THE UTILITY OF LIDAR FOR RECOVERING ECOLOGICAL VARIABLES

N. Miura [a,] * and S. D. Jones [a]

[a] School of Mathematical and Geospatial Sciences, RMIT University, GPO Box 2476V, Melbourne VIC 3001 Australia naoko.miura@student.rmit.edu.au, simon.jones@rmit.edu.au

Commission VIII, ThS-21

KEY WORDS: LIDAR, Ecology, Vegetation, Return Intensity, Landscape, Point Cloud

ABSTRACT:

The results of an investigation of the utility of LiDAR (Light Detection and Ranging) for recovering ecological variables are detailed. Mean LiDAR intensity and standard deviation of intensity were calculated for the classified groups; First return intensity in Canopy stratum (FRI_C), Last return intensity in Canopy stratum (LRI_C), First return intensity in Ground stratum (FRI_G) and Last return intensity in Ground stratum (LRI_G). These were analyzed and compared to the field derived variables; canopy, grass, leaf and bare-ground cover and the quantity of fallen trees, over twenty five sites in the Barmah Mellewa Forest, Australia. First return intensity did show significant correlations with key ecological data: a high negative correlation (-0.509 $P\leq 0.01$) was found between mean canopy cover and FRI_C and a high positive correlation (+0.620 $P\leq 0.01$) between mean grass cover and FRI_C. First return intensity in the ground stratum (FRI_G) was highly correlated with mean canopy cover (+0.580 $P\leq 0.01$) and fallen trees (log density, +0.698 $P\leq 0.01$). Mean canopy cover and fallen trees were found to be inversely proportional to the standard deviation of First return intensity in the ground stratum (-0.519 $P\leq 0.01$ and -0.686 $P\leq 0.01$ respectively).

1. INTRODUCTION

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 (so providing 3-dimensional information). Some LiDAR instruments can also record the intensity of the backscattered laser pulses. This allows for the characterisation of objects and their attributes. Such LiDAR information (along with appropriate positional data from GPS -Global Positioning System and INS -inertial navigation system) now provide the potential for accurate, fast and versatile measurements in renewable natural resource management (Wehr and Lohr, 1999). To date, most natural resource remote sensing has been undertaken using passive sensing technologies, mainly in the visible near infrared red portions of the electro-magnetic spectrum. Compared to these 2D information sources, LiDAR provides 3D information on the target, which enables the estimation of such variables as tree height (Suarez et al., 2005) and foliage biomass (Riano et al., 2003) in forestry. Characterisation of forest attributes at the level of a community, or stand, is required to better manage terrestrial resources such as forestry, Carbon sequestration, water resource management, soil stability and biodiversity. 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). Therefore, measurement of forest attributes and evaluation of their variety is often advocated as a good indicator of biodiversity in the context of conservation management. The potential for using LiDAR data for deriving forest attributes at the level of the forest stand has received strong attention recently (Brandtberg et al., 2003; Holmgren and Persson, 2004; Morsdorf et al., 2004; Riano et al., 2003; Suarez et al., 2005; Zimble et al., 2003) and there is an increasing interest in developing forest structure for habitat assessment (Airborne Laser Survey Working Group, 2004).

The focus of this paper is to investigate LiDAR intensity. There are few studies utilising LiDAR intensity, although they show promising results. In some early work, Means et al. (1999) estimated canopy height, basal area, stand biomass and foliage biomass in coniferous forest using LiDAR derived metrics which included canopy intensity sum, ground intensity sum and canopy closure calculated from intensity. These authors concluded that tree foliage biomass was best predicted by canopy intensity sum. Van Aardt et al. (2006) also included intensity-based parameters such as intensity mean and median to estimate forest volume and above ground biomass in a mixed forest, and indicated that multiple returns and intensity associated with each LiDAR hit might well be necessary for effective modelling of variation in more complex forests. For tree species classification, Brandtberg et al. (2003) included the intensity kurtosis, the intensity skewness and the maximum intensity value for individual leaf-off tree crowns in the six best single individual tree-based variables. Compared with the individual tree approach in these previous studies, this paper evaluates site condition at a landscape level utilising LiDAR intensity.

