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Reduced model complexity for efficient characterisation of savanna woodland structure using terrestrial laser scanning

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ABSTRACT

Advances in terrestrial laser scanning (TLS) enable the extraction of ecologically meaningful data from detailed 3D representations of individual trees. Computer models deliver a comprehensive suite of tree structural metrics that are difficult, if not impossible, to obtain using traditional field methods. However, best practice high-end TLS equipment and computer modelling are expensive and complex, and ground-based data acquisition is spatially limited, thus presenting significant hurdles for the implementation of this technology in land management. We investigated the utility of lower-cost TLS data acquisition and processing for efficient, large-scale assessment of tree volume as an ecologically meaningful parameter. A 1 ha plot in a tropical savanna woodland was scanned twice over consecutive years using an entry-level TLS scanner (Leica BLK360), with the second survey conducted immediately after a high-intensity fire event. The performance of low-complexity voxel models for calculating individual tree volume was tested and calibrated against more established and more complex Quantitative Structure Models (QSM) estimates of a 100-tree subset. Of the models tested, a filled voxel model with a voxel size of 0.04 m achieved 96% accuracy when compared to QSM estimates. Processing time for individual trees was over 100 times faster. To further explore the utility of lower-cost, lower-complexity data in large-scale monitoring, the best-performing optimised volume model was then applied to the hectare-scale data set and used to establish an allometric model based on metrics that can be obtained from aerial surveys. The best-performing allometric model used tree height and crown area as a compound variable in a logarithmic linear regression and was able to explain 99% of variance in the total tree volume. Furthermore, as the training data contained trees from recently burnt vegetation, the model was able to account for fire damage, important for carbon accounting in fire prone ecosystems such as savannas. With the utility of LiDAR scanning for vegetation mapping and monitoring firmly established in the literature, development of methods for non-specialist practitioners is now essential for greater utilisation of this technology by land managers. We provide a case study highlighting the utility of lower-cost data acquisition and efficient processing for locally adapted vegetation mapping and monitoring.

1. Introduction

Savannas are a mixture of trees and grasses, spatially and temporally heterogeneous ecosystems shaped by highly seasonal rainfall and local disturbance processes. In the Eucalypt-dominated north Australian tropical savannas, the main disturbance processes include frequent fire, convective storms, and cyclones, which in combination with termite impacts (Hill and Hanan, 2010; Williams and Douglas, 1995) drive rapid turnover of vegetation (Chen et al., 2003). Exacerbated by climate and land use change, these interactions result in high spatial and temporal heterogeneity in stand structure and above-ground biomass (AGB). Mapping, monitoring and modelling of this heterogeneity is challenging with traditional field inventory methods, which are time-consuming and expensive to deploy at scale. As such, the use of remote sensing solutions to provide cost-effective mapping is an active field of research. LiDAR (Light Detecting and Ranging) remote sensing methods, in particular, show promise in quantifying the spatio-temporal heterogeneity of vegetation structure more effectively and accurately in tropical savannas (Levick et al., 2021).

Initially recognised in the early 2000s as having potential to replicate traditional forest inventory metrics (Hopkinson et al., 2004; Lefsky et al., 2002; Lovell et al., 2003), terrestrial LiDAR has seen a steady rise in the number and diversity of applications. For quantifying tree

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and stand structural change and diversity (Calders et al., 2020; Disney, 2019; Maeda et al., 2022), the versatility of high-resolution point cloud data derived from terrestrial laser scanning (TLS) enables the extraction of metrics that had previously been challenging, if not impossible, to obtain using traditional field methods. In open forests, the scanning viewpoint from beneath the canopy provides little occlusion of tree crowns by woody components and generally allows for near-complete reconstruction of entire trees across all size classes (Calders et al., 2020; Maeda et al., 2022). However, due to its ground-based collection platform, the spatial resolution of TLS data is limited by low mobility and horizontal occlusion by tree trunks (Disney, 2019). In contrast, airborne data collection such as airborne LiDAR, UAV LiDAR or photogrammetry (here summarised as airborne platforms) allows for faster data acquisition over far larger areas but is subject to reduced point density, occlusion beneath the canopy, and increased noise. Despite these restrictions, data captured from above the canopy allows users to calculate a limited number of individual tree metrics including tree height and crown projected area (Terryn et al., 2022). Due to its larger spatial footprint compared to TLS, airborne data collection is a widely used tool for vegetation mapping and monitoring, and although limited, the data available may be used to estimate metrics otherwise only obtainable from TLS by using allometric models.

Allometric models allow us to estimate target metrics such as AGB from more readily obtainable metrics, but are susceptible to uncertainty arising from heterogeneity not captured in the training data. Traditional allometric models commonly estimate AGB from field-derived stem diameter at 1.3 m (DBH) often in combination with tree height, and are typically based on destructive sampling. Destructive sampling, by necessity, focuses on a limited number of ideal or representative trees while aiming to capture a range of ecological communities within a landscape (for the north Australian tropical savanna, see Williams et al., 2005). Models constructed from such data can therefore be subject to bias unless calibrated across the full range of tree sizes and species (Roxburgh et al., 2015). Furthermore, the stability of allometric models decreases with sample size (Duncanson et al., 2015), especially where a high degree of variability is present (Roxburgh et al., 2015). In savannas, this potential for error is particularly prevalent in large trees, given the increased structural heterogeneity due to damage and the effort required to statistically sample large individuals (Luck et al., 2020). Remote sensing such as airborne platforms is increasingly used to construct allometric models using larger sample sizes that include trees of all sizes and species (Graves et al., 2018; Jucker et al., 2017). Thus, constructing robust allometric models calibrated for local to regional vegetation communities from TLS would allow the mapping and monitoring of ecologically meaningful metrics at the spatial scale accessible to a variety of airborne data collection platforms.

