specific models for either mixed-species (group of species) or species-specific (individual species). While site-specific equations are developed for a specific geographic region, generalized equations are applied to different geographical areas. Consequently, various researchers suggest the development of generalized regional and national biomass equations from composite site and species data that can be applied to larger geographic scales (Schmitt and Grigal, 1981; Lambert *et al.*, 2005; Bombelli *et al.*, 2009). In general, species-specific equations are preferred over mixed-species, due to the differences in tree architecture and wood density (Ketterings *et al.*, 2001). However, in humid and tropical forests, with large numbers of different tree species, developing species-specific equations is practically impossible. Mixed-species equations can also be useful for uncommon species that lack regression models (Sah *et al.*, 2004).

2.2.1 *Common variables used in allometric equations*

Different independent variables have been used for allometric equations, with DBH being the most common, practical and easily measured (Wang, 2006; Cienciala *et al.*, 2008; Ruiz-Peinado Gertrudix *et al.*, 2012). A large number of equations have been compiled and summarized for American (e.g. Ter-Mikaelian and Korzukhin, 1997; Jenkins *et al.*, 2003), European (e.g. Zianis *et al.*, 2005), African (e.g. Henry *et al.*, 2011) and Australian species (e.g. Eamus *et al.*, 2000; Keith *et al.*, 2002) almost exclusively based on DBH as the prime predictor variable.

Height is another important variable used in biomass equations, although it is less frequently used than DBH. However, few equations are based solely on height (see Table 2.1); and most are combined with DBH and used as a secondary variable in allometric equations (Tumwebaze *et al.*, 2013).

Tree age is another variable that has been used in a number of equations, especially in different age class forests. Tree age brings a significant amount of additional information for biomass estimation of stem, foliage and branch compartments (Shaiek *et al.*, 2011). Numerous studies have reported biomass variations with different age classes in several species and have suggested incorporating tree or stand age in allometric equations (Zavitkovski, 1971; Saint-André *et al.*, 2005; António *et al.*, 2007).

Other variables, such as crown width, crown diameter, wood density, site index and tree diameters (circumference), including the collar diameter, diameter at 30 cm height, diameter at 50 cm height, diameter at base of the crown and diameter at base of the tree, have also been shown to be good predictors of forest dynamics and indicators of growth and yield rate (Table 2.1) (Canadell *et al.*, 1988; O'Brien, 1998; Jenkins *et al.*, 2004; Cienciala *et al.*, 2006; Henry *et al.*, 2011).

Table 2.1: Examples of several allometric equations, with their formula, species type and statistical report. EMS is the error mean squares, R^2 is the coefficient of determination, CV is the coefficient of variation and is reported in percentage (%) , AIC is the Akaike Information Criterion, RMSE is the root mean square error and SE is the standard error.

Study	Function	EMS	R^2	CV	AIC	RMSE	SE	Species
	DBH as only variable							
Snowdon *et al.* (2000)	$\ln Y = -2.413 + 2.391 \ln DBH$	0.038	-	-	-	-	-	Radiata pine
Moore (2010)	$\ln Y = -1.940 + 2.1824 \ln DBH$	-	0.92	-	323.5	0.292	-	Radiata pine
	H as only variable							
Snowdon *et al.* (2000)	$\ln Y = -1.731 + 2.388 \ \ln H$	0.376	-	-	-	-	-	Radiata pine
Delitti *et al.* (2006)	$Y = 207.11 \ e^{0.977 \ H}$	0.73	0.77	-	-	-	0.977	Woody species
Zianis *et al.* (2005)	$Y = 0.0023 \ H^{\ 4.1398}$	-	0.82	-	-	-	-	European beech
	Incorporation of Wood Density							
Chave *et al.* (2005)	$Y = WD \ \exp\ (-1.499 + 2.148 \ \ln DBH + 0.207 \ (\ln DBH)^2 - 0.0281 \ (\ln DBH)^3)$	-	0.95	-	-	-	-	Tropical moist forest
Chave *et al.* (2005)	$Y = 0.0776 \times (WD \ (DBH^2) \ H)^{0.940}$	-	0.95	-	-	-	-	Tropical wet forest
	Incorporation of Crown Diameter/Area							
Sah *et al.* (2004)	$Y = 0.077 - 0.086 \ CA + 0.175 \ CA^2$	-	0.99	-	-	-	0.045	Pineland Croton (shrub)
Henry *et al.* (2010)	$Y = 0.03 \times \ DBH^{0.0816} \times CD^{0.03} + WD^{0.04}$	-	-	-	611	1750	-	African tropical
Jonson and Freudenberger (2011)	$\ln Y = 1.558 + 2.236 \ \ln CD$	0.196	0.914	45.3	-	-	-	Eucalypt genera
	Other variable							
Canadell *et al.* (1988)	$\log Y = -1.047 + 2.461 \log D50$	-	0.934	-	-	-	0.083	Holm oak
Siddique *et al.* (2012)	$Y = 8.717 \ G^2 - 53.95 \ H^2 - 0.013 \ M^2 + 0.15 \ G \ (H^2) \ M$	-	0.95	19.12	-	249.20	-	Mangrove species
Jonson and Freudenberger (2011)	$\log Y = 0.619 + 1.651 \ln D30 + 0.619 \ln CD$	0.019	0.972	16.2	-	-	-	Mallee woodlands

Y is total aboveground biomass (kg), DBH is diameter at breast height (cm), H is height (m), WD is wood density (g cm^{-3}), CA is crown area (m^2), CD is crown diameter (m), G is girth at collar height (cm) M is height of girth measuring point (m), D50 is diameter at height of 50 cm (cm) and D30 is diameter at height of 30 cm (cm).

2.3 Factors affecting allometric equations

Any factor that can affect tree growth may potentially be a significant variable in allometric equations (Cooke, 1987). Aboveground biomass and carbon stocks are affected by the size-frequency distribution of plants (Niklas *et al.*, 2003; Henry *et al.*, 2010), productivity and forest management factors. Knowledge of factors affecting the forest structure can improve the biomass estimation within a landscape (Clark and Clark, 2000). Environmental or ecological factors, such as slope, aspect, terrain position, seasonality, soil type, soil quality, moisture availability and climate conditions, including temperature and rainfall, and shading and solar radiation can affect both the amount of biomass and canopy structure (Beets and Pollock, 1987; Chave *et al.*, 2005; Ryan *et al.*, 2006; Jonson and Freudenberger, 2011). Santos-Martin *et al*. (2010) concluded that soils, vegetation, climate conditions, overstorey structure and nutrient deficiency can affect biomass formation. The amount of aboveground biomass was lower in nutrient-poor surfaces compared to areas with nutrient-rich surfaces (Oliver and Larson, 1990; Kimmins, 1997). Factors such as topographic gradients can influence the amount of organic carbon and nutrients in the soil (Kumhalova *et al.*, 2008). The shape of a terrain can affect the water flow, which can further affect the movements of sediments, nutrients and solutes. Taken together, these factors can all influence plant growth (Blaszczynski, 1997), forest structure and stand structural characteristics (Clark and Clark, 2000).

Variation in soils, which are primarily determined by geological actions and climate (Tuomisto *et al.*, 1995), can cause differences in nutrient availability and water retention properties and can therefore host different forest structures. For example, clay soils generally retain more nutrients than other soil types, which provide better growth for the canopy (Powell *et al.*, 1996; Bonan, 2002). Solar radiation and light use efficiency are critical factors that affect tree growth and the estimation of biomass and carbon in ecosystems. Atmospheric conditions, such as clouds and aerosols, can lead to lower visible light on the surface of a canopy, thus affecting the understorey levels. Diffuse radiation also causes less shadowing by spreading the light throughout the entire canopy (Jenkins *et al.*, 2007). Fire frequency and intensity can also affect both the biomass distribution and structure of forest ecosystems (Sah *et al.*, 2004; Gerten *et al.*, 2005).

Additionally, forest management practices, such as thinning, fertilizing (Beets and Pollock, 1987) and nutrient status, can affect the productivity of trees and biomass (Feller, 1992). For example, Snowdon (1985) found that the effect of fertilizer treatments on *P. radiata* did not impact the stem allometric equations but did affect the intercepts of the crown and root equations. Lesser amounts of forest biomass were reported on Jack pine stands which were exposed to environmental stress including xeric outwash sand (Crow, 1978).

