Airborne lidar resource inventory in NSW softwood plantations

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Abstract:

With the introduction of airborne laser scanner technology, plantation wood resource inventory in Australia is undergoing a significant transformation. Plantation managers now have the option of utilising high accuracy wall-to-wall height data and this has created a demand for practical techniques and procedures for extracting lidar metrics to estimate key stand variables. The aims of this paper are firstly to demonstrate different options for implementing an airborne lidar resource inventory in a commercial softwood plantation (in New South Wales, Australia), and secondly to introduce innovative Lidar Point Interpretation (LPI) software currently under development.

Keywords: lidar, softwood plantation, lidar point interpretation software, and resource inventory

1 Introduction

The traditional approach to predicting current stand volume has been driven by plot-based field sampling often supported by Geographic Information Systems (GIS), Global Positioning Systems (GPS) and Aerial Photograph Interpretation (API). However, as the cost of field sampling increases, there is a need to find more cost-effective techniques. Airborne laser scanning (ALS) instruments (sensors that utilise light detection and ranging (lidar) technology) offer a viable alternative as demonstrated by various studies around the world (e.g. Brandtberg et al. 2003, Hyyppä et al. 2008 and Maltamo et al. 2009).

In this paper results are presented from a trial airborne lidar resource inventory undertaken in a commercial softwood plantation in New South Wales (NSW), Australia. The study focused on both area-based and object-based approaches to derive wood resource estimates of maximum height, mean height, stocking and total stand volume and achieved predictive models with R-squared values ranging from 0.81 to 0.97.

In addition to demonstrating the application of lidar-based resource inventories, there is also a need for more user-friendly software to facilitate the uptake of this technology into mainstream forestry. This paper also introduces a new commercial software package under development that incorporates the concept of Lidar Point Interpretation (LPI).
2 Airborne lidar resource inventory case study

2.1 Study area

The Plantation Airborne Resource Inventory Appraisal (PARIA) was a two year collaborative project (2008 -2010) between Forests New South Wales (FNSW) and the Forest Science Centre (FSC) within the NSW Department of Primary Industries (DPI). The project was primarily funded by Forest and Wood Products Australia (FWPA) and the final report (Stone et al. 2010) is available from their website (www.fwpa.com.au). The study also provided a user manual - “Guide to Acquisition and Processing of Remote Sensing Data for Softwood Plantations” (Turner and Stone 2010) which offers a useful introduction to the operational acquisition of imagery for wood resource inventory.

The project demonstrated an airborne resource inventory program in a softwood plantation and compared different lidar processing approaches for deriving common plantation stand level attributes (including maximum tree height, mean tree height, stocking per hectare, and total stand volume per hectare). The study area consisted of a 5,000 ha *Pinus radiata* plantation within Hume Forestry Region located in Southern Tablelands of NSW. The plantation contained a full range of age classes (0 to 40 years), silvicultural treatments (unthinned, first thinning and second thinning) and ground slope categories (0 to 30+ degrees).

2.2 Lidar acquisition

Lidar data was acquired in July 2008 using a Riegl LMS-Q560 laser scanner configured for a pulse rate of 88,000 pulses per second, mean footprint size of 60 cm, maximum scan angle of 15° (off vertical), and a mean point density of 2 pulses/m² (Turner et al. 2011). 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)

2.3 Field sampling

The plantation was divided into16 strata based on age class, silvicultural treatment and ground slope class. A stratified random approach was used to allocate 63 research plots across the estate and these plots were subsequently located and measured in September 2008. A total of 978 individual trees were accurately located using precision survey techniques and each tree height measured twice with a Vertex Hypsometer.

In addition to the research plots, regional staff also measured another 100 conventional inventory plots to provide an independent dataset. Plots were measured in four compartments which included two unthinned compartments (1998 and 1983 age classes) and two second thinning compartments (1983 and 1979 age classes).
2.4 Results

This paper will focus on three key result areas investigated in the more comprehensive PARIA project (Stone et al. 2010) namely the estimation of:

- Tree height
- Net Stocked Area, and
- Stand attributes at plot level.

