Characterising the ecological structure of a dry Eucalypt forest landscape

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Abstract

Characterising forest structure is an essential part of any comprehensive biodiversity assessment. In this study, the utility of LiDAR for characterising the ecological structure of a dry Eucalypt forest landscape was examined. An eight class scheme derived from LiDAR point density is proposed. This was validated using a network of field sites that recorded commonly used metrics of biodiversity. The proposed categories allow for the mapping of gaps (both above bare ground and low vegetation), canopy cover and its density as well as the presence of various canopy strata (low, medium and high). Regression analysis showed a high correlation between LiDAR derived variables and field recorded variables reporting the highest R-square 0.82 between LiDAR derived presence of low vegetation and field derived LAI for low vegetation. Although some refinement is necessary, the proposed scheme clearly shows the potential of LiDAR to provide information on the complexity of habitat structure.

Keywords: LiDAR, point density, canopy cover, ecological structure

1. Introduction

Characterising forest structure is an essential part of any comprehensive biodiversity assessment. There is often a good correlation between biodiversity and measures of the variety and / or complexity of arrangement of structural components within an ecosystem (Mac Nally et al., 2001). Furthermore, the habitat complexity of a forest can be used to predict the occurrence of some species, since such information provides locally specific descriptions of faunal habitat (Catling and Burt, 1995; Jorgensen, 2002).

In order to characterise the ecological structure of forests, a series of generally applicable, robust, reliable measurements are required. LiDAR (Light Detection and Ranging) has been recognized as a powerful tool for forest structure characterisation. Numerous papers have documented the utility of LiDAR for the estimation of forest attributes. Næsset (1997) showed the potential of LiDAR to estimate fractional cover. Næsset derived fractional cover from LiDAR as the ratio of canopy returns to the total number of returns per unit area. Similar methods utilising the point density of LiDAR returns to estimate fractional cover were presented in other studies (e.g. Coops et al., 2007; Hopkinson and Chasmer, 2007; Morsdorf et al., 2006; Riaño et al., 2004; Solberg et al., 2006) and showed promising results. Hopkinson and Chasmer (2007) also incorporated the intensity of LiDAR returns into this algorithm. These authors estimated gap fraction calculating the ratio of the sum of all ground level return intensities to the sum of total return intensity, and achieved a high correlation with gap fraction recovered from ground-based digital hemispherical photography. Vertical forest structure is also an important component. Zimble et al. (2003) used LiDAR derived tree height variance to differentiate single-storey and multi-storey vertical structural classes with a 97% accuracy. Riaño et al. (2003) used a cluster analysis of LiDAR height information to discriminate between overstorey and understorey canopies. Maltamo et al. (2005) tested the existence and the number of understorey trees by analysing the height distribution of LiDAR returns. These authors found that multi-layered stand structures can be recognised and quantified, however, the accuracy of the results depends on the density of the dominant tree layer. The main focus of many previous studies has been on forest resource measurement rather than ecological applications. The later requires an assessment of complexity of habitat structure at a landscape scale.

The purpose of this paper is to present a draft methodology for characterising the ecological structure of a dry Eucalypt forest landscape using LiDAR data alone. An eight class scheme is proposed and validated using a network of field sites that recorded commonly used metric of biodiversity.

2. Method

2.1 Study area

The study area (Upper left S 41.12º, E 146.45º; Lower right S 41.32º, E 146.58º) covers the Rubicon catchment in the Cradle Coast Region of Tasmania, Australia and is 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 (Harris and Kitchener, 2005). 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, forestry and fishing), mining, 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 values has also become an issue. This is the major threat to biodiversity in this area (The Cradle Coast Natural Resource Management Committee, 2005). Assessment of the present state of ecological structure in forests is useful to make conservation strategy.

2.2 LiDAR data

LiDAR data was acquired over the study area using a RIEGL LMS-Q560 sensor in February 2007. This is a waveform system and was configured to record up to six returns for this study. The scan angle for this mission was set to ±22.5º. The flying height was 500m above the ground, yielding a footprint of approximately 20cm in diameter. For this study, the pulse repetition frequency was 100 kHz and the wavelength of interaction was 1500 nm. The overall survey was coordinated using static and rapid static GPS methods. This was undertaken to establish a small accurate network of points.

2.3 Field data

Fieldwork was conducted in February 2007 and 2008. Initial ground data collection assessed native vegetation condition using the ‘Biometric’ tool – a generic plot-based ecological survey method designed to guide natural resource managers (Gibbons et al., 2004). Subsequently, an additional ground survey was developed and implemented specifically to collect ecological structural information. In this paper, the later information is used to validate the LiDAR data.

Fourteen plots were surveyed within remnant dry Eucalypt forests across the study area. A 25m radius circular plot was established by defining a centre point and taking a hand-held GPS (eTrex of GARMIN Corporation) measurement. This includes resident positional error ± 5.5m of x y on average. Five transects running from East to West, parallel to each other were deployed in each plot (Figure 1). Assessment points were located every 7m along each transect, comprising twenty seven assessment points in a plot. Canopy Cover (*CC*) as a percentage was recorded in two ways. The first method (*CC_1*) assessed only photosynthetic elements and was conducted in situ with the aide of reference photographs. The second method (*CC_2*) assessed both photosynthetic and non-photosynthetic facets by acquiring vertical images from a 1.7m vantage point and calculating *CC* later in the laboratory. Bare ground cover, grass cover, litter cover and low vegetation (*Low veg*; 0-1m from the ground) cover were also recorded as a percentage within a 3.5m radius of each assessment point. Coarse woody debris on the ground (defined as woody components ≥10cm in diameter) was recorded noting the diameter and length of logs on each transect. The Leaf Area Index (LAI) for low vegetation was measured using LAI2000 Plant Canopy Analyzer of LI-COR, INC for each plot. It should be noted that the LAI values recorded using this instrument include non-leaf elements such as stems and branches. Tree top and the height to the first branch were measured using a Total Station, TCR705 of Leica Geosystems. All tree height information was then classified into two classes. First, the height information was divided into two categories (vegetation upto 5m and vegetation greater than 5m). Next the relative proportion of each of these categories was calculated by comparing them to the total number of height records. It is noted that the height to the first branch was not recorded for all trees due to the field of view being obscured at times**.** In this case, only tree top height information was used for the classification.

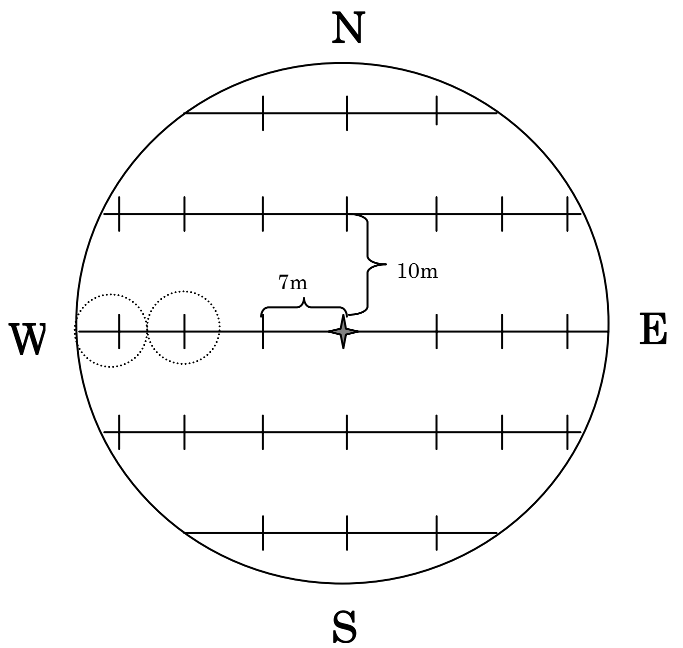

Figure 1: Each field plot comprises five transects running from East to West, parallel to each other, with assessment points located every 7m. In total this yields twenty seven assessment points for each plot. Small circles (only two shows for clarity) indicate the 3.5m radius assessment areas for understorey cover measurement (these were recorded for each assessment point).

3. Proposed forest characterisation

In order to create a scheme to characterise the ecological structure of a dry Eucalypt forest landscape, LiDAR data was first classified into four groups; *Ground*, Low vegetation (*Low veg*, 0-1m from the ground), Medium vegetation (*Medium veg*, 1-5m from the ground) and High vegetation (*High veg*, 5m<) using TerraScan software of Terrasolid, Ltd. The number of singular (Type 1), first of many (Type 2), intermediate (Type 3) and last of many returns (Type 4) was calculated for each of the four groups and divided by the total number of returns in each plot. Type 1 and Type 2 returns are the result of the first interaction with objects, which suggests that there is opening above this pulse interaction (i.e. no interaction above these points). The number of returns in *Low veg*, *Medium veg* and *High veg* groups suggests presence of vegetation in each of these strata. Of particular importance is the presence of Type 3 and Type 4 returns in *High veg* strata, since these indicate a dense canopy. Using calculated ratios, we propose the following scheme (Table 1). Where, 1) *Ground* Type 1; opening above the ground. 2) *Low veg* Type 1 & 2; opening above low vegetation. 3) *Low veg* total (Type 1, 2, 3 & 4); presence of understorey vegetation. 4) Canopy cover (*CC*) is defined as the following equation;

$$CC = \frac{\sum MediumVegType1\,\&\,2 + HighVegType1\,\&\,2}{\sum GroundType1 + LowVegType1\,\&\,2 + MediumVegType1\,\&\,2 + HighVegType1\,\&\,2} \quad (1)$$

5) *Medium veg* Type 1 & 2; opening above medium vegetation. 6) *Medium veg* total (Type 1, 2, 3 & 4); presence of mid-storey vegetation. 7) *High veg* Type 3 & 4; dense canopy of high trees. 8) *High veg* total (Type 1, 2, 3 & 4); presence of high trees. This scheme was subsequently compared to the field data to validate its utility in characterising ecological structure.

Table 1: Forest characterization scheme

	LiDAR return ratio	Description
1	*Ground* Type 1	opening above the ground
2	*Low veg* Type 1 & 2	opening above low vegetation
3	*Low veg* total (Type 1, 2, 3 & 4)	presence of understorey vegetation
4	See equation (1)	canopy cover
5	*Medium veg* Type 1 & 2	opening above medium vegetation
6	*Medium veg* total (Type 1, 2, 3 & 4)	presence of mid-storey vegetation
7	*High veg* Type 3 & 4	dense canopy of high trees
8	*High veg* total (Type 1, 2, 3 & 4)	presence of high trees

4. Result

The comparison between the LiDAR derived structural characterisation scheme and the field data is shown in Figure 2. In this paper, we will focus on four variables only; canopy cover, low vegetation, medium vegetation and high vegetation.

4.1 Canopy cover

Figure 2(a) and (b) show LiDAR derived *CC* (scheme 4) was strongly correlated with the two ground-based measures of *CC* (photosynthetic / photosynthetic and non-photosynthetic), with an R-square value of 0.78 and 0.77 respectively. As displayed in Figure 2(a) and (b), LiDAR *CC* and Field *CC* were highly correlated across a broad range of *CC* values. It was noted that the ground-based measures consistently reported a lower *CC* than LiDAR derived measures. This will be discussed in section 5. Both *CC_1* and *CC_2* report an anomaly whereby the canopy cover for plot 4a was higher in LiDAR *CC*. This can be explained by the difference in canopy cover estimation between LiDAR and field methods. LiDAR *CC* assessed vegetation cover higher than 1m from the ground, while field *CC* was recorded at the height of 1.7m from the ground. If there are dense vegetation components between 1m and 1.7m, field measured *CC* estimation would miss this strata and therefore underestimate *CC*. Our field data confirms that plot 4a has extremely dense mid-storey vegetation; 553 trees (mostly shrubs, *Melaleuca squarrosa* and *Leptospermum scoparium*, approximately 98% of the trees in the plot) are less than 5m in height and with less than 30 cm DBH.

4.2 Low vegetation

LiDAR derived *Low veg* presence (scheme 3) showed strong correlation with field recorded LAI for *Low veg* (R-square value 0.82), and moderate correlation with field recorded mean *Low veg* cover (R-square value 0.58) (Figure 2(c) & (d)). As can be seen in Figure 2(c), LiDAR derived *Low veg presence* and Field LAI for *Low veg* were significantly correlated across a range of LAI values. Comparison between LiDAR derived *Low veg* presence and field recorded mean *Low veg* cover reveal that plot 13a was underestimated in the LiDAR. Plot 13a has grass and blackberry as understorey vegetation. It was noted in the field that the southern half of the plot was covered with very short grass. This could lead to misclassification of LiDAR returns. The grass is too short to be classified as *Low veg* and the LAI2000 is not designed to measure such low vegetation. This explains the good correlation between LiDAR derived *Low veg* presence and Field LAI for *Low veg*.

4.3 Medium vegetation

LiDAR derived *Medium veg* presence (scheme 6) displayed a good correlation with field recorded *Medium veg* class with R-square value 0.66 (Figure 2(e)). Again, this association was observed across a range of *Medium veg* class ratios. Plot 6a was underestimated by LiDAR. In this plot, significant recruitment of small trees and annual growth was noted in the field for all 52 trees (average height 2.27m with less than 10cm DBH) in *Medium veg*. Since there is a one year difference between the LiDAR acquisition date and tree height measurement, these trees would have been much smaller and classified as *Low veg* when the LiDAR data was acquired.

4.4 High vegetation

LiDAR derived *High veg* presence (scheme 8) showed moderate correlation with field recorded *High veg* class with R-square value 0.46 (Figure 2(f)). Comparison between the field derived height measurements and LiDAR derived *High veg* presence scheme proved problematic. This could be due to a number of issues.

- Problems with field measurement, in particular siting true tree top height
- Problems in categorising the field data into height classes (canopy strata)

Further work is being undertaken to resolve these issues.

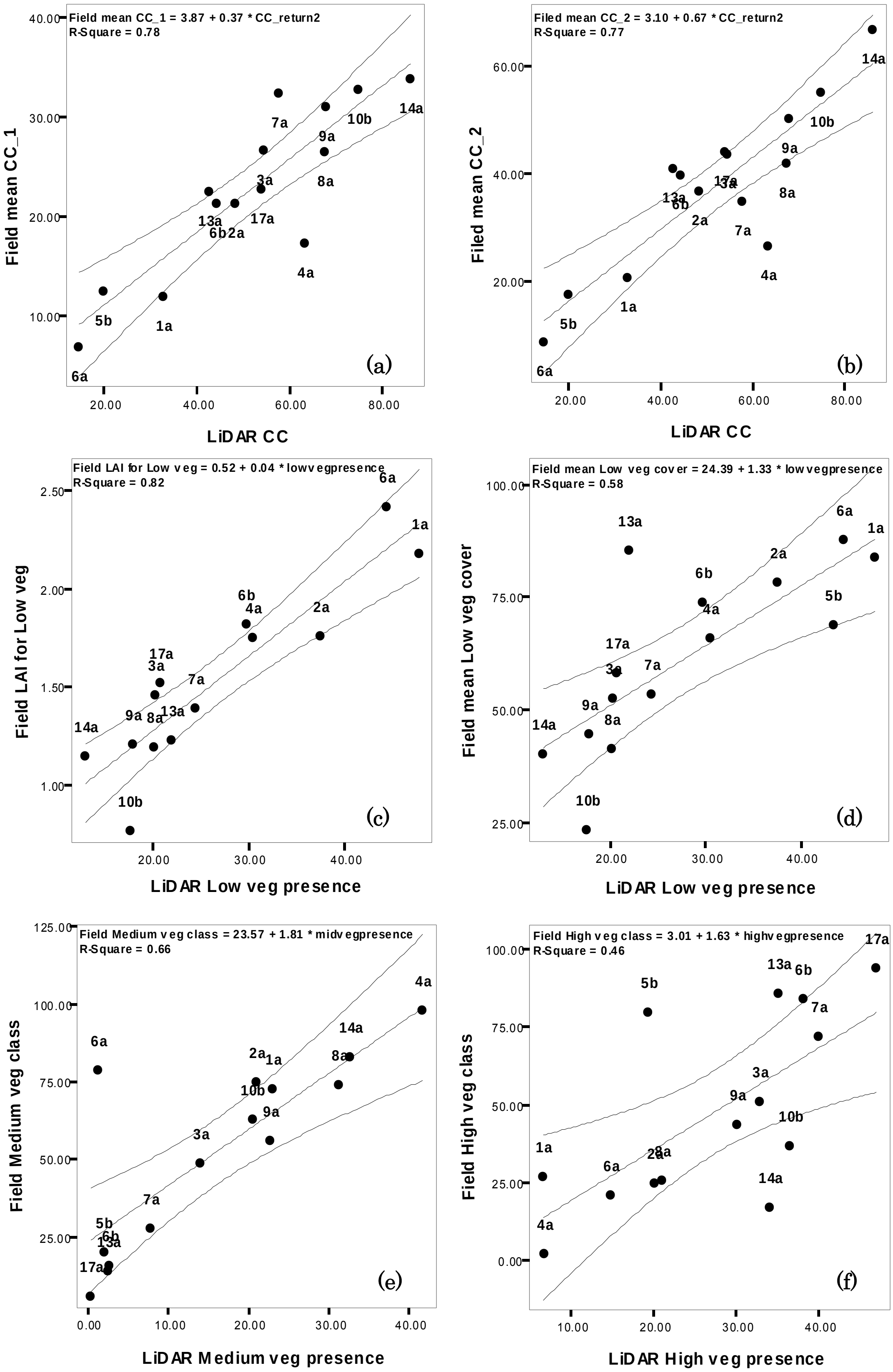

Figure 2: Linear regression between LiDAR derived structural characterization scheme and field data with 95% mean prediction interval. The labels are surveyed plot names.

5. Discussion

In the comparison between LiDAR derived *CC* and the two field measured *CC* assessments, strong correlation was observed. Interestingly, the two different assessment methods of canopy cover described in section 2.3 showed the similar results (R-square 0.77 and 0.78). One would expect higher correlation between LiDAR *CC* and Field *CC_2*, since both variables measure all perturbing canopy objects from laser pulse or sun light, while Field *CC_1* measures only some portion of these objects. In our study site, the vegetation community of the canopy strata is all evergreen and dominated by Eucalypt species. The ratio of leaf area to non-photosynthetic elements (stems and branches) should be consistent unless there is defoliation caused by disease. In fact, *CC_1* and *CC_2* were significantly correlated with each other presenting Pearson Correlation Coefficient value 0.903 ($P \leq 0.01$) in our companion study. In terms of *CC* values, Field *CC* reports a consistently lower value than LiDAR *CC*. We assume that ground based measurements underestimate "true" *CC*. Since field derived measures are based on twenty seven independent observations over an approximately 0.2ha plot area, while LiDAR derived measures are based on more than seven thousand returns in average over the 0.2ha plot. LiDAR would be more capable of assessing *CC* at a landscape scale.

The result of regression analysis between LiDAR *High veg* presence and Field *Hig veg* class provided relatively lower R-square value (0.46). The method to classify field tree height information (see section 2.3) may not represent vertical structure of the plots sufficiently. Further improvement would be required to validate LiDAR scheme.

In conclusion, the proposed method to characterise the ecological structure of a dry Eucalypt forest landscape was promising. Regression analysis reported high correlation between LiDAR derived variables and field recorded variables across a different range of forest structural types. Although some refinement is necessary, particularly in the high vegetation class, the proposed scheme clearly showed the potential of LiDAR to provide information on the complexity of habitat structure. Future work will concentrate on examining the applicability of this scheme to develop habitat suitability models.

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