Competition factors, such as stocking density, have also been shown to affect the biomass distribution among tree components. Stand density is an important factor that can help explain biomass variations and also reduce variability in stand or ecosystem-scale equations for forests (Snowdon *et al.*, 2000). The stocking rates in natural stands are not sustainable and self-thinning becomes evident as the trees grow over time, which can also affect the amount of biomass in stands (Ryan, 1995). In a number of studies at high stocking densities, the mean stem height of trees was lower than average, which led to lower levels of biomass estimation (Coetzee, 1999; Saint-André *et al.*, 2005).

According to a study by Shen *et al*. (2000), tree size, stand density and parent material have a direct effect on the tree basal area. Their results also demonstrated that in an experimental stand, the moisture regime had greater effects on suppressing tree growth than the dominant trees. Within even-aged stands, significant differences have also been reported in tree size and structure as a result of competitive status (Wirth *et al.*, 2004; Repola, 2009). In general, increased stocking density leads to more competition for site resources, such as nutrients (Harris, 2007).

Apart from environmental factors, genetic factors can also affect the amount of biomass in plants (Beets and Pollock, 1987). According to Jonson and Freudenberger (2011), genetic depositions along with other regional biophysical parameters, such as rainfall and soil depth, influence tree development and biomass prediction.

2.4 Environmental factors used in allometric equations

As mentioned earlier, environmental factors are considered as significant contributors to tree growth and productivity. Several studies have developed allometric equations by using these variables. For example, altitude has been applied as a climatic function in branching equations to improve biomass prediction (Cienciala *et al.*, 2008). Hamilton and Brack (1998) developed volume models based on mathematical relationships between stand heights, crown cover and crown form; however, the addition of environmental variables, such as slope, aspect and altitude, resulted in an increase in the precision of the models.

Altitude has also been included in several studies (Table 2.2) and has been reported to be an important predictor that improves the estimation of aboveground biomass (e.g. Joosten *et al.*, 2004; Wirth *et al.*, 2004; Cienciala *et al.*, 2006; Wutzler *et al.*, 2008). Soil texture is another site-variable that has been considered in several allometric equations (Jenkins *et al.*, 2003). Cairns *et al.* (1997) included age and latitudinal zone (tropical, temperate and boreal) in allometric equations and observed a significant improvement (R^2 = 0.84) in their predictions of biomass.

Site quality and stocking have been shown to influence the amount of biomass allocated to crown, stem and roots (Pereira *et al.*, 1997), where total biomass increased as tree density decreased (Saint-André *et al.*, 2005). Basal area is also used to compare the density of trees and it has been applied in several equations. Snowdon *et al.* (2000) observed a significant relationship between stocking and basal area and stand aboveground biomass with the Error Mean Squares (EMS) notably reduced when included to their radiata pine allometric equation. They also reported that factors such as stocking, age and basal area indirectly affected biomass estimation and improved the allometric relationships. Madgwick (1994) has also incorporated stocking as an independent variable in radiata pine stand-level equations in New Zealand (Table 2.2).

The nutrient and water availabilities and the "social status" or the position of the crown in relation to the main canopy of trees (e.g. dominant, intermediate, suppressed) have also been shown to modify the growth rate and tree shape (Wirth *et al.*, 2004). Trees with different social status compete differently for light, water and other resources and thus respond differently to environmental stress (Rathgeber *et al.*, 2011). However, there has been considerable debate over the inclusion of these factors when constructing allometric equations (Shaiek *et al.*, 2011).

Table 2.2: Some examples of allometric equations with environmental factors. EMS is the error mean squares, R^2 is the coefficient of determination, CV is the coefficient of variation and is reported in percentage (%) , AIC is the Akaike Information Criterion, RMSE is the root mean square error and SE is the standard error.

Study	Function	EMS	R^2	AIC	RMSE	SE	Species
Wirth *et al.* (2004)	$\ln B = -1.65561 + 1.36040 \ln DBH - 0.15198 \ln A - 0.02299 \ln SI + 0.00125\, Alt$	0.237	0.802	280.8	0.511	-	Norway spruce
Joosten *et al.* (2004)	$\ln Y = -3.4698 + 2.1675 \ln DBH + 0.5104 \ln H - 0.0648 \ln Alt + 0.0992 \ln A$	-	0.996	103.6	-	0.1503	European beech
Wutzler *et al.* (2008)	$Y = \left(0.0551 + (4.06E\text{-}04 \times A) + (2.39E\text{-}04 \times SI) - (4.68E\text{-}06 \times Alt)\right) DBH^{2.11} H^{0.589}$	-	0.95	1507.3	-	-	European beech
Madgwick (1994)	$\ln S = -3.56 + 1.10 \ln H + 0.62 \ln (BA + 1) + 0.36 \ln A + 0.28 \ln N$	0.0225	0.99	-	-	0.150	Radiata pine

Y is total aboveground biomass (kg), B is dry branches (kg m^{-2}), DBH is diameter at breast height (cm), H is height (m), A is age (years), SI is site index (m), Alt is the altitude (m), S is stem biomass (ton ha^{-1}), BA is basal area ($m^2\,ha^{-1}$) and N is stocking (trees ha^{-1}).

2.5 Deficiencies in allometric equations

2.5.1 *Non-incorporation of different explanatory variables*

Within the literature, additional explanatory variables and environmental factors have been reported to improve the performance of the allometric equations and therefore the reliability of biomass predictions (Eamus *et al.*, 2000; Siddique *et al.*, 2012). The addition of the crown width increased the R^2 value of the equation predicting the aboveground, branch and foliage biomass, and the addition of the height variable improved the accuracy of the stem biomass (Wagner and Ter-Mikaelian, 1999). In radiata pine (*Pinus radiata* D. Don) stands, for example, the inclusion of both height and basal area, rather than one alone, have reduced the standard error of estimates from 28% to 18% (Snowdon *et al.*, 2000). Some of the variables that were used to develop accurate allometric equations included wood specific gravities or wood density (Jenkins *et al.*, 2003; Dietz and Kuyah, 2011), girth at collar height (Siddique *et al.*, 2012), crown width (Jonson and Freudenberger, 2011) and stocking (Snowdon *et al.*, 2000).

Although the inclusion of such variables has been shown to improve biomass and volume estimations, few studies have looked at the addition of stand structure variables into allometric equations. Variables such as crown width, crown length, stand density, basal area and even height are not often used in allometric equations, due to diverse plant structures, difficulties in measurements, time factors and reduced accuracy (Curtis, 1967; Jenkins *et al.*, 2003).

Several studies have suggested that difficulties in accurate measurements of tree height, especially in closed canopy stands, is one of the reasons that height is not included in biomass estimation procedures (Williams and Schreuder, 2000; Jenkins *et al.*, 2003). Ruiz-Peinado Gertrudix *et al.* (2012) stated that since height provides information about growth and site conditions, the inclusion of height can improve the accuracy of models and the validity of equations in a wider range of stands. In several studies, the combination of diameter and height together as independent variables have shown improvements in the performance of the equations and the level of precision (e.g. Sah *et al.*, 2004; Chave *et al.*, 2005; Vieira *et al.*, 2008). According to Zeng and Tang (2012), the application of the fitting method and the expansion of allometric equation from one variable (DBH) to three variables (inclusion of height and crown width) resulted in notable improvements in the performance of equations applied to Masson pine in South China. In Brazil, the use of height and DBH, as single variables, showed good relationships with the biomass of 60 wood plants; however, the combination of these two variables resulted in higher R^2 values and estimation accuracy (Delitti *et al.*, 2006). António *et al.* (2007) also observed an improvement in the predictions of aboveground biomass when the height and crown length were added as predictors in addition to DBH in eucalyptus trees. When DBH and basal area variables are not available, height metrics can be used as a surrogate for these variables (Nelson *et al.*, 1988; Næsset and Økland, 2002). Given all the examples of the importance of the inclusion of height, it is still not incorporated in most of the allometric equations and the primary reason for this is the difficulties in its measurement.

