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Deriving metrics of vertical structure at the plot level for use in regional characterisation of S.E. Australian forests

Phil Wilkes[*a], Simon Jones[a], Lola Suarez[a], Andrew Haywood[b], Mariela Soto-Berelov[a], Andrew Mellor[ab], Christoffer Axelsson[a] and Will Woodgate[a]

Efficient characterisation of forest structure is integral to regional scale biomass and carbon stock estimation, habitat management and forest condition assessment. Key descriptors or data primitives of forest structure, such as Canopy Height (CH) and Canopy Height Profile (CHP) can be used to model indirectly measurable characteristics. Existing methods that utilise Light Detection and Ranging (LiDAR) data to estimate dominant CH and CHP are utilised at a field site in S.E. Australia. Techniques to estimate CH and CHP in the field are also presented using data from three field sites representative of sclerophyll forest in S.E. Australia. The use of different point-cloud components (e.g. first returns, first-and-last returns etc.) has little effect on either derived CH or CHP parameters. On the contrary, choice of method has a significant impact on estimates of dominant height (inter-technique range >4 m). Localised and regional structural variability can also be determined from traditional field inventory. Finally, suggestions of future research directions are presented including utilising different point cloud components; fitting multi-modal distribution function to vertical profiles; landscape scale measurements of CH and CHP; and incorporation of landscape estimates in regional modelling.

Keywords: LiDAR, canopy height, canopy height profile, forest inventory, regional assessment

[a] School of Mathematics and Geospatial Science, RMIT University, GPO Box 2476, Melbourne, VIC 3001

[b] Victorian Department of Sustainability and Environment, PO Box 500, East Melbourne, VIC 3002

* Corresponding author (phil.wilkes@rmit.edu.au)

Phil Wilkes has a background in remote sensing, GIS and environmental chemistry. After completing an undergraduate degree in Environmental Science at the University of Plymouth, Phil trained as an arborist before returning to science as an air quality consultant. Having found an interest in spatial science, he studied a Masters degree at Kings College London in 2009. Since then he has worked for the Marine Biological Society and the Victorian Department of Sustainability and Environment and is currently studying for a PhD at RMIT. Phil's research interests include application of remote sensing to forest assessment, forest carbon dynamics and the use of open source software in spatial sciences.

1. Introduction

Descriptors of forest structure and function are inputs to empirical and physical modelling of forest health, condition and characterisation, therefore descriptors can also be described as data primitives. Examples of data primitives are Canopy Height (CH) and Canopy Height Profile (CHP), canopy coverage and chlorophyll concentration. For a regional assessment data primitives are required to be scale independent, transferable (e.g. not bespoke), applicable to different forest types and multi-use in regard to modelling indirectly measureable forest characteristics (e.g. biomass, forest extent, canopy health etc.).

CH and CHP are elemental descriptors of vertical forest structure and function (Means *et al.* 1999) and are of high importance to Australian land managers (Axelsson *et al.* 2012); for this reason they are the focus of this paper. These key data primitives are the building blocks for biomass and carbon volume estimation (Asner *et al.* 2010; Hudak *et al.* 2012; Hurtt *et al.* 2004; Garcia *et al.* 2010), forest management and timber production (Næsset 1997; Stone and Turner 2008), habitat mapping (Goetz *et al.* 2007) and land cover assessment (Mellor *et al.* 2012). CH is also listed as essential climate variables by the World Meteorological Organisation (WMO), for example to infer biomass from forest height (WMO 2006).

Australian forests present unique challenges with regard to the collection and interpretation of data primitives. Access to remote forest sites is often difficult, time consuming and expensive (Tickle *et al.* 2006). The unique biophysical characteristics of S.E. Australian forests such as erectophile leaf angle distribution (Anderson 1981), leaf "clumpiness" and heterogeneous forest type could present particular challenges with regard to remote sensing of structure. Additionally, remote sensing techniques have been developed in northern hemisphere deciduous broadleaf or evergreen needleleaf forests and their application to S.E. Australia may not be appropriate.

