

Using terrestrial laser scanning and empirical allometries to develop error estimates for tree biomass in mangroves

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Abstract

Given the value of ecosystem services provided by mangrove forests, land managers and conservationists are increasingly interested in quantifying their structure and biomass at multiple scales. Due to numerous challenges with traditional forest mensuration methods in these forests, scientists are increasingly exploring remote sensing-based approaches. Here we report on efforts to quantify mangrove volume and biomass in monospecific *Avicennia germinans* stands. Using high density terrestrial laser scanning (TLS), we measured 176 trees in three plots in Cedar Key, Florida, USA. Following merging, cleaning and segmentation of the collected point clouds, we fit quantitative structure models (QSM) to estimate the volume and mass (volume times density) of the main trunk and lower branches of 176 individual trees. Comparing the QSM mass estimates to mass predicted from empirical allometric relationships, we show that TLS captures approximately 65% of the trees volume (and thus mass) on average. We also show that the mean estimate does not change as a function of tree size. Our work highlights the potential of TLS to aid scientists and land managers in their efforts to measure trees, provides error estimates to aid similar research efforts, and identifies areas in need of methodological improvements for future work.

Introduction

Mangrove forests are recognized as recruitment zones and critical habitats for diverse marine and terrestrial species (Nagelkerken, Dorenbosch, Verberk, de la Morinière, & van der Velde, 2000; Mumby, Edwards, Arias-Gonzalez, Lindeman, Blackwell, Gall, Gorczynska, Harborne, Pescod, Renken, Wabnitz, & Llewellyn, 2004). Mangroves forests have also been highlighted for their capacity to attenuate storm damage from hurricanes or cyclones (Alongi, 2008; Zhang, Liu, Li, Xu, Shen, Rhome, & Smith, 2012). With average production levels of $2.5 \text{ g C m}^{-2} \text{ day}^{-1}$ (Jennerjahn & Ittekkot, 2002) mangroves are amongst the most productive forests on Earth and their importance in blue carbon economics has been gained recognition (McLeod, Chmura, Bouillon, Salm, Björk, Duarte, Lovelock, Schlesinger, & Silliman, 2011; Bertram, Quaas, Reusch, Vafeidis, Wolff, & Rickels, 2021). In addition, they store substantial C belowground, with 40% higher soil C density than saltmarsh and 10 times greater annual soil C sequestration than peatlands (Chmura, Anisfeld, Cahoon, & Lynch, 2003). In fact, the soils in mangrove forests contain carbon levels that are among the highest in the tropics (Donato, Kauffman, Murdiyarso, Kurnianto, Stidham, & Kanninen, 2011). The array of ecosystem services and functions provided by mangroves highlights the importance of accurate methods to estimate community and landscape biomass of these forests to assist in management and further understand their role and influence on community structure, stability and resource flux.

Coastal mangrove forests are adapted to peat and muck soils, as well as sandy and silty loam soils, that are subject to regular tidal inundation which can make them difficult to access and traverse (Cooray, Chalmers, & Chittleborough, 2024). Red mangroves (*Rhizophora mangle*) have numerous, strong prop roots to provide stability in soft soils which can also make walking among them quite challenging. Mangroves in many regions are also home to potentially dangerous, yet threatened, fauna such as the American crocodile (*Crocodylus acutus*) in South Florida and the Caribbean, or the Royal Bengal Tiger (*Panthera tigris tigris*) in the Sundarbans National Park, Bangladesh.

A variety of approaches have been used to estimate biomass in mangrove forests. Many studies have relied on traditional allometric approaches based on individual tree measurements (Golley, Howard, & Ronald, 1962; Day, Conner, Ley-Lou, Day, & Navarro, 1987; Soares & Schaeffer-Novelli, 2005; Smith & Whelan, 2006). However, such approaches are labor intensive, typically limited in spatial scale, and require harvesting of trees which is currently prohibited in many locations due to conservation concerns.