2.5.2 *Non-incorporation of environmental variables*

The general lack of spatial data has been considered an uncertainty with regard to the amount of carbon in forests (Harrell *et al.*, 1995). Several authors have reported significant interactions between environmental parameters and stand variables (Beets and Madgwick, 1988; DeLucia *et al.*, 2000). Moreover, the examples mentioned in section 2.3 reveal the importance of environmental factors in forest estimations; however, despite such examples, less attention has been paid to these factors due to the cost and time involved in obtaining and characterizing these variables with traditional field operations.

In addition, according to Brown (2002), factors such as age, soil texture and latitude can affect the variability of the biomass. Knowing the spatial variations of forests can provide information about the biomass and volume variations of the stands. Considerable variation in biomass has been explained by topography, through changes in species composition, physiological constraints and forest dynamics (Mascaro *et al.*, 2011; Lin *et al.*, 2012). Variables such as wood density have been reported to be influenced by soil nutrients and terrain gradients (Henry *et al.*, 2010). Height has also been seen to be associated with several environmental factors such as stocking density and topographical factors (Jonson and Freudenberger, 2011). Hence, understanding the environmental factors causing the variations in forests is critical in reducing the error of estimations.

2.6 Data acquisition solution

Generally, field surveying, particularly in dense canopy forests, is costly and requires a great deal of time. However, with the advent of remote sensing techniques, a new dimension has been opened to the modeling, mapping and understanding of natural and environmental resources. As remote sensing data have become more readily available, the number of applications has grown (Elachi and Van Zyl, 2006). According to Lu (2006), remote sensing techniques have recently become essential as the primary source of biomass estimation. Traditional remote sensing systems involved either passive optical systems such as aerial photography or active sensors such as RADAR (Lefsky *et al.*, 2002b). Although these sensors have proven to be satisfactory for many ecological and forestry applications, they have also shown limited accuracy, sensitivity and ability to represent spatial patterns in detailed structure (only producing two-dimensional images) (Waring *et al.*, 1995; Lefsky *et al.*, 2002b).

2.7 LiDAR and its application in forest studies

Light Detection and Ranging (LiDAR), has been proven to provide accurate and detailed information on canopy structure in difficult to reach areas in a cost-effective and -efficient way. Airborne LiDAR is currently the most common and viable option for forestry applications (Leeuwen and Nieuwenhuis, 2010). LiDAR is capable of providing high accuracy measurements in both horizontal and vertical dimensions (three dimensional - 3D) (Lim *et al.*, 2003). This technology has received much attention in the last two decades, for its geo-referencing accuracy, acquisition flexibility, fast data delivery and increased availability in post-processing software (Turner, 2006). Significant development has been made with LiDAR in the field of forest inventory, forest structure and biomass assessment and carbon inventory (Lefsky *et al.*, 2002b; Hyyppä *et al.*, 2008).

Although LiDAR is subjected to the same scattering characteristics of light as optical remote sensing, it determines the range to an object by measuring the time delay between transmission of a pulse and detection of the reflected signal. LiDAR is less sensitive to weather conditions and is not dependent on daily illumination; therefore, LiDAR can operate both day and night and under cloud cover (Baltsavias, 1999; Patenaude *et al.*, 2004). LiDAR data can be acquired from terrestrial or ground-based, airborne and satellite platforms, with each platform type suited to specific forest information needs (i.e. global scale (satellites), individual trees (ground-based)). Ground-based LiDAR systems have been used with considerable success, but only at local or fine scales.

The application of LiDAR remote sensing in forests consists of the production of accurate ground topography (e.g. digital terrain models or topographical maps), 3D structure of vegetation canopies (e.g. canopy height model) and forest stand structure attributes (e.g. tree height, vertical distributions of canopies, total aboveground biomass, basal area, Leaf Area Index (LAI) and stand density) (Lefsky *et al.*, 2002b). LiDAR high density points and different processing algorithms can identify single trees or groups of trees over a range of scales (Hyyppä and Inkinen, 2002). LiDAR-detailed vegetation information can improve the identification of tree species and ground cover vegetation (Chauve *et al.*, 2007). This technology has also been used to predict the aerodynamic properties (Menenti and Ritchie, 1994) and biophysical characteristics (Dubayah and Drake, 2000) of plant canopies and landscapes.

As discussed earlier, LiDAR can potentially estimate various forest metrics and obtain information from difficult to reach places. Some of the variables that have been used in allometric equations derived from LiDAR are described below.

2.7.1 *Tree height*

As mentioned earlier, measuring the height of all trees at broad scales can be very difficult and time-consuming because detecting the tops of trees can be problematic; therefore, researchers have excluded this variable from allometric equations (Brown, 2002; Jenkins *et al.*, 2003). Moreover, historical tree inventories have not recorded tree heights due to difficulties in field measurement. For these reasons, it has been claimed that the addition of height does not improve the forestry estimation, and it has been suggested to simply use DBH as a predictive variable (for more detail see Chave *et al.*, 2005). However, LiDAR can overcome these complexities and drawbacks.

To date, the LiDAR-derived parameters that have received the most attention have been the retrieval of tree height, plot height (e.g. Lorey's mean height, which is the contribution of trees to the stand height by their basal area) and predominant tree height. Tree heights have been calculated from different scanning LiDAR datasets and compared to ground-based canopy height measurements with varying accuracies and strengths of correlation (Magnussen and Boudewyn, 1998; Vincent *et al.*, 2012). A strong correlation between LiDAR and field measured vegetation heights has been seen, with the majority of R^2 values greater than 0.8 (e.g. Persson *et al.*, 2002; Lee and Lucas, 2007; Turner *et al.*, 2011a). Chen and Hay (2011) developed a new airborne LiDAR sampling strategy for modeling forest canopy height using Quickbird data, LiDAR data and Geographic Object-Based Image Analysis (GEOBIA). Their results showed that the Quickbird pseudo-height map contained more errors than the LiDAR-derived map and that different LiDAR transect data produced different height estimations.

The LiDAR height estimation process is relatively simple and direct. There are different tools which classify Lidar dataset that differentiate ground (bare earth) returns from vegetation returns, including FUSION, GRASS GIS, SAGA GIS and Merrick's MARS. For example, in FUSION canopy- and ground-level surface models can be computed from the LiDAR point cloud, and by simple differing canopy height models can be generated (McGaughey, 2007).

2.7.2 *Crown diameter*

Crown/canopy closures is used as a measure of stand density and stand volume and relies on visual canopy assessments (Whitney and Johnson, 1984). Canopy cover is an important indicator for estimating biomass distribution and variables, such as LAI, stem diameter and tree volume (Hyyppä *et al.*, 2005; Korhonen *et al.*, 2011). Obtaining information from the tree crown provides additional information from live branches and the aboveground biomass. Various studies have shown that the addition of crown width to other variables, such as DBH and height, positively affects the precision of biomass predictions (Wirth *et al.*, 2004; Cienciala *et al.*, 2008; Zeng and Tang, 2012). Jonson and Freudenberger (2011) observed a strong correlation between biomass and crown diameter of trees with uniform canopy form and suggested the use of remotely sensed measurements for accurate estimation of biomass and carbon across large areas. Common techniques for crown measurements are costly and time-consuming, particularly for mature trees, yet LiDAR has yielded promising results of crown estimations. Weltz *et al*. (1994) compared height and crown measurements from both LiDAR and field surveys and found no meaningful differences. Because DBH cannot be estimated directly from LiDAR, studies have used crown diameter as a substitute for DBH (e.g. Popescu, 2007; Anjin *et al.*, 2012). They applied regression models to assess the accuracy of the DBH from the LiDAR-derived crown diameter. The linear regression models were able to explain 53% of the variability in tree DBH in Anjin's study and 90% of the DBH variability in Popescu's study.

A number of studies have explored the importance of LiDAR-derived crown diameters for volume and biomass measurements (Persson *et al.*, 2002; Holmgren *et al.*, 2003; Tan *et al.*, 2010). LiDAR has also been used to monitor the growth and mortality of the tree crown over a period of time (Holmgren *et al.*, 2003; Reutebuch *et al.*, 2005). Estimation of trees crown using LiDAR involves detection and delineation of trees from the data. Using appropriate segmentation and marker functions, the individual crown boundaries can be identified (Korhonen *et al.*, 2013).