2. DATA COMPOSITION

2.1 Study area

The study area is situated in the Barmah Mellewa Forest, located on the border of New South Wales (NSW) and Victoria (VIC) in Australia. The area is a riparian complex which comprises approximately 70,000 ha of wetland and forests. This system has a variety of land tenures including areas of national park and state forest reserves. In the latter, logging

* Corresponding author.

operations exist which can hinder the monitoring process. The area is important since it represents the largest remaining river red gum (Eucalyptus camaldulensis ssp. obtusa Dehnh) forest in the world (Bacon et al., 1993). This landscape contains important rare and endangered Flora and Fauna (Harris and Rawson, 1992). The Barmah-Millewa Forests are recognised as a significant habitat for migratory birds in international treaties such as the Ramsar convention, the Japan-Australia Migratory Birds Agreement and the China-Australia Migratory Birds Agreement (Chong, 2003). Conservation of biodiversity is therefore critical in this area.

2.2 LiDAR (Light Detection And Ranging) data

The LiDAR data used in this research was gathered in July 2001 and acquired by the Murray Darling Basin Commission, using ALTM, Optech airborne laser scanning system (small footprint and discrete return). Table 1 details the specifications of the sensor at the time of acquisition. The instrument output comprises three data sets: First return pulse, Last return pulse “ground” and Last return pulse “non-ground”. Each data set contains two variables: elevation information and an intensity of return value.

Scanner Model	ALTM 1225 (now ALTM 3025)
Sampling intensity	11000 Hz and 12500Hz
Flying height	1100m
Laser swath width	800m gross, 600m net (25% overlap between swathes)
Laser wavelength & foot-print	1.047 microns ; 0.22m diameter
Vertical Accuracy	0.15m (1 sigma)
ALS Internal precision	0.05m
Acquisition Date	July 2001

Table 1. LiDAR acquisition specifications

2.3 Field data

Initial ground data collection commenced in July 2002 and comprised standard ecological surveys collected using the Birds Australia Atlas Habitat template as well as state government “Ecological Vegetation” surveys. Preliminary comparisons of this ground data to the LiDAR information were not promising. In July and September, 2005 a further field survey was completed specifically to explore and validate the ecological content of the LiDAR dataset. The four year time difference between LiDAR acquisition date and field observation is unfortunate. However, the research team confirmed there was no major logging or wild fires during this period, and forest condition was similar. Twenty five plots were randomly positioned throughout the forest with a caveat of accessibility. Surveys were established as two hectare circular plots. A plot was established by defining a centre point and taking a GPS measurement. This includes resident positional error of x y, ± 7m on average. Tree height (m) was determined using a clinometer. Canopy and understorey cover (%) such as grass, leaf and bare ground, were assessed with the reference photography. These measurements were conducted at the plot centre and at three of the four peripheral cardinal points. The quantity of fallen trees was assessed over each plot in four classes; absent, 1-5 logs, 6-15 logs and more than 15 logs.

3. DATA ANALYSIS

Data for the 2ha plots was extracted from the LiDAR point cloud for the three data sets (First, Ground and Non-ground). To allow for positioning inaccuracies in locating the plot areas a 10% buffer was placed around each plot yielding an amended plot size of 2.2ha (84m radius circular plot). The first stage in processing was to group the three data sets (First, Ground and Non-ground) into a singular combined point cloud. This was then reclassified into two strata; Canopy and Ground. This was achieved using the maximum elevation value of the Ground dataset as a threshold (derived from Ground return statistics on a plot by plot basis). This was necessary since there were pronounced variations in ground elevation between plots which required a local definition of what constitutes ground. Subsequently, the data in each stratum was reclassified into two groups; First return and Last return, to determine if there was any difference between these two interactions. This yielded four data sets that correspond to elevation and intensity information for two strata canopy and ground; with First pulse returns and Last pulse returns recorded for each.

4. EXPLORATORY ANALYSIS OF THE LIDAR RETURN INTENSITY

In order to assess the biodiversity information content of the LiDAR data the mean values for a range of ecological variables were calculated. Canopy, grass, leaf and bare-ground cover information were summed in each plot and presented as a mean. As the quantity of fallen trees was assessed over each plot in four classes; absent, 1-5 logs, 6-15 logs and more than 15 logs, we used this class value as an ecological variable.

For comparison with field data, mean LiDAR intensity and standard deviation of intensity were calculated for the classified groups; First return intensity in Canopy stratum (FRI_C), Last return intensity in Canopy stratum (LRI_C), First return intensity in Ground stratum (FRI_G) and Last return intensity in Ground stratum (LRI_G). To examine the relationship between LiDAR data and collected ecological variables, Peason correlation coefficient was calculated to test the relationship between intensity values; mean intensity and standard deviation of intensity, and mean canopy cover, mean grass cover, mean leaf cover and mean bare-ground cover. The Spearman rank correlation coefficient was used to evaluate the relationship between intensity values and the quantity of fallen trees.

4.1 First return intensity in Canopy stratum (FRI_C)

FRI_C shows a strong negative correlation with canopy cover (Table 2). In other words, where canopy cover is high, first return intensity in canopy stratum is low. We assume the following scenario. At 1.047 µm, reflectance and transmittance components are the dominant radiation transfer processes (Bauer et al., 1986; Curran, 1985; Lillesand et al., 2004). Effectively the downward-welling radiation pulse is randomised on the interaction with the canopy layer. Therefore weak pulses are often returned to the LiDAR sensor. On the other hand, where the canopy is sparse, laser pulses are much less likely to interact with canopy objects but when they do, the nature of the interaction is different. The pulse is more likely to interact with solid materials such as branches and boles, and stronger returned pulses therefore result.

FRI_C also displays a strong positive relationship with grass cover (Table 2). This provides strong anecdotal evidence since one would expect more grass growth where the canopy is sparse, if light is a limiting growth factor. In other words, grass does not grow thickly where canopy is dense, because FAPAR is reduced. Although the correlation between mean leaf cover and FRI_C is only significant at the 0.05 level, a similar relationship was observed.

	FRI_C	LRI_C	FRI_G	LRI_G
Mean canopy cover	-.509(**)	0.077	.580(**)	0.045
Mean grass cover	.620(**)	0.367	-.429(*)	.424(*)
Mean leaf cover	-.435(*)	-0.346	0.33	-0.355
Mean bare-ground cover	-0.309	-0.235	0.02	-.406(*)

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 2. Correlations between mean intensity and field data

4.2 First return intensity in Ground stratum (FRI_G)

FRI_G also exhibits significant positive association with canopy cover (Table 2). Where canopy cover is high, the first return intensity in the ground stratum is high. Our field data demonstrates a positive association between large trees and dense canopies. Large fallen trees and debris are therefore more likely to be on the ground and stronger pulses result. FRI_G also shows a strong positive correlation with the amount of fallen trees (Table 3), which suggests where fallen trees are abundant, first return intensity in ground stratum is high. We hypothesise that when laser pulses hit solid materials such as logs and fallen trees, strong pulses are returned.

The standard deviation of FRI_G displays a negative correlation with canopy cover (Table 4) and the amount of fallen trees (Table 5). This can be explained as where canopy cover is high (fallen trees are abundant), the standard deviation of first return intensity in the ground stratum is low. The standard deviation of intensity is a measure of variation in intensity values. Assuming that each component on the ground has a distinct interaction with the LiDAR pulse, standard deviation of FRI_G could be used as an index of heterogeneity of ground condition. A high standard deviation of FRI_G indicates heterogeneous ground, and lower standard deviation of FRI_G suggests homogeneous ground. Where the canopy is dense or fallen trees are abundant, ground is more likely homogeneous.

