LIDAR REMOTE SENSING OF STRUCTURAL PROPERTIES OF SUBTROPICAL RAINFOREST AND EUCALYPT FOREST IN COMPLEX TERRAIN IN NORTH-EASTERN AUSTRALIA

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EDIRIWEERA S, PATHIRANA S, DANAHER T & NICHOLS D. 2014. LiDAR remote sensing of structural properties of subtropical rainforest and eucalypt forest in complex terrain in north-eastern Australia. LiDAR remote sensing can be considered a key instrument for studies related to quantifying the vegetation structure. We utilised LiDAR metrics to estimate plot-scale structural parameters of subtropical rainforest and eucalypt-dominated open forest in topographically dissected landscape in north-eastern Australia. This study is considered an extreme application of LiDAR technology for structurally complex subtropical forests in complex terrain. A total of 31 LiDAR metrics of vegetation functional parameters were examined. Multiple linear regression models were able to explain 62% of the variability associated with basal area, 66% for mean diameter at breast height, 61% for dominant height and 60% for foliage projective cover in subtropical rainforest. In contrast, mean height (adjusted r^2 = 0.90) and dominant height (adjusted r^2 = 0.81) were predicted with highest accuracy in the eucalypt-dominated open canopy forest. Nevertheless, the magnitude of error for predicting structural parameters of vegetation was much higher in subtropical rainforest than those documented in the literature. Our findings reinforce that obtaining accurate LiDAR estimates of vegetation structure is a function of the complexity of horizontal and vertical structural diversity of vegetation.

Keywords: Vegetation structure, hilly terrain, horizontal and vertical structural diversity

INTRODUCTION

Light Detection and Ranging (LiDAR) is an active remote sensing technique to assess vegetation due to its ability to retrieve detailed three-dimensional profiles of vegetation structure (Lefsky et al. 1999). LiDAR systems utilise laser pulses to scan and sample objects on or above the surface of the earth. The data consist of a set of laser returns (points) that are accurately and precisely georeferenced in three dimensions (Baltsavias 1999). Continued technical advances of LiDAR and its decreasing cost have resulted in increased use of this technology for forestry and ecological studies (Gatziolis et al. 2010).

The extraction of estimates of structural components of vegetation (e.g. height, average stem density, aboveground biomass) using LiDAR data is often based on LiDAR metrics or statistical measures from the distribution of laser data points. These LiDAR metrics include maximum heights, mean heights, height percentiles, standard deviations of the canopy height and proportions of laser penetration through the canopy, which are extracted either from raw laser points or interpolated grid corresponding to a canopy height model. Several studies have employed LiDAR metrics in conjunction with regression equations to estimate plot-scale tree height, basal area, stem density, timber volume, crown length and stem diameter.

To date, most evaluation of LiDAR for characterising vegetation structure has been carried out with relatively simple structures of vegetation and flat terrain in plantations and coniferous or temperate forests (Næsset 2002, Næsset & Okland 2002, Jensen et al. 2006, Heurich & Thoma 2008). These conditions generally facilitate precise characterisation of the biophysical attributes of vegetation structure

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using LiDAR. However, the complexity of vegetation structure and dissected topography in most subtropical and tropical forested area does not allow for precise characterisation of vegetation structure using discrete return LiDAR. Despite numerous publications on structural assessment of vegetation using small footprint LiDAR, there are few studies relating to the application of LiDAR for characterising vegetation structure with multiple layered, closed canopy subtropical rainforests in dissected topography (Zhang et al. 2011) in Australia. Therefore, the main objective of our study was to evaluate the use of different discrete-return LiDAR metrics for estimating plot-scale structural parameters including mean tree height, dominant tree height, mean diameter at breast height (dbh), dominant dbh, mean basal area, foliage projective cover and stem density of closed canopy subtropical rainforest and open canopy eucalypt-dominated forest.

MATERIALS AND METHODS

Study area

Two study areas were selected in north-eastern New South Wales (NSW), Australia (Figure 1) including the Richmond Range National Park (RRNP) (28.69° S, 152.72° E) and the Border Ranges National Park (BRNP) (28.36° S, 152.86° E). The elevation of RRNP study area

