Towards an operational lidar resource inventory process in Australian softwood plantations

R.Turner[a*], C.Stone[a], A.Kathuria[a] and T.Penman[a]

[a] Department of Industry and Investment New South Wales, Sydney, Australia. - Russell.Turner@industry.nsw.gov.au

Abstract – Airborne lidar technology can play a significant role in revolutionising wood resource inventories in Australian softwood plantations. Plantation managers are interested in the technology but unsure of how to implement it. Hence there is a need to demonstrate and compare various lidar analysis techniques to provide guidance for future operational inventory programs. This paper presents findings from a trial airborne lidar inventory undertaken in a 5,000 ha *Pinus radiata* plantation in the Southern Tablelands of New South Wales (NSW), Australia. The study demonstrates that both area-based and object-based approaches for extracting key plot level attributes (i.e. maximum height, mean height, stocking density and total stand volume) can achieve predictive models with R-squared values ranging from 0.81 to 0.97.

Keywords: lidar, softwood plantation, wood resource inventory

1. INTRODUCTION

Systematic assessment of plantations is essential for predicting current and future stand volumes and implementing silvicultural regimes aimed at maximizing returns. This has traditionally been driven by plot-based inventory and GPS (global positioning system) measurements and supported by Aerial Photogrammetric Interpretation (API). Numerous studies have utilised airborne laser scanning (ALS) instruments (a type of light detection and ranging (lidar) system) for a range of inventory parameters (e.g. Brandtberg et al. 2003 and Maltamo et al. 2009). Airborne lidar now offers a viable alternative to traditional methods and has the potential to revolutionise resource inventory procedures. Today various countries (e.g. Nordic and North American) are incorporating lidar data into their forest management inventories (Hyyppä et al. 2008).

With a total estate of more than 220,000 ha, Forests New South Wales (FNSW) is the largest softwood plantation owner in Australia. FNSW have been investigating the use of airborne lidar for various forestry applications since 2001 and is now entering an operational phase with larger trials underway in some forestry regions.

This study focused on several area-based and object-based approaches to an airborne lidar program in a softwood plantation to demonstrate different techniques for deriving wood resource estimates. Particular attention was paid to stand level attributes that are common to many inventory systems (i.e. maximum height, mean height, stocking density and total stand volume).

1.1 Area-based versus object-based extraction of lidar data

There are two broad sampling approaches to forest resource assessment using airborne small-footprint, discrete return lidar. The first is area-based analysis (ABA) which is also known as plot-based, regression-based or distribution-based analysis. ABA entails the use of artificial plot boundaries (circular or grid polygons) as sampling templates to extract lidar data directly from the original point cloud data (vector points) or from derived Canopy Height Models (rasters) (Yu et al. 2010). This offers a very efficient means of analysing point or pixel data to extract descriptive statistics (e.g. maximum, standard deviation, etc) within a nominated spatial unit.

The second approach is object-based image analysis (OBIA) in which a lidar height image is initially segmented to delineate ‘objects’ that become the carriers of image information and form the basic units of subsequent analysis. In addition to standard descriptive statistics, object polygons can also provide useful metrics such as size (area), shape and spacing. Moreover, because OBIA follows natural boundaries (e.g. crown edges, canopy gaps, road corridors) the sampling units are easier to visually interpret and to relate to ground survey measurements.

OBIA can utilise the hierarchical and multi-scale spatial relationships that inherently exist within plantations. When implemented at an individual tree scale OBIA is sometimes referred to as an individual tree crown (ITC) approach (Gougeon & Leckie 2006), and usually involves the initial detection or delineation of individual crowns and then extraction of key variables such as tree height and spacing (stocking). Individual tree data can then be converted to volume estimates and summed at the plot, stand level or compartment level. Crown delineation can be achieved either from the original lidar point clouds or from a derived Canopy Height Model (CHM) raster, and there are numerous methods available (e.g. Brandtberg et al. 2003 and Lee et al. 2010). However, for this study, only two methods were evaluated; local maxima and crown template based on surface morphology.

The first OBIA method, a local maxima procedure, is technically a crown-detection (tree location) rather than crown delineation approach since it only involves finding crown apices or peaks. Peaks are objectively defined as the highest pixel (or point) within a localised search window called a ‘local maxima filter’. The detection of local maxima is computationally simple, and hence much faster than more complex crown segmentation algorithms.

