ESTIMATE FOREST BIOMASS DYNAMICS USING MULTI-TEMPORAL LIDAR AND SINGLE-DATE INVENTORY DATA

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ABSTRACT

Estimating change in forest biomass is important for monitoring carbon dynamics and understanding the global carbon cycle. Multi-temporal airborne lidar data has been recently used to accurately predict change in forest attributes such as aboveground biomass (AGB). In this study, we assessed the ability of multi-temporal airborne lidar (2008 and 2016) and single-date inventory data to estimate forest biomass dynamics. To do so, we compared different imputation approaches to predict biomass, specifically direct (i.e., a model trained by the biomass variable or AGB) and indirect (i.e., a model trained by structure variables – basal area, tree volume and stem density) approaches. We also evaluated the ability of the selected model in temporally estimating biomass by relating biomass predictions with forest disturbance data. Our results demonstrated that AGB can be better predicted using an indirect imputation method in which lidar metrics were trained by a structure variable (basal area, RMSE = 95.09, $R^2 = 0.89$). While the model was developed for the date of inventory measurements (2016), the model was successfully applied to predict biomass for a historical date (2008). For both years, biomass predictions were highly consistent with disturbance history. This study further informs the benefits of multi-temporal lidar data to estimate forest biomass dynamics in instances when only single-date inventory data are available. The work thus can support forest researchers and managers in improving their scientific and practical tasks in forest management.

***Index Terms*—** Lidar, single-date inventory, biomass

1. INTRODUCTION

Forest biomass monitoring is crucial to supporting sustainable forest management in the context of climate change. From local to global scale, a comprehensive reporting of forest biomass dynamics is urgently required to inform policy making processes that aim to preserve forest ecosystems and reduce greenhouse gas emissions while simultaneously accommodating/maintaining human needs. Field-based approaches are the most accurate but have limited spatial and temporal coverage, especially for large jurisdictions or remote areas [1]. To address this problem, researchers and practitioners often combine field measurements with remote sensing data to estimate forest biomass across large areas. Many studies have recently demonstrated the ability of lidar (light detection and ranging) data in providing high accuracy estimates of forest biomass and structure [2-7]. Lidar can be integrated with forest inventory data to produce lidar-based biomass maps where data is available wall-to-wall [8].

The utility of multi-temporal lidar data in forest monitoring has been investigated in several previous studies [3, 4, 6, 7]. These studies found that repeated airborne lidar data can provide accurate and spatially explicit predictions of aboveground biomass (AGB) which can be used to characterize biomass dynamics and carbon fluxes. Although previous studies used various modelling approaches to estimate biomass, they often developed model based on multi-temporal or re-measured inventory data that temporally coincide with lidar data [3, 6, 7]. Repeat inventory data, however, are not available in many forest regions. It is a reasonably common phenomenon in developing regions that only recently have started generating their first iteration of a comprehensive National Forest Inventory [9]. Thus, the ability of using multi-temporal lidar in combination with single-date inventory data for monitoring forest biomass dynamics need to be urgently investigated.

This study investigates the potential of multi-temporal airborne lidar and single-date inventory data to predictively estimate forest biomass dynamics (AGB). To achieve this, we first develop and compare different biomass imputation models to determine the most accurate method for biomass predictions. We then evaluated the ability of the selected model in temporally estimating biomass by relating biomass predictions with forest disturbance data. The study area is located in the Central Forest Management Area (FMA) in Victoria, Australia (Figure 1). There are a variety of forest types covering this area including ash species (mountain ash and alpine ash), messmate and gum eucalypts.

Forests within the study area were intensively disturbed by fires and logging during the processing period (2008-2016), with large fires in 2009 [10]. The study area is also subject to routine intensive hardwood timber harvesting.

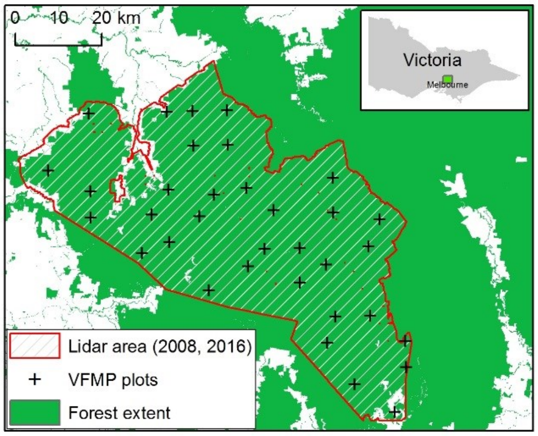

Figure 1. Study area in Victoria, Australia

2. METHODS

Airborne Laser Scanning (ALS) were acquired during summer months in 2008 and 2016 by Victorian Department of Environment, Land, Water and Planning. Point cloud data in 2008 were captured using an Optech ALTM 3100 EA sensor at a normal density of 0.96 pulses per m^2 while the data in 2016 were captured by a Trimble AX60 sensor at a normal density of 4.38 pulses per m^2. The overlapping areas between these two surveys is nearly 350 thousand hectares (Figure 1). Raw lidar point cloud data of each survey were first classified into either ground or non-ground points using an iterative TIN-based method [11]. A suite of 54 common lidar vegetation metrics were then computed from both lidar datasets based on the height, density and intensity of the lidar returns within 20m x 20m grid cells. The selection of the cell size aligned with the size of inventory plots (400 m^2). Rasters of all metrics were created based on a defined common origin and pixels exactly overlaid.