This research seeks to compare methodologies previously used to estimate CH and CHP in Australian sclerophyll forests and eucalypt forests worldwide. Methods are tested using different components of the Light Detection and Ranging (LiDAR) point cloud as a data reduction paradigm. Decomposed waveform LiDAR data is utilised as an analogue for discrete return LiDAR, the latter more commonly used for large-area operational campaigns. Methodologies to measure CH and CHP in the field are also presented and discussed.

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1.1. Canopy height derivation

Tree height is defined as the vertical height from the ground to the top of the live crown (Zimble *et al.* 2003). CH is the arithmetic mean height of all or a subset of tree height within a plot (Næsset 1997) and is either reported as a categorical (Mellor *et al.* 2012) or continuous variable (e.g. Hudak *et al.* 2002). CH is scale independent, reported at the plot (Lovell *et al.* 2003; Means *et al.* 1999; Tesfamichael *et al.* 2010), stand (Næsset 1997), regional (Hudak *et al.* 2002) and global scale (Simard *et al.* 2011; Lefsky 2010). At extents beyond a plot, CH is often represented as a 3-dimensional Canopy Height surface Model (CHM). A term synonymous with mean CH is dominant height, defined as the mean height of all trees that are not overtopped and whose crowns are not shaded by adjacent trees (Lefsky *et al.* 1999a). Estimates of CH that weight taller trees are also reported, for example "Lorey's height" (h_{L}) [1] weights trees on their basal area (Næsset 1997; Lim *et al.* 2003):

$$h_{\mathrm{L}} = \frac{\sum_{i=1}^{n} h_i\, a_i}{a} \qquad [1]$$

where h_i and a_i are the height and basal area of individual tress. Dominant height (Lovell *et al.* 2003; Næsset 2004; Tesfamichael *et al.* 2010) and Lorey's height (Næsset 1997) are commonly presented in remote sensing derived estimates of CH. CH is measured in the field by a trained operator using a clinometer, electronic total station or a hypsometer (Hollaus *et al.* 2006) to measure angle and distance from the bottom to the live top of individual trees (Zimble *et al.* 2003). Methodologies that use a terrestrial laser scanner to estimate height have also been presented (e.g. Jupp *et al.* 2008).

Aerial photo interpretation has been applied successfully to stratify landscapes into categorical CH (Mellor *et al.* 2012) as well as aerial photography derived point clouds (Bohlin *et al.* 2012). Donoghue and Watt (2006) compared CH derived from Landsat ETM+ and Ikonos noting that the higher spatial resolution of the latter did not improve estimates. The intrinsic limitations of passive optical remote sensing with regard to the direct measurement of CH include the inability to penetrate the canopy and to distinguish surface topography (Ni-meister *et al.* 2001).

Conversely LiDAR derived CH at the plot scale is widely regarded as a more accurate method when compared with other techniques (Næsset and Økland 2002; Tickle *et al.* 2006). LiDAR is a laser ranging technique where distance to an object is measured as half the time between a laser pulse being emitted and received at a sensor which produces a three-dimensional, georeferenced point-cloud (Baltsavias 1999). CH is estimated using both discrete return (Lovell *et al.* 2003; Næsset 1997, 2004; Næsset and Bjerknes 2001; Garcia *et al.* 2010; Zhao *et al.* 2011) and waveform LiDAR (Means et al. 1999; Lefsky *et al.* 1999a; Drake et al. 2002). Discrete return LiDAR is more commonly utilised for regional assessment due to the large swath width of scanning systems, capability of georegistering data with field plots and commercial availability of sensors (Wulder 2012). For discrete return sensors, CH can be inferred as the vertical distance between a ground surface model (e.g. DTM) to a top-of-canopy metric, for example maximum return height (Næsset 1997) or 99$^{\mathrm{th}}$ percentile (Jenkins 2012). LiDAR derived canopy surface models are subtracted from a DTM to produce a CHM. Lovell *et al.* (2003) derived CH from a 1 m CHM as the arithmetic mean of localised (e.g. 1 canopy width) maxima. LiDAR can underestimate height (Lim *et al.* 2003; Hyyppä *et al.* 2008; Lovell *et al.* 2003) and therefore LiDAR derived height metrics are often used to empirically model CH (Næsset and Bjerknes 2001).