Current best practice for obtaining non-destructive detailed tree measurements from individual TLS point clouds is the use of Quantitative Structure Modelling (QSM). Quantitative Structure Models are sophisticated geometrical models used to produce a suite of detailed tree metrics, including the volume, area, length, diameter, angle, or order of individual tree components (stem/branches), which had previously been challenging to obtain (Lecigne, 2020; Raumonen et al., 2013). Tree volume as calculated by QSM has been shown to be a highly accurate predictor for AGB in a range of biomes, including Australian Eucalypt forests (Burt et al., 2013; Calders et al., 2015). However, QSMs are computationally expensive and the level of detail they provide is often not required for individual inventory projects or ecological studies. Thus, the required computational power for data analysis is needlessly inflated, presenting a barrier to some users. Alternatively, a range of less complex but potentially less precise models are available (Atkins et al., 2022) that can calculate individual metrics, such as tree height, volume and crown area (Newnham et al., 2015). Such models often rely on simplified mathematical approaches to calculate selected metrics, thereby removing the need for complex calculations. The alternative models tested in this study included approaches based on voxels, alpha shapes or convex hulls. Of interest is the ability of these simple models to reliably replicate these metrics from TLS data. Our study was conducted in multi-storey tropical savanna woodlands and captured the spatial and temporal variability of this vegetation type, which dominates northern Australia (Hutley and Setterfield, 2019); such detailed assessment of structural change has not previously been examined. In this context, QSMs applied to a data subset may be a valuable tool for calibrating simpler models, in turn allowing for efficient processing of large data sets and the construction of robust allometric models.

In this study, we define total tree volume as a measure of the 3D space occupied by a tree. This further reduces computational costs by removing the need for leaf-stem separation algorithms generally used for evergreen vegetation (Krishna Moorthy et al., 2020; Vicari et al., 2019; Yun et al., 2016) but also allows the inclusion of non-woody components in the mapping and monitoring of habitat structure and structural changes. Monitoring of total tree volume can provide insight into the severity of disturbances such as fire across all height strata. In contrast to fire intensity (Keeley, 2009), fire severity measures the impact of fire on the ecosystem, an essential aspect of ecosystem response to disturbance that remains challenging to map and monitor at scale (Edwards et al., 2018). If recorded along with traditional fire mapping, monitoring changes in total tree volume as indicator for fire severity would find applications in areas such as the assessment of fire impacts on habitat structure and biodiversity, or estimation of greenhouse gas emissions and carbon management (Edwards et al., 2013).

This study aimed to utilise highly detailed TLS data to improve the utility of airborne platforms for collecting ecologically meaningful information without the need for access to high-performing computing infrastructure. The key objectives were to: (a) identify a suitable volumetric model to obtain training data from TLS, and (b) use this training data to establish an allometric model that predicts total tree volume from crown area and tree height. We thus hope to provide a workflow that can be applied locally to map and monitor savanna vegetation at ecologically meaningful spatial scales.

2. Methods

2.1. Field site

The study was carried out on a 1 ha plot at the Litchfield Savanna Supersite (LSS) approximately 80 km southwest of Darwin in the Northern Territory, Australia. The LSS is a component of a national vegetation monitoring network (Terrestrial Ecosystem Research Network, TERN) (Karan et al., 2016). Vegetation is mesic tropical savanna woodland with mean annual precipitation of ~1890 mm y^{-1} (Australian Bureau of Meteorology, 2021), where 90% of rainfall occurs between October to April during the wet season (Fig. 1). Fire frequency is high and, over the last 20 years, the site has received 13 fire events, with 7 of these considered of high severity — fires that occur after August, burning fuel loads that have accumulated and experienced a degree of curing throughout the dry season (May–September). Fire frequency was derived from the North Australian Fire Information (North Australia & Rangelands Fire Information (NAFI), 2022) system observations.

Overstorey tree species are dominated by *Eucalyptus miniata*, *E. tetrodonta* and *E. latifolia*, with a mean canopy height of 18 m. A mid-layer (2–7 m height) exists and consists of *Eucalyptus* juveniles and other deciduous non-Eucalypts trees and shrub species, plus an understory dominated by C4 grasses and *Eucalyptus* spp. resprouts. Stand density is ~700 stems per ha^{-1} with a basal area of 8.2 m^2 ha^{-1} (Karan et al., 2016).

The plot was scanned twice using TLS during August 2018, following a wet season of 1172 mm, which was ~730 mm below average, and

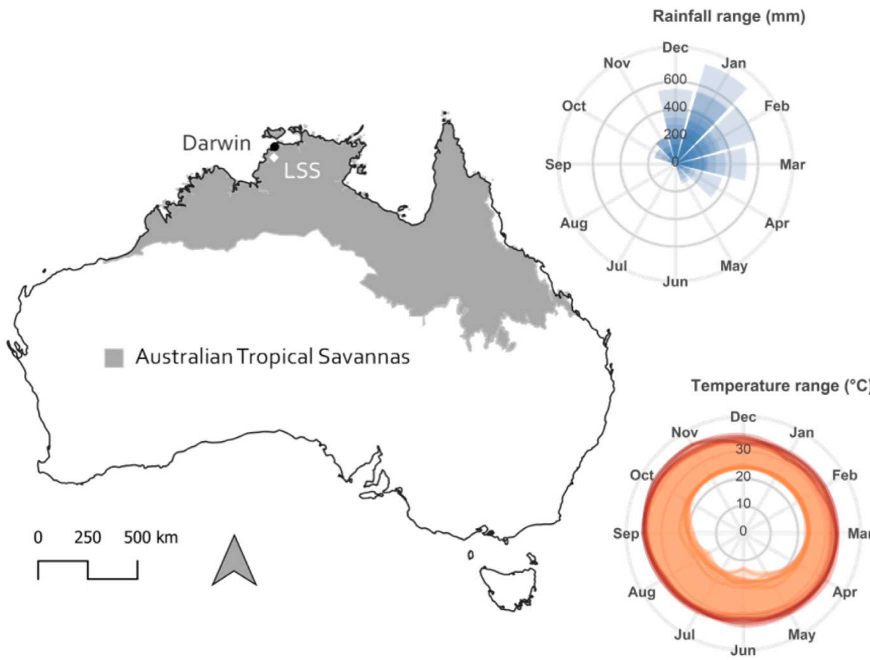

Fig. 1. Location map of field site (left), showing Litchfield Supersite (LSS), with temperature and rainfall range 2010–2020 (right) at Batchelor AP (Australian Bureau of Meteorology, 2021).

Fig. 2. Scans were undertaken using a Leica BLK360 at the field site pre-fire in August 2018 (left) and post-fire in September 2019 (right). The vegetation was visibly affected by a severe fire event two weeks prior to the 2019 scan.

again in September 2019, following a second low-rainfall wet season of 1342 mm. Back-to-back below-average wet seasons resulted in an extended dry season, and the site was subjected to a high-severity fire event that burned 90% of Litchfield National Park between 2–7 September 2019, including the LSS plot, with most trees experiencing near-100% leaf scorch. Scanning in 2019 was undertaken two weeks following this event (Fig. 2).