2.7.3 *Basal area and DBH*

Forest studies have focused much attention on the size and number of tree stems because they are important parameters in forestry applications. Strong relationships between biomass and basal area have been observed in numerous studies (Lefsky *et al.*, 1999a; Tian *et al.*, 2011). Because there is a close relationship between the basal area and tree parameters, such as height, crown size and bole volume, basal area can be derived from these relationships (Philip, 1994; Dubayah and Drake, 2000). Prediction models have also been developed for the basal area using LiDAR data. Holmgren (2004) estimated the basal area and stem volume using regression functions with variables extracted from laser measurements in small stands of Norway spruce, Scots pine and birch forests. Other physical dimensions of trees that were derived directly from LiDAR, such as height, crown diameter, crown shape and crown area, have also been reported in the calculation of the basal area (Means *et al.*, 2000; Hyyppä *et al.*, 2005; Turner, 2006).

DBH is another attribute that cannot currently be measured directly with airborne LiDAR. Many attempts have been made to estimate DBH from different regression analyses using the aforementioned LiDAR-derived dimensions (e.g. Popescu, 2007; Rowell *et al.*, 2009; Zhao *et al.*, 2009). Their results indicate that the models can accurately predict DBH with an R^2 of 76% to 90%.

2.7.4 *Stand density*

Stand density (stocking) is an important variable in forestry applications, including mapping programs, forestry management and conservation strategies (Specht and Specht, 1999). Hyyppä (2000) suggested that by gaining detailed information from individual tree characteristics, stand-level attributes such as stand density can be calculated. The delineation of tree canopies and tree stocking estimations using LiDAR has been performed in a number of studies. Tree isolation from LiDAR is typically based on Canopy Height Model (CHM), which is the difference between Digital Surface Model (DSM) and a Digital Elevation Model (DEM) of the earth surface. Several studies have used the CHM for detecting trees (crown delineation) and estimating stand density (Hyyppä *et al.*, 2001; Suárez *et al.*, 2005). The specific percentile of the height distribution of LiDAR pulses have also been used for stem density estimation (Maltamo *et al.*, 2004). Stephens (2007) suggested a canopy return algorithm for the tree stocking determination. However, his results showed that only models with a single height percentile provided a significant relationship between LiDAR and tree stockings and therefore better estimations. He also stated that the algorithm depended on several factors, such as the laser return density and the tree crown size, height and growth stage. McCombs *et al*. (2003) used both LiDAR and multispectral data fusion to estimate the stand density and tree height. Their results showed that tree identifications were more accurate when using both datasets compared to the LiDAR data alone.

In a recent approach, the Height-Scaled Crown Openness Index (HSCOI) was developed from LiDAR data (Lee and Lucas, 2007). This index provides measurement of the LiDAR pulse penetrations through the forest canopy. The index, along with several algorithms, has been shown to locate tree stems in open canopy woodland regardless of their positions.

2.7.5 *Topography factors*

There is considerable literature on the effect of topography on tree growth and productivity, since it affects regional biophysical variables such as rainfall, soil formation and nutrient availability and subsequently influences the demographic processes of tree growth and mortality (e.g. Stathers *et al.*, 1994; Stage and Salas, 2007). For instance, in central Amazonian forests, plateau and slope areas showed higher rates of nitrogen in the top soil than the valley (Luiza˜o *et al.*, 2004). Differences in slope and aspect affect primary topoclimatic conditions such as solar radiation, wind exposure and soil water balance that influence tree growth and productivity. Aspect caused significant differences in tree architecture of holm oaks in Spain, where less biomass was found on southern aspects for the same DBH size trees (Canadell *et al.*, 1988). Almost 20% of the spatial variations in aboveground biomass estimates of forests in the central Amazonia were predicted from soil and slope gradients (de Castilho *et al.*, 2006).

Altitude has often been used as a proxy of climatic conditions where other climatic data are not available. It represents a dominant factor that differentiates the temperature and precipitation regime mainly for species that grow in a large elevation range. Altitude was included in biomass functions for Norway spruce branch needle, stem and roots; the results varied according to compartments but the stem and roots equation obtained a smaller Residual Mean Square Error (RMSE) compared to the other models (Wirth *et al.*, 2004). Altitude was also found to be a useful predictor for the branch biomass in oak trees (Cienciala *et al.*, 2008) and for aboveground biomass of beech (Joosten *et al.*, 2004).

Such examples indicate the importance of topography on forestry estimations, *per se* and as environmental conditions defined by topography. Topographic variables can be obtained from maps or DEMs; however, LiDAR-derived high resolution DEM represents terrain surface in more accurate detail while consuming less time than traditional methods (Patenaude *et al.*, 2004; Turner, 2006). LiDAR DEMs are described as the variation of elevation across a landscape and provide a great deal of information, particularly in closed forests where the ground is difficult to see. In addition to LiDAR-derived slope and aspect metrics, solar radiation can be calculated from the LiDAR-derived data. The spatial and temporal heterogeneity of incoming solar radiation can affect soil temperature, soil moisture, photosynthesis, etc. (Tovar-Pescador *et al.*, 2006), which can impact on trees growth and productivity; therefore quantifying its influence could be of immense benefit. Table 2.3 shows several examples of biomass models using LiDAR-derived metrics.

Table 2.3: Examples of biomass equations integrated with LiDAR metrics.

Study	LiDAR metrics	Function	R^2	Species	Remarks
Patenaude *et al.* (2004)	Height	$C = 8.694\, e^{0.1256\, LH}$	0.74	Mixed deciduous woodlands (Monks wood)	C is aboveground carbon (Tonnes ha^{-1}) and LH is LiDAR-derived height (m).
Lefsky *et al.* (2002a)	Mean canopy height	$Y = 0.378 \times MCH^2$	0.84	Temperate coniferous and deciduous	Y is aboveground biomass (Mg ha^{-1}) and MCH is mean canopy height (m^2).
Boudreau *et al.* (2008)	DEM	$Y = 0.27\, wflen - 0.83\theta - 0.06\, range + 2.67$	0.59	Deciduous and mixed wood forests	Y is aboveground biomass (Mg ha^{-1}), wflen is distance from signal beginning to signal end (m), θ is GLAS waveform front rising slope angle (radians) and range is DEM terrain index (m).
Drake *et al.* (2002)	Height	$\log Y = 2.06 + 0.07 \times LH - 0.08 \times HOME - 1.05 \times GRND + 3.51 \times HTRT$	0.73	Tropical forest (0.05 ha)	Y is aboveground biomass (Mg ha^{-1}), LH is LiDAR height (m), HOME is height of median energy (m), GRND is ground return ratio.
Ferster *et al.* (2009)	Height	$\ln Y = 8.3 + 1.09 \ln x - 0.64\, TH$	0.72	Douglas-fir forest	Y is aboveground biomass (Mg ha^{-1}) X is return density and TH is TreeVaW (LiDAR software application) maximum height.
Næsset and Gobakken (2008)	Canopy density	$\ln Y = 1.7413 + 1.2208 \ln h90 + 1.0374 \ln d$	0.82	Coniferous forests	Y is aboveground biomass (Mg ha^{-1}), h90 is 90% percentile of the laser canopy heights and d is canopy density corresponding to the proportions of laser echoes >2 m to total number of echoes.

2.8 Summary

The most commonly used functional variable in the allometric equations is DBH, either alone or in combination with other independent variables, such as height. Most forestry models are based on a small number of harvested trees, which include mostly smaller diameter trees and few large diameter trees, or trees from an isolated study site (Brown, 1997; Houghton *et al.*, 2001). However, this can lead to substantial errors in forestry estimations, in particular if significant variation exists between trees. In addition, uncertainties in field measurements, insufficient plots, incomplete and biased study designs, absence of different tree measurements and environmental factors and lack of more destructive harvested data can result in poor forestry estimation (Feller, 1992; Houghton *et al.*, 2001). Therefore, to reduce errors in estimation, attention should be paid to developing new equations and selecting the appropriate variables.

