Reducing uncertainties in above-ground biomass estimates using terrestrial laser scanning

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Highlights: This work compares nondestructive estimates of AGB made using terrestrial laser scanning (TLS) with destructively harvested measurements. We show that estimates using our TLS approach agree to within 10% of the reference measurements. More traditional AGB estimates based on allometric equations show an underestimation of approximately 30%. Moreover, uncertainty in the TLS-derived estimates can be quantified accurately and explicitly, unlike that from allometric methods.

Key words: *Terrestrial LiDAR; biomass; destructive harvesting; tree reconstruction*

Introduction

Above-ground biomass (AGB) is a good indicator for forest productivity, carbon storage and sequestration of forests. The global distribution and magnitude of forest carbon sources and sinks remain uncertain and, as a result, carbon emissions based on these poorly-constrained stock estimates are even more uncertain, and variable across different scales. Remote sensing can be used to monitor AGB and carbon emissions at a large scale. Recent work of [1] and [2] used similar input data to generate pan-tropical satellite derived AGB maps. [3] reported substantial differences in mapped AGB between these two maps and spatial patterns were different when compared to field data distributed across the region. These disagreements demonstrate that accurate ground data are needed to improve the calibration and validation of global satellite derived AGB datasets.

Traditional field methods generally infer AGB based on indirect, empirical allometric (size-to-mass) relationships with tree parameters, such as tree height and diameter at breast height (DBH). [4] identified four types of uncertainty in AGB assessment using traditional forest inventory data: (i) errors in tree inventory, (ii) errors in the allometric equations, (iii) errors related to the size of the sampling plots, and (iv) errors related to the landscape-scale representation of these sampling plots. Terrestrial laser scanning (TLS) offers opportunities for a consistent and robust framework to support AGB estimates using 3D point clouds. TLS data has the potential to reduce errors (i) and (ii) by improving the traditional field methods to estimate AGB. It can also provide insight into errors (iii) and (iv), which are related to the spatial variance of the forest and its structure. We demonstrated in [5] that TLS inferred estimates of AGB agree better with 65 destructively sampled trees than traditional allometric equations. Our TLS approach uses quantitative structure models (QSMs) to estimate volume and showed a total AGB overestimation of 9.7% compared to an underestimation of 36.6 to 29.9% for the allometric equations. A key finding in [5] is that the errors for allometric estimates of AGB increase exponentially with increasing DBH, whereas the error for TLS estimates of AGB are independent of DBH.

The main limitation for efficiently using the method in [5] at plot level is the required visual evaluation of input parameters for the QSM tree modelling. A more objective QSM parameter setting is essential for applying this method in more challenging and complex biomes and larger plots. In this paper we compare a new automated approach for estimating the parameters required for QSM modelling and compare AGB results against the values obtained in [5].

Materials and method

Study area and data collection

Two plots in native Eucalypt Open Forest (dry sclerophyll Box-Ironbark forest) in Victoria, Australia were partially harvested in 2012-2013 to acquire accurate estimates of AGB of 65 trees. The plots had a 40 m radius and were established in Rushworth forest, with the main tree species in these plots being *Eucalyptus leucoxylon, E. microcarpa* and *E. tricarpa*. Measurements of fresh weight and tree structure were collected for each harvested tree. Dry weight to fresh weight conversion factors and basic density for each species were derived from a limited number of samples across a range of diameters. TLS data were collected with the RIEGL VZ-400 scanner, which records multiple return LiDAR data (up to four returns per emitted pulse). Full hemispherical scan data was collected at five scan locations per plot using a 0.06° angular sampling.