2.2. Data acquisition and processing

The 1 ha plot was scanned using a Leica BLK360 TLS (wavelength 830 nm, maximum range 60 m at 78% albedo, beam divergence 0.4 mrad, range accuracy of 4 mm at 10 m and 7 mm at 20 m, Geosystems (2017)) in high point density collection mode (resolution 5 mm at 10 m, scan size approx. 65 M points). The plot was scanned using a grid with

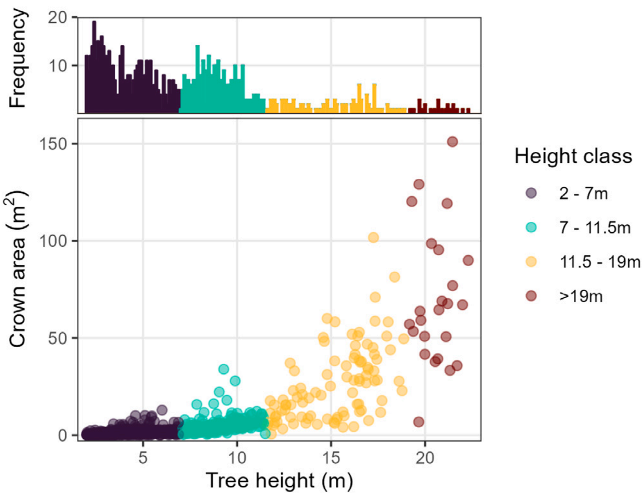

Fig. 3. Tree height classes used for the 100-tree subset using variables obtained from LiDAR360. The upper panel shows the tree height-class distributions for the four groupings. The lower panel shows the distribution of tree crown area (m^2) and height (m). The majority of trees detected on site were in the smaller height classes.

evenly spaced scan points, where the August 2018 survey used a 25 m spacing between points (totalling 25 scan points), and the September 2019 survey used a 20 m spacing (totalling 36 scan points). Scanning took place in the morning and afternoon to avoid branch movement during windier periods of the day. Point clouds were processed using the workflow as documented in Luck et al. (2020). The individual point clouds were visually aligned in CloudCompare v 2.11.3 (Anoia) and co-registered using RIEGL RiSCAN PRO v 2.9 software. The co-registered 1 ha point cloud was then processed in LiDAR360 v 5.2 software, where a Digital Elevation Model (DEM) generated from the ground points was used to normalise the point cloud, before segmentation of individual trees. For the instance segmentation, the LiDAR360 Point Cloud Segmentation tool was used, and any segmentation errors manually edited using the Individual Tree Editor. This process was repeated for the 2018 and 2019 field campaigns, and we extracted 1018 trees from the pre-fire scan in 2018 and 920 trees from the post-fire scan in 2019. The LiDAR360 software calculates tree height and crown area after the segmentation process, which were used to group trees into four inclusive tree height classes (2–7 m, 7–11.5 m, 11.5–19 m and > 19 m), based on the grouping apparent in the observed tree heights (Fig. 3). From each height class, 25 trees were randomly chosen and spatially matched between years. This subset of 100 trees was analysed using QSM, and specific outputs were used to evaluate and tune the performance of less complex tree structure models (Section 2.3). The tuned models were then applied to the entire data set, and the outputs used to construct a highly localised allometric model.

2.3. TLS tree structure modelling

Current best practice for quantifying individual tree structure from point clouds is the use of geometrical QSM (e.g. Raumonen et al., 2013). These QSMs are based on a cylinder model and describe a wide range of tree characteristics, including metrics such as tree volume, tree height and crown area. While sophisticated and versatile, timely processing of large numbers of trees at hectare or coarser scales using this approach is unrealistic using standard desktop devices. In this study, we used a set of key QSM outputs to test and calibrate the less complex alternative models. Of the available QSM metrics, we selected crown area and tree height to predict total tree volume in an empirical allometric model. Tree height and crown area can be derived from airborne LiDAR data with high precision and collected at scale, making them ideal predictor variables. We tested three alternative packages that run in the R statistical environment (R Core Team, 2021), rTLS (Guzman et al., 2021), alphashape3d (Lafarge and Pateiro-Lopez, 2020) and VoxR (Lecigne, 2020). Each package uses a different approach, including a convex hull, a 3D alpha shape and a voxel model respectively (Fig. 4; Section 2.3.2). To compare the model sensitivity to change over time between approaches, the average total change and percent total change for each height class were plotted for individual models with standard deviation.

2.3.1. Structural estimates using QSM

Quantitative Structure Models are generally constructed from trees without leaves; however, in this study, we opted to retain existing foliage on the trees. The QSM analysis was undertaken on a 100-tree subsample for each year using a modified version of TreeQSM (as described by Calders et al., 2015; Lecigne, 2020; Markku et al., 2015; Raumonen et al., 2013) version 2.4.0 (Åkerblom, 2020), running on MATLAB software (MATLAB, 2021) version r2021b. We used the workflow described in the QSM manual (IPRG, 2020), applying the parallel computing option. Adjusted input variables included patch and cover set size and ball radius. Input ranges for the initial QSM model iterations were adopted from the manual guidelines for the 2–7 m and > 19 m height classes and extrapolated for the 7–11.5 m and 11.5–19 m height classes (*see* Supplementary material for input parameters). For each input parameter combination, five model iterations were run and the (default) average cylinder point-model distance used to select optimal inputs. A further ten model iterations were run using the optimised inputs for each tree. From the QSM outputs, the mean and standard deviation of total tree volume, tree height and crown area (convex hull of the crown planar projection) were extracted.

To investigate the impact of foliage on calculated total tree volume, a subsample of 35 trees was analysed before and after applying a leaf-stem separation algorithm based on Krishna Moorthy et al. (2020). The leaf-wood separation model was initially trained on ten trees from within the plot, representing seven common species (*Eucalyptus miniata, E. tetrodonta, Corymbia latifolia, Buchanania obovata, Grevillea decurrens, G. pteridifolia* and *Persoonia falcata*).

2.3.2. Structural estimates using alternative models

Tree height and crown area were extracted using the R packages VoxR and rTLS. Both models use a 2D convex hull to estimate the projected crown area, and the elevation difference between the lowest and highest points for tree height.