The inclusion of height in a single variable equation has been reported to modify the coefficients of the DBH variable and improve biomass estimation (Keith *et al.*, 2002; Cienciala *et al.*, 2006; Bombelli *et al.*, 2009). According to Snowdon *et al.* (2000), the inclusion of explanatory variables such as height, wood density, stocking and age will improve the reliability of prediction. Even though the inclusion of such variables has shown significant improvements in forestry estimations, various studies have used DBH as the only independent variable for predicting inventories due to cost and time constraints associated with traditional field measurements.

In developing new equations in the future, or improving current equations, reliable techniques such as LiDAR can be used to facilitate the development process of models. LiDAR has been confirmed as a very useful technology to obtain accurate data over large forested areas with respect to the shape of the terrain (Vazirabad and Karslioglu, 2011). Detailed information from LiDAR can quantify the variability within the trees and allow more accurate inventory predictions. Tickle *et al.* (1998) postulated that LiDAR can bridge the gap between mapping and ground survey and can provide information regarding places where data is difficult to obtain.

In this review, some of the variables that can be estimated with LiDAR have been explained. Tree characteristics extraction from LiDAR data may play an important role in the forestry estimation models, particularly in dense forests where the ground is not visible. Various studies have shown a high correlation of LiDAR-derived forest structures with aboveground biomass (Drake *et al.*, 2002; Vazirabad and Karslioglu, 2011; Anjin *et al.*, 2012).

LiDAR point clouds can provide simple and direct measurement of tree structure and its surroundings and enable the characterization of the complex structure of forest ecosystems for improving efficiencies of forestry inventory attributes. Based on LiDAR metrics reliable forest attributes, such as height, crown diameter and stand density, can be obtained and be taken into consideration with other variables. In addition to deriving forest structural information, LiDAR detailed DEM can produce terrain information at micro scales which can be used in tree attribute predictions and forestry applications. Topographic variables derived from LiDAR DEMs have been used in terrain-based estimation procedures of forest productivity, forest structure and water flow accumulation models (Kraus *et al.*, 2006; Watt *et al.*, 2006; Turner *et al.*, 2011a). It should also be noted that, if a weak relationship is observed between a variable and forestry inventory and the variable cannot explain the variance at different sites, then it should not be incorporated in the allometric equations (Makungwa *et al.*, 2013). Although the equations may use many variables to reduce the prediction bias, it is always desirable to keep the set of predictors as small as possible to reduce the variability of predictions (Wirth *et al.*, 2004).

Despite the advantages of LiDAR, there are some drawbacks in its applications that should be mentioned, including the high cost of LiDAR, especially for small scale areas, its weather-dependent operation in terms of aircraft mounted systems, the steep learning curve on using the entire point cloud, the challenge on the use of the data and the acquisition of appropriate software.

2.9 Conclusion

The importance of additional variables, such as various tree dimensions (e.g. height and crown width) and environmental factors (e.g. elevation), which have led to improvements in forestry estimations and a reduction in prediction errors, have been reported in numerous studies. Data acquisition complexity, time-consuming field work and high cost are some of the reasons that these additional variables are not included for resource inventories. LiDAR offers the possibility of estimating tree attributes more precisely, efficiently and economically compared to other remote sensing and ground-based methods. In addition, the topographical information provided by LiDAR, such as slope, aspect and altitude along with LiDAR-derived tree characteristics, can identify relationships that can be used for improving allometric equations and forestry estimations in the future. However, further investigation and measurements are necessary before this information can be used to improve the prediction of forest biomass and productivity.

The main focus of this research is to create different LiDAR models such as DEM, DSM and CHM to identify relationships between spatial variation in tree attributes and environmental factors using LiDAR data. The effect of topography (slope and aspect), solar radiation and stand density (stocking) on tree height and DBH will be examined. The work undertaken as part of this research will explore some of these relationships.

CHAPTER 3: Airborne LiDAR derived canopy height model reveals a significant difference in radiata pine (*Pinus radiata* D. Don) heights based on slope and aspect of sites

This chapter has been published as:

Saremi, H., Kumar, L., Turner, R., & Stone, C. (2014). Airborne LiDAR derived canopy height model reveals a significant difference in radiata pine (*Pinus radiata* D. Don) heights based on slope and aspect of sites. *Trees - Structure and Function*, *28*(3), 733-744.

CHAPTER 4: Impact of local slope and aspect assessed from LiDAR records on tree diameter in radiata pine (*Pinus radiata* D. Don) plantations

This chapter has been published as:

Saremi, H., Kumar, L., Turner, R., Stone, C., & Melville, G. (2014). Impact of local slope and aspect assessed from LiDAR records on tree diameter in radiata pine (*Pinus radiata* D. Don) plantations. *Annals of Forest Science*, 1-10. doi: 10.1007/s13595-014-0374-4.

CHAPTER 5: Diameter at Breast Height (DBH) and height show significant correlation with incoming solar radiation: A case study of a radiata pine (*Pinus radiata* D. Don) plantation in New South Wales, Australia

This chapter has been published as:

Saremi, H., Kumar, L., Turner, R., Stone, C., & Melville, G. (2014). DBH and height show significant correlation with incoming solar radiation: a case study of a radiata pine (*Pinus radiata* D. Don) plantation in New South Wales, Australia. *GIScience & Remote Sensing*, 1-18. doi: 10.1080/15481603.2014.937901.

CHAPTER 6: Sub-compartment variation in tree height, stem diameter and stocking in a radiata pine (*Pinus radiata* D. Don) plantation examined using airborne LiDAR data

This chapter has been published as:

Saremi, H., Kumar, L., Stone, C., Melville, G., & Turner, R. (2014). Sub-compartment variation in tree height, stem diameter and stocking in a *Pinus radiata* D. Don plantation examined using airborne LiDAR data. *Remote Sensing, 6*(8), 7592-7609.

CHAPTER 7: Synthesis and Conclusion

The potential of LiDAR-derived topography in improving sampling designs and inventory estimates for softwood plantations

7.1 Research summary

This study was undertaken to investigate the impact of environmental factors in Diameter at Breast Height (DBH) and height variation with the use of airborne Light Detection and Ranging (LiDAR) in two even-aged radiata pine plantation sites in New South Wales. Tree height and DBH are key variables used in allometric equations for numerous forest inventory parameters, including stand stem volume and biomass. Significant variations in these variables, however, can influence the levels of precision and bias of the inventory estimates of total stem volume and biomass. A detailed understanding of environmental factors affecting the tree structure variations can improve the DBH and height derived inventory attributes and sampling efficiencies.

This chapter summarizes the major findings and outcomes from this research study. The objectives of this chapter are to: (1) look at the current operational practices and inventory estimates carried out in Hanging Rock State Forest and New South Wales (NSW) in general and the main deficiencies, (2) discuss how LiDAR can overcome some of these limitations, (3) highlight possible factors that could cause variations between height and DBH of *P. radiata* trees across the plantations and (4) propose recommendations and future research needs.

7.2 Forest inventory estimations and some of their deficiencies

Planners and foresters have strongly emphasized the need for accurate predictions of various forest inventory estimates, as over a long-term they can affect timber yield and carbon stock predictions. However, uncertainties are associated with forest inventory estimates at all stages; for example, the uncertainty due to the use of the allometric model for predicting the biomass or stem volume of an individual tree or the uncertainty derived from the measurement of tree variables (Zianis, 2008). Failing to account for uncertainty during the estimation process can lead to the under/over estimation of final predictions (Dietze *et al.*, 2008).

In radiata pine (*Pinus radiata* D. Don), like many other softwood species, the above-ground biomass/stem volume of trees is commonly estimated by the use of allometric equations (derived from regression analysis) which are based on one or more easily measurable tree variables (e.g. DBH, height). For measuring these variables in the plots in the field, firstly a stratification procedure is undertaken which involves grouping similar forest stands in an attempt to gain a number of relatively homogeneous strata of forest. The inventory area is often stratified on the basis of earlier stand inventory data, including silvicultural history (stocking) and stand age. The field plots (representative sample plots) are then allocated to these strata for the generation of representative reference data for the interpretation of forest variables. The recommended sampling intensity for inventory plots prescribed by radiata plantation growers in Australia is 1 plot per 4 ha and the plot size is often varied depending on the stocking density of forest trees (Mike Sutton, Manager Forest Information & Planning, Forestry Corporation NSW, pers. comm., April 2014). After selecting the sample plots, attributes of all trees located in the plots are gathered; means and total measurements of forest characteristics across the strata are measured and finally different databases are developed and predictive forestry estimates and equations are calculated.