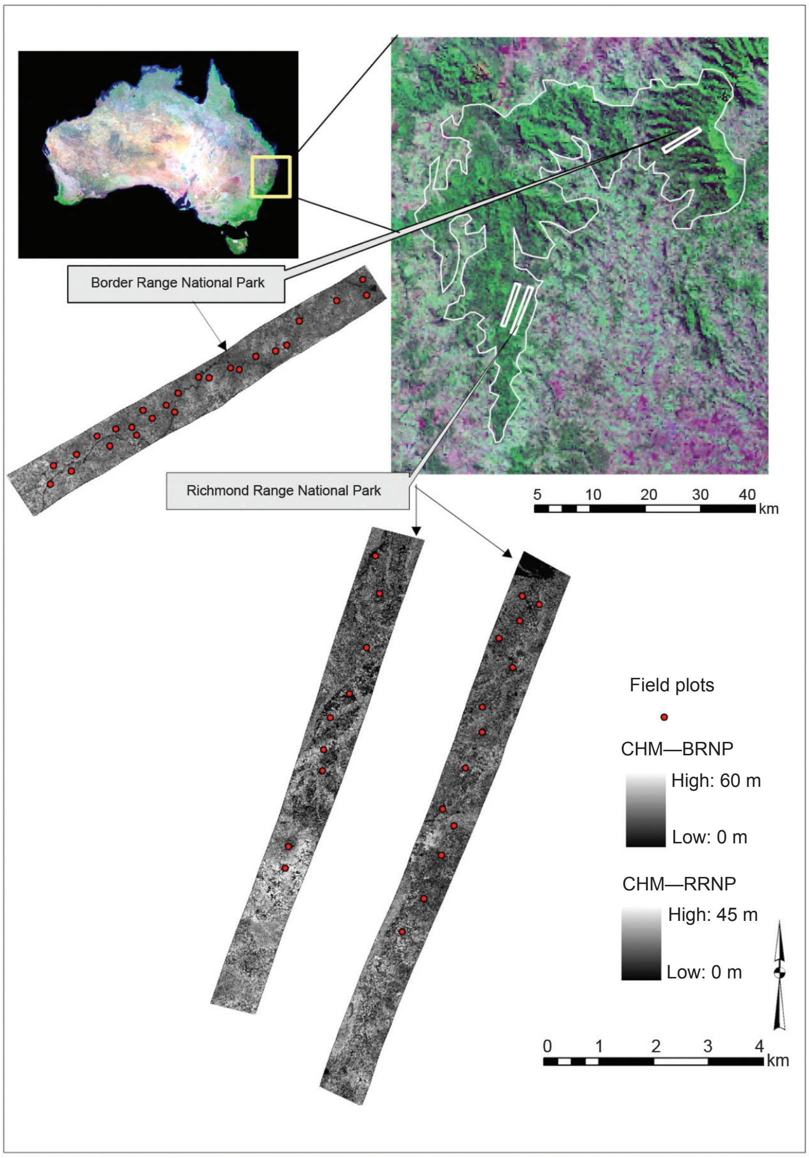

Figure 1 Location map of Border Range National Park (BRNP) and Richmond Range National Park (RRNP) plots and LiDAR acquisition areas, New South Wales; CHM = canopy height model

ranges from 150 to 750 m above mean sea level with an average slope of 27°. Annual rainfall is approximately 1200 mm and the average temperature ranges in winter and summer are 12–21 and 25–31 °C respectively (Anonymous 2010). The RRNP is an open canopy eucalypt-dominated forest with 30–70% foliage projective cover (vertically projected percentage cover of photosynthetic foliage of all strata) (Specht & Specht 1999). The most common species based on basal area dominance are found in the overstorey of the RRNP and include *Corymbia maculata*, *Eucalyptus propinqua*, *Eucalyptus siderophloia* and *Lophostemon confertus*. The understorey is mainly covered by native grass and shrub species.

The elevation of the BRNP study area ranges from 600 to 1200 m above mean sea level with an average slope of 36°. Annual rainfall is approximately 3000 mm and the average temperature ranges are 3–19 °C in winter and 15–31°C in summer (Anonymous 2010). The BRNP is a tall, closed canopy subtropical rainforest with 70–100% foliage projective cover (Specht & Specht 1999). The most common species based on proportional basal area are *Planchonella australis*, *Heritiera actinophylla*, *Sloanea woollsii, Geissois benthamiana* and *Syzygium crebrinerve* (Smith et al. 2005). Both study areas are managed by the NSW Office of Environment and Heritage.

Field data collection and processing

Field data collection was conducted between July and December 2010. A total of 50 sampling plots representing 25 plots of 50 m × 50 m (0.25 ha) for each study site were used to measure and estimate structural parameters. A random sampling method was adopted to assure that sampling measurements acquired all possible variability of forests conditions. The central location of each plot was determined using a global positioning system (GPS) handheld navigator. Five coordinates were recorded for each plot over 20 min and averaged (standard deviations (SD) for BRNP = 5–8 m and RRNP = 3–6 m). Foliage projective cover, mean tree height, dominant tree height, dbh, dominant dbh, mean basal area and stem density at plot scale in both study areas were recorded.

In each sampling plot, tree heights of all trees with 10-cm dbh were measured using a forestry 550 laser rangefinder/height meter and averaged. Height of dominant trees in each plot were separately recorded and then averaged. All trees with dbh greater than 10 cm were measured using diameter tape. Diameters for buttressed trees were measured immediately above the buttresses. Dbh of all dominant trees in each plot were also separately measured, then averaged. The sum of the basal area of all living trees in a stand ($m^2\ ha^{-1}$) was calculated from diameters of all trees in a sampling plot.

Field foliage projective cover measurements were recorded using the methodology developed by the Queensland Remote Sensing Centre (Armston et al. 2009). Three 50-m transects were laid in each plot radiating in N–S, NE–SW and SE–NW directions using a compass (Figure 2). At 1-m intervals along each transect, overstorey (woody plants ≥ 2 m height) and understorey (woody or herbaceous plants ≤ 2 m height) covers were recorded. Overstorey plant intercepts were recorded using a densitometer with intercepts classified as green leaf, dead leaf, branch or sky (Johansson 1985). Understorey herbaceous measurements were made with a laser pointer at zenith of zero with intercepts classified as green leaf, dead leaf, rock, etc. Table 1 provides a statistical summary of structural parameters of vegetation of the sampling plots.