Total tree volume was extracted using the alphashape3d and VoxR R packages. The alphashape3d package builds a 3D alpha shape defining the surface that ‘wraps around’ the point cloud (Edelsbrunner and Mücke, 1994). The VoxR package offers three different approaches to estimating tree volume, where two are voxel-based models with clusters of points within the point cloud wrapped in voxels (3D pixels) of a given size. Volume is then calculated based on a filled voxel approach (Lecigne et al., 2018) and a second approach, where voxels containing only a small number of points are removed prior to volume calculation (after Vonderach et al., 2012). For both approaches, the total tree volume is then calculated as the sum of the volume of all voxels fitted to the point cloud. The VoxR package uses an efficient voxelization method, and once voxel size is optimised (Pimont et al., 2018), results in fast and accurate volume calculation. The third approach offered by the VoxR package uses a convex hull to define the wrapped surface of the point cloud. This approach does not offer an option for calibration, but was included in the testing process.

To calibrate the models, the respective tuning parameters were tested with different resolutions, and performance statistics calculated for the optimised models. For the alpha-shape model, the tuning parameter α defines the spherical cap radius used to establish the boundary of the convex hull within the point cloud. For the voxel models (Vonderach and filled voxel), the tuning parameter cluster distance defines the size of individual voxels (3D pixels). Multiple resolutions were tested; to highlight the impact of change in resolution, we plotted three resolutions for each model (alpha-shape model: 0.015 m, 0.025 m and 0.035 m; voxel models: 0.04 m, 0.05 m and 0.06 m).

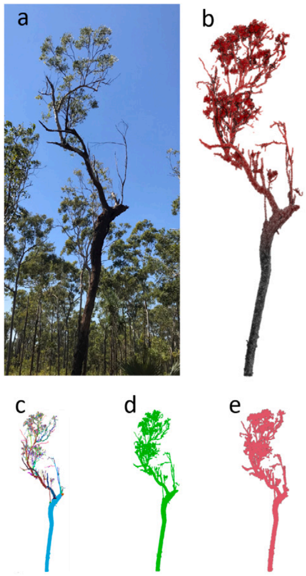

Fig. 4. A *Eucalyptus miniata* tree from the plot area, showing (a) a photograph taken on-site, (b) a co-registered point cloud (raw data for subsequent analyses), (c) a final corrected QSM segmentation, (d) a voxel model and (e) an alpha shape model.

2.4. Allometric model for variables that can be derived from airborne platforms (tree height and crown area)

We constructed a new allometric model, predicting tree volume from crown area and tree height — two metrics commonly extracted from airborne observations. To do so, we first examined the relationship between the two predictor variables and tree volume from the QSM output of the 100-tree subset. We then calibrated and tested the alternative models estimating both predictor and outcome variables and compared them with the reference QSM estimates. Once optimised, the alternative models were used to calculate the training data for the allometric model, where the filled voxel model from the VoxR package was used to estimate the outcome variable total volume, and the rTLS package was used to estimate the predictor variables tree height and crown area.

2.5. Statistical analysis

Statistical analyses were carried out in the R statistical environment (R Core Team, 2021). The correlation between leaf-on and leaf-off QSM outputs for a subset of trees was calculated using a linear regression. Correlations between QSM, alpha shape, voxel and convex hull model outputs were calculated using a linear regression with year as the covariate and the significance of year as a factor tested using an Analysis of Covariance (ANCOVA). If the relationship between QSM volume and voxel volume significantly depended on year (i.e. fire damage), the data was split, and two models were reported for individual years (i.e. with and without fire damage). The quality of predictions was assessed using the Coefficient of Determination (R^2), Root Mean Square Error (RMSE) and Mean Average Error (MAE). For the correlation between volume models, Lin's Concordance Correlation Coefficient (CCC) (Lin, 1989, 2000) was added to compare QSM outputs to the respective alternative model (alpha shape or voxel model).

To investigate model sensitivity to change, we first tested the difference in tree volume between years (before and after fire) using a Welch's t-test. The difference in volume between years was then calculated for each tree as measured by each volume model. The means of the difference measured by each model were then used in a paired t-test, comparing them to the QSM as baseline data.

The allometric relationship between QSM volume and the potential predictors crown area and tree height was generalised using a multiple linear regression. Applying a log transformation to predictor and outcome variables produced the best linear relationship with total tree volume. To account for strong collinearity between the predictors, the two predictor variables were combined to create a compound variable (CV).

$$CV = crown\ area \times tree\ height$$

We compared five covariate structures; three allometric models were built using the compound variable by itself, in combination with and as interaction with year as fire impact factor (the compound variable was centred at its mean when year was used as interaction). A further two allometric models were built with tree height and crown area as predictors and the multiplicative interaction between them (with both centred at their mean). Model validation and selection of covariate structure were based on cross-validation, RMSE, relative error and Studentized Breusch–Pagan heteroscedasticity test. Predictor selection within model category was based on model residual diagnostics and Second-order Akaike Information Criterion (AICc) (Burnham and Anderson, 2002), a default option adapted for smaller sample size which converges towards AIC with a large sample size.

We compared the allometric models based on the entire data set to the same model structures based on a binned and a thinned data set (Jucker et al., 2017). Data binning was undertaken to account for residual heteroscedasticity and errors in predictors leading to regression dilution bias. Total tree volume as the outcome variable was assigned to eight log scale bins, and the mean of all variables calculated for each bin. To allow inclusion of fire as a factor, the data was split into years before binning. Data thinning was undertaken by taking equal random sub-samples from data bins. Model validation and selection of training data structure were based on cross-validated test data, which was not binned or thinned. All allometric models were validated by checking for homoscedasticity of residuals, lack of pattern in residuals across fitted values and predictors, an approximately normal distribution of residuals, no overly influential outliers and no collinearity issues. For more information, please refer to the Supplementary Material.

3. Results

3.1. Alternative tree volume modelling

Before starting our analysis, we investigated the effect of leaf removal on volume estimates. We compared QSM volume estimates with and without leaves for a subset of 35 trees with samples from all four height classes (Fig. 5). A linear regression indicated an overestimation of tree volume in the leaf-on stage by approximately a factor of two. However, this overestimation is likely to be exaggerated due to excessive point removal by the leaf-stem separation algorithm used to prepare the trees for comparison. Nevertheless, the high coefficient of determination ($R^2 = 0.96$) of the explorative linear regression indicates that calibration is possible should wood volume be the desired outcome, and the use of a leaf-stem separation algorithm is not feasible.

While current best practice, building QSM models can be time-consuming, as they calculate an extensive range of outputs. We test the accuracy of targeted outputs from less complex models once calibrated. Calibration of the alternative models resulted in correlations between QSM volume estimates and all three models that explained over 90% of variance (Fig. 6). No influential outliers were detected in any of the models. The filled voxel model was the most robust, with no significant difference in slope or intercept between years (burnt and unburnt vegetation).