Forest inventory plot data included 33 permanent ground circular plots (400 m^2) measured between 2012 to 2016 as a part of Victorian Forest Monitoring Program or VFMP [12]. Each plot consists of multi-measurement components taken on large trees, small trees, herbs and shrubs, and down woody debris [12]. For each plot, total AGB ($Mg.ha^{-1}$), basal area (BA, m^2 per hectare), tree volume (VOL, m^3 per hectare) and stem density (TD, trees per hectare) were calculated [13, 14]. These metrics were then used as response variables for biomass imputation models. AGB values within inventory plots ranged from 18.1 to 1036.0 $Mg.ha^1$, with a mean value of 493.6 $Mg.ha^1$.

The kNN imputation approach (with k=1) based on the Random Forest (RF) algorithm was used to develop biomass model in this study. This model searches the most similar (or the nearest) measured sample and imputes values from that sample to a given target (non-measured) sample [15]. The similarity between training and target samples is evaluated based on a non-Euclidean distance metric computed by developing a series of RF models across model response variables (one model for each of response variable). Prior to model testing, a variable selection was performed using the least absolute shrinkage and selection operator model (LASSO) [16] to objectively choose the most important lidar metrics for predicting the response variables. Highly correlated variables were also identified and removed. Predictor values were extracted from lidar metrics of 2016.

We developed and compared eight model scenarios to predict AGB using different group of response variables. The first model scenario was the direct biomass imputation approach since it was trained by the biomass variable (AGB). The other seven models were the indirect biomass imputation approaches as the nearest neighbour was found based on the relationships between predictor variables and forest structure variables (combinations of BA, VOL and TD) rather than AGB. AGB values of the corresponding training plots were not included in these models but were subsequently attached as ancillary variables to impute each target pixel [14]. We evaluated the accuracy of each model scenario using a leave-one-out cross validation approach. Imputed biomass values were compared to observed values using the root mean square error (RMSE), relative RMSE (rRMSE) and the coefficient of determination (R^2).

Following model comparisons, we applied the best model to estimate biomass mapS for both years 2008 and 2016. As field data for independently validating biomass predictions were not available for both years, we assessed biomass predictions by relating them with forest disturbance history from 2008 to 2016 [10]. Specifically, we grouped representative pixels randomly selected by defined disturbance levels and performed the Kruskal-Wallis test [17] to evaluate the significance of differences between groups. In addition, AGB values of pixels experiencing a stand-replacing disturbance between 2009 and 2016 were grouped by time (years) since disturbance to explore the trend of forest biomass recovery.

3. RESULTS

Results of model assessments are shown in Table 1. The model with BA as response variable, which was an indirect imputation approach, was the most accurate for predicting biomass. The model achieved a RMSE value of 95.09 $Mg.ha^{-1}$, rRMSE of 0.19 and R^2 of 0.89. The direct imputation model with AGB as response variable obtained a moderate accuracy level while the TD model reported the lowest accuracy.

Examples of biomass predictions for 2008 and 2016, and biomass change between the two years are shown in Figure 2. Change in biomass due to forest disturbance can be clearly identified on the maps. Results from the Kruskal-Wallis test (Figure 3) indicate that there were significant differences in AGB values between forests grouped by levels of disturbance severity (p <2.2e-16). For both years, a higher disturbance level was associated with significantly lower biomass values. In addition, undisturbed forests had higher AGB values than disturbed forests. Predicted AGB values in 2016 were generally consistent with time since disturbance (Figure 4), with an increased trend in biomass values for a higher number of years since disturbance. However, AGB values in 2016 were much lower than that in 2008, which were considered as pre-disturbance values.

Table 1. Biomass imputation model accuracies (BA = basal area, VOL = tree volume, TD = stem density)

Model scenario	RMSE	rRMSE	R2
AGB	129.03	0.26	0.83
BA	95.09	0.19	0.89
VOL	172.51	0.35	0.80
TD	194.77	0.39	0.75
BA-VOL	115.32	0.23	0.87
BA-TD	149.89	0.30	0.82
VOL-TD	139.07	0.28	0.83
BA-VOL-TD	135.59	0.27	0.84