CH at the landscape level and beyond can either be measured using wall-to-wall LiDAR or modelled using parametric or non-parametric techniques. For example Musk *et al.* (2012) captured LiDAR for 24,000 ha in Tasmania. Field data was used to calibrate LiDAR "plot" data which was in turn used as training data in a random forest machine learning algorithm to estimate CH for the entire study area. Hudak et al. (2002) used plot scale LiDAR derived CH with Landsat TM, a number of statistical techniques were tested including regression, kriging, co-kriging and co-kriging of regression residulas. Lee *et al.* (2009) present a method for estimating CH across continental Australia using the Geoscience Laser Altimeter System (GLAS) on board the NASA Ice, Cloud, and Land Elevation Satellite (ICESat). Similar approaches that utilise GLAS have been presented to estimate CH at a global scale (Simard *et al.* 2011; Lefsky 2010).

1.2. Canopy height profile

Canopy height profile can be defined as the structural organisation of phytoelements (i.e. stems, branches, leaves etc.) from the forest floor to the top of the canopy (Lovell *et al.* 2003; Brokaw and Lent 1999). CHP can be described as a function of gap probability vertically through the canopy [2];

$$\mathrm{CHP_c}(h) = -\ln(1 - \mathrm{cover}(h)) \qquad [2]$$

where $\mathrm{CHP_c}(h)$ is plant area index expressed as a fraction of projected ground area above height h, and *cover(h)* is the fraction of sky obscured by phytoelements above h (MacArthur and Horn 1969, Lefsky *et al.* 1999a). Terms synonymous with CHP are differentiate by element measured, derivation technique or metric reported. For example foliage height profile refers to the distribution of leaves (MacArthur and Horn 1969) whereas CHP refers to the distribution of all phytoelements (Lefsky *et al*

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1999b); "apparent" and "actual" foliage density profiles relate to inability of LiDAR to resolve the actual profile; Zhao *et al.* (2009) present two different metrics of vertical structure, namely canopy height distributions and canopy height quantiles. For this study CHP is the most appropriate definition.

Measurement of CHP at the plot has been achieved using a number of techniques including the use of occular vertical transect diagrams and measurement of vertical light profiles (Means *et al.* 1999), however the mostly widely utilised method is that of MacArthur and Horn (1969) and Aber (1979). A calibrated telephoto lens is used to estimate the distance to phytoelement interception across an optical point grid (OPG), heights are transformed to account for occlusion and aggregated to form a vertical profile (Parker *et al.* 2004). As with estimates of CH, field measured CHP is time consuming and expensive (Means *et al.* 1999).

LiDAR derived estimates of CHP has also been widely described in the literature. As with CH derivation, both discrete (Lovell *et al* 2003; Riaño *et al.* 2003; Jaskierniak *et al.* 2011; Coops *et al.* 2007) and waveform (Lefsky *et al* 1999a, 1999b; Means *et al* 1999; Drake *et al* 2002) LiDAR have been utilised to estimate CHP. Again discrete return LIDAR is suited to continuous regional assessment (Wulder 2012). Using discrete return LiDAR, the probability of a gap from the top of the canopy to a given height (z) is calculated as a proportion of the total number of LiDAR pulses [3];

$$P_{gap}(\mathrm{z}) = \frac{(\#z_j|z_j > z)}{N} \qquad [3]$$

Where $\#z_j$ is the number of returns above *z* zand *N* is the total number of laser pulses. The cumulative projected foliage area index is then calculated by a modified exponential transformation (Aber 1979) of 1-P_{gap}(z) [4];

$$L(z) = -\log\left(P_{gap}(\mathrm{z})\right) \qquad [4]$$

where the derivative of *L*(z) is the CHP (Lovell *et al.* 2003). To stabilise *L*(z) a distribution function can then be fitted, for example a Weibull function [5] where *H* is maximum canopy height and α and β are fitted parameters (Lovell *et al.* 2003; Jaskierniak *et al.* 2011; Coops *et al.* 2007). Coops *et al.* (2007) fitted Weibull distributions to canopy profiles derived from OPG, inventories and LiDAR data; they noted a good agreement between Weibull parameters (α and β) and mid crown depth as a ratio of total height and crown length respectively.

$$L(z) = 1 - \left[e^{-\left(\frac{1-P_{gap}(z)/H}{\alpha}\right)^{\beta}}\right] \qquad [5]$$

Jaskierniak *et al.* (2011) fitted bimodal distributions to multi-strata forests experimenting with combinations of different functions e.g. Weibull, Gumbel, Inverse Gaussian, the authors noted that in some cases multi-modal distributions are required. An alternative to fitted distribution functions is presented by Zhang *et al.* (2011) who stratify canopy profiles using a *k*-means clustering algorithm.