The filled voxel model reached 95% accuracy, and performance was not affected by fire damage. Filled voxel volume increased significantly with QSM volume (linear regression, $F = 1415$, $df = 3, 196$, $p < 0.001$,

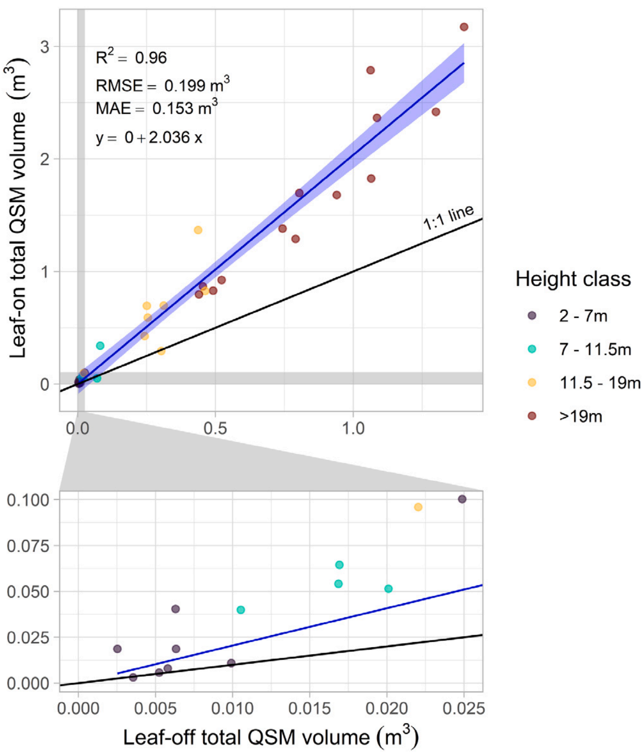

Fig. 5. Leaf-on and leaf-off state of the Quantitative Structure Model (QSM)-derived total tree volume (2018 scan) (n = 35) with a zoom into small trees in the bottom panel.

R^2 = 0.95). The relationship between QSM volume and voxel volume did not significantly depend on year (F = 2.57, df, 1, 196, p > 0.05, Fig. 6d).

The Vonderach model reached 94% accuracy, and performance was also not affected by fire damage. Vonderach volume increased significantly with QSM volume (linear regression, F = 1235, df = 3, 98, p < 0.001, R^2 = 0.94). As with the filled voxel model, the relationship between QSM and Vonderach volumes did not significantly depended on year as a factor (F = 2.3, df = 1, 196, p > 0.5, Fig. 6e).

The alpha shape model reached similar accuracy to the voxel models, but performance was affected by fire damage, and statistics were therefore split into individual years. Alpha shape volume increased significantly with QSM volume for both years (linear regression, F = 1183 for 2018 and 1200 for 2019, df = 1, 96, p < 0.001, R^2 = 0.93). However, the relationship between QSM volume and alpha shape volume significantly depended on year as a factor (F = 15.97, df = 3, 192, p < 0.5, Fig. 6f). The intercept of the relationship was greater in 2018 (0.052 versus 0.023), indicating an overall higher estimate of volume in the alpha shape model compared to the QSM. However, the slope was greater in 2019 (1.018 versus 0.861), indicating a slower increase in alpha shape volume with increasing QSM volume for unburnt vegetation.

The convex hull model could not be calibrated and was not included in Fig. 6. This model consistently overestimated the QSM volume by a factor of 3 (R^2 = 0.91, RMSE = 0.849 m^3, MAE = 0.5068 m^3, ab = −0.01269 + 3.107x).

Model performance was further tested to assess sensitivity to change over time. Overall, all models predict similar rates of mean total change and mean percent change in occupied space (calculated by subtracting 2019 values from 2018 values for individual trees) for each tree height class (Fig. 7). The average volume change detected by the alternative models was not significantly different from the QSM model, according to the t-test at the two-tailed probability (alpha) level a = 0.05. For the filled voxel model t(3) = 1.56, for the Vonderach model t(3) = 1.40 and for the alpha shape model t(3) = −1.38, where p > 0.05 for all models.

For most height classes, the voxel models (filled voxel and Vonderach) tend to overestimate volume change, while the alpha shape model tends to underestimate. The evidence of fire impact visible in the field was reflected in a strong, if not quite significant difference in mean volume between years (t(184) = 1.72, p = 0.09). The majority of total volume was lost in the mid to upper canopy (11.5–19 m and > 19 m height classes, Fig. 7a). While total loss in the understory was minimal in comparison, it showed the highest relative volume loss (Fig. 7b).

Failure to build tree models was an issue for the QSM, as well as some of the alternative models. Of the models run in R to obtain metrics from all trees (n = 1938), only VoxR (the voxel model) successfully processed every tree, while errors were returned for 185 trees using alphashape3d and 32 trees using rTLS. Only one tree returned an error by both the alphashape3d and rTLS model, suggesting that data quality was not the issue.

3.2. Allometric model for variables that can be derived from airborne platforms (tree height and crown area)

Results show that crown area and tree height are good predictors for total volume, as there is a strong linear relationship between crown area and tree volume (R^2 = 0.93 in unburnt and 0.88 in burnt vegetation, Fig. 8a) and a strong log-linear relationship between tree height and crown area (R^2 = 0.89 in unburnt and 0.91 in burnt vegetation, Fig. 8b).

Results also show that both predictors (crown area and tree height) can be reliably replicated by the computationally simpler alternative models. For crown area, there is a strong linear relationship between the QSM and the rTLS package (R^2 = 1) (Fig. 8c) and a strong log-linear relationship between the QSM and the VoxR package (R^2 = 0.99) (Fig. 8c). For tree height, the rTLS and VoxR package predicted identical values with a strong linear relationship to QSM estimates (R^2 = 0.99 for both) (Fig. 8d).

Initial investigation of tree height and crown area in relation to tree volume shows strong relationships between individual metrics. The linear relationship between crown area and total volume shows evidence of heteroskedasticity. Conversely, the relationship between tree height and total volume plateaus for small trees but has a very strong gradient for larger trees. In combination, these parameters may be very well suited as parameters for a new allometric model predicting total volume.