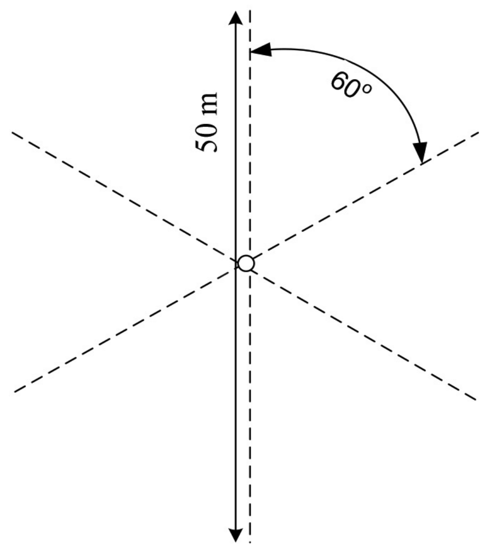

Figure 2 Orientation of transects used for foliage projective cover collection in the field (Armston et al. 2009)

Table 1 Statistical summary of structural parameters of vegetation of the sampling plots

Target parameter	Mean		Minimum		Maximum		Standard deviation	
	BRNP	RRNP	BRNP	RRNP	BRNP	RRNP	BRNP	RRNP
Mean tree height (m)	32	27	17.5	12.5	36	31.5	9.1	13.5
Dominant tree height (m)	40.6	34.3	28.4	25.2	48	38.6	6.5	9.3
Mean dbh (cm)	31	20.1	10	10	49.5	39	10.8	10.6
Dominant dbh (cm)	64.8	49.2	41	34	140	123	14.7	12.7
Mean basal area (m^2 ha^{-1})	32.3	16.8	24.3	11.3	48.1	31.6	5.7	4.7
Stem density (ha^{-1})	388	264	272	148	564	440	72	92
Foliage projective cover (%)	87	70.6	69.7	57.3	96.6	87.1	6.8	7.4

BRNP = Border Range National Park, RRNP = Richmond Range National Park

LiDAR data

LiDAR data were collected in July and August 2010 using a Leica ALS50-II LiDAR system at a flying height of 2000 m. The laser pulse repetition frequency was 109 kHz. The laser scanner was configured to record up to four returns per laser pulse. The average point spacing and point density were 1 m and 1.3 points per square meter respectively and the footprint diameter was 0.5 m. Average range varied between 524 m and 1018 m (mean 800 m) for the BRNP, and 157 m and 460 m (mean 256 m) for the RRNP. Mean rates of penetration through the vegetation varied from 4.3% in the closed canopy of BRNP to 19% in the open canopy of RRNP. The LiDAR data were documented as 0.07 m for vertical accuracy and 0.17 m for horizontal accuracy by the data provider. The LiDAR data were classified into ground and non-ground points using proprietary software by the NSW Land and Property Information and were delivered in LAS 1.2 file format.

Data processing

Figure 3 shows a flowchart of the processing steps carried out in this study. All returns were considered for subsequent analysis for both study areas. Ground and non-ground returns were separated and a 1-m digital terrain model (DTM) was produced using ground returns via Kriging interpolation to the nearest 6 data points. The accuracy of LiDAR-derived digital terrain model was evaluated using 70 and 55 post-processed differential GPS points for the BRNP and RRNP respectively. The GPS points were collected using a MobileMapper and included 4 transects for the BRNP and 3 for the RRNP. Collected GPS points were distributed over flat to slope terrain in open ground (park roads) and under forest canopies in different densities. The calculated root mean square errors (RMSE) were 5.7 and 1.9 m for closed canopy BRNP and open canopy RRNP respectively.

Computation of LiDAR metrics

LiDAR metrics were calculated from separated non-ground laser returns. Observations with height values < 2 m for the RRNP and < 0.5 m for the BRNP were discarded from existing non-ground data in order to remove undulation of the terrain and other objects (herbaceous vegetation, fallen logs). Thus, most reflectance would correspond to understorey and overstorey vegetation. The non-ground returns used to extract co-located 50 m × 50 m field sample plots of each study area and subsequently a series of LiDAR metrics were computed. The computed variables comprised height, rate of laser point penetration and proportion of laser points within different height bins related variables corresponding to sample plots of each study site. The computed 31 LiDAR metrics used in this study were based on previous studies (Magnussen & Boudewyn 1998, Næsset 2002, 2004, Heurich & Thoma 2008, Nord-Larsen & Riis-Nielsen 2010). LiDAR fractional cover metric (Lovell et al. 2003) were employed in this study (Table 2).