CHP at scales beyond the plot has been achieved using LiDAR. For example Means *et al.* (1999) used a waveform system with an across track width of 50 m and footprint diameter of 10 m to characterise a coniferous forest. Riaño *et al.* (2003) derived CHP using discrete return LiDAR along a 2 km transect, the authors simulated full-waveform footprints so as to apply a modified log transformation.

2. Methodology

2.1. Study area

Three sites, each representative of a S.E. Australian major forest type have been selected in Victoria, Australia. These are a wet sclerophyll forest (384000, 5827800), box iron bark (318400, 5930600) and mixed species dry sclerophyll (618400, 5851700), all site centres are given in the projected MGA Zone 55 coordinate system. Each 5 km^2 site is chosen so to have not been subject to recent natural or anthropogenic disturbance and located on public land.

2.2. Field data

A total of twenty seven 0.1 ha permanent forest inventory plots are installed across the three sites, plots were established in the summer/autumn 2011-12 following the Victorian Department of Sustainability and Environment (DSE) protocol (DSE, 2012). At each plot tree height was measured for a subsample of individuals with a diameter at breast height (dbh) >10 cm, the subsample consisted of the three tallest trees and a maximum of 5 others covering the range of observed dbh (DSE 2012). Height was estimated using a TruPulse 200B (Laser Technology, Colorado, USA) measuring from the base of the tree to the top of the live

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crown (DSE, 2012). CH was estimated as (1) the arithmetic mean of all trees with a dbh >10 cm (2) dbh weighted mean height (modified Lorey's height [1]) and (3) mean height of the three tallest trees ("predominant height"; Lovell *et al.* 2003).

A modified version of the Aber (1979) methodology was used to estimate vertical canopy structure. A 50 x 50 m grid was established around the plot centre and observations were taken every 2 m in the *x* and *y* direction across the grid. At each observation a staff with a densitometer (GSR, California, USA) mounted at ~1.7 m was used to record crown gaps (within or outside crown) or an interception of a phytoelemnt (i.e. leaf, branch, and stem). If an interception was observed then height to interception was estimated using the TruPulse 200B. Additionally, the height of understorey vegetation (>0.2 m) was recorded along with ground cover type (<0.2 m).

2.3. LiDAR data

Specifications for the LiDAR data acquisition are provided in Table 1. The Riegl LMS-Q560 is a waveform recoding instrument; waveforms have been decomposed to represent discrete return LiDAR data using a Gaussian Pulse Fitting method (Riegl 2006). Data is not yet available for the three sites, analysis methods are demonstrated utilising data from a similar acquisition at Tumbarumba State Forest (TERN 2010). A 30 x 30 m point cloud subsample (approximate to a Landsat pixel) has been extracted where each return (point) is attributed with a global coordinate (*xyz*), return intensity (*i*) and classification of reflecting surface (Table 1). As *z* values are imputed relative to sea level, calculation of height values for non-ground returns relative to ground requires the creation of a DTM. For this a triangulated irregular network (TIN) surface is created using all points classified as ground, from which the vertical height of non-ground points is calculated. All .LAS file manipulation is done using LASTools v.120913 (Isenburg 2012) and statistical analysis is carried out with Matlab R2008b (MathWorks Inc., Natick, MA).

When generating height statistics from LiDAR previous authors have imposed a threshold below which all returns are discarded. This has been done for reasons including; to ensure that only the canopy is analysed (Næsset 2002), to fit descriptive bimodal models (Jaskierniak *et al.* 2011) or to avoid noise from misclassified ground returns (García *et al.* 2010). As the aim of this research is to analyse the complete vertical profile a threshold of 0.3 m has been utilised after García *et al.* (2010).