To explore alternatives to harvesting, scientists are increasingly relying on remote sensing approaches to measure tree dimensions (height, diameter at breast height (DBH), bole volume) using data from terrestrial laser scanners (TLS), unmanned aerial vehicles (UAV), airborne laser scanners (ALS), or satellite based lidar. Using remotely sense tree dimensions one can then estimate stand or landscape level biomass (Heumann, 2011; Kuenzer, Bluemel, Gebhardt, Quoc, & Dech, 2011; Feliciano, Wdowinski, Potts, Lee, & Fatoyinbo, 2017) using previously published empirical allometric equations [13, 15]. Images and point clouds derived from these platforms have dramatically expanded the amount of data available to estimate mangrove stand structure and biomass both above and below canopy (Fromard, Vega, & Proisy, 2004; Simard, Zhang, Rivera-Monroy, Ross, Ruiz, Castaneda-Moya, Twilley, & Rodriguez, 2006).

While some forest types, such as managed conifer plantations, have been areas of considerable research into the use of TLS combined with quantitative structural models (QSM) to estimate tree volume, mangroves have seen much less activity due in part to the various challenges associated with scanning in these forest types (Feliciano, Wdowinski, & Potts, 2014; Olagoke, Proisy, Féret, Blanchard, Fromard, Mehlig, de Menezes, dos Santos, & Berger, 2016; Warfield & Leon, 2019; Kargar, MacKenzie, Apwong, Hughes, & van Aardt, 2020). In contrast to some forest stands which contain straight, tall, clearly identifiable boles and relatively few lateral branches bearing leaves in the upper canopy, mangrove forests are often dense, with lateral, overlapping branching and leaves throughout. This is

particularly true of forest stands that are subject to periodic disturbance due to wind or flooding which results in canopy openings facilitating new growth in the understory. The use of TLS in such forests is problematic due to the high levels of occlusion that occurs when laser beams are intercepted by the numerous leaves, branches and small trees, resulting in scans that do not fully resolve the boles and branches of the trees within them. This is especially true for the upper canopy where wind and occlusion combine to both limit and degrade points, resulting in noisy data which cannot be fit with a QSM.

For researchers working in these systems, it is understood that the QSMs represent some fraction of the true volume of the trees they are meant to approximate (Feliciano et al., 2014; Olagoke et al., 2016). *But what fraction, and does that fraction depend on the size of the scanned tree?* Without harvesting trees, or painstakingly collecting hand measurements of the entire tree volume, the missing fraction of tree volume is difficult to estimate. In many terrestrial forests such approaches can be validated by harvesting trees post scan and weighing them to determine the accuracy of the fitted QSM models (Gonzalez de Tanago, Lau, Bartholomeus, Herold, Avitabile, Raumonon, Martius, Goodman, Disney, Manuri, Burt, & Calders, 2018). However, mangroves are protected species in many areas so harvesting them is not an option.

To address this limitation, Feliciano et al (2014) obtained TLS data for 40 individuals from two mangrove species (*Rhizophora mangle* and *Avicennia germinans*) in the Everglades National Park, Florida, and used published mass estimates for canopy branches (Clough, Dixon, & Dalhaus, 1998; Fromard, Puig, Mougou, Marty, Betoulle, & Cadamuro, 1998; Komiyama, Pongpan, & Kato, 2005) to arrive at a canopy correction factor of $20 \pm 10\%$. Unfortunately, only one of the three studies of mass estimates contained the two target species. Moreover, the demarcation between canopy branches and non-canopy within these studies is subjective. Olagoke et al. (2016) scanned 36 *A. germinans* trees in French Guiana and compared them to previously collected reference allometric data (Fromard et al., 1998) for 25 locally harvested trees and estimated a root mean squared error for their QSMs of 13.5% of tree biomass, albeit for a range of tree sizes considerably larger than our current study.

Our approach is to combine measurements from QSMs derived from TLS data with recently compiled allometric data for *A. germinans*. In an analysis of allometric data from nine sites spread across the Atlantic/East Pacific biogeographic region, performed by members of our group, it was shown that the best single predictor of above ground biomass was diameter at breast height (DBH). The R^2 value for this relationship in *A. germinans* across sites was 0.935 and the mean site specific R^2 was 0.937. Thus, in mangroves, as is true in many tree species, DBH is a strong predictor of above ground biomass.

Our TLS data come from a field campaign of scanning mangroves at three plots in Cedar Key, Florida comprised solely of *A. germinans* individuals. We used the DBH from each tree we scanned to predict its allometric-mass. We then took the volume obtained from QSM fitting and multiplied it by published wood density values to arrive at a QSM-mass estimate. The difference between the two mass estimates is taken to be the fraction of the canopy volume missing from the QSM fitting.