Using the best-performing filled voxel model (voxel size = 0.04 m), we processed all trees in the 1 ha plot from 2018 (unburnt) and 2019 (burnt). To access the three variables, we used the calibrated filled voxel volume from the VoxR package and crown area and tree height from the rTLS package. The severe fire allowed us to include trees with and without recent fire damage with minimal risk of collinearity between years. With the exception of one extremely large tree, outliers with large residuals stemming from large damaged trees (such as stumps or boles without crowns) were not removed from the model, as they form part of the natural variability in tree structure observed in a natural stand as is used here.

For the final model, a multiple linear regression was calculated to predict total tree volume based on the compound variable and recent fire effect (F(2, 13) = 907.9, p < 0.000) with an R^2 of 0.993 and trained on binned data (Fig. 9). The equation of the model was:

$$Total\ tree\ volume = exp(-5.447 + 0.805 \times log_e(H \times CA) - 0.332 \times fire\ damage)$$

where the total tree volume is measured in m^3, H is tree height in m, CA is crown area in m^2 and fire damage is coded as present (1) or absent (0). For every 10% increase in the compound variable, there was an estimated average increase of 7.97% in total tree volume (95% CI 7.6% to 8.4%). If the vegetation was affected by recent severe fire,

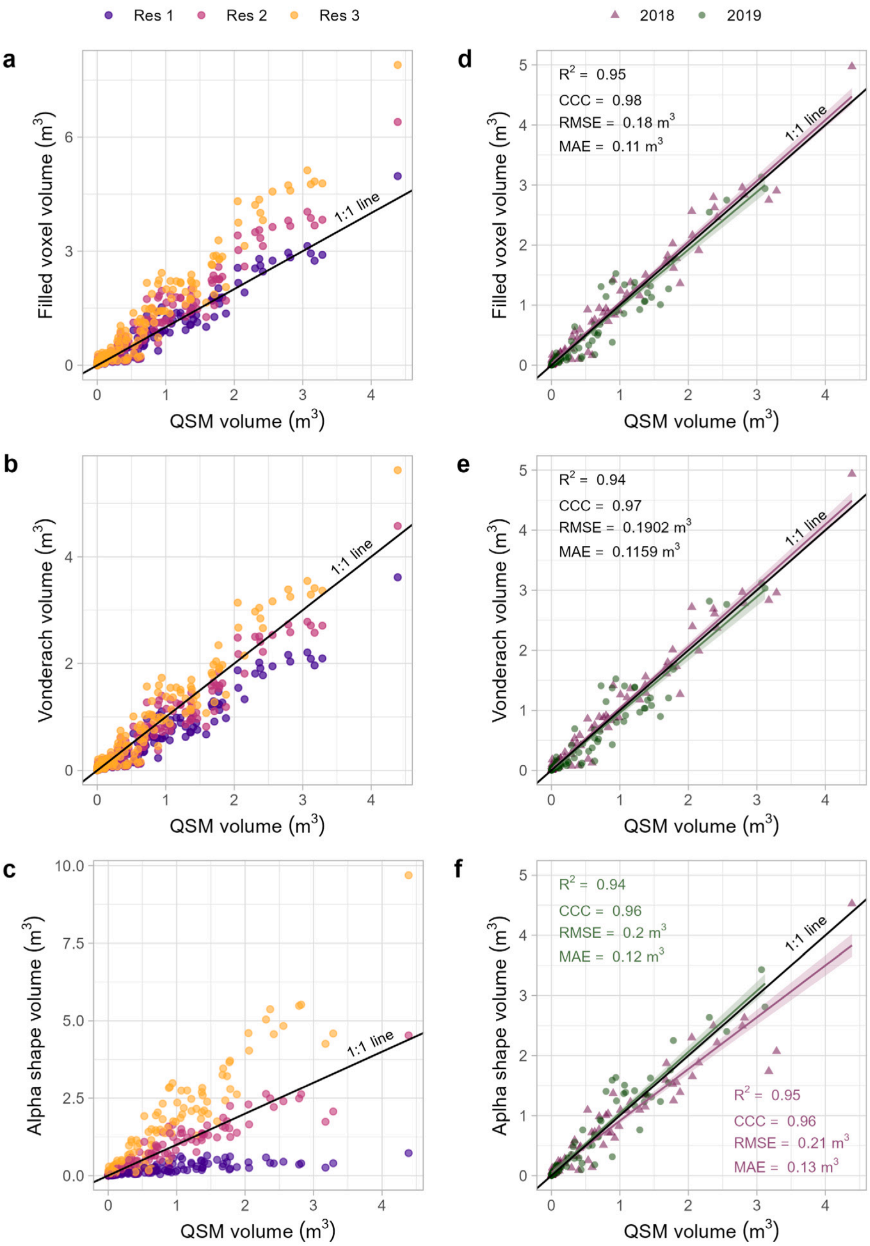

Fig. 6. Model calibration for voxel models (filled voxel and Vonderach) and alpha shape model using 100 randomly chosen trees evenly distributed across the four height classes. Panels a–c show the range of model resolutions tested with a 1:1 line indicating best fit for predicting Quantitative Structure Model (QSM) volume. Panels d–f show the optimised resolution for each model with model statistics and regression lines for individual years (unburnt in 2018 and burnt in 2019). Example resolutions shown for Vonderach and filled voxel volume: 0.04 m, 0.05 m, 0.06 m (Res 1–3 respectively). Example resolutions shown for alpha shape volume: 0.015 m, 0.025 m, 0.035 m (Res 1–3 respectively). Best resolutions for predicting QSM volume were 0.04 m for the filled voxel model, 0.053 m for the Vonderach model and 0.025 m for the alpha shape model. There was no significant difference between years for the voxel-based models (d, e).

there was mean 28% loss in total volume (95% CI 7.5% to 44.4%). Both the compound variable and fire damage were significant predictors of total tree volume. The binned final model outperformed other models tested on the entire data and thinned data based on model residual diagnostics and AICc (Supplementary Material).

4. Discussion

Our results show that once calibrated, simpler models can closely match the ability of highly detailed but computationally expensive QSMs in estimating and tracking changes in total tree volume. The filled voxel model (VoxR package) performed best and equally well in disturbed and undisturbed vegetation, replicating QSM estimates with 95% accuracy (Fig. 6d). For the less complex metrics of crown area and tree height, the alternative models reproduced QSM estimates with 99% and 100% accuracy, respectively (Fig. 8c,d). This near-perfect alignment is not surprising, given that crown area in both the QSM and the rTLS model uses a convex hull of the crown planar projection, while tree height is simply the difference between the lowest and highest point. Sporadic deviations may be due to differences in the noise filtering between models. Of the alternative models trialled, the voxel-based models appeared to be the most robust, being the only models to process every tree in the data set, while all the other models returned seemingly random errors.

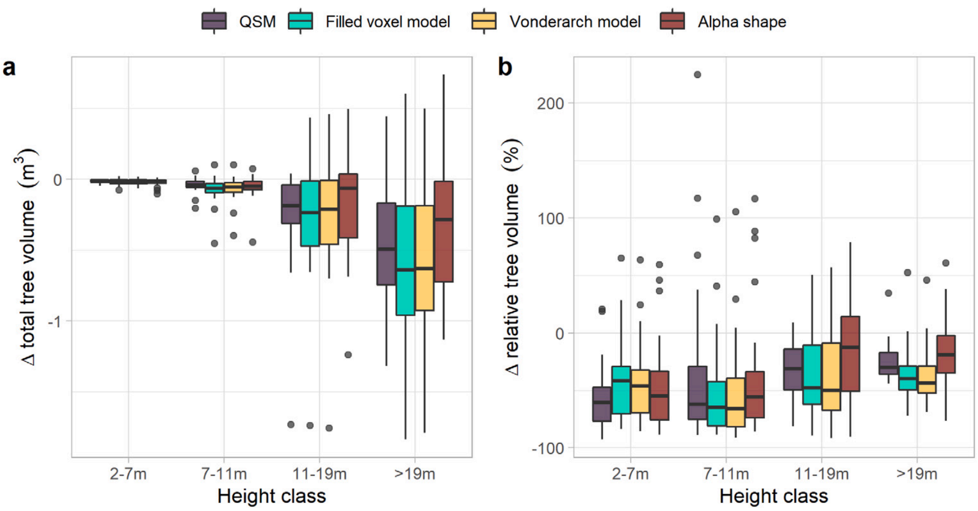

Fig. 7. Model sensitivity to change due to the fire event, showing median, upper and lower quartiles and range. Panel (a) total change in occupied space with SD and (b) relative change in occupied space with standard deviation (SD). Showing alternative models as compared to Quantitative Structure Model (QSM) estimated change (first bar) between 2018 and 2019. The voxel model estimates are generally closer to the QSM but mostly slightly overestimate median change, while the alpha shape model mostly underestimates change.

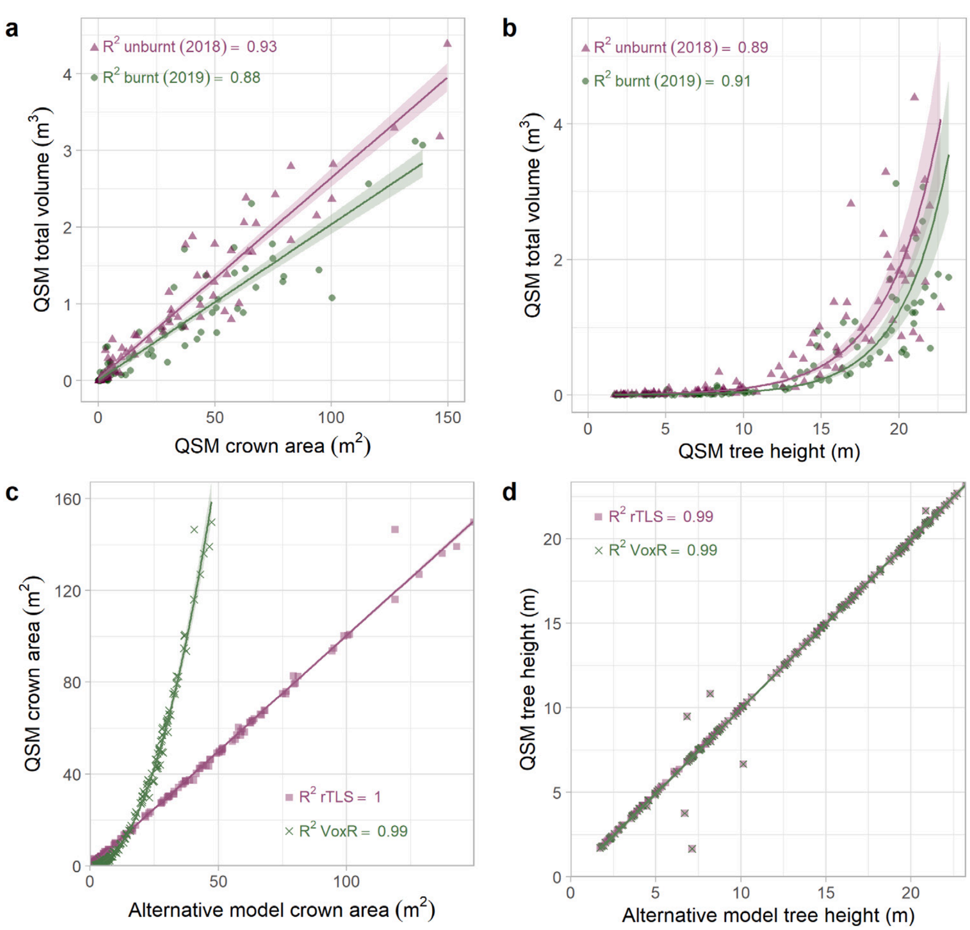

Fig. 8. Correlation between volume from Quantitative Structure Model (QSM) and two potential predictors for burnt (2019) and unburnt (2018) vegetation for (a) crown area (2D convex hull) and (b) tree height (distance between lowest and lightest point), with a log transformation applied to the explanatory variable. Correlation between QSM estimates and alternative model estimates for (c) crown area and (d) tree height. A log transformation was applied to both the predictor and the explanatory variable for the VoxR model predicting crown area (c).