2.4. Derivation of LiDAR canopy height

To compare CH estimate techniques the commonly reported dominant height metric is used. The implication of utilising different point cloud components is tested where returns classified as vegetation are divided into first returns only (Lovell *et al.* 2003), first-and-last returns only (Næsset and Bjerknes 2001) and all returns (Jaskierniak *et al.* 2011). Point-cloud components are analysed using three techniques; maximum return height (Næsset 1997), 99th percentile (Jenkins 2012), arithmetic mean of returns ≥80 percentile (Tesfamichael *et al.* 2010) and "predominant height" (Lovell *et al.* 2003). Predominant height is estimated from a 1 m CHM of maximum return height, the CHM is divided into areas equal to crown width (~10 m) and the mean of local maxima is equal to predominant height. All except the maximum return height have been previously used to estimate dominant height in Australian sclerophyll or Eucalyptus forests worldwide.

Table 1. Flight and sensor specifications for the LiDAR acquisition at three forested sites in Victoria.

Specifications	
Date	15/4 - 18/4/2012
Instrument	Riegl LMS-Q560 laser scanner (Horn, Austria)
Flying height	<600 m
Point density (50% overlap of flight lines)	>20 points m^{-2}
Mean footprint diameter	<30 cm
Max off-nadir angle	22.5°
Absolute vertical accuracy	±20 cm
Absolute horizontal accuracy	±30 cm
Classification	Unclassified, ground, low vegetation (0 – 0.3 m), medium vegetation (0.3 – 2.0 m) and high vegetation (>2 m)
File format	LAS 1.2

2.1. Derivation of LiDAR canopy height profile

A probability distribution of return height (*z*) is generated for the sample plot using a 0.3 m bin size using first returns and all returns. Probability distribution are analogous with CHP (Ni-meister *et al.* 2001). Distribution functions have been applied to CHP with respect to canopy gaps and provide a summary of vertical form (Coops *et al.* 2007; Lovell *et al.* 2003). A Weibull distribution [5] is fitted to the example data to stabilise response and derive distribution α and β parameters (Coops *et al.* 2007).

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3. Results and Discussion

3.1. Field data metrics of height and vertical structure

CH (Table 2) and geographic distribution of the principal species found at the three sites are in accord with the literature (Costermans 2009). Variation in estimated CH calculated with three different techniques is observed, particularly for the wet sclerophyll forest. This and the large standard deviation for mean height would suggest a multilayered canopy (Zimble *et al.* 2003).

Table 2. Forest inventory data across three sites (27 plots) in Victoria, Australia. Mean height is the arithmetic mean (and standard deviation) of all measured trees, h_L is a modified Lorey's mean height and dominant height is the arithmetic mean of three tallest trees per plot.

Site	Dominant species by count (common name in parentheses)	Canopy height (m)		
		Mean (std dev)	h_L	Dominant
Wet sclerophyll forest	*Northofagus cunninghamii* (u.) (Myrtle Beech) *Acacia melanoxylon* (u.) (Australian Blackwood) *E. Reganan* (c.) (Mountain Ash)	21.9 (21.29)	42.6	47.7
Box iron bark	*E. tricarpa* (Red Ironbark) *E .polyanthemos* (Red Box) *E. macrorhyncha* (Red Stringybark)	11.6 (3.45)	13.2	16.9
Mixed species dry sclerophyll	*E. macrorhyncha* (Red Stringybark) *E. consideniana* (Yertchuk) *E. croajingalensis* (East Gippsland Peppermint)	13.6 (5.74)	16.4	22.3

Vertical profiles were derived at four sites in a Box Iron Bark forest (Figure 1A) using a modified Aber (1979) technique. At three locations (Plots 1, 8, and 9) structure is characterised by a dominant canopy base mean height of 8 – 12 m with a less dense understorey at <2 m. Plot 3 is characterised by a dense vegetation strata of <2 m with sparse vegetation between 2 – 10 m. This study highlights the high variation of structural composition over a limited geographical extent, for example plot 9 and 3 (Figure 1B and C respectively) are <2 km apart. It is suggested that post-LiDAR stratification for inventory plot location is considered to ensure capture of structural compositions range (Maltamo *et al.* 2010).

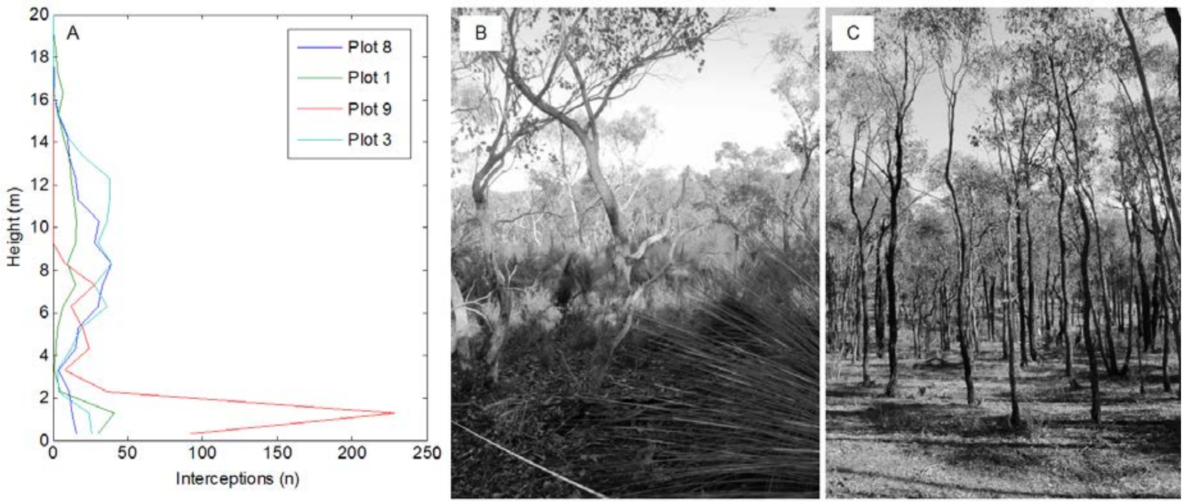

Figure 1. Characterising vertical profile of four plots in a Box Iron Bark forest, (A) profiles derived using a modified Aber (1979) methodology; (B) Plot 9, characterised by absence of a tall canopy and dense understorey; and (C) Plot 3, characterised by a tall single layered canopy.

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3.2. LiDAR derived metrics

LiDAR processing and return classification is often carried out by the data provider using propriety 'black box' software that may conceal error in derived products. Misclassified ground returns, particularly in high biomass forests have been noted (Evans and Hudak 2007) and may cause errors in a derived DEM that could propagate to subsequent height estimations. There are now however a number of "open source" solutions (LASTools and SPDlib for example) that allow researchers more control over analysis. LiDAR datasets may also require "cleaning up" before further analysis (Jaskierniak *et al.* 2011), this is illustrated in the example data (Figure 2) where overlapping flight lines have resulted in an uneven point density.