2.4.1 Estimation of tree height

As suggested in other studies, the results confirmed that lidar tree height estimates across all strata were highly correlated with ground-based height estimates (figure 1). However, results also revealed a slight negative bias on ground slopes under 20° (-55 cm) and a positive bias on slopes above 20° (+47 cm).

![Figure 1: Correlation between field survey tree height and lidar-derived tree height](image)

The positive height bias on steeper slopes may be due to the slope skew effect (Turner 2006). The relationship between height bias and ground slope offers the potential to generate a lidar height error surface based on ground slope values from a lidar-derived Digital Terrain Model (DTM). A subsequent predictive model developed for the study area achieved an R-square of 0.97.

2.4.2 Estimation of Net Stocked Area

Net Stocked Area (NSA) is important for plantation surveys as it defines the sample population. The traditional approach involves subdividing a plantation into relatively uniform strata groups (or resource units) that are usually spatially defined with existing GIS thematic layers such as road,
compartment, age class and silvicultural treatment boundaries etc. The PARIA project explored an object-based classification approach utilising eCognition® software (www.ecognition.com). Customised classification rule-sets were developed and proved to be effective in mapping land-cover and NSA. However, the process was considered semi-automated as some manual correction was still required to produce the final product. The lidar-derived classification for Net Stocked Area produced an overall mapping accuracy of 96%, with a Kappa coefficient of 96%. An example of the eCognition classification is illustrated in figure 2.

![Figure 2: An example of eCognition-derived NSA strata from the study area.](image)

Object-based NSA classification results were also compared to traditional NSA estimates for the four independent compartments surveyed by regional staff. The lidar-derived NSA estimates were shown to be within 10% of conventional estimates (Table 1), but with better spatial accuracy.

<table>
<thead>
<tr>
<th>Resource Unit</th>
<th>Conventional NSA (ha)</th>
<th>Lidar-derived NSA (ha)</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998 (10y)-UT</td>
<td>157.8</td>
<td>143.5</td>
<td>9%</td>
</tr>
<tr>
<td>1983 (25y)-UT</td>
<td>106.9</td>
<td>110.6</td>
<td>3%</td>
</tr>
<tr>
<td>1983 (25y)-T2</td>
<td>159.6</td>
<td>154.9</td>
<td>3%</td>
</tr>
<tr>
<td>1979 (29y)-T2</td>
<td>124.8</td>
<td>117.1</td>
<td>6%</td>
</tr>
</tbody>
</table>

Table 1: Comparison between conventional NSA and eCognition NSA estimates
2.4.3 Estimation of stand attributes at the plot level

There are two common sampling approaches for extracting plot level forest data from airborne lidar. Firstly, an area-based analysis involves the extraction of lidar statistics from either the original lidar point cloud data or the derived Canopy Height Model (CHM) raster. In this approach the smallest unit is a plot or grid cell. Using the area statistics (e.g. mean height, skewness, height percentiles etc) plot-level regression relationships are explored with field data. Secondly, there is an object-based approach that involves the spatial detection or delineation of relatively uniform sampling units prior to extracting descriptive statistics. If this is undertaken at tree level it involves either tree detection (vector points) or crown delineation (vector polygons). In this approach the smallest unit is the tree, and this can be converted to plot level estimates by summarising tree statistics.

For this study three methods (Figure 3) which were all derived from either area-base and object-based approaches were evaluated. The processing techniques used included:

a) lidar point cloud data (area-based) with point statistics extracted within each circular plot,

b) peak points (object-based) with trees first detected using local maxima filters and the statistics extracted for each plot, and

c) crown mapping (object-based) using a crown delineation algorithm to create crown polygons prior to extraction of plot level statistics.