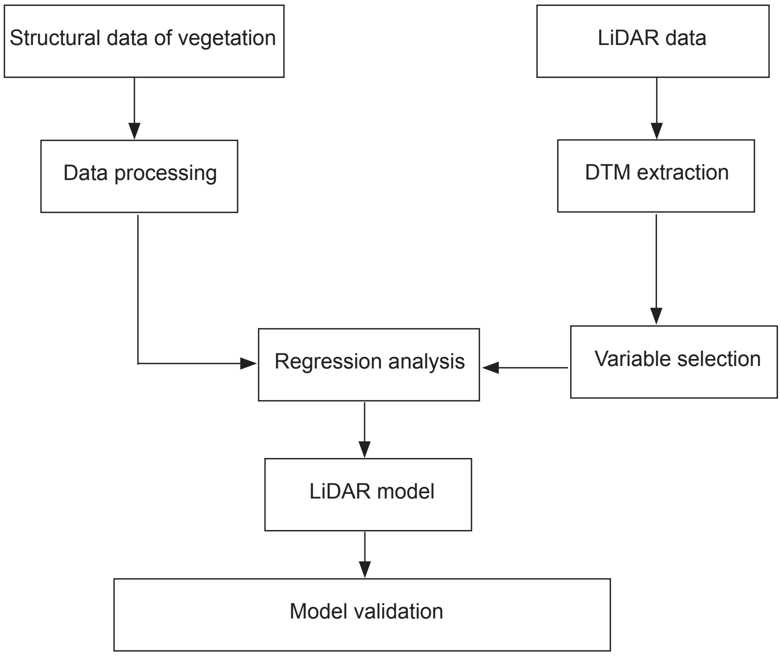

Figure 3 Flowchart of the model building method; DTM = digital terrain model

Table 2 Summary of LiDAR metrics

Variable	Description
(Z_max)	Maximum laser height
(Z_m)	Mean laser height
(Z_med)	Median laser height
(Z_rmed)	Relative median laser height [Z_rmed= Z_med/ Z_max ×100]
(p_10th ….., p_90th)	Laser height percentile from 10th, 20th to 90th percentiles
(Z_sd)	Standard deviation of height dispersion
(Z_k)	Kurtosis = distribution form parameter
(Z_cv)	Coefficient of variation = distribution form parameter
(PR_{gl})	Proportion of LiDAR points at ground layer PR_{gl} = sum of penetrated all laser pulses (pr) < m^a/total number of all pulses measured (TP); m^a for BRNP = 1.5 m, RRNP = 1 m
(PR_{ol})	Proportion of LiDAR points at overstorey PR_{ol} = pr < 0.75 * Z_max/ TP
(PR_{ml})	Proportion of LiDAR points at middlestorey PR_{ml} = pr < 0. 5* Z_max/ TP
(PR_{ul})	Proportion of LiDAR points at understorey PR_{op} = pr < h^a × Z_max/ TP; h^a for BRNP = 8 m and RRNP = 3 m
(P_1, P_2, P_3 .... P_9)	Proportion of LiDAR point within different height bins: Z_max divided into 10 equally sized bins the proportion of LiDAR points were calculated within different bins of vertical forest profile
Fracov	LiDAR fractional cover: $1 - P_{gap} = \dfrac{C_v\ (z)}{C_v\ (0)\ + C_G}$ $C_v(z)$ = number of first returns higher than Z, $C_{G=}$ number of first return points from ground level; Z for BRNP =1.5 m, RRNP = 1 m

Model fitting and validation

For model fitting, each vegetation type representing the study areas was considered separately. Multiple linear regression analysis was selected to develop estimation models for prediction of structural parameters of vegetation. Multiple linear regression analysis had ground-measured structural parameters of vegetation as dependent variables and the LiDAR-derived metrics as independent variables. Estimation models were constructed as follows:

$$X = \beta^{\circ} + \beta_1 Z\_max + \beta_2 Z\_m + \beta_3 Z\_med + \beta_4 Z\_rmed + \beta_5\, p\_10^{th} + \beta_6\, p\_20^{th} + \beta_7\, p\_30^{th} + \beta_8\, p\_40^{th} + \beta_9\, p\_50^{th} + \beta_{10}\, p\_60^{th} + \beta_{11}\, p\_70^{th} + \beta_{12}\, p\_80^{th} + \beta_{13}\, p\_90^{th} + \beta_{14} Z\_sd + \beta_{15} Z\_k + \beta_{16} Z\_cv + \beta_{17} PR_{gl} + \beta_{18} PR_{ol} + \beta_{19} PR_{ml} + \beta_{20} PR_{ul} + \beta_{21} Fra_{ccov} + \beta_{22} P_1 + \beta_{23} P_2 + \beta_{24} P_3 + \beta_{25} P_4 + \beta_{26} P_5 + \beta_{27} P_6 + \beta_{28} P_7 + \beta_{29} P_8 + \beta_{30} P_9 \quad (1)$$

where X = ground-measured structural parameters of vegetation (mean overstorey height, dominant overstorey height, mean dbh, dominant dbh, mean basal area, foliage projective cover and stem density); Z_max = maximum laser height (m); Z_m = mean laser height (m); Z_med = median laser height (m); Z_rmed = relative median laser height; p_10^{th}, p_20^{th}, p_30^{th}, p_40^{th}, p_50^{th}, p_60^{th}, p_70^{th}, p_80^{th}, p_90^{th} = laser height percentiles from the 10, 20, 30, 40, 50, 60, 70, 80, and 90 percentiles of the all pulse laser canopy heights (m) respectively; Z_sd = standard deviation of height dispersion (m); Z_k = Kurtosis of height; Z_cv = coefficient of variation; PR_{gl} = proportion of LiDAR points at ground layer; PR_{ml}= proportion of LiDAR points at middlestorey layer; PR_{ul}= proportion of LiDAR points at understorey layer; PR_{ol} = proportion of LiDAR points at overstorey; Fra_{ccov}= LiDAR fractional cover; P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8, P_9 = proportion of LiDAR point within different height bin and β^{o} – β_{30} = constants that must be estimated.

Stepwise selection was performed to select independent variables to be included in final models. No independent variables were left in the models with a partial F statistic with level of significance > 0.1. The variance inflation factors > 10 was considered to detect multicollinearity of independent variables. Regression diagnostics including adjusted r^2, coefficient of variance of the root mean square error (CVRMSE) and residual plots were used to select optimal models. RMSE was directly interpretable in terms of measurement units. RMSE of two models both measured the magnitude of residuals. However, they cannot be compared in order to determine which model provided better performance. The RMSE of model and mean of the predicted variables were expressed in the same units, so taking the ratio of these two allowed the units to cancel. This ratio can then be compared with other such ratios in a meaningful way. Between two models, the model with the smaller coefficient of variance, i.e. CVRMSE had predicted values that were closer to the actual values. Thus, CVRMSE was used in this study for model selection.

Since ground-measured data of all sampling plots were used for model development, cross-validation was performed for validation process. One observation (sample plot) was removed from the dataset at a time and the selected model was fitted to the dataset from the sample plots. Bias and coefficient of variation were used to assess prediction error of candidate models.

RESULTS

Dominant overstorey height and mean overstorey height in the BRNP were relatively less accurate compared with results obtained for the same parameters in the RRNP (Table 3). Overall adjusted r^2 was 0.40–0.61 for BRNP closed canopy and 0.81–0.90 for RRNP open vegetation. Figures 4 and 5 show the observed versus the predicted structural parameters of vegetation with the respective CVRMSE per cent values in the BRNP and RRNP respectively. Figure 5a indicated that the CVRMSE was greatest (18.4%) for mean height for closed canopy data. For mean (Figure 4a) and dominant tree height in RRNP (Figure 4b), the CVRMSE was below 5%. The best subset of the model for tree height with least error was obtained for open canopy RRNP sites.

The adjusted r^2 for LiDAR metrics and field-measured mean and dominant dbh were between 0.35 and 0.70 for both sites. The highest adjusted r^2 value (0.66) was obtained for mean dbh for closed canopy site and the respective CVRMSE was 11.3% (Figure 4c). Figure 5c showed that estimation of mean dbh for the open canopy RRNP site was particularly poor in terms of the higher

Table 3 Summary of best subset regression models obtained from ground-measured structural parameters of vegetation and different LiDAR metrics for subtropical rainforest at Border Range National Park (BRNP) and open canopy eucalypt forest at Richmond Range National Park (RRNP)

Structural parameter of vegetation	Subtropical rainforest BRNP (n = 25)	Adj. r^2	CVRMSE (%)	Open canopy forest RRNP(n = 25)	Adj. r^2	CVRMSE (%)
Mean tree height (m)	$= 24.7 - 0.72 \times P\_70^{th}$	0.40	18.4	$= 37.96 + 0.512 \times P\_70^{th} - 27.31 \times P_9$	0.90	2.9
Dominant tree height (m)	$= 20.33 + 2.17 \times P\_80^{th} - 1.82 \times P\_70^{th}$	0. 61	10.5	$= 20.5 + 2.3 \times P_6 - 0.486 \times Z\_sd+1.0$ x $Z\_med +0.371 \times P\_80^{th}$	0.81	1.1
Mean dbh (cm)	$= 48.376 + 1.383 \times ht\_m - 16.035 \times PR_{ul}$	0.66	11.3	$= 12.70 + 0.610 \times P\_10^{th} + 0.60 \times Z\_sd$	0.35	14.5
Dominant dbh (cm)	$= 42.46 - 6.40 \times P\_ 60^{th} + 8.02 \times Z\_m$	0.47	10.2	$= 31.99 + 4.336 \times Z\_m -0.837 \times Z\_rmed$	0.70	9.6
Mean basal area (m^2 ha^{-1})	$= 33.88 + 1.442 \times P\_10^{th} - 1.507 \times P\_90^{th} + 4.393 \times Z\_sd -1.595 \times P\_70^{th}$	0.62	10.8	$= 45.14 + 0.035 \times$ Fracov $-0.436 \times P\_50^{th} - 50.05 \times P_2$	0.65	9.4
Stem density (ha^{-1})	$= 1255.7 - 1182 \times PR_{gl}$	0.21	29.1	$= 877.77 - 11.82 \times Z\_max$	0.2	24.5
Foliage projective cover (%)	$= 51.4 - 1.20$x $P\_90^{th} - 66.4\ PR_{ul} - 31.1 \times P_6 + 80.4\ Frac_{cov} + 3.49 \times Z\_sd$	0.60	14.2	$= 75.74 - 100.46 \times P_4 + 75.85 \times PR_{ml} - 0.774 \times P\_40^{th}$	0.72	4.6

Adj. = adjusted, CV = coefficient of variance, Fracov = LiDAR fractional cover (see Table 2 for details)

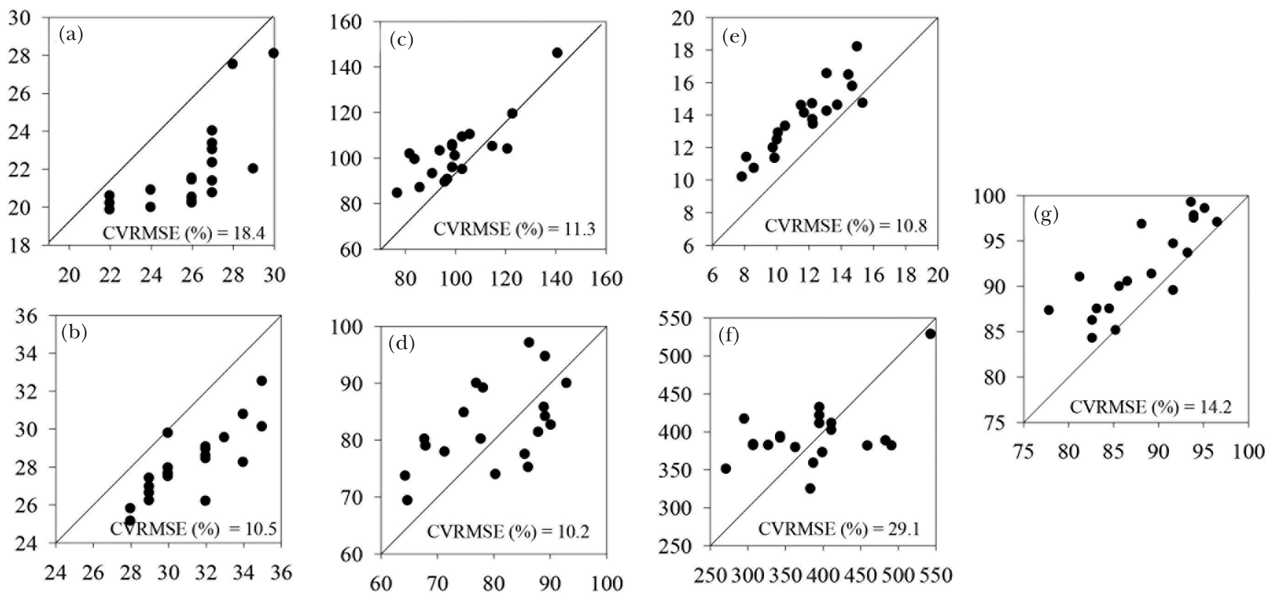

Figure 4 Ground-measured (x-axis) versus predicted (y-axis) structural parameters of vegetation: (a) mean height (m), (b) dominant height (m), (c) mean dbh (cm), (d) dominant dbh (cm), (e) basal area (m^2 ha^{-1}), (f) stem density (ha^{-1}) and (g) foliage projective cover (%) for models for at Border Range National Park; solid lines show 1:1 relationship; CVRMSE = coefficient of variance of the root mean square error

CVRMSE observed (14.5%). The least accurate result for dominant dbh estimation (adjusted r^2 0.47) was obtained for the BRNP site with 10.2% of CVRMSE. The best result for dominant dbh estimation was obtained for the RRNP site with least error 9.6% CVRMSE (Figure 5d).

The adjusted r^2 produced by the equation for basal area was between 0.62 and 0.65. Table 3 and Figure 5e showed that the best results were obtained for the RRNP site data and adjusted r^2 and CVRMSE were 0.65 and 9.4% respectively. In comparison, least accurate result were obtained for estimation of basal area with CVRMSE at 10.8% (see Figure 4e) for the BRNP. Results for estimation of stem density for both BRNP and RRNP site data were not as accurate as other investigated structural parameters, as the adjusted r^2 were only 21 and 20 respectively. The CVRMSE for the BRNP and RRNP which were shown in Figures 4 and 5f were 29.1 and 24.5% respectively.

The percentage of foliage projective cover was also relatively accurate for the closed canopy BRNP showing the adjusted r^2 value of 0.60. A comparison between study site vegetation showed that the best results were obtained for the open canopy RRNP site (adjusted r^2 = 0.72), while the least accurate results were produced for the closed canopy BRNP data. The CVRMSE values were between 14.2 (BRNP) and 4.6% (RRNP) (Figures 4g and 5g respectively). In the current study, all developed equations were parsimonious models with four or less independent variables. Results for most structural attributes in the subtropical rainforest of the BRNP were less accurate compared with the RRNP site.

Validation of the regression models prediction

Table 4 summarises results of cross-validation of all candidate models. Mean difference between predicted and ground-measured (bias) was relatively accurate for most of the models developed indicating the least bias error of both sites. However, for the closed canopy subtropical rainforest site at the BRNP, the calculated bias values were relatively high. The greater CV showed that estimation of stem density of the BRNP was almost 58%. Some of the CV in this site was even smaller than the values for open canopy site at RRNP. For instance, CV for estimation of mean dbh for BRNP and RRNP were 14.8 and

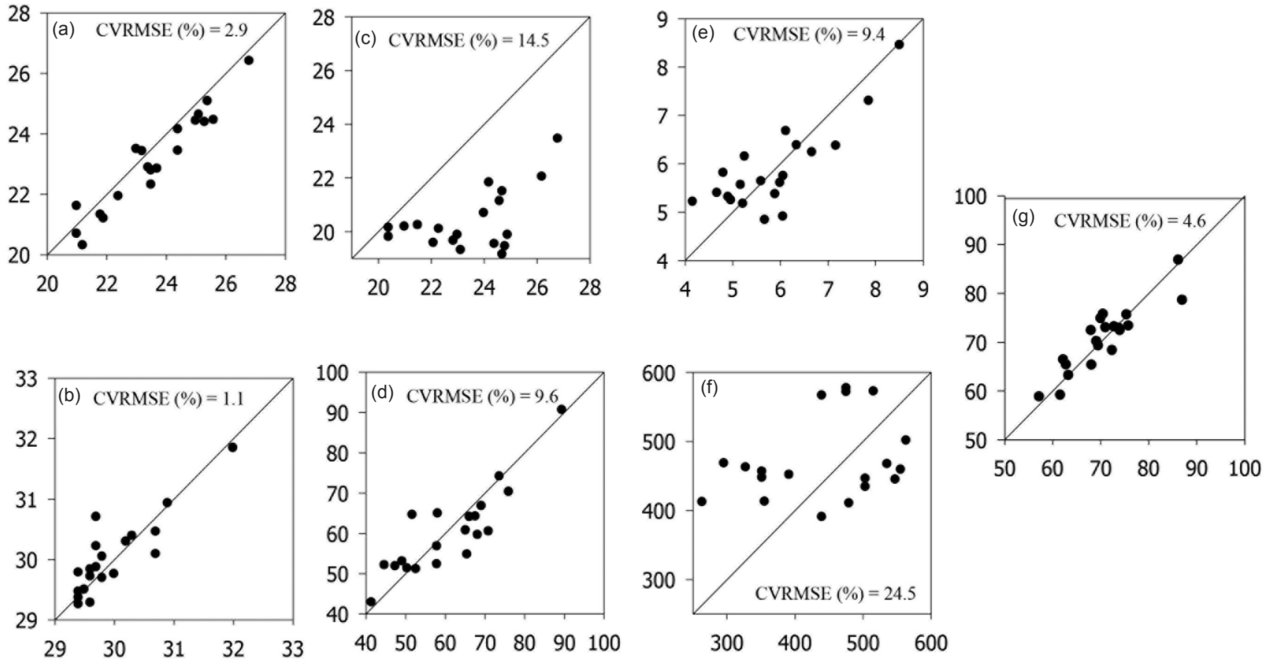

Figure 5 Ground-measured (x-axis) versus predicted (y-axis) structural parameters of vegetation: (a) mean height (m), (b) dominant height (m), (c) mean dbh (cm), (d) dominant dbh (cm), (e) basal area (m^2 ha^{-1}), (f) stem density (ha^{-1}) and (g) foliage projective cover (%) for models at Richmond Range National Park; solid lines show 1:1 relationship; CVRMSE = coefficient of variance of the root mean square error

Table 4 Summary of cross-validation results for Border Range National Park (BRNP) and Richmond Range National Park (RRNP)

Dependent variable	BRNP (n = 25)		RRNP (n = 25)	
	Bias	% CV	Bias	% CV
Mean tree height (m)	-4.2	11.7	-0.03	5.6
Dominant tree height (m)	-2.0	9.0	-0.04	2
Mean dbh (cm)	1.5	14.8	4	22.5
Dominant dbh (cm)	0.9	17.1	0.12	9.2
Mean basal area (m^2 ha^{-1})	-0.8	17.6	0.03	15
Stem density (ha^{-1})	15.6	57.9	7.8	60
Foliage projective cover (%)	1.3	9.3	0.0	6.5

CV = coefficient of variation

22.5% respectively. Results showed that least bias values were obtained for dominant tree height (-2.0) and mean tree height (-4.2) at BRNP site. However, the lowest CV (9%) was obtained for estimation of dominant height at BRNP.

Most of the developed candidate models for RRNP had relatively least bias (bias for foliage projective cover was almost zero) and the CV values were relatively low. The lowest CV (2%) was obtained for estimation of dominant tree height at RRNP. Furthermore, the CV for estimation of mean height, foliage projective cover and dominant dbh were 5.6, 6.5 and 9.2% respectively. The CV for mean basal area was 15% and the greatest CV was obtained for stems per hectare (60%).

DISCUSSION

Metric measures from the distribution of LiDAR data points utilised in this study demonstrated the potential of biophysical parameter estimation of vegetation structure, even in the closed canopy with complex vegetation structure and topography. However, the accuracy of dominant tree height and mean tree height of the closed canopy BRNP was relatively low compared with that of the open canopy RRNP. Incorporated LiDAR metrics did not account for large amount of variations in mean and dominant tree heights (see Table 3), indicating that magnitude of error for these predictions was considerably high in closed canopy subtropical rainforest. The accuracy of height models derived using the present method for closed canopy BRNP was similar to those found by Gatziolis et al. (2010) in temperate rainforest. This was probably due to the fact that as complexity of canopy structure increased, the probability that LiDAR pulses penetrated below the canopy decreased by interference of middle and understorey strata. This caused considerable impact on density of LiDAR points below the canopy which could affect the accuracy of laser metrics. In contrast, the estimation of dominant and mean canopy heights from LiDAR data achieved high level of accuracy (error < 3%) and explained over 80% of total variation in dominant height for open canopy eucalypt forest of the RRNP. Overall accuracy for estimation of dominant canopy height in open canopy conditions was comparable with other studies of Australian eucalypt forests (Tickle et al. 2006, Haywood & Stone 2011) and globally with structurally similar sparse canopy coniferous forests (Roberts et al. 2005, Heurich & Thoma 2008). Most studies assumed that the proportion of laser pulse returned from, or above a given reference height is proportional to the fraction of leaf area above it (Magnussen & Boudewyn 1998, Roberts et al. 2005, Haywood & Stone 2011). The findings of this study are consistent with this assumption as greater relationships between ground-measured tree heights (both mean and dominant tree heights) and LiDAR-derived heights were observed above the 70th percentile with other LiDAR-derived statistical parameters for the RRNP and the BRNP sites.

Dbh estimates for RRNP and BRNP tree species based on LiDAR metrics were less accurate than tree height estimation models. The least accurate model was mean dbh estimation at RRNP and the best model found for estimation of dominant dbh was at BRNP. Dbh estimations in this study were similar to Jensen et al. (2006) who investigated diverse vegetation structure and composition of the topographically complex terrain in North America. Our results were also similar to findings by Heurich and Thoma (2008) who studied structurally rich natural European beech and spruce forests in Germany. Mean basal area estimates using LiDAR metrics gave satisfactory results for both RRNP and BRNP; however, the best model for basal area estimates was for RRNP. When ground-measured basal area was regressed against LiDAR derived variables of vegetation on data from natural regrowth eucalypt forest in Australia, similar r^2 values of 0.56 with an RMSE of 14 m^2 was observed (Haywood & Stone 2011).

In this study, results for estimation of stem density were low in accuracy for both subtropical and open canopy forests. Conversely, r^2 value of 0.58 was obtained when stem density was regressed against mean height of LiDAR metric derived from all laser-scanning returns based on data from mixed-species forest in Canada (Lim & Treitz 2004). Haywood and Stone (2011) found $r^2 = 0.41$ for regression against two height percentiles and measure of intensity from young Australian eucalypt forest while Heurich and Thoma (2008) reported $r^2 = 0.90$, 0.71 and 0.69 for deciduous forest, coniferous forest and combined all deciduous and coniferous forests plots respectively. Incorporated LiDAR metrics of this study explained 18–21% of the variation in the stem density for both vegetation conditions. In this study, the estimation of stem density from the fitted variables is related to the penetration of laser points into ground layer and maximum tree height. Together, the variation of laser pulse penetration rate may determine stem density of the stand. The method tested in our study revealed that estimating stem density of subtropical plant communities from LiDAR data was rather difficult. An alternative method described by Turner (2006) estimate stem density by an automated tree detection approach over the LiDAR data. However, the author described that crown segmentation was challenging for structurally complex closed canopy environment.

Foliage projective cover estimates in the open canopy RRNP site based on LiDAR scanning measurements showed strong relationship with ground-measured foliage projective cover. A study done in an Australian eucalypt forest has reported strong linear relationship ($r^2 = 0.90–0.95$) with just LiDAR fractional cover and ground-measured foliage projective cover (Weller et al. 2003). This finding is similar to the finding of our study. However, the foliage projective cover estimate model for BRNP was found to be less accurate compared with RRNP where eucalypt forest was dominant. This was probably due to the presence of large crowns with planar outer surface being distinguishable in the BRNP, thus decreasing return energy due to occlusion in a horizontally uniform way. This situation may prohibit exploiting necessary LiDAR derived information of other lower strata at high level of accuracy.

Limitations

Overall this study raised three issues: (1) limitations encountered when relating LiDAR metrics, (2) field measurements in particular to closed canopy subtropical rainforest and (3) technical specification in LiDAR data acquisition. A major limitation was the effect of structural complexity of vegetation on the reflection of laser pulses. Due to the large tree crowns in overstorey layers in the BRNP site, there was a tendency for more first returns from the upper level of canopy recorded by the LiDAR system. As such, important information from the lower strata may be overlooked. Due to variations in sunlight penetration to the forest floor, leaf inclination and orientation of the middle and understorey layers of rainforest species may vary. Thus, modifications of leaf morphology may also affect the reflectance of laser energy throughout the forest profile. Considering the physiognomy of the eucalypt-dominated RRNP, the loosely aggregated leaves in tree crowns and 30–70% foliage projective cover (Specht & Specht 1999) affect maximum laser pulse penetration to the forest floor.

The limitations of gaining accurate field data measurements are likely to affect the accuracy of predicted models. In the sampling plots of closed canopy BRNP with tall trees, accurate measurement of tree heights was difficult due to hindrance from lower strata.

Furthermore, the 10-cm threshold for dbh was critical at the RRNP site as most of the stems were small and medium sized representing young regrowth (approximately 20 years). LiDAR sensor configuration and specification of LiDAR data acquisition have strong influence on the accuracy of data (Goodwin et al. 2006) due to high flying altitude (2 km for the present study), high point spacing (1 m) and low point density (1.3 point per m^2) which may also have affected the quantification of structural attributes of vegetation in this study.

In conclusion, this study demonstrated the application of LiDAR metrics for obtaining important structural parameters of vegetation of closed canopy subtropical rainforest and open canopy eucalypt-dominated forest in topographically complex terrain using LiDAR data. Accuracies of most of the estimates in open canopy eucalypt-dominated forest were of high levels and comparable with findings from related studies despite the complexity of topography, species composition and density of vegetation. The current study provided evidence that this could be achieved even in a subtropical rainforest with rugged terrain. Our findings revealed that predicting accuracies of structural attributes by LiDAR metrics in closed canopy subtropical rainforest with high species diversity was inferior to predicting the accuracies in sparse canopy with low species diversity. Nevertheless, it was notable that, despite structurally complex subtropical rainforest with rugged terrain, it was possible to obtain estimation of structural parameters with satisfactory level of accuracy. Our findings reinforced that obtaining accurate LiDAR estimates of vegetation structure was a function of complexity of horizontal and vertical structural diversity of vegetation.

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