	FRI_C	LRI_C	FRI_G	LRI_G
fallen trees	-.450(*)	-0.251	.698(**)	0.126

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 3. Correlation between mean intensity and the amount of fallen trees

	FRI_C STDEV	LRI_C STDEV	FRI_G STDEV	LRI_G STDEV
Mean canopy cover	0.085	0.134	-.519(**)	0.133
Mean grass cover	0.003	0.27	0.287	0.202
Mean leaf cover	-0.091	-0.319	-0.302	-0.241
Mean bare-ground cover	-0.037	-0.223	0.177	-0.189

** Correlation is significant at the 0.01 level (2-tailed).

Table 4. Correlations between standard deviation of intensity and field data

	FRI_C STDEV	LRI_C STDEV	FRI_G STDEV	LRI_G STDEV
fallen trees	0.301	0.288	-.686(**)	0.352

** Correlation is significant at the 0.01 level (2-tailed).

Table 5. Correlation between standard deviation of intensity and the amount of fallen trees

5. DISCUSSION

The results of the analysis revealed that the last return intensity for both canopy and ground returns (LRI_C and LRI_G) does not show significant correlation with the field based ecological variables (Table 2 & 4). This fits with the results of Brandtberg et al. (2003) who report lower accuracy in classifying species when using last return information. Moffiet et al. (2005) asserted that the last return intensity is affected by the pulse energy remaining within the portion of footprint as well as reflective surface properties. This can have a profound impact. In other words, the return is a result not just of the ground cover but also the amount of energy remaining in the pulse. In our study, this was explained by the standard deviation of intensity in each plot. A higher standard deviation of intensity was observed in the last return (LRI_C and LRI_G) as compared to the first return (FRI_C and FRI_G), indicating the last return has greater variation in intensity. This is especially salient since there is no species difference in Canopy stratum. We propose the difference in intensity variation between first return and last return in canopy stratum (FRI_C and LRI_C) could be due to the amount of pulse energy that remains to interact with the vegetation component in the canopy stratum. However, mean intensity of LRI_C is higher than FRI_C in all plots.

It is possible, but unlikely that emitted pulse intercepted a vegetation component initially, but the majority of pulse energy remained for the next vegetation interaction. As our data set can not identify whether FRI_C is singular or the first return out of two returns, we can not conclude if this is the case. It is also possible that the last return interacts with a solid material such as a branch or a large fallen tree on the ground, since most of LRI_C were found in lower level of Canopy stratum. This would explain why mean intensity in LRI_C was higher than FRI_C.

The mean intensity of FRI_G is higher than LRI_G in most plots. This is because FRI_G is the first return and therefore did not lose any energy before it interacted with the ground with sufficient pulse energy, while the pulse energy of LRI_G was reduced being intercepted by vegetation component in Canopy stratum.

6. CONCLUSION

Significant correlations were found between first return data (FRI_C, FRI_G and FRI_G_STDEV) and field based ecological observations (mean canopy cover, mean grass cover and fallen trees). The automated mapping of these important ecological variables is key to the successful management of at risk ecological communities worldwide.

7. FUTURE WORK

Another case study is being undertaken using new LiDAR data within a forest ecosystem, located in the Rubicon catchment of the Cradle coast region of Tasmania, Australia. This LiDAR data is derived using a RIEGL LMS-Q560 sensor. This is a full waveform system, it can record up to six returns. More detailed analysis of the relationship between LiDAR intensity variables and field data will be analyzed to examine whether LiDAR can recover ecological variables such as structure and biodiversity information about native vegetation.

REFERENCE

Airborne Laser Survey Working Group, 2004. Handbook of Airborne Laser Survey. Association of Precise Survey & Applied Technology, Tokyo.