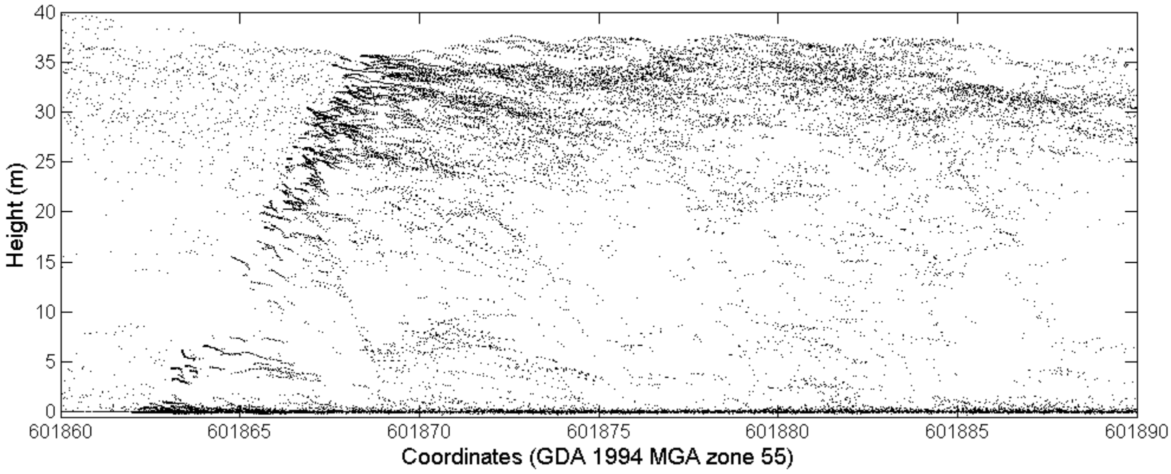

Figure 2. Point cloud derived from all returns for a 30 x 30 m example plot at Tumbarumba (TERN, 2010). The ground and a dominant canopy layer between 25 - 35 m are clearly visible as well as an uneven point density caused by overlapping flight lines.

3.2.1. Canopy height

Estimates of predominant height estimated using different techniques and point-cloud components are presented in Table 3. It is clear that the range in estimated dominant height between methods is greater than between point cloud component (Table 3). As can be seen in Table 3, using the first return component only derives similar estimates of height when compared with using first-and-last and all returns. Utilising the first return component only reduces data volume by 37%; this would decrease computation time particularly when considering regional LiDAR campaigns. A laser pulse may not interact with the apex of a tree crown (Hyyppä *et al.* 2008) penetrating deeper into the canopy and therefore underestimating dominant height, this is important when considering techniques for application in Eucalypt forests where canopy density can be low (Lee and Lucas 2007).

Table 3. Dominant height estimated using different techniques and point cloud components for the example plot, Tumbarumba (TERN, 2010).

Point cloud component	Height (m)				**Between method range (m)**
	mean of highest 80%	"predominant"	99^{th} percentile	max	
First	35.8	37.1	37.3	39.7	**3.9**
First-and-last	35.5	37.1	37.3	39.7	**4.2**
All	35.2	37.1	37.2	39.7	**4.5**
Between component range (m)	**0.6**	**0**	**0.1**	**0**	

3.2.2. Vertical structure

A CHP (Figure 3) suggests a single dominant canopy at ~30 m with a less prominent understorey at <10 m. Four Weibull distributions are fitted to the vertical profile for first and all returns with thresholds >0.3 m and >20 m (i.e. all vegetation strata and upper canopy respectively). This illustrates the need for selecting the correct distribution function dependent on forest structure and LiDAR component used, for example, the function for first returns >20 m is a much better fit than that fitted to all

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returns >0.3 m. Although the Weibull functions have been widely used to describe forest canopies (Wulder *et al.* 2008), they tend to be applied to single layered forests or to a single strata e.g. upper canopy (Lovell *et al.* 2003; Coops *et al.* 2007). Even with a relatively sparse understorey a multi-modal distribution would be a better descriptor of CHP (Jaskierniak *et al.* 2011), this would also assist with identification of multilayered forests. Selection of appropriate alternative distribution functions or a combination is therefore necessary (Jaskierniak *et al.* 2011). Utilising *n*-of-many return LiDAR provides a more detailed description of internal structural complexity as a laser pulse is more likely to penetrate deeper into the canopy, again a single Weibull distribution may not always be an appropriate function.

With regard to modelling CHP over large spatial extents, the extraction of distribution parameters reduces data volumes for further analysis. Function parameters have also correlated well forest inventory variables, for example Coops *et al.* (2007) found good agreement with α and crown position and β with mean dbh, crown length and stem density. For the example plot, the α parameter for upper canopy first (30.8 m) and all (29.3 m) returns and first returns >0.3 (29.4 m) was in good agreement with mean CH (29.9 m).

4. Conclusion

The aim of this paper was to present a methodology to derive forest structure data primitives at the plot level using LiDAR and forest inventory data. Techniques described could be suitable for inclusion in a multi-scale regional assessment. Preliminary results suggest using field techniques can distinguish structural variability at local and regional scales. Augmentation of field inventory with remote sensing is an important consideration owing to the relative low cost when compared to field campaigns. LiDAR derived parameters of CH and CHP show applicability in Australian forests and data reduction techniques proved successful. Derivation method has a significant effect on dominant height estimation; however a comparison with field derived height is necessary to determine appropriate method. On the contrary, point cloud component utilised to derive statistics of CH and CHP (i.e. Weilbull α parameter) seems to be of less importance.

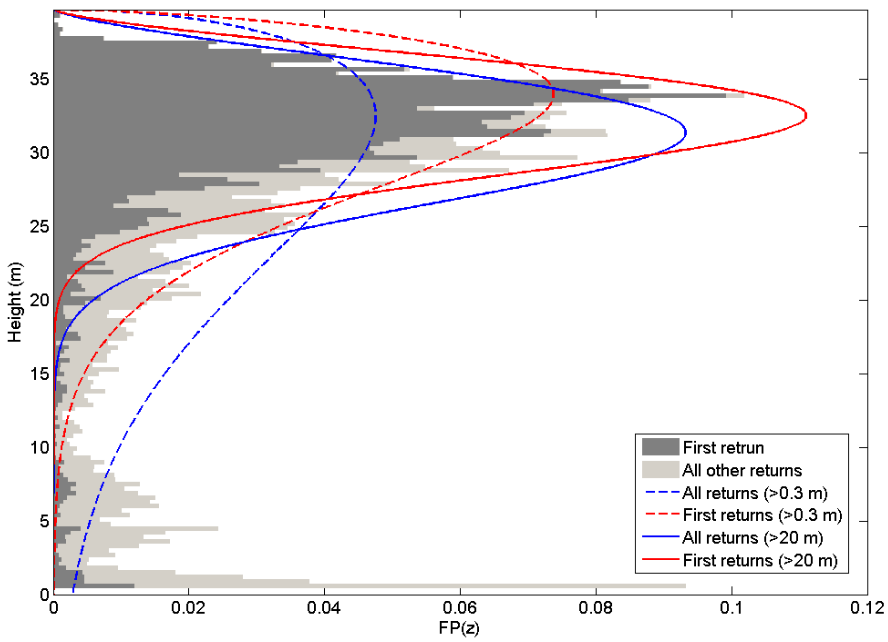

Figure 3. Probability distribution for first and all returns representative of CHP for sample plot, Tumbarumba (TERN, 2010). Weibull distributions for first returns (red) and all returns (blue) using canopy thresholds of 0.3 m (dashed) and 20 m (solid) are also displayed.

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5. Future direction

The question of whether data primitives are useful to model forest structure at regional scales as part of a multi-scale framework is yet to be answered. The future direction of this research will therefore address the themes outlined below;

- **Comparison of different LiDAR point-cloud components, point densities and "plot" size when modelling CH and CHP.** The computation of continuous raster layers of vertical structure metrics, such as dominant height and distribution function parameters, are required for further regional scale analysis. The large data volumes required to derive these metrics at regional scales may be computationally limiting. Therefore the robustness of point-cloud data to accurately measure vertical structure after data reduction techniques will be tested in a variety of forest types.
- **Efficient and robust statistical description of CHPs across heterogeneous forest types.** Previous research has highlighted the requirement of multi-modal distribution functions to accurately describe vertical of multi strata forests (Jaskierniak *et al.* 2011; Coops *et al.*2007). Techniques will be developed to efficiently describe vertical profile derived in different forest types using, for example, distribution functions or clustering methods (Riaño *et al.* 2003, Zhang *et al.* 2012). Derived parameters will then be tested for their ability to accurately represent vertical structure.
- **Derivation of landscape scale estimates of vertical structure**. LiDAR derived metrics calibrated using field plot data will be scaled to the landscape level across LiDAR transects. This will be achieved using empirical modelling techniques such as regression. Attention will be focused on sample design including location and number of field plots and resolution of LiDAR sample unit size i.e. modifiable area unit problem (Jelinski and Wu 1996).
- **Derivation of regional scale estimates of vertical structure.** Landscape scale derived vertical data primitives will be up-scaled to the regional extent in combination with a satellite remote sensing product e.g. ICESat (Lee et al. 2008; Simard et al. 2010) or Landsat ETM+ (Hudak *et al.* 2002). Suggested techniques include the use of a machine learning algorithm such as random forest (Breiman 2001) where subsets of LiDAR transects are used as training data. Sample design will again be a focus where, for example, number and total area of LiDAR transects required is tested.

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