Figure 3: Samples of lidar data using each of the three data extraction techniques utilised in this study; a) lidar point cloud data, b) peak points and c) crown maps. The white circles indicate plot boundaries.

For the point cloud analysis a range of lidar height metrics were extracted (e.g. Chen et al. 2007 and Maltamo et al. 2009) including 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). All lidar point metrics were modelled as independent variables to empirically estimate dependent plot-level attributes using three modelling approaches – regression trees, random forest and Bayesian Model Averaging (Stone, Penman and Turner 2011). 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 variable was the 95th percentile height metric with variables of lesser influence including minimum height, GPR, skewness, 5th percentile height metric and slope.

Two methods were applied for the object-based approach. The simplest method utilised local maxima search windows (Wulder et al. 2000) to scan the CHM raster to locate peak points. The more complex method used a crown delineation algorithm called the Spatially and Morphologically Isolated Crest (SMIC) process (Turner 2006). Both object-based methods were coded in Interactive Data Language (IDL) script and then applied in ENVI 4.6 software.

Results for the peak points and crown mapping methods were similar for individual tree detection with both techniques achieving a large proportion of 1 to 1 matches with field survey data and located dominant trees representing 90% of total stand volume. As both methods are very sensitive to search window size relative to crown size and spacing, different search window sizes were applied to each age class and thinning combination. Depending on the strata class, peak point matches ranged from 65 to 77% while crown mapping ranged from 65 to 85%. Given the similarity in results, the peak point method (utilising local maxima filters) may have the edge as it is computationally simpler, much faster to apply, and vector points use less storage space than polygons. However, the selection of the right local maxima search window to suit each crown is a critical limiting factor and future work will explore the optimisation of window selection.

Overall, the three approaches (i.e. point cloud, peak points and crown mapping) were very successful in predicting plot level stand attributes. The regression analysis results, summarised in Table 2, reveal similar results for all extraction methods.

### Table 2: Adjusted R-squared results for predictive models in research plots

<table>
<thead>
<tr>
<th>Plot variable</th>
<th>Point Clouds</th>
<th>Peak points</th>
<th>Crown Mapping</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum height</td>
<td>0.95</td>
<td>0.97</td>
<td>0.97</td>
</tr>
<tr>
<td>Mean height</td>
<td>0.94</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>Stocking</td>
<td>0.85</td>
<td>0.88</td>
<td>0.90</td>
</tr>
<tr>
<td>Total stand vol.</td>
<td>0.81</td>
<td>0.81</td>
<td>0.83</td>
</tr>
</tbody>
</table>

In addition, the predictive models based on peak points and crown mapping were shown to be very robust when applied to the 100 independent survey plots from Hume region (Table 3). Again, these models were highly correlated with conventional inventory plots (values ranging from $r^2$ 0.86 to 0.97). In some cases the predictive models actually obtained better results in the independent operational plots across fewer strata.


### Table 3: Adjusted R-squared results for models projected into independent survey plots

<table>
<thead>
<tr>
<th>Plot variable</th>
<th>Peak points</th>
<th>Crown Mapping</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum height</td>
<td>0.97</td>
<td>0.96</td>
</tr>
<tr>
<td>Mean height</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td>Stocking</td>
<td>0.91</td>
<td>0.86</td>
</tr>
<tr>
<td>Total stand vol.</td>
<td>0.93</td>
<td>0.92</td>
</tr>
</tbody>
</table>

2.5 Project summary

The case study demonstrated that an airborne lidar resource inventory can be successfully applied in a commercial softwood plantation using both area-based and object-based extraction approaches. All three methods provided 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). Moreover the two object-based approaches (peak points and crown mapping) were able to identify most dominant trees (i.e. 65 to 85% depending on the age class and thinning class). Clearly there are potential gains to be made by further exploring airborne lidar resource inventory and it is hoped that plantation managers will be encouraged to adopt this new technology.

3 Lidar point Interpretation software

3.1 Background

Although the previous section supports the premise that airborne lidar resource inventory can be implemented successfully, there still remains the need to collect field data to build predictive models and validate them. Unfortunately, ground survey costs continue to represent the greatest expenditure in wood resource assessments and there is a strong need to both reduce the number of field plots required and to better position plot locations to cover stand variation. Remote sensing may offer a more cost-effective alternative to collecting plot data.

Most foresters would be familiar with the concept of Aerial Photograph Interpretation (API) as it is a well established method of extracting forest information that is difficult to achieve using automated approaches. Even with the new generation of digital cameras and line scanners, there is still a demand for API techniques and there are commercial software packages available to enable stereo on-screen manual interpretation. With the advent of airborne laser scanners there is now another source of remote sensing data that could also facilitate manual interpretation for forestry purposes.

Lidar processing is currently dominated by automated approaches to data extraction; however, there is far more information within lidar point clouds than can currently be extracted automatically. The new concept of Lidar Point Interpretation (LPI) encapsulates the manual interpretation of on-screen virtual plots with the capacity to develop new ways of extracting forest attributes previously unattainable. LPI involves a paradigm shift from 100% field survey dependent sampling to a mix of...
LPI virtual plots with fewer, and better placed, field plots. It is postulated that one analyst using LPI techniques could potentially manually interpret dozens of lidar plots per day compared to a field team measuring only 4 to 6 plots per day. If feasible, this innovative assessment approach has the potential to provide significant savings in future resource inventory programs in all types of forest.

To investigate the potential of LPI, a two year collaborative research project between the University of New South Wales (UNSW), FNSW and FSC is currently in progress. Funded primarily by an Australian Research Council grant, the project will evaluate the feasibility of LPI for forest inventory and the design, development and testing of an innovative software platform with a suite of operational tools for on-screen manual interpretation of virtual lidar plots. The software will accommodate lidar point cloud data in LAS format from any laser scanner (i.e. terrestrial or airborne) and enable visualisation in 2D and 3D displays. A range of manual tools will be available to add markers, measure stem and crown parameters and tag key attributes such as form quality, species and growth stage for each tree. In addition, a series of automated plot statistics will also be available for extraction of variables such as height percentiles, common descriptive statistics (e.g. max, mean, mode, median, standard deviation etc) and canopy cover percentage.

3.2 Software features

Written in C++ programming language, the software is designed in three parts. Module one offers the user the ability to customise the manual and automated attributes required for their survey needs. Localised functions and equations can also be entered to convert prime attributes to other derived products (e.g. convert height to diameter, or diameter to gross volume). Module 2 provides an LPI interface where users can extract plot level lidar point data from the original LAS files and visualise the data in 2D and 3D. A suite of manual tools also enable the user to add markers, trace stem lines, label attributes and make on-screen measurements (figure 3). And lastly, Module 3 provides data management functions where customised outputs (e.g. databases, raster images, vector points and polygons, graphs, text reports etc) can be designed to deliver datasets to suit other software packages and meet reporting requirements.

Figure 3: Sample of a 3D visualisation of point cloud data with manual markers, labels and stem traces.
3.3 Project summary

Software development is well underway and a working prototype should be available for field testing in early 2012. The software will be evaluated using established field survey plots from other airborne lidar inventory projects (native forest and plantation). Following the field evaluation, and any subsequent modification, the final software package should be commercially available in late 2012 or early 2013. In addition, future research through the University of NSW will investigate optimum lidar acquisition parameters for LPI (e.g. high sampling density, different scan angles, multi-directional passes etc) with the goal of providing lidar acquisition specifications to optimize the capacity for on-screen manual interpretation.

The new LPI software should provide plantation managers with the option to process their own lidar datasets with fewer technical skills than would normally be required for remote sensing projects. It is hoped that the new software, coupled with the demonstrated success of airborne lidar resource inventory procedures, will encourage wider adoption across the forestry sector in Australia.

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References:


