

# Estimation of the Volume of Coarse Woody Debris in Eucalyptus Forest using LiDAR Derived Forest Structure Variables

Naoko Miura<sup>1</sup>, Susumu Goto<sup>1</sup> and Simon Jones<sup>2</sup>

1. Graduate School of Agricultural and Life Sciences, the University of Tokyo, Tokyo 113-8657, Japan

2. School of Mathematical and Geospatial Sciences, RMIT University, Melbourne, Victoria 3001, Australia

Received: July 11, 2013 / Accepted: August 02, 2013 / Published: August 20, 2013.

**Abstract:** CWD (coarse woody debris) plays an important role in nutrient cycling, habitat for species and more recently carbon accounting in forest ecosystems. LiDAR (light detection and ranging) technology has demonstrated utility in capturing forest structure information. This paper proposes an indirect method of assessing downed CWD using LiDAR derived forest structure variables. Fieldwork was conducted to measure CWD volume in an Eucalyptus forest in Tasmania. A GLM (generalized linear model) to statistically estimate CWD volume in the Eucalyptus forest was developed using a LiDAR derived FCS (forest characterisation scheme): the openings above the ground, low and medium vegetation, canopy cover, presence of understorey and mid-storey vegetation and high trees, and the vertical canopy density of high trees. Five structural variables were selected for the best model based on AIC (Akaike's Information Criterion) by stepwise selection. The applicability of the model was then compared to the outcome of model using field derived variables such as diameter at breast height of trees. The results show that the model using LiDAR derived variables better estimated the amount of CWD. It is concluded that LiDAR derived forest structural variables has the potential to predict the amount of downed CWD in Eucalyptus forest.

**Key words:** CWD (Coarse woody debris), LiDAR (light detection and ranging), forest, generalized liner model.

## 1. Introduction

CWD (Coarse woody debris) is defined as standing dead trees and downed wood. CWD plays an important role in nutrient cycling, habitat for species and more recently carbon accounting in forest ecosystems [1, 2]. However, the reduction of CWD is widely reported [3, 4] and recognized as one of the threats to biodiversity. Therefore, assessment of CWD is critical in the monitoring of forest ecosystems. The amount of CWD is generally estimated based on various field sampling techniques such as the line-intersect method [5]. These field sampling methods often require intensive and costly fieldwork, however, only cover a small sample fraction of the

system studied.

Remote sensing data derived from satellite and airborne sensors are superior to field survey data in terms of high-spatial coverage, near simultaneous acquisition, repeated regional accounting and cost. LiDAR (light detection and ranging) is an active sensing technology that emits laser pulses and measures the range distance between sensor and the illuminated target, providing 3-dimensional information. Numerous papers have documented the utility of LiDAR for the estimation of forest attributes in forestry [6-8]. CWD is associated with stand composition, structure and dynamics as its quality and quantity rely on the stand characteristics [9], therefore, structural attributes derived from LiDAR should be useful in estimation of CWD. However, small number of studies have been published to estimate the amount

---

**Corresponding author:** Naoko Miura, Ph.D., project assistant professor, research fields: remote sensing, GIS and environmental science. E-mail: miura@uf.a.u-tokyo.ac.jp.

of CWD using LiDAR [10, 11]. In the study of fuel models in the closed-canopy conifer forests of the western United States, Seielstad and Queen [11] showed the possibility of estimating CWD loads using a surface roughness metric and obstacle density, which was defined as the number of non-ground points less than 6 feet in height per square meter, normalized by the total number of ground and points greater than 6 feet. This “direct” method to assess CWD using laser points may be susceptible to site condition such as closeness of canopy, existence of understory vegetation and decay stage of CWD. On the other hand, Pesonen et al. [10] “indirectly” estimated downed dead wood volume using the predictive variables of canopy height distribution, cumulative proportional canopy densities, the laser pulse intensities accumulating in percentiles, the average intensity value of above-ground hits, the proportion of ground hits versus canopy hits and the average height and standard deviation of the above-ground hits derived from first and last laser returns respectively. These authors found that the standard deviation of first return laser heights was the most significant variable in the models, and achieved the adjusted multiple correlation coefficient of 0.6099 with the combination of the standard deviation of first return laser heights and last return laser pulse intensity accumulating in 10th percentile as predictors.

In this paper, an indirect method of assessing downed CWD is proposed using LiDAR derived forest structure variables since the amount of CWD may be explained by the forest structure at the site as Bobiec [9] suggested. A GLM (generalized linear model) to statistically estimate CWD volume in an Eucalyptus forest was developed using previously proposed LiDAR derived FCS (forest characterisation scheme) [12] the openings above the ground, low and medium vegetation, canopy cover, presence of understory and mid-storey vegetation and high trees, and the vertical canopy density of high trees. The applicability of the model is then compared to the

outcome of model using field derived variables which are commonly collected in the fieldwork for natural resource management.

## **2. Material and Methods**

### *2.1 Study Area*

The study area (upper left S 41.12°, E 146.45°; lower right S 41.32°, E 146.58°) locates in the Rubicon catchment of the Cradle Coast Region of Tasmania, Australia, and covers approximately 20,000 ha. The area is classified as *Eucalyptus amygdalina* coastal forest and woodland. The forests are dry sclerophyll communities dominated by *E. amygdalina* and have heathy, sedgy and shrubby understorey variants [13]. In this area, the human population is growing in coastal towns such as Devonport which is one of the two major centres in this region. Most people are employed in primary industries (agriculture, mining, forestry and fishing), manufacturing, retail and tourism. As the population grows, change in land use such as land clearing for grazing, and conversion of native forest to plantation is causing terrestrial habitat loss or modification. Subdivision for urban or industrial development in areas of high vegetation conservation is the major threat to biodiversity in this area [14].

### *2.2 LiDAR Data*

LiDAR data were acquired over the study area using a RIEGL LMS-Q560 sensor in February 2007. This is a full waveform system. The data provided were decomposed in up to six returns for this study. The scan angle for this mission was set to  $\pm 22.5^\circ$ . The flying height was 500 m above the ground, yielding an individual return footprint of approximately 20 cm in diameter. For this study, the pulse repetition frequency was 100 kHz and the wavelength of interaction was 1550 nm. Using this data, the authors previously proposed a FCS to assess forest ecological structure, which consists of 8 categories: opening above the ground (OG), low vegetation (OL) and medium

vegetation (OM), presence of understorey vegetation (VL), medium vegetation (VM) and high vegetation (VH), canopy cover (CC) and vertically dense canopy of high trees (DH). Table 1 summarises the FCS. The detail of the method can be found in Miura and Jones [12]. These LiDAR derived forest structure variables was used to develop a model to estimate the amount of CWD.

### 2.3 Field Data

Fieldwork was conducted in Feb.2008. It was conducted in an anniversary (one year) of the data capture. It was unfortunate to have one year time difference between LiDAR data acquisition and fieldwork. However, no major logging or bush fires were confirmed by the research team during this period and the forest condition was similar. Fourteen plots were established and surveyed in the study area. The forest structure varies among these plots. The plot locations were selected by Landscape Logic project team scientists in terms of the plant community and the degree of human disturbance. All plots were established in natural forests/remnant forest patches of *Eucalyptus amygdalina* coastal forest and woodland, and without any silvicultural practice. They are the representative of the plant community in this region. At each site a 25 m radius circular plot (0.2 ha) was established by defining a centre point and taking a GPS (eTrex of GARMIN Corporation) measurement. Five transects, running from East to West, parallel to each other were deployed in each plot. Assessment points were located every 7 m along each transect

comprising 27 assessment points in a plot. These assessment points were used for ground cover assessment. CWD on the ground (defined as woody components  $\geq 10$  cm in diameter) was recorded noting diameter and length of every woody element on each transect within a plot. The values of diameter and length are used later for total volume calculation of CWD in each plot. Canopy and bare ground covers were recorded visually as a percentage within a 3.5 m radius of each assessment point. These values from each assessment point were summed for each plot and presented as a mean. The number of trees, tree top height and DBH (diameter at breast height) were also recorded for each plot. A mean value was computed for the tree top height and DBH in each plot.

### 2.4 Generalized Linear Model

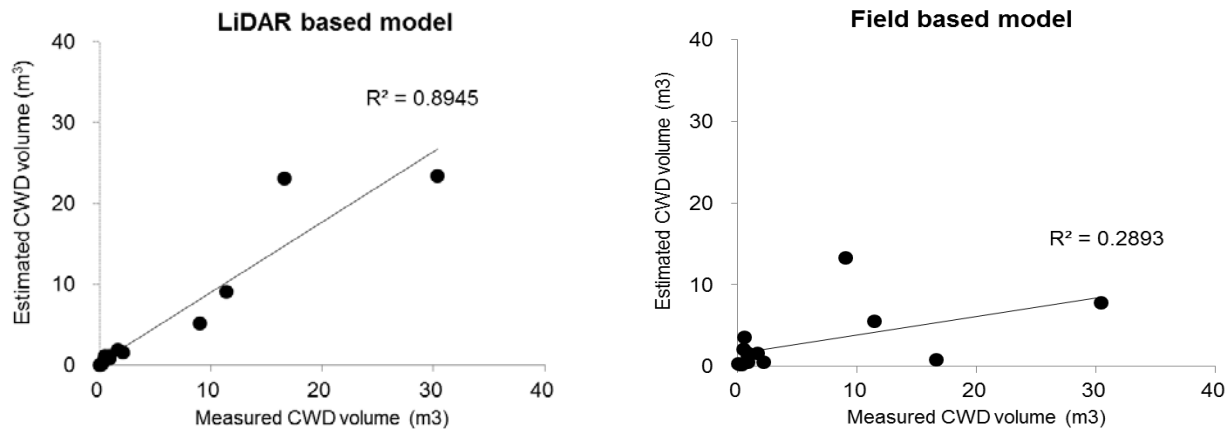
In order to estimate the CWD volume, a GLM (generalized linear model) was developed using the LiDAR derived FCS categories: OG, OL, VL, CC, OM, VM, VH and DH as independent variables. Logarithmic transformation was applied to the CWD volume in each plot for its normalization. Model selection in the GLM was performed based on AIC (Akaike's Information Criterion) [15] in a stepwise procedure. The applicability of the model was then compared to the outcome of model using field derived variables: F\_CC (canopy cover), F\_Bare\_G (bare ground cover), F\_Num\_T (the number of trees), F\_T\_TOP (tree top height) and F\_DBH (DBH). All statistical analysis was performed with the software R version 2.15.0 [16].

**Table 1 FCS (Forest characterisation scheme).**

Category	Description	
1	OG	Opening above the ground
2	OL	Opening above low vegetation
3	VL	Presence of understorey vegetation
4	CC	Canopy cover
5	OM	Opening above medium vegetation
6	VM	Presence of mid-storey vegetation
7	VH	Presence of high trees
8	DH	Vertically dense canopy of high trees

**Table 2** Selected variables in GLM for estimation of CWD volume.

	Estimate	Standard Error
LiDAR based model		
(Intercept)	-1.21294	2.52168
OG	0.15065	0.05076
CC	0.23414	0.04698
VM	-0.26414	0.09149
VH	-0.41426	0.08807
DH	0.75923	0.11876
AIC: 24.511		
Field based model		
(Intercept)	-1.2024	0.6880
F_DBH	-10.0497	5.4751
F_T_TOP	0.4152	0.1701
AIC: 56.632		

**Fig. 1** Goodness of fits obtained for the estimated CWD volume by LiDAR based model and field based model.

### 3. Results

As a result of GLM model selection, OG, CC, VM, VH and DH were selected as independent variables for LiDAR based model, and F\_DBH and F\_T\_TOP for field based model (Table 2). The goodness of fits obtained for the estimated CWD volumes was presented in Fig. 1. The R-square values between measured and estimated CWD volumes were 0.89 for LiDAR based model and 0.29 for field based model.

### 4. Discussion

Of the eight candidate variables of LiDAR derived FCS categories, five structural variables (OG; opening above the ground, CC; canopy cover, VM; presence of mid-storey vegetation, VH; presence of high trees and DH; vertically dense canopy of high trees) were

selected for the model of CWD volume estimation (Table 2). OG represents the total gap, that is to say, opening from the ground to canopy, and the rest of selected variables characterise the amount of foliage in higher layers than mid-storey vegetation. This suggests that in a forest where large amount of CWD is found, large trees with horizontally and/or vertically dense canopies and gaps from the ground to canopy are present. This is considered logical in natural forests since when a mature tree dies and falls, and it will create a gap in this area. The relationship between CWD volume and the canopy gap also fits with the findings of Pesonen et al. [10]. These authors found that the standard deviation in height pulses was the most significant predictor for CWD volume, and explained that higher variations in height distribution

would result from gaps, that is to say, tree falls. In this study, all the structural variables of FCS represent different structural components of the forest in each plot, and the combination of these components may play a key role to predict the amount of CWD in the study area.

In the comparison with the outcome of field derived model, LiDAR derived model outperformed, achieving R-square value of 0.89 between measured and estimated CWD volumes, while field derived model presented R-square value of 0.29 (Fig. 1). The result indicates that the field variables, which are commonly surveyed in natural resource management, may not be sufficient to characterise the state of forest stands where more CWD is found. The two field variables (DBH and tree top height) selected in the best field based model (Table 2) could show the presence of large trees in the forest stand, however, could not represent the presence of gap nor 3-dimensional distribution of foliage as LiDAR derived model is capable of. This shows the great potential of LiDAR derived structural variables in the estimation of CWD volume.

Proposed indirect method of assessing downed CWD using LiDAR derived forest structure variables was promising in the Eucalyptus forest. Next step would be an investigation of the applicability of the model in various forested landscape.

## 5. Conclusions

This paper proposed an indirect method of assessing downed CWD using LiDAR derived forest structure variables. As a result of model selection with stepwise procedure, five variables (OG; opening above the ground, CC; canopy cover, VM; presence of mid-storey vegetation, VH; presence of high trees and DH; vertically dense canopy of high trees) were found to be good predictor for estimation of downed CWD volume. The comparison with outcome of field derived model showed that the LiDAR derived model was a better model. It is concluded that LiDAR

derived forest structural variables has the potential to predict the amount of downed CWD in Eucalyptus forest.

## Acknowledgements

The authors would like to thank the Australian Commonwealth Environment Research Fund “Landscape Logic” Project for its support.

## References

- [1] M.E. Harmon, J.F. Franklin, F.J. Swanson, P. Sollins, S.V. Gregory, J.D. Lattin, et al., Ecology of Coarse Woody Debris in Temperate Ecosystems, in: H. Caswell (Ed.), *Advances in Ecological Research*, Academic Press, 2004, pp. 59-234.
- [2] W. Wilcke, T. Hess, C. Bengel, J. Homeier, C. Valarezo, W. Zech, Coarse woody debris in a montane forest in Ecuador: Mass, C and nutrient stock, and turnover, *Forest Ecology and Management* 205 (2005) 139-147.
- [3] R. MacNally, A. Parkinson, G. Horrocks, M. Young, Current loads of coarse woody debris on southeastern Australian floodplains: Evaluation of change and implications for restoration, *Restoration Ecology* 10 (2002) 627-635.
- [4] M.T. Jonsson, B.G. Jonsson, Assessing coarse woody debris in Swedish woodland key habitats: Implications for conservation and management, *Forest Ecology and Management* 242 (2007) 363-373.
- [5] J.K. Brown, Handbook for inventorying downed woody material, Gen. Tech. Rep. INT-16, in, Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, 1974.
- [6] M.A. Lefsky, W.B. Cohen, S.A. Acker, G.G. Parker, T.A. Spies, D. Harding, Lidar remote sensing of the canopy structure and biophysical properties of Douglas-Fir western hemlock forests, *Remote Sensing of Environment* 70 (1999) 339-361.
- [7] E. Næsset, Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data, *Remote Sensing of Environment* 80 (2002) 88-99.
- [8] R. Nelson, W. Krabill, G. MacLean, Determining forest canopy characteristics using airborne laser data, *Remote Sensing of Environment* 15 (1984) 201-212.
- [9] A. Bobiec, Living stands and dead wood in the Białowieża forest: Suggestions for restoration management, *Forest Ecology and Management* 165 (2002) 125-140.
- [10] A. Pesonen, M. Maltamo, K. Eerikäinen, P. Packalèn,

**Estimation of the Volume of Coarse Woody Debris in Eucalyptus Forest using  
LiDAR Derived Forest Structure Variables**

Airborne laser scanning-based prediction of coarse woody debris volumes in a conservation area, *Forest Ecology and Management* 255 (2008) 3288-3296.

- [11] C.A. Seielstad, L.P. Queen, Using airborne laser altimetry to determine fuel models for estimating fire behavior, *Journal of Forestry* 101 (2003) 10.
- [12] N. Miura, S.D. Jones, Characterizing forest ecological structure using pulse types and heights of airborne laser scanning, *Remote Sensing of Environment* 114 (2010) 1069-1076.
- [13] S. Harris, A. Kitchener, From Forest to Fjaeldmark: Descriptions of Tasmania's Vegetation, Department of Primary Industries, Water and Environment, Printing Authority of Tasmania, Hobart, 2005.
- [14] The Cradle Coast Natural Resource Management Committee, Cradle Coast natural Resource Management Strategy, in, Burnie, 2005, pp. 214.
- [15] H. Akaike, Information theory and an extension of the maximum likelihood principle, in: B. Petrov, F. Csaki (Eds.) *Second international symposium on information theory*, Akademiai Kiado, Budapest, 1973, pp. 267-281.
- [16] R Development Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, 2012.