The second OBIA technique is based on a crown template process utilising the lidar CHM surface morphology in the vertical plane. The Spatially and Morphologically Isolated Crest (SMIC) process essentially defines elevated convex crests using a series of directional filters and algorithms to segment a lidar CHM into small objects called SMIC units (Turner 2006). SMIC units then constitute the basic sampling, analysis and reporting units for wall-to-wall forest inventory.

*Corresponding author
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Both of these approaches can be effective in locating tree crowns provided that the search filter size and prior image smoothing parameters are appropriate for a particular tree size, spacing and image resolution (Wulder et al. 2000 and Lee et al. 2010). A major challenge in this study was the development of variable filter size lookup tables to suit the wide range of conditions within the plantation study area

2. STUDY AREA

The study formed part of a much larger two year remote sensing project called the Plantation Airborne Resource Inventory Appraisal (PARIA) sponsored by the Forest & Wood Products Australia (FWPA) (www.fwpa.com.au) and FNSW (www.dpi.nsw.gov.au/forests). This project investigated the use of airborne lidar and digital multispectral aerial photography for a range of plantation applications (Stone *et al* 2010) and produced a useful guide for softwood plantation managers (Turner and Stone 2010).

A 5,000 ha study area was selected within Green Hills State Forest (SF), located near the town of Batlow in the Southern Tablelands of NSW, Australia (Figure 1). The *Pinus Radiata* plantation is managed by the Hume Forestry Region of FNSW. Green Hills SF has undulating hilly topography and a mean elevation of 750m. The site was considered representative of the broader softwood plantation estate with the full range of age classes, silvicultural treatments and terrain steepness categories.

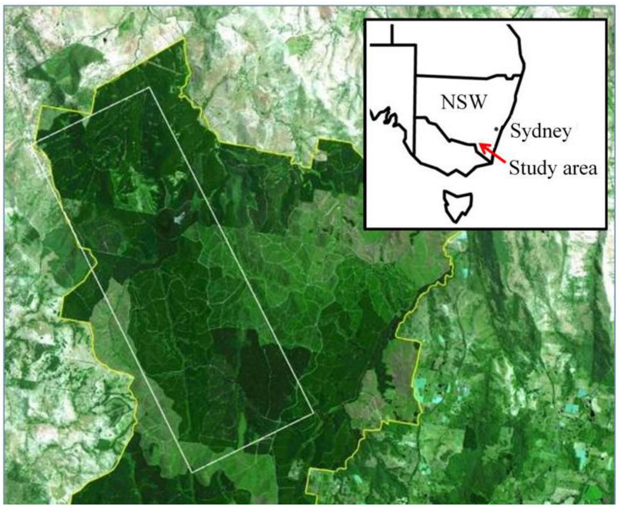

Figure 1. Location of the study area (white outline rectangle) within Green Hills State Forest near Batlow, NSW.

3. METHODOLOGY

3.1 Field data and sampling design

Using existing Geographic Information System (GIS) thematic layers the sample population was stratified by three factors (i.e. age class, thinning treatment and ground slope categories) into 16 strata classes (Stone el al 2010). Each class was randomly allocated four circular plots for a total of 63 plots (one strata class only contained 3 plots due to its small area). Due to known differences in stocking between strata classes, variable sized plots (with radii ranging from 7 m – 20 m) were utilised to achieve at least 15 trees per plot.

The centre of each plot and location of each tree was very accurately surveyed using a laser theodolite (Leica 2 second T1100 total station) and a Differential Global Positioning System (dGPS). For each plot, every tree was labelled and stem diameter and tree height measured. Tree height was measured twice using a Vertex hypsometer by two different operators in order to examine variation due to assessors.

3.2 Lidar imagery acquisition and processing

Small-footprint, discrete return lidar data was acquired in July 2008 using a Lite Mapper LMS-Q560 ALS system (Riegl, Austria) mounted in a fixed-wing aircraft and supplied through Digital Mapping Australia Pty Ltd (Perth, Australia). The near infra-red (NIR) lidar system was configured for a pulse rate of 88,000 pulses per second, mean footprint size of 60 cm, maximum scan angle of 15^o (off vertical), mean swath width 500 m and a mean point density of 2 pulses/m2 (based on the non-overlap portion of the swath) in parallel scanning lines.