Although this method has been used for many years in softwood plantations across Australia, it appears that it does not explain the variability observed in areas with major spatial variations. For example, most of the estimates, such as stand volume, are typically determined from inventory measurements such as DBH. However, it is not unusual to find that traditional plot sampling strategies within assumed homogeneous strata can still exhibit significant variation in DBH, basal area and other inventory variables. Moreover, such variation can affect the overall precision of stand volume predictions. Hence, significant intra-compartment variation in tree characteristics can challenge the acceptable level of precision and bias required for such estimates. To minimize or remove the differences between the sampling units within strata, more reliable and suitable variables are required for stratification so that the limited sample within each stratum provides a generally precise estimate of the mean of that stratum (Crawford, 1990).

In addition, most of the biomass and volume estimations are based on a single variable, mainly the DBH. In Hanging Rock radiata pine plantation the allometric equation model used for the estimation of aboveground biomass is solely based on DBH and takes the general model as follows:

$$\ln B = \beta_1 + \beta_2 \ln(D + 1) \qquad \text{(Equation 7.1)}$$

where B is the total aboveground biomass (kg), β_1 and β_2 are the coefficients and D is the DBH (cm). The β_1 and β_2 coefficients were estimated as -3.287 and 2.67, respectively (O'Brien, 1998). This model is based on 5 datasets from destructive harvests conducted around NSW and is assumed to perform well across different environmental gradients in the plantation. So in order to measure the total biomass of an area, plots are established, the diameter of every tree is measured and recorded, then the allomteric equation 7.1 is applied to the DBH of each individual tree and the biomass is calculated and consequently the values are summed for the plot estimate. If the selected plots and trees do not represent different range of tree sizes, then an overestimation of biomass is expected from larger trees and an underestimation from the smaller ones. In other words, even though the number of plots (1 per 4 ha) suggested by NSW forestry seems appropriate for capturing variation, in an area with high spatial variability, it is critical to ensure that these plots represent the sample area and are capable of explaining the great diversity present in the area. Gonzalez-Benecke *et al*. (2014) stated that although the vast majority of forestry models rely on DBH as the only predictive variable, the models are widely limited to certain stand characteristics, in particular those from which the data originated. Therefore when such equations are used at different sites, they can lead to large errors when monitoring and estimating biomass or carbon.

To reduce the internal variability within the stands and mitigate the uncertainty in estimates, an increase in the number/size of plots or tree samples has been suggested (Hayashi *et al.*, 2014). However, calculating a new plot size for each stratum is an added cost and introduces a complexity that can result in additional measurement errors (Pearson *et al.*, 2007). McRoberts *et al*. (2006) stated that because of budgetary limitations and natural variability within stands, numbers of plots measured are often insufficient to capture the variation observed within the forest and provide estimates with the desired level of precision. But an efficient sampling design/stratification can explain the variation within stands and improve estimates for any parameter of interest with less number of plots.

Another option to increase the quality of inventory predictions and reduce the error of estimations is to incorporate additional variables to drive different equations and models in addition to the initial response inputs. For example, Gonzalez-Benecke *et al*. (2014) found that the incorporation of stand parameters such as age and basal area in longleaf pine stem volume models reduced the bias in estimates from 1.4% to 0.6%. In a number of equations the use of additional variables, such as height, has been reported to improve the performance of the regression models (e.g. Pearson *et al.*, 2007; Zhao *et al.*, 2012). Stage and Salas (2007) suggested a combination of slope, aspect, and elevation factors to be incorporated into growth modeling for use in predicting forest productivity or species composition. Altitude, site index, age and stand density index have also been added to *P. radiata* models to improve the predictive ability of model performances (e.g. Woollons and Hayward, 1985; Woollons *et al.*, 1997; Álvarez *et al.*, 2013; van der Colff and Kimberley, 2013). In all the above studies, environmental factors were considered as an important contribution to the tree growth, and therefore incorporated into the models.

The impact of environmental factors in radiata trees have been studied for many years. In Southeastern Australia, soil parent material was shown to be related to the growth of *P. radiata*; the soil unit not only affected the tree productivity but also factors such as nutrient availability and trafficability (workability) during wet weather (Turvey, 1980). Variation in stocking, which in turn influences exposure to wind and competition for light, has also been reported to affect the structure pattern of height and DBH (Mason, 1992). Although the importance of these environmental factors has been reported widely, obtaining and characterizing these variables in a forest is very time-consuming and prohibitively expensive.

In order to select and measure different forest and environmental variables to improve estimates of common forest attributes, traditional field operations have been typically undertaken over the years. Although different variables can be measured directly in the field, the field-based methods can be relatively expensive, difficult and time-consuming and sometimes affected by human induced errors. However, in recent years, the collection of spatial information has been facilitated by the use of remote sensing techniques as they provide a unique insight into forest structure and terrain surface.

7.3 The use of LiDAR in forestry

In recent years, Airborne Light Detection and Ranging (ALS or LiDAR) has been accepted as a major data source for forest inventory analysis. LiDAR provides detailed three-dimensional (3D) characterization of features and biophysical measurements of forest structure as well as underlying topography. Unlike visible, near-infrared and radar remote sensing techniques that require complex models to measure different objects, LiDAR provides a simple, direct measurement of vertical structure of objects in a straightforward process (Dubayah *et al.*, 2000). Passive optical systems with medium spectral and spatial resolution, such as Landsat Thematic Mapper (TM), have proven to be satisfactory for many ecological applications and forest mapping (Gu and Gillespie, 1998). However, such sensors have a critical limitation in data saturation (when the received radiance at the satellite exceeds the maximum value that can be measured by the sensor) which can result in large uncertainties in characterizing and quantifying topographic conditions for sites with complex forest stand structure and high densities (Lu, 2005). Moreover, the low level of sensitivity and accuracy of the passive devices are also limited to represent two-dimensional spatial patterns, which can affect biomass and productivity estimations (Lefsky *et al.*, 2002b).

There are two common methods for measuring forest inventory attributes from LiDAR: predictive modeling and image processing (Chen and Zhu, 2013). Above-ground biomass and stand volume can be predicted using empirical models (e.g. regression models) from descriptive statistics of LiDAR data (such as height, horizontal and vertical distribution of forest structure and coefficients of variation for first/single returns) (Lefsky *et al.*, 1999b; Dubayah *et al.*, 2000; Stone *et al.*, 2011). However, recent image processing techniques have allowed an objective-based approach such as individual tree detection and tree crown delineation from LiDAR (Turner, 2006), which in turn enables forestry inventory estimates made at the tree-level within large areas in a timely and economic fashion (Chen and Zhu, 2013).

Although understanding the factors affecting the variability in forest structure is important, few studies have used LiDAR to explain this variation. However, the recent improvements in LiDAR posting density and multi-return sensors have improved LiDAR performance at the individual tree-level (e.g. Roberts *et al.*, 2005). This implies that more detailed information can be generated at finer scales and spatial variations can be quantified within trees, allowing more accurate inventory predictions. For example, Zhao *et al.* (2012) showed that individual tree metrics were capable of explaining a large proportion of stand variation leading to better predictive inventory estimations.

Moreover, the Digital Elevation Models (DEMs, also referred to as digital terrain models or DTMs) and Canopy Height Model (CHM) derived from LiDAR provide spatially explicit stand structure data over the landscape and accurate information of the ground surface compared with the traditional field survey methods. The use of such LiDAR-derived metrics can help explore and quantify the spatial variability of canopy structures in *P. radiata* and understand the substantial variation across sample plots and further improve forestry estimates.