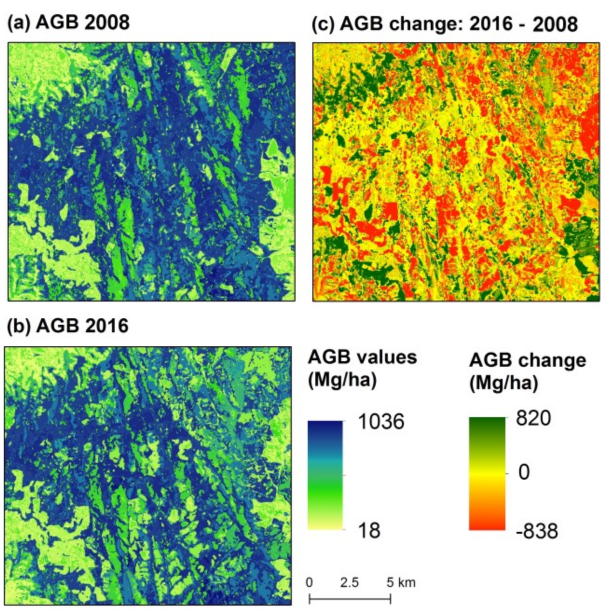

Figure 2. Maps biomass predictions of 2008 (a) and 2016 (b), and biomass change between the two years (c).

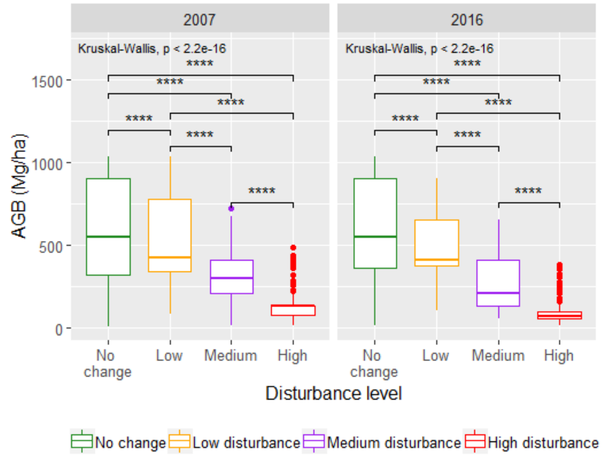

Figure 3. Distribution of biomass values according to disturbance levels, with results from the Kruskal-Wallis test (**** is noted for p < 0.001).

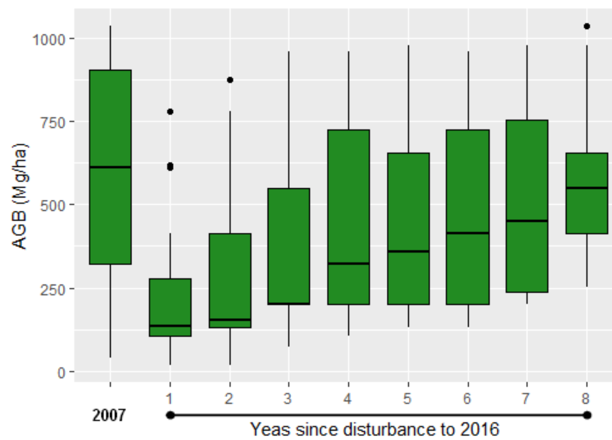

Figure 4. Trend of AGB values (2016) by time since disturbance, in comparison with pre-disturbance values (2008). The analysis was done for pixels with stand-replacing disturbance during 2009-2016.

4. DISCUSSION

Our results of model comparisons indicate that AGB can be better predicted from lidar data using an indirect imputation method in which lidar metrics were trained by the basal area variable (BA). The biomass variable was not included in the model but were then indirectly imputed as an ancillary variable. Although the results could be different when testing in another study area, similar comparisons are necessarily to determine the best approach for predicting forest biomass from airborne lidar data. The findings from this work are consistent with results from our previous study when we compared the biomass imputation models using Landsat time-series [14].

Our results also indicate the potential of using an imputation model developed from single-date inventory data for temporally predicting forest biomass from lidar data. While the model predictors were extracted from the lidar dataset from 2016, the model was successfully applied to predict biomass for a historical date (2008). Similar to 2016, when field data are available, biomass predictions of 2008 were highly consistent with disturbance history (Figure 3). It is expected when the trend of biomass values in 2016 increased by time since disturbance (Figure 4). Higher pre-disturbance values (2008) are also reasonable as a nine-year duration is generally not long enough for a full biomass recovery following a stand-replacing disturbance [18]. Further map validations using temporal inventory data, unfortunately not available in our case study, should be conducted in future research.

5. CONCLUSION

Overall, multi-temporal airborne lidar and single-date inventory data can be combined to efficiently estimate forest biomass dynamics. Different imputation approaches were compared to determine the most accurate model to predict biomass. AGB can be better predicted using an indirect imputation method in which lidar metrics were trained using a structure variable (basal area). The selected model proved its ability to successfully predict biomass for a historical date. For both modelled years, biomass predictions were highly consistent with disturbance history. This work represents a first in linking single-date inventory with multi-temporal lidar data to estimate forest biomass dynamics and has potential to support forest researchers and managers in improving their scientific and practical tasks in forest management.

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