These combined approaches will allow us gain insight to the following three questions:

1. What fraction of tree volume are QSMs capturing?
2. Does that fraction depend on tree size?
3. How does the mass predicted by DBH compare to that predicted by height?

Methods

Here we use tree measurements from a recent study compiling allometric data from nine sites across the Atlantic/East Pacific biogeographic region for three common species *A. germinans*, *R. mangle*, and *Laguncularia racemosa* (Price, Branoff, Cummins, Kakaï, Ogurcak, Papeş, Ross, Whelan, & Schroeder, 2024). To compare relationships across the same size range we limited our analysis in this paper to those empirical data that fell within the same range of DBH values observed in our TLS dataset. Sample sizes for each relationship are given in Table 1.

Table 1

SMA regression results. Each row contains the y-variable, x-variable, group, number of trees (n), R^2 , slope with low and high 95% confidence intervals, intercept with low and high 95% confidence intervals, and the corresponding figure. Note that the slopes of the lines in Fig. 2A are not different from one another ($p < 0.05$). The 95% confidence intervals for the slopes in the last two rows include 1 in both cases, however the confidence intervals for the intercept do not include 0 for the relationship between $Mass_{DBH}$ and $Mass_{QSM}$ (see Fig. 4A).

Log ₁₀ Y-variable	Log ₁₀ X-variable	Group	n	R ²	Slope	LowCI	UppCI	Interc	LowCI	UppCI	Figure
Mass	DBH	Empirical	160	0.937	2.343	2.253	2.438	4.005	3.891	4.119	2A
$Mass_{QSM}$	DBH_{QSM}	QSM	176	0.894	2.32	2.209	2.435	3.76	3.636	3.885	2A
Height	DBH	Empirical	132	0.631	0.7995	0.7197	0.8881	1.772	1.672	1.873	2B
$Height_{CC}$	DBH_{QSM}	QSM	176	0.514	0.6564	0.5915	0.7285	1.562	1.487	1.638	2B
Mass	Height	Empirical	154	0.626	4.66	4.225	5.139	-2.541	-2.9	-2.181	2C
$Mass_{Height}$	$Height_{CC}$	QSM	176	0.545	3.534	3.195	3.908	-1.76	-2.068	-1.453	2C
$Mass_{DBH}$	$Mass_{QSM}$	-	176	0.894	0.9777	0.9313	1.0265	0.2383	0.1751	0.3016	4A
$Mass_{Height}$	$Mass_{QSM}$	-	176	0.545	1.043	0.943	1.154	0.04018	-0.10089	0.18124	4B

The mangrove trees we scanned were part of a field campaign to explore the use of TLS in mangrove forests. Trees were scanned in three plots in the Cedar Key area of Florida, USA. The latitude and longitude of the center points of the three plots were obtained using a Javad Triumph 2 professional grade GPS receiver and were as follows: Plot 1–29.142384, -83.031444; Plot 2–29.102487, -83.070206; Plot 3–29.102523, -83.070490.

A handful of studies have examined how the number of scans, the spatial arrangement, and distance from one another influenced tree detection rates and measurement accuracy (Heinzel & Huber, 2018; Liu, Wang, Dong, Chen, & Liu, 2018; Reddy, Fararoda, Jha, & Rajan, 2018; Gollob, Ritter, Wassermann, & Nothdurft, 2019). A review by Liang et al. (2016) found that detection rates ranged from 62.1 to 100% in plots with multiple scans, with results dependent on scanner position and spacing. However, these studies were all performed in closed canopy forests where tree boles are large and spaced out compared to typical mangrove forests. As such, we adopted a modified sampling design with one central scan and four perimeter scans at the corners of a square at an approximate distance of 7.32 m from each other. This is equivalent to the diameter of the US Forest Service's phase 2 subplot (Woudenberg, Conkling, O'Connell, LaPoint, Turner, & Waddell, 2010).

We used a FARO Focus S350 HDR lidar scanner. Twelve target spheres were placed around the perimeter of each scan to facilitate subsequent merging of the point clouds corresponding to the five scan positions. Each scan was 360 degrees at a range of 613m. Scan times were roughly 12 minutes per scan. Following collection in the field, the five scans were aligned and processed in FARO SCENE software (FARO Technologies, Lake Mary, Florida), and saved as LAS files for subsequent analysis.