Bacon, P.E., Stone, C., Binns, D.L., Edwards, D.E. and Leslie, D.J., 1993. Inception Report on Development of Watering Strategies to Maintain the Millewa Group of River Red Gum (Eucalyptus camaldulensis), Research Division, Forestry Commission of New South Wales, Sydney.

Bauer, M.E., Daughtry, C.S.T., Biehl, L.L., Kanemasu, E.T. and Hall, F.G., 1986. Field Spectroscopy of Agricultural Crops. Geoscience and Remote Sensing, IEEE Transactions on, GE-24(1): 65-75.

Brandtberg, T., Warner, T.A., Landenberger, R.E. and McGraw, J.B., 2003. Detection and analysis of individual leaf-off tree crowns in small footprint, high sampling density lidar data from the eastern deciduous forest in North America. Remote Sensing of Environment, 85(3): 290-303.

Chong, J., 2003. Analysis and Management of Unseasonal Surplus Flows in the Barmah-Millewa Forest. Technical report 03/2, Cooperarive Research Center for Catchment Hydrology.

Curran, P.J., 1985. Principles of Remote Sensing. Longman, England.

Harris, I. and Rawson, R., 1992. Management Plan for Barmah State Park and Barmah State Forest, Department of Conservation and Environment, Australia.

Holmgren, J. and Persson, A., 2004. Identifying species of individual trees using airborne laser scanner. Remote Sensing of Environment, 90(4): 415-423.

Lillesand, T.M., Kiefer, R.W. and Chipman, J.W., 2004. REMOTE SENSING AND IMAGE INTERPRETATION. John Wiley & Sons, Inc.

Mac Nally, R., Parkinson, A., Horrocks, G., Conole, L. and Tzaros, C., 2001. Relationships between terrestrial vertebrate diversity, abundance and availability of coarse woody debris on south-eastern Australian floodplains. Biological Conservation, 99(2): 191-205.

Means, J.E. et al., 1999. Use of Large-Footprint Scanning Airborne Lidar To Estimate Forest Stand Characteristics in the Western Cascades of Oregon. Remote Sensing of Environment, 67(3): 298-308.

Moffiet, T., Mengersen, K., Witte, C., King, R. and Denham, R., 2005. Airborne laser scanning: Exploratory data analysis indicates potential variables for classification of individual trees or forest stands according to species. ISPRS Journal of Photogrammetry and Remote Sensing, 59(5): 289-309.

Morsdorf, F. et al., 2004. LIDAR-based geometric reconstruction of boreal type forest stands at single tree level for forest and wildland fire management. Remote Sensing of Environment, 92(3): 353-362.

Riano, D., Meier, E., Allgower, B., Chuvieco, E. and Ustin, S.L., 2003. Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling. Remote Sensing of Environment, 86(2): 177-186.

Suarez, J.C., Ontiveros, C., Smith, S. and Snape, S., 2005. Use of airborne LiDAR and aerial photography in the estimation of individual tree heights in forestry. Computers & Geosciences, 31(2): 253-262.

van Aardt, J.A.N., Wynne, R.H. and Oderwald, R.G., 2006. Forest volume and biomass estimation using small-footprint lidar-distributional parameters on a per-segment basis. Forest Science, 52(6): 636-649.

Wehr, A. and Lohr, U., 1999. Airborne laser scanning--an introduction and overview. ISPRS Journal of Photogrammetry and Remote Sensing, 54(2-3): 68-82.

Zimble, D.A. et al., 2003. Characterizing vertical forest structure using small-footprint airborne LiDAR. Remote Sensing of Environment, 87(2-3): 171-182.

ACKNOWLEDGEMENTS

We would like to thank the Royal Melbourne Institute of Technology, Melbourne –Australia, for support via its RUIS scholarship scheme. We also acknowledge the Australian Commonwealth Environment Research Fund “Landscape Logic” Project for its support. We would like to thank the Murray Darling Basin Commission for offering the LiDAR data set, and Kathryn Sheffield for her support in the fieldwork.