While there is good agreement in volume estimates between the QSM, voxel and alpha-shape models, computing time differed dramatically. For instance, to process the tree pictured in Fig. 4 on a standard laptop (2.8 GHz CPU, 16 GB RAM) took three minutes using the basic QSM function and 80 min using the more detailed QSM process described in Section 2.3.1. In contrast, calculating the target variables of total volume, crown area, and tree height using the alternative models took 36 s combined. We argue that in a resource-restricted

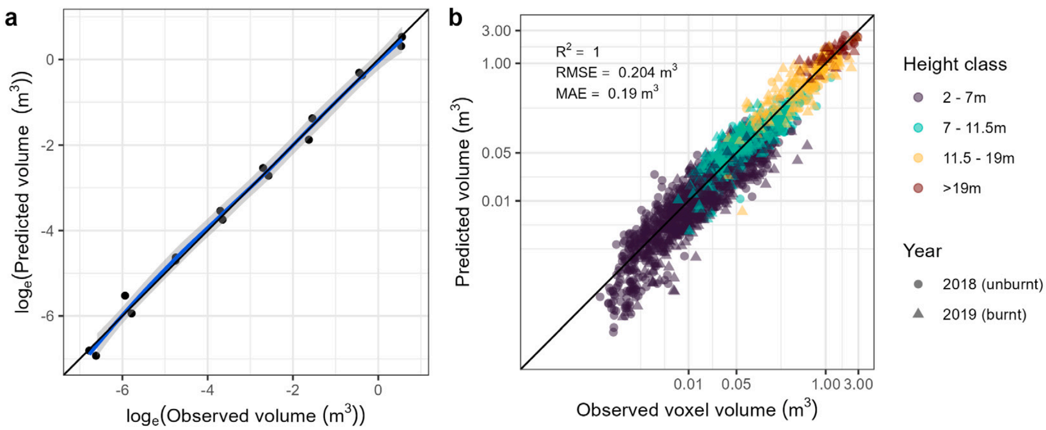

Fig. 9. Performance of the allometric model predicting total tree volume from tree height and canopy area with observed and predicted volume log-transformed. The model was trained on binned data (a), and model performance measures are based on cross-validated test data (not binned) (b).

Fig. 10. Visualisation of sample trees representing all four height classes: (a) 11.5–19 m, (b) 2–7 m, (c) 7–11.5 m, (d) > 19 m in 2018 (left panel) and 2019 post-fire (right panel). Fire damage is evident in all four height strata with some damage evident to branches in tree (d).

environment, QSMs can serve as a valuable tool for providing the reference data required to calibrate more efficient models ideal for fast extraction of target metrics. By reducing model complexity, we enhance the usability of TLS data for mapping and monitoring changes in tree volume across research and land management sectors.

Mature canopy trees represent the majority of total tree volume within a plot, and airborne platforms allow for these trees to be monitored at an increased spatial scale compared to TLS. However, due to occlusion from the canopy and reduced point density, data from airborne platforms is limited regarding the metrics that can be reliably extracted (Terryn et al., 2022) and does not allow us to directly measure changes in total tree volume. Using TLS data, we constructed a localised allometric model to predict total tree volume from crown area and tree height, both metrics that can be observed from airborne platforms. By using voxel models in extracting tree metrics from our training data and adopting a data binning approach for training the model (Duncanson et al., 2015; Jucker et al., 2017), we reduced the computational resources required for the construction of such a model.

The ability to accurately map and monitor habitat structure and severity of disturbance impact on mature versus regenerating individuals is crucial, as changes can affect habitat use across taxa and height strata (Andersen et al., 2006; González et al., 2021; Tassicker et al., 2006). In this study, a 2019 fire occurred late in the dry season, a period of high fire risk and generally increased fire intensity. It is evident that there was a direct impact on all four strata investigated, including large trees (Figs. 2 and 10; 2018 versus 2019), and all volume models reflected this change (Fig. 7). When testing sensitivity to change between the different models, a variance exceeding the mean is unsurprising, as the height class groups investigated are coarse and contain multiple tree species. Spatial variation in fire intensity may have further contributed to the wide range of tree volume changes within each height class. The use of efficient tree structure characterisation enables mapping and quantification of this spatial variability in change both horizontally and vertically.

By reducing computational complexity in the establishment of allometric models, we improved accessibility of mapping and monitoring of total tree volume at an increased spatial scale. Incorporating burnt and unburnt vegetation in the allometric model allowed us to account for fire as a local disturbance factor, an aspect particularly relevant in fire-prone savannas. Calibration to local tree composition and incorporation of relevant disturbance factors such as fire make localised allometric models a valuable tool for assessing change as a result of disturbance events or changed growing conditions (e.g. from drought through to high wet season growth). In future research the utility of airborne data collection may be greatly enhanced by applying the allometric model over an extended area in Litchfield National Park. Further research may also investigate allometry between total tree volume and AGB. Applications of this approach may also include habitat structure monitoring, vegetation change following mine site rehabilitation, carbon accounting or agroforestry.

Reliably quantifying changes in the juvenile tree re-sprouts and shrubs is particularly important in savanna, as this cohort is the main driver of regeneration (Higgins et al., 2000; Bond and Keeley, 2005).

However, the often-high stem densities in this stratum present a challenge to capturing change using traditional field inventories, whereas vegetation volume modelling from TLS shows great promise for monitoring of this fire-sensitive layer and warrants further investigation. Further research is also needed to investigate the link between structural change and net environmental fluxes such as carbon, water and energy, linking changes in phenology, disturbance and climate extremes to flux dynamics (Moore et al., 2016; Portillo-Quintero et al., 2014).

The wider spacing between scan points used in 2018 (25 m versus 20 m in 2019) may have reduced the completeness of individual tree point clouds due to increased occlusion, particularly in the denser shrub layer. Although we were still able to show a volumetric reduction in the understory, we consider this a limitation of this study and recommend a consistent sampling method suitable to the local vegetation density.

5. Conclusion

Characterisation of vegetation structure is particularly challenging in tropical savannas; they are extensive, and in Australia, remote with a high degree of spatial and temporal heterogeneity. We demonstrate the utility of entry-level hardware and reduced model complexity to facilitate fast and accurate processing of terrestrial laser scanning data. The associated cost reduction facilitates application of this technology to access ecologically meaningful tree metrics such as total tree volume, tree height and crown area from plot to potentially catchment scales for a wide range of stakeholders. The approaches investigated in the study will facilitate rapid quantification of spatial and temporal changes in stand structure, wood volume, and ultimately above ground biomass. Future work is required to translate volume to biomass in this ecosystem, and to integrate the efficient evaluation of changes in vegetation structure with environmental metrics such as greenhouse gas fluxes to characterise ecosystem processes as determined by structural change.

CRediT authorship contribution statement

Linda Luck: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization. **Mirjam Kaestli:** Methodology, Formal analysis, Writing – review & editing. **Lindsay B. Hutley:** Conceptualization, Resources, Writing – review & editing, Supervision. **Kim Calders:** Writing – review & editing, Supervision. **Shaun R. Levick:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared a link to the relevant code in the manuscript.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jag.2023.103255. Training and calibration of the allometric model are documented in this repository:

https://github.com/LindaLuck/Luck2023Reducing

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