Deriving AGB from TLS data

Tree volume is directly inferred from 3D quantitative structure models (QSMs) of individual trees reconstructed from the TLS data; AGB is then inferred via basic density. Inferring tree volume consists of two steps: i) extracting single trees from the registered point cloud; and ii) 3D reconstruction of isolated trees using QSMs. The QSM method has two important input parameters: the cover patch size (*d)* and the minimum threshold of LiDAR points within a single patch for inclusion in the reconstruction (*nmin*). The reader is referred to [5] for full details of tree extraction method and the QSM modelling using visual evaluation of the input parameters. Volumetric estimation increases of 5000% are generally observed over the patch size range 0.02 to 0.09, so getting this value 'right' is critical. QSM results are far more stable with varying *nmin*, and more related to the point cloud density. As a result, we focus here on *d*. The following automated framework has been developed for autonomous optimisation of cover patch size *d*:

1. The TLS point cloud is reconstructed 10 times over the desired *d* range 0.02 to 0.09 at an increment of 0.05, with *nmin* set to 4.
2. For each of the 10 QSM models at each *d* value, 4 trunk cylinders at 7.5%, 10%, 12.5% and 15% of the trunk length are extracted from the QSM model. The coordinates of these 4 cylinders drive a pass-through filter to extract the TLS point cloud from which the QSM was formed.
3. To obtain trunk diameter estimates, a least squares circle fit is executed on the resultant clouds and the diameters compared with the cylinders as a percentage change to quantify model conformity to the cloud. A single result ($trunk_{match}$) is generated by averaging the 4 cylinders for each of the 10 models.
4. For each *d* value the mean and standard deviation are generated from the 10 models and then the coefficients of variation, *CV*, are calculated as standard deviation / mean.
5. The second highest *CV* (CV_{max2}) is identified across all *d* values and the lowest value that conforms to ($CV <= CV_{max2}*CV_{factor}$) and ($trunk_{match} >= trunk_{conformity}$) is selected as the optimised *d* where $CV_{factor} = 0.5$ and $trunk_{conformity} = 0.9$. We use the second highest *CV* instead of the highest *CV* to avoid outliers.
6. If no optimised *d* is identified in step 4, the method falls back onto the *d* with the highest $trunk_{match}$.

We compare results derived using the above process with those derived from 'visual assessment' i.e. a manual inspection of the resulting QSM form for each value of *d*, and an heuristic decision to accept/reject, based on the analyst's experience and expectations [5].

Results and discussion

Individual tree estimates of AGB using the visual and automated optimisation assessment for QSM modelling are compared against destructively harvested reference measures of AGB in figure 1. The RMSE with respect to the 1:1 line is 171 kg for the visual QSM assessment and is 306 kg for the automated QSM assessment. The concordance correlation coefficient, CCC, computes the agreement on a continuous measure obtained by two methods and ranges between 1 (perfect concordance) and -1 (perfect discordance). Both the visual and automated approach show CCC ranging from 0.94 to 0.98.

The mean absolute deviation for the visual assessment is lower (110 kg) compared to the automated assessment (214 kg). This is not surprising since the visual assessment is better suited to address different issues with the input TLS point cloud. For example, a partially occluded lower stem (by leaves or other, smaller branches) can result in a higher *d* value via the automated optimisation (and an overestimation of volume) because $trunk_{match}$ will be relatively low. On the other hand, the volume can be underestimated when $trunk_{match}$ is high, but large branches are not modelled well. The maximum absolute AGB deviation values for the automated QSM assessment are still lower than those reported for the allometric equations (> 1500 kg) in [5]. The advantage of the automated approach is that it requires no user input and therefore can efficiently be applied to large forest stands.

[6] showed that tree-level uncertainty in AGB estimation from their allometric model was about of 50% the mean, but they showed that uncertainty dropped to 5 to 15% when considering whole-plot AGB. The total AGB

of the 65 trees in our study area is 75.70 t for the visual assessment and 73.73 t for the automated assessment. The destructive harvesting yielded 69.02 t, so the TLS QSM approach results in an overall overestimation of 6.8% (automated optimisation) to 9.7% (visual assessment).