7.4 Factors involved in DBH and height variability

In this study LiDAR was used to identify the intra-compartment variability and factors causing these variations in tree height and DBH within radiata plantations of the same age class. Despite the relatively homogeneous environmental factors across the area, significant variations existed amongst DBH and height, for example, in the 34-year-old plantation height ranged from 10 m to 43 m and DBH from 10.2 to 85.6 cm.

The first factor which was identified to have significant correlation with height variations across the stands was topography. Since LiDAR heights were shown to have high correlation with field heights, LiDAR heights were selected for the data analysis throughout the research. A LiDAR-derived DEM was created and different terrain parameters such as slope and aspect were generated. LiDAR heights of individual trees at both study sites (young and mature stands) were then linked to the LiDAR-derived topography metrics. Significant differences were observed between the tree heights across different slope and aspect classes. At both studies, taller trees were mainly seen on southerly aspects and on gentle slopes, whereas shorter trees were found on northerly aspects and on steeper slopes.

The effect and the relationship of topography on the DBH of the trees were also evaluated. DBH variation between trees was significantly influenced by slope and aspect. Similar to the tree heights, large diameter trees were seen on gentle slopes (less than 20°) and on southerly aspects. The results of these two experiments indicated topography as a strong parameter influencing variation in size and height of trees. The mean DBH and height of measured trees on the aspect and slope classes at both sites are provided in Table 7.1.

Table 7.1: The mean (standard error) DBH and height of measured in both study sites.

	1977 site				2002 site			
	Mean height (m)	Standard error	Mean DBH (cm)	Standard error	Mean height (m)	Standard error	Mean DBH (cm)	Standard error
North	34.13	0.31	42.5	0.72	9.91	0.11	16.76	0.35
South	36.89	0.24	48.96	0.83	11.26	0.11	19.16	0.38
>20°	34.51	0.46	43.48	0.87	10.28	0.10	16.87	0.29
<20°	35.96	0.23	47.37	0.71	11	0.16	21.27	0.51

Terrain parameters can influence local conditions, such as daily solar radiation, which can in turn affect soil moisture, hydrology and wind speed. Further, in this study, the relationship between height and DBH variation with winter and summer solar radiation was investigated. Solar radiation was calculated using the high resolution LiDAR-derived DEM integrated in GIS software and was matched to each tree location. Significant relationships were seen between the height and DBH with both summer and winter solar radiations and indicated that taller trees and trees with larger DBH were seen in areas with lower values of both winter and summer radiation.

The final factor which was examined in this study was stocking (stand density). Stocking influences both internal and external characteristics of trees between and within a stand. Although the manipulation of stocking through initial planting densities was practiced throughout the management unit of the radiata plantations, significant variations were still observed. The spatial variability of LiDAR height and DBH and their relationships with stocking were determined at both sites. The results revealed that significant relationships existed between these variables and stocking, as trees with larger diameter were located on lower stocking densities, wherein taller trees were found within higher stocking densities. LiDAR data was also used for tree detection and estimations of stem counts in fixed plots.

The strong correlation between field stocking and LiDAR-derived stocking confirmed the feasibility of using LiDAR data for tree detection and estimation of stand densities in moderately dense coniferous forests.

7.5 The use of these factors in forestry estimates

The findings of this research have confirmed the impact of various environmental factors on height and DBH of *P. radiata*. Topography has played a major role in the variations observed within the tree structure due to the location of the study area, which is situated in an undulating plateau characterized by hilly topography. Terrain parameters are stable variables which hardly change over time; as a result, unlike other ephemeral factors, they can facilitate subsequent inventory comparisons (e.g. Scott and Gove, 2002). There is considerable literature on the effect of topography affecting growth, since it affects edaphic conditions, soil formation, wind flow variability and turbulence, and consequently influences the demographic processes of tree growth and mortality (Stathers *et al.*, 1994; Stage and Salas, 2007). The effect of solar radiation on tree height and DBH variations also reveals the importance of the topographic factor in the area, as the distribution of incoming solar radiation is affected by topographic features (e.g. Kumar *et al.*, 1997). Topography has been suggested to be used as an indicator or integrator of the effects of solar radiation and soil humidity factors on forest productivity (Carmean, 1975). Although several studies have attempted to quantify the strong linkage of topography features and forest stand attributes such as productivity, basal area and forest composition in different species, not many studies have looked at these relationships in *P. radiata* (Bolstad *et al.*, 2001; Wang *et al.*, 2011).

The use of LiDAR data has shown the ability of this promising technique to provide accurate surface description at different levels (from tree- to stand-level) in a timelier and cost-effective way. Using LiDAR is an easy way to obtain high resolution and high accuracy topographic data. For accurate forest parameter estimation, creating an accurate terrain surface is essential, as an incorrect terrain surface model propagates the error to its derivatives in forest parameter estimation (Lee *et al.*, 2013). The LiDAR-derived DEM and consequently the topographic characteristics such as elevation, aspect and slope can be readily attained from computer software packages such as FUSION (McGaughey, 2013) and TreeVaW (Popescu, 2007) with no need of additional field data to support their accuracy.

The observed correlations between topography with DBH and height variation illustrate the suitability of this environmental parameter for use as a sub-compartment stratification variable in small area estimates. Stone *et al*. (2011) stated that field-based and conventional inventory methods and sampling designs can only be considered accurate if sufficient plots capture the full range of structural variability within and between stands. The sampling design in the State Forest, like most forests, have been stratified widely based on stocking and age variables for years; however, the differences between height and DBH within even-aged compartments shows that age class cannot explain the variability within the trees and therefore it should not be considered for plot establishment strategies. Yet, the relationships between *P. radiata* height and size with topography identifies the potential use of this factor as a suitable explicit attribute for improving efficiencies of height/DBH-derived inventory attributes as well as in the sampling design. The local topography can be an important contributor to compartments stratification for inventory field surveys and stand and forest measurements. Since the main purpose of stratification is to reduce the variation within the forest subdivisions and increase the precision of population estimate (Husch *et al.*, 2003), topography can be used as a sub-compartment stratification variable, instead of using age and stocking in these areas. The presence of such strata enables the representation of conditions over smaller sub-areas and provides spatial context to aid in developing model based inventories (Wulder *et al.*, 2012). Moreover, a suitable auxiliary variable can reduce the number of plots or plot size and therefore decrease the total cost of field inventory and the time required for data collection. For example, instead of establishing 1 plot per 4 ha, to accurately capture the variation observed in the stands, plots can be established on different aspect/slope classes and as a result more accurate inventory data could be gathered.

The effect of environmental factors in the *P. radiata* height and DBH variations also suggests that DBH as the sole explanatory variable may not be sufficiently accurate for biomass and volume analysis. The observed differences in radiata tree size (Table 7.1) caused by microsite terrain attributes can cause under/over estimation of biomass accounting. The uncounted variability within the trees can lead to uncertainties which potentially can limit the ability to track forest biomass and carbon with the precision and accuracy required by carbon accounting protocols. As mentioned previously, several studies have reported that the inclusion of environmental factors have significantly increased the accuracy of forest inventory measurements and estimates (e.g. wood elasticity; growth models) (Watt *et al.*, 2006; Álvarez *et al.*, 2013). Their results indicate that a constant relationship between diameter and height with other variables cannot be assumed for plantation-grown *P. radiata* growing across an environmental gradient. Given the large variability into the tree structure, the incorporation of the environmental factors reported in this study into the regression equations may also improve the biomass, growth and productivity estimates.

It is well documented that if a strong relationship exists between the forest response variable and remote sensed covariates, then the available covariates could be used as auxiliary data to guide the selection of inventory plot locations and to maximize information gain and hence efficiency (Nelson *et al.*, 2009; Junttila *et al.*, 2013). Therefore, multisource forest inventory methods attempt to determine a relationship between the forest variable of interest (response variable), and the remotely sensed variables (covariates) (Junttila *et al.*, 2013). In such cases, the variability and spatial distribution of the forest variables can be reasonably well estimated using the LiDAR covariates, even in the absence of field sampling (Junttila *et al.*, 2013). Several studies have demonstrated that the LiDAR metrics extracted from the CHM can significantly improve sampling survey efficiencies and ultimately for vegetation structure and biomass assessments (van Aardt *et al.*, 2006; Hawbaker *et al.*, 2009; Junttila *et al.*, 2013). These studies suggest that the use of LiDAR or other remotely sensed data to delineate stratum prior to collection of field data will result in a more efficient collection of field data and produce higher predictive accuracy. However, these studies are mainly based on metrics extracted from CHM and further research is needed to explore whether metrics derived or modeled from LiDAR DEM, such as topography and solar radiation, have any relationship to the forest variables such as biomass or volume. If there is a strong relationship, these parameters can be considered as auxiliary data and be used in plot selection and stratification processes, therefore better results can be achieved with reduced number of field sample plots.

7.6 Recommendations

1) *LiDAR DEM application*

Time and funds are two vital factors in planning inventory operations. For large-area monitoring and characterization, LiDAR can provide a means to measure vegetation structure and estimates in a timely and cost-effective manner. One of the common LiDAR products is the Digital Surface Model (DSM) or the surface of the highest data points, which changes over time and is used with DEM to derive the CHM. The majority of the current forestry studies have focused on the use of the CHM and the direct extraction of forest attributes, such as mean height. However, as the plantation grows and is actively managed, the CHM changes and the data can only be valid for a specific point in time or for a short period; therefore it needs to be routinely updated. Therefore, repeated acquisitions of LiDAR over the same area are required to capture and monitor temporal and spatial differences of the forest canopy. However, repeated acquisition of LiDAR data remains relatively expensive for commercial forestry compared to the camera photogrammetry (White *et al.*, 2013b). Many Australian forest organizations have purchased at least one LiDAR image over their estate (Turner *et al.*, 2011b) but are sometimes hesitant about subsequent acquisitions because of their specific cost. Given the cost of LiDAR data, it would likely be more beneficial to reduce the flying time and acquisition costs by using a single LiDAR mission across a large area of the plantation estate than annual LiDAR operations. A highly detailed, bare earth DEM as a fixed asset, that captures topography, does not change over time and can be used for continued use after the first LiDAR acquisition can be a better option for improving efficiencies in forestry estimations. The DEM can be used to obtain topographical parameters that can be used in forest operations design. An accurate DEM with lower pulse densities can be obtained in less flying time, swath coverage and through higher altitudes (Watt *et al.*, 2013a). This could markedly increase detecting spatial variation in canopy metrics with relatively less costs, without influencing other specifications such as footprint diameter and ability of the laser to penetrate the canopy (Magnusson *et al.*, 2010).

2) *Generating LiDAR-derived models*

Most of the recent studies utilizing LiDAR data as *a priori* auxiliary data have relied mainly on metrics extracted from the CHM; however, this has proved only partially useful for mapping and attributing stems in particular in complex multi-layered forests. Numerous studies have demonstrated the increase in prediction and estimation accuracy of a greater range of forest attributes when applying LiDAR metrics models to predict inventory attributes. For example Chen and Zhu (2012) proposed a site index model in which individual trees were identified and heights were estimated from the CHM using marker-controlled watershed segmentation. Height-Scaled Crown Openness Index (HSCOI) model is another example which relates as a canopy density model and provides a quantitative measure of the relative penetration of LiDAR pulses into the canopy and can delineate tree crowns (Lee and Lucas, 2007). Watt *et al*. (2013b) constructed models from LiDAR metrics, stand age and stand density which characterized spatial variation in tree characteristics allowing stratification of within-stand thinning operations. Their LiDAR-derived models appeared to be quite robust and were able to predict mean height, basal area, stem volume and mean diameter with a high degree of precision. These examples show the wide range of modeling techniques that can be used by companies with their LiDAR data.

3) *The use of topography as a suitable explicit attribute in forestry inventories*

In this study, topography, derived from LiDAR DEM, showed substantial differences of height and DBH within and between sample plots and therefore, to improve sampling designs, topography is suggested as a suitable variable for defining strata within compartments. For this aim, after creating LiDAR-derived DEM, the area should be stratified based on the topography factors, so the forest can be classified initially by aspect classes and further by slope classes depending on the aspect and slope ranges in the area. In our case, the forests could have been classified into six categories: two aspect classes, northerly and southerly, and three slope classes, 0°-10°, 10°-20° and >20°. To represent the sample area, from each of these categories, equal number of plots should be established. It should be ensured that the plots are allocated to the equal proportion of the whole population, so for instance if 50% of the forest is located in one category, 50% of the plots should be measured from that category. This method will reasonably explain the variability and the spatial distribution of the area, resulting in an accurate forestry estimate. It will also improve the sampling design while minimizing the number of forest inventory plots and maximizing predictive performance and minimizing bias.

The use of topography can also improve the efficiencies of height/DBH-derived inventory attributes. Our study showed the variation in radiata tree DBH to be associated with variation of different topography classes. Creating a continuous DBH surface in the study area, might improve the inventory estimates. If after measuring the DBHs of the selected trees of the plots, the exact locations of the trees were identified with GPS; with the interpolation technique, a continuous DBH surface could be created in GIS. Based on the common equation used in the area (usually single variable DBH equation), biomass can be calculated for each of the trees and the average biomass value calculated for the entire forest. This method could allow more accurate biomass/volume predictions, as it covers most of the area and captures the variations within the forest stand.

Although the responses of height and diameter of *P. radiata* to topographical variables could determine the importance of this factor; further studies need to be undertaken to evaluate the influence of including slope and aspect on biomass models, as we were unable to obtain raw biomass data due to funding limitations. It should also be noted that this study focused on the Hanging Rock State Forest region, which is located in a hilly topography, nevertheless for plantations that grow on relatively flat sites with little topography, topography will not be considered a suitable stratification factor. Further studies from different locations are needed to validate the results of this research.

Appendix

Appendix 4.1: The mean (standard error) DBH of height classes at both sites.

Height (m)	North: Tree samples	North: Mean DBH (cm)	North: Standard error	South: Tree samples	South: Mean DBH (cm)	South: Standard error	>20°: Tree samples	>20°: Mean DBH (cm)	>20°: Standard error	<20°: Tree samples	<20°: Mean DBH (cm)	<20°: Standard error
1977 site												
≤31.5	15	53.61	2.10	1	56.50	-	11	53.31	2.83	5	54.86	1.47
31.6-32.5	6	54.95	3.09	3	63.67	2.28	3	63.67	2.28	6	54.95	3.09
32.6-33.5	18	53.83	1.40	3	54.73	4.24	7	55.94	2.47	13	53.03	1.62
33.6-34.5	21	57.13	2.14	7	66.64	7.50	11	64.86	5.66	17	56.05	1.62
34.6-35.5	14	52.09	2.77	9	66.17	2.59	10	62.83	3.31	14	53.46	2.86
35.6-36.5	5	59.82	1.79	16	63.70	2.75	4	69.85	5.71	17	61.11	2.28
36.6-37.5	10	61.65	3.71	18	64.93	1.78	3	70.02	10.40	25	62.99	1.57
37.6-38.5	7	56.16	2.64	15	60.89	1.46	5	57.12	4.28	17	60.05	1.28
≥38.5	4	65.7	7.01	21	64.61	1.64	6	71.95	2.38	19	62.52	1.83
2002 site												
≤ 8.5	19	22.37	0.86	3	22.73	2.69	19	22.58	0.75	3	21.4	4.07
8.51-9.5	28	20.66	1.01	2	27.5	0.60	27	20.38	1.01	3	27.7	0.71
9.51-10.0	43	21.70	0.58	3	23.03	1.42	41	21.89	0.60	5	21.04	1.09
10.01-10.5	15	23.85	1.15	22	25.62	1.00	24	24.19	0.95	13	26.21	1.46
10.51-11.5	17	23.89	1.10	22	21.87	0.97	24	22.62	0.79	15	22.96	1.43
11.51-12.0	19	24.55	1.06	27	23.83	0.79	29	24.35	0.79	17	23.75	1.07
12.01-12.5	3	28.83	2.64	16	24.42	0.85	12	24.88	1.19	7	25.53	1.33
≥12.51	3	25.23	2.12	12	24.43	0.98	8	23.85	0.71	7	25.43	1.67

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