LAS files (point clouds) for each plot were processed using the CloudCompare software interface (CloudCompare, 2023). Point clouds were cleaned using the Statistical Outlier Removal (SOR) filter and Noise filter options under default settings. The height for each tree ($Height_{CC}$) was measured on-screen using the distance measuring tool by drawing a straight line from the base of each tree to the tree's highest leaf lidar return (Fig. 1).

To separate tree boles and branches within a point cloud, we utilized the segmentation function, "Label Connected Components" with an octree level of 10 and a minimum of 30,000 points per component. The largest connected component was invariably the bole and large connected branches. Any remaining leaves or noisy branch sections were manually removed using the cutting tool.

To create quantitative structural models for each tree branching structure, we utilized the TreeQSM software version 2.4.1 (Raumonen, Kaasalainen, Åkerblom, Kaasalainen, Kaartinen, Vastaranta, Holopainen, Disney, & Lewis, 2013; Calders, Newnham, Burt, Murphy, Raumonen, Herold, Culvenor, Avitabile, Disney, Armston, & Kaasalainen, 2015; Markku, Raumonen, Kaasalainen, & Casella, 2015), a free software program written in Matlab and available online (github.com/InverseTampere/TreeQSM). From the processed point clouds representing the boles and branches TreeQSM estimates geometric and volumetric traits by fitting cylinders to branch sections. We

measured *DBH* in the field for trees 7.62 cm or greater (3 inches). However, our analyses here used trees that had smaller *DBH* values. Thus, for consistency, we utilized the *DBH* estimated by TreeQSM for all trees.

TreeQSM fits QSMs based on the values of several parameters (<https://github.com/InverseTampere/TreeQSM/tree/master/Manual>), however as per the documentation, three of these parameters are most important: the patch size of the first uniform-size cover (inputs.PatchDiam1), minimum patch size of the cover sets second cover (inputs.PatchDiam2Min), and the maximum patch size of the stems base in the second cover (inputs.PatchDiam2Max). These parameters are populated with two values each in the default settings resulting in $2^3=8$ different QSM estimates for each point cloud. All other values were left as the default values populated by the software developers.

We found five published estimates of wood density (0.67, 0.792, 0.9, 0.77 0.75, g/cm^3) for *A. germinans* contained within a global compilation (Chave, Coomes, Jansen, Lewis, Swenson, & Zanne, 2009) and used the mean of these values (0.776). This is close to the mean values utilized by Feliciano et al. [0.770, 20] and Olagoke et al. [0.728, 23]. To estimate biomass for each tree we multiplied the mean wood density (0.776) by the volume derived from the QSM fitting (Eq. 1).

$$Mass_{QSM} = Volume_{QSM} \times Density$$

1

To create allometric models that could be used to predict biomass from *DBH* or height, we used ordinary least squares regression (OLS). OLS is recommended in situations where one is attempting to predict *Y* from *X* (Warton, Wright, Falster, & Westoby, 2006). We fit OLS regression equations to data for the following two relationships, *Mass* vs *DBH* (*MvD*) and *Mass* vs *Height* (*MvH*).

We used the OLS allometric models to then predict the mass of our scanned trees based on the *DBH* measured by TreeQSM (Eq. 2), or based on their height (Eq. 3) which was manually measured in CloudCompare (*Height_{CC}*, see above). We also used the *DBH* measured by TreeQSM to predict tree height, which was then compared to measured height.

$$Mass_{DBH} = MvD_{slope} \times Log_{10}(DBH_{QSM}) + MvD_{intercept}$$

2

$$Mass_{height} = MvH_{slope} \times Log_{10}(Height_{CloudCompare}) + MvH_{intercept}$$

3

To analyze differences between mass predicted from the empirical regression equations (Eqs. 2 and 3) and mass from QSM fitting (Eq. 1) we used standardized major axis regression (SMA). Regression exponents were estimated using the software package Standardized Major Axis Tests and Routines (SMATR) (Falster, 2006; Warton et al., 2006). SMA regression is typically used in allometric studies where both variables have associated measurement error and one wants to test if slopes from different datasets are equal, as is the case here (Warton et al., 2006). All data were log transformed before regression fitting to meet the regression assumption of homogeneity of variance.

To compare the mass estimated using Eq. 1 to that using Eqs. 2 and 3, we calculated mass ratios, which are simply $Mass_{QSM}/Mass_{DBH}$ and $Mass_{QSM}/Mass_{Height}$. We examined the mass ratios in two ways, by looking at a histogram of their values to understand the central tendency and dispersion, and by plotting the mass ratios as a function of tree size (indexed using *DBH*) to see if there is any systematic change as a function of tree size.

We also plotted $Mass_{QSM}$ vs $Mass_{DBH}$ and $Mass_{QSM}$ vs $Mass_{Height}$ and fit SMA regression slopes to each bivariate relationship to examine the strength of each relationship (R^2) and compare it to a reference 1:1 line.

Results

Following cleaning and segmentation of point cloud data, we had 176 individual tree point clouds. Eight different QSMs were fit to each point cloud resulting in 1408 QSMs (SI Figs. 1-1408). The smallest point cloud had 10,316 points, the largest 1,278,252, and the mean was 127,852 points.

SMA regression statistics for the three relationships shown in Fig. 2 are in Table 1. The slopes of the relationship between *Mass* and *DBH* and *Mass_{QSM}* and *DBH_{QSM}* were statistically indistinguishable (Fig. 2A), but the empirically obtained mass data are higher in the ordinate axis than the QSM estimates ($p = 0$). In contrast, the slopes between *Mass_{Height}* and *Height_{CC}* and between *Mass* and *Height* (Fig. 2C) are statistically different. We also obtained statistically different slopes for the relationship between *DBH* and height from empirical and from QSM estimates (Fig. 2B).

The distribution of the estimated mass ratio percentages (*Mass_{QSM}*/*Mass_{DBH}* × 100) is slightly right skewed (Fig. 3A), but the mean (65.85) and median (61.16) are close to each other. The distribution of *Mass_{QSM}*/*Mass_{Height}* × 100 is more strongly skewed (Fig. 3C), with a mean value of 113.45 and median value of 77.60.

OLS lines indicated that there is no significant relationship between *DBH_{QSM}* and *Mass_{QSM}*/*Mass_{DBH}* (Fig. 3B), but there is a weak positive relationship between *DBH_{QSM}* and *Mass_{QSM}*/*Mass_{Height}* (Fig. 3D).

SMA regression between *Mass_{DBH}* and *Mass_{QSM}* had a slope of 0.978 and R^2 of 0.894 (Fig. 4A). The slope is not different than 1 for this relationship, however, the y-intercept is higher than zero, indicating an upward shift in the data (Table 1). SMA regression between *Mass_{Height}* and *Mass_{QSM}* had a slope of 1.043 and R^2 of 0.545 (Fig. 4B) and the fitted line was not different than the 1:1 line (Table 1).

Discussion

We have shown that the slope for the allometric relationship between mass and DBH is very similar to that of the relationship between mass estimated from QSM volume and QSM derived DBH (Fig. 2A). Despite being collected in very different ways and representing different measures, these slopes are statistically indistinguishable. Moreover, there is no significant relationship between tree size (as measured by DBH) and the *Mass_{QSM}*/*Mass_{DBH}* ratio (Fig. 3B). This suggests that plant volume estimates obtained with QSMs from TLS lidar scans can reliably and repeatedly capture a majority fraction of the true volume of a tree and that this fraction does not change systematically with size on average, at least within our data.

Our work supports the idea that a correction factor can be used to estimate the quantity of missing canopy volume when calculating tree volume from TLS, as done by Feliciano et al. (2014). Our results indicate a correction factor of about 35% which is just above the upper bound of the 20% (+/-10%) correction factor utilized in their work. Our correction factor is higher than the 13.5% mean error reported by Olagoke et al. (Olagoke et al., 2016). This may be due in part to the fact that our trees were generally smaller than the trees in their study. Further, our sample plots occur in an area that is subject to semi-periodic disturbance in the form of tropical storms or hurricanes. Northwestern Florida is one of the most hurricane prone places in the region. Such disturbances can strip leaves and branches from trees, leading to denser understory growth which can cause significant occlusions in lidar scans, hampering the ability to resolve canopy branches. These limitations to our data are counterbalanced by our higher sample sizes, over four times that used in Feliciano et al. and Olagoke et al. (Feliciano et al., 2014; Olagoke et al., 2016).

Should the opportunity arise to scan mangrove trees and then harvest them, to directly measure above ground mass, this would provide the most direct test of the ability of TLS to capture mangrove tree volume, and estimate what volume fraction is missing from the small branches and leaves in the upper canopy that are difficult to account for in current approaches. However, as mentioned, the fact that these mangrove species are protected throughout much of their range, makes the possibility of such an opportunity less likely.

Unfortunately, there appears to be high variance in the mass ratio percentage estimates (*Mass_{QSM}*/*Mass_{DBH}* or *Mass_{QSM}*/*Mass_{Height}* × 100) in Fig. 3. While a majority of the *Mass_{QSM}* estimates (122/176) appear to capture 50% of the tree or greater, close to a third of the estimates (54/176) capture less than that. Further, a small fraction of the values are overestimates, with ~ 10% of the estimates (18/176) over 100%. Similarly, about 35% of the height-based estimates (61/176) are greater than 100%.

As seen in Fig. 3, the mean value of *Mass_{QSM}*/*Mass_{DBH}* (Panel A) and *Mass_{QSM}*/*Mass_{Height}* (Panel C) were within a reasonable range, however some of the values in each distribution were overestimated. These values can be better understood by looking at the point clouds and resulting QSMs that generated them. Figure 3, Panel A includes trees that had lots of branching and not a single straight bole (e.g. Figs S969-976 or S985-992). Figure 3, Panel C displays results from trees that have lots of branches but did not grow very tall (e.g. see Figs S1054-1061 or S1318-1325), or trees for which our segmentation pipeline captured a large bole, but not much of the tree height (see Figs S881-888, or S1017-1024).

There are numerous challenges to gathering TLS data in mangrove forests. Mangroves occur in areas that are tidally inundated with thick mud and so walking amongst them is challenging. Many species have abundant pneumatophores, including *A. germinans*, which, along with standing water make identifying the ground difficult for algorithms such as the cloth simulation filter (CSF) in CloudCompare. Other species (e.g. *R. mangle*) have prop roots which intertwine and can extend several meters up the trunk. Aerial roots are also common, which can extend from high branches to the ground. This can make identifying, segmenting and assigning individual roots to a specific tree within QSMs extremely challenging. Most QSM algorithms begin with the assumption that the tree form will be that of a relatively straight bole with lateral branches in the upper canopy.

Mangroves also frequently occur in areas of high disturbance due to wind, waves and storms that strip leaves and branches from trees. This can create gaps in the canopy which promotes new branch and leaf growth in the understory. This growth can extend both vertically and horizontally, resulting in a high density of leaves and stems throughout the canopy. The dense stand structure can lead to high levels of occlusion in TLS scans, making reconstruction of branches within point clouds very difficult, especially in the upper canopy. Given current technology and unavoidable constraints of scanning in coastal environments, most TLS campaigns in mangroves will not obtain enough quality data to fit QSMs across the full tree. Our results suggest a canopy correction factor of 35% is suitable to account for unresolved mass in *A. germinans* stands. This confirms a similar range of canopy correction used previously in other studies (Feliciano et al., 2014). Until more specific corrections are developed, this factor can likely be generalized to use with other mangrove species given their common growth forms and similar size distributions.

Despite these challenges, we have shown that mangrove stands, when scanned at sufficient density of TLS positions, can yield reasonable estimates of stem volume, albeit with higher variance than desired. Future improvements may yield even better results. For example, lidar scanning from small drones that can navigate tree canopies (Zhou, Wen, Wang, Gao, Li, Wang, Yang, Lu, Cao, Xu, & Gao, 2022) will allow for lidar returns from what is effectively a very large number of positions, as opposed to the relative small number (5 in our study) that is usually employed with TLS. Furthermore, such drones could potentially scan at multiple elevations, increasing point coverage in the upper canopy which is the most problematic area for coverage in all forest types. While the technology to support such approaches is in its infancy, drone based scientific research is a rapidly progressing research area, thus solutions such as this are likely pending.

Declarations

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Author contributions

Charles A. Price: Conceptualization, Methodology, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft – Reviewing and Editing, Project Administration. **Karen Cummins:** Methodology, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft – Reviewing and Editing. **Todd A. Schroeder:** Conceptualization, Methodology, Formal Analysis, Investigation, Resources, Writing – Reviewing and Editing, Project Administration. **Monica Papeş:** Conceptualization, Methodology, Formal Analysis, Investigation, Resources, Writing – Reviewing and Editing, Project Administration.

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

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Figures