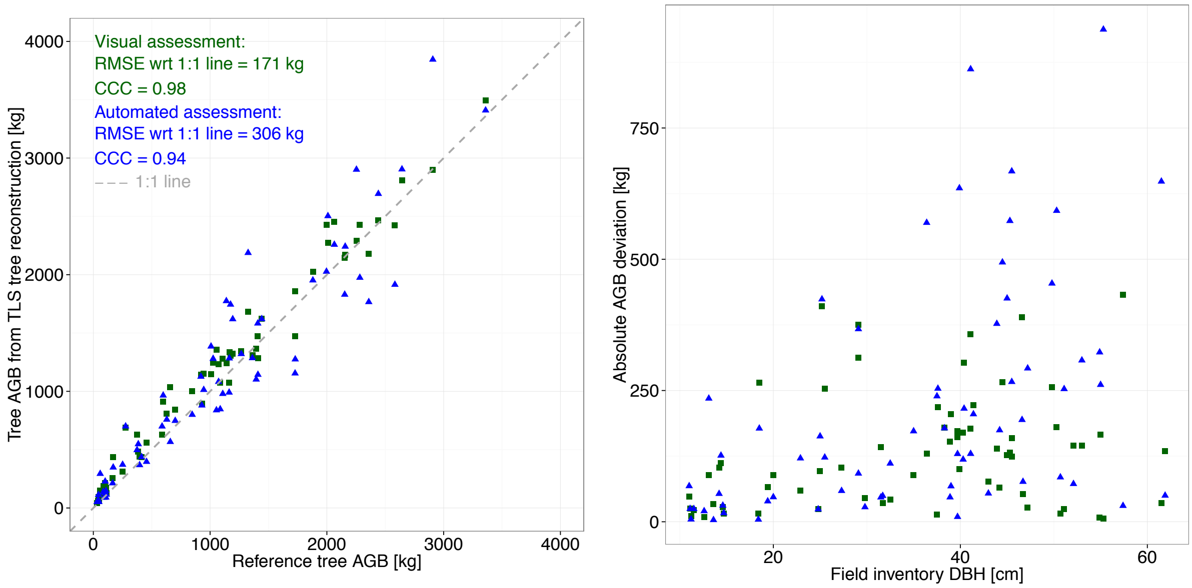

Figure 1: (Left) Comparison of destructively measured reference tree AGB with AGB inferred from TLS volume estimates through tree reconstruction and basic density information: visual QSM assessment vs. automated QSM assessment. (Right) Comparison of absolute tree AGB deviation.

Conclusion

In this work we contribute towards a nondestructive and robust method to infer AGB from TLS data. We demonstrate that AGB estimates from automated QSM parameter setting agreed well with those values derived from visual assessment. The uncertainties at tree level are higher for the automated QSM assessment, but the total AGB of the 65 sampled trees agrees to within 6.8% with the reference data. This is important for efficiently applying this TLS approach to larger areas or more challenging and complex biomes, such as tropical rainforests. Terrestrial laser scanning offers opportunities for a consistent and robust framework to support REDD+ monitoring capacities in developing countries. Limited research has been carried out in these countries to reduce the uncertainty of emission estimates of forest degradation activities, such as selective logging. Improving emission estimates relating to forest change requires better biomass estimates before and after change events at local levels [7]. The work presented here shows the possibility for applying TLS to larger areas more rapidly and consistently, as well as for combining with (and benchmarking) allometric estimates from traditional survey data, airborne lidar and other remotely sensed data.

References

[1] Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M. et al. (2012). Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nature Climate Change, 2, 182–185.
[2] Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T.A. et al. (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. PNAS, 108, 9899–9904.
[3] Mitchard, E.T.A., Feldpausch, T.R., Brienen, R.J.W., Lopez-Gonzalez, G., Monteagudo, A. et al. (2014). Markedly divergent estimates of amazon forest carbon density from ground plots and satellites. Global Ecology and Biogeography, 23, 935–946.
[4] Chave, J., Condit, R., Aguilar, S., Hernandez, A., Lao, S. et al. (2004). Error propagation and scaling for tropical forest biomass estimates. Philosophical Transactions of the Royal Society B: Biological Sciences, 359, 409–420.
[5] Calders, K., Newnham, G., Burt, A., Murphy, S., Raumonen, P. et al. (2015). Nondestructive estimates of above-ground biomass using terrestrial laser scanning. Methods Ecol Evol, 6, 198–208.
[6] Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M.S. et al. (2014). Improved allometric models to estimate the aboveground biomass of tropical trees. Glob Change Biol, 20, 3177–3190.
[7] Hill, T.C., Williams, M., Bloom, A.A., Mitchard, E.T.A. and Ryan, C.M. (2013). Are inventory based and remotely sensed above-ground biomass estimates consistent? PLoS ONE, 8, e74170.