Processed lidar point data was supplied on an external drive in LAS file format with each file representing a 1 km x 1 km area (tile). The first and last return for each laser pulse was extracted and tagged with their associated return signal intensity (echo strength) values. A Digital Terrain Model (DTM) at both 1.0 m and 0.5 m pixel resolution was constructed from ground point data using a standard linear triangulation surface modelling technique in Environment for Visualizing Images (ENVI) software (Research Systems Incorporated, USA). A Vegetation Elevation Model (VEM) was generated from all laser points and the DTM was then subtracted from the VEM to derive a Canopy Height Model (CHM).

3.3 Area-based extraction with plot polygons

Lidar metrics were extracted for each of the 63 reference plots using ground and non-ground point data (binary LAS format). Point elevation values were converted to height values by subtracting the ground elevation values derived from the DTM.

A number of lidar height metrics from the literature (e.g. Chen et al. 2007 and Maltamo et al. 2009) were extracted. These included mean, median, mode, maximum, minimum, quadratic mean, variance, standard deviation, coefficient of variation, range, height of the 5th and 95th percentiles, skewness, kurtosis, ground point ratio *(ground point count divided by the total count)* and rumple index *(non-ground point surface area divided by total area (Kane et al. 2010))*. These statistics were generated for a series of lidar point data subsets including all points, first points only, points above 2m height and variable plot sizes (7 to 30m radius). All data extraction and analyses were conducted using open source software packages: R-statistical package v.2.11.1 (R-Development Core Team 2007) and the GIS package GRASS (GRASS Development Team 2010) interfaced using the spgrass6 package. All lidar point metrics were modelled as independent variables to empirically estimate dependent plot-level attributes using a three modelling approaches – regression trees, random forest and Bayesian Model Averaging (BMA) (De'ath and Fabricius. 2000, and Breiman, 2001).

3.4 Object-based extraction with local maxima

The process of extracting the maxima pixels was coded in Interactive Data Language (IDL) script. A series of local maxima search filters (3x3, 5x5, 7x7, 9x9, 11x11, 13x13 and 15x15 pixels) were applied to the CHM raster. This created a series of binary rasters with maxima pixels having a value of 1 and all other pixels having a value of 0. Using standard ENVI routines, the maxima binary layer was then converted to a Region of Interest (ROI) and subsequently used to export both the original CHM height value and the maxima count value to a text files, along with a unique ID number for each maxima, and x and y coordinates. The maxima text files were then imported into the open-source R-statistical package v.2.11.1 (R-Development Core Team 2007) for statistical analysis.

Local maxima results are known to be sensitive to search window size relative to crown size and hence require careful selection of the filter dimensions (Wulder et al. 2000). The optimal dimensions of this moving window are dependent on the shape, size and density of tree crowns. Our approach was to identify the optimum set of window sizes for six combinations of age class categories and thinning status (i.e. (AC 10-20, UT); (AC 10-20, T1); (AC 20-30, UT); (AC 20-30, T1); (AC 20-30, T2) and (AC 30+, T2)). Consequently, based on the statistical analysis of the 63 research plots, a new lookup table was developed and tested.

3.5 Object-based extraction with canopy segmentation

Given the initial lidar point sampling density of 2 pulses per m^2 many of the larger pine crowns in the CHM possessed numerous within-crown gaps which were known to affect the performance of the SMIC canopy segmentation process. To minimise this problem the CHM surface was initially optimised. An algorithm, based on the Crown Infill, Trim and Smooth (CITS) process developed by Turner (2006), was used to fill in crown holes and smooth the crown surface to enhance the CHM surface prior to canopy segmentation.

A series of SMIC filter sizes were tested ranging from 3x3 to 15x15 pixels and applied to three different treatments. Firstly, it was applied directly to the original CHM as a control (method 1), then secondly to a CITS processed CHM to see if the smoothing process improved results (method 2) and thirdly it was applied to the CITS smoothed CHM with post-processing of SMIC units to remove any noise from the dataset (method 3). Lastly, the application of seven different filter sizes for the three different methods was also repeated for CHMs with 0.5m and 1m pixel resolutions to determine if pixel size was a factor in performance. Consequently this generated 42 SMIC polygon datasets for analysis.

As a control dataset, manually drawn crowns were prepared for almost 900 tree crowns in the 63 research plots. When comparing automated crowns to manual crowns, SMIC crowns were labelled as matches, aggregates, splits or omissions. To assist in the semi-automated selection of the most appropriate SMIC method for each age class and thinning combination an optimisation rule was developed in R software (Stone et al 2010). The most appropriate filter size and treatment for each stratum was incorporated into a look-up table which was re-applied to the plot dataset to predict inventory parameters.

4. RESULTS AND DISCUSSION

4.1 Area-based approach - plot polygons

To reduce the large number of predictor variables a Spearman's correlation matrix was used to remove the potential for multi-co linearity in the models. For those variables found to have a correlation greater than 0.7, one variable was retained and all highly correlated variables removed. The remaining set of non-correlated variables were minimum height (hMin), rumple index - based on the 0.5 m grid cell corrected by the mean height (rumple), mean ground slope (slope), height of the 5th and 95th percentiles (h5 and h95), skewness (skew), and ground point ratio (GPR). Model fit was high for all variables tested (r^2 0.58 to 0.95), however regression trees had the best model fit compared to the other statistical approaches. R-squared values for the best regression tree models were maximum height 0.95, mean height 0.94, stocking 0.85 and total stand volume 0.81. The most influential lidar point variable was the 95th percentile height (h95) metric. Variables of much lesser influence included minimum height, GPR, skewness, h5 and slope.

4.2 Object-based approach – local maxima

For the local maxima analysis, the proportions of matches, splits and omissions were plotted against the various search window sizes (3x3 to 15x15 pixels) for each age class and thinning combination. In general, splits and omission errors tended to counter balance each other (e.g. when split errors decrease omission errors increase).

Results indicated that not only age class (surrogate for crown size) but also thinning treatment (surrogate for stocking density) appear to influence the selection of optimal local maxima search window size. Table A summarizes the results of the error analysis and presents the look-up table used for selecting the optimum window sizes for each age class and thinning combination for a CHM with a 0.5 m pixel resolution. Note that this analysis is based on individual tree data not plot totals.

Table A. The best maxima filters and percentage 1:1 matches.

Age class	Thinning Treatment		
	UT	T1	T2
10 -20	*5x5 & 7x7 (72%)	7x7 (72%)	-
20 – 30	7x7 (65%)	9x9 (67%)	*9x9 & 11x11 (77%)
30+	-	-	*9x9 & 11x11 (77%)

* Average of two filter sizes

Based on the regression analysis predicting plot level dependent inventory variables, the associated R-square values were maximum height 0.97, mean height 0.95, stocking 0.88 and total stand volume 0.81. It is likely that estimates improved at the plot level because the sum of split and omitted crowns tend to balance each other out.

4.3 Object-based approach – canopy segmentation

The proportions of SMIC crown matches, omissions, splits and aggregations were calculated for each window size ranging from 3x3 to 15x15, the three treatments (methods 1,2 & 3) and also for pixel sizes of 1 m and 0.5 m. An optimisation algorithm was used to select the most suitable window size for each stratum. Results showed that the 0.5m CHM was superior to the 1m CHM; consequently it was decided to use only the 0.5 m pixel size lidar data for further analysis.

Table B summarizes the results of the error analysis and presents the look-up table used for selecting the optimum window sizes/method for each age class and thinning combination using CHMs with 0.5 m and 1 m pixels. This analysis is based on individual tree data not plot totals.

Table B. The best SMIC models and percentage 1:1 matches.

Age class	Thinning Treatment		
	UT	T1	T2
10 -20	Method3* (78%)	Method3* (81%)	-
20 – 30	Method1* (65%)	Method3# (75%)	Method3# (79%)
30+	-	-	Method3# (85%)

* Based on 0.5m CHM, # Based on 1m CHM

Results of plot level regression analysis indicated R-square values ranging from maximum height 0.97, mean height 0.94, stocking 0.90 to total stand volume 0.83. Method 3 proved to be the best performing SMIC model (i.e. CITS smoothed CHM with SMIC rounding) with the exception of unthinned older stands (20-30ys) where method 1 (original CHM) performed best primarily due to their more closed canopy structure.

5. CONCLUSION

This study has demonstrated the feasibility of obtaining wood resource estimates in an Australian softwood plantation using both area-based and object-based extraction approaches for small-footprint airborne lidar. Results have shown that all three alternative approaches can provide accurate plot level estimates of maximum height (r^2 0.95 to 0.97), mean height (r^2 0.94 to 0.95), stocking density (r^2 0.85 to 0.90) and total stand volume (r^2 0.81 to 0.83). At an individual tree level, both OBIA approaches (local maxima and SMIC) were able to identify most dominant trees (i.e. 65 to 85% depending on the age class and thinning class).

Forest managers are faced with ever increasing costs of field surveys and the growing demand for more rapid, accurate and cost-effective spatial information. It is hoped that this study will encourage plantation managers to adopt new airborne lidar technology into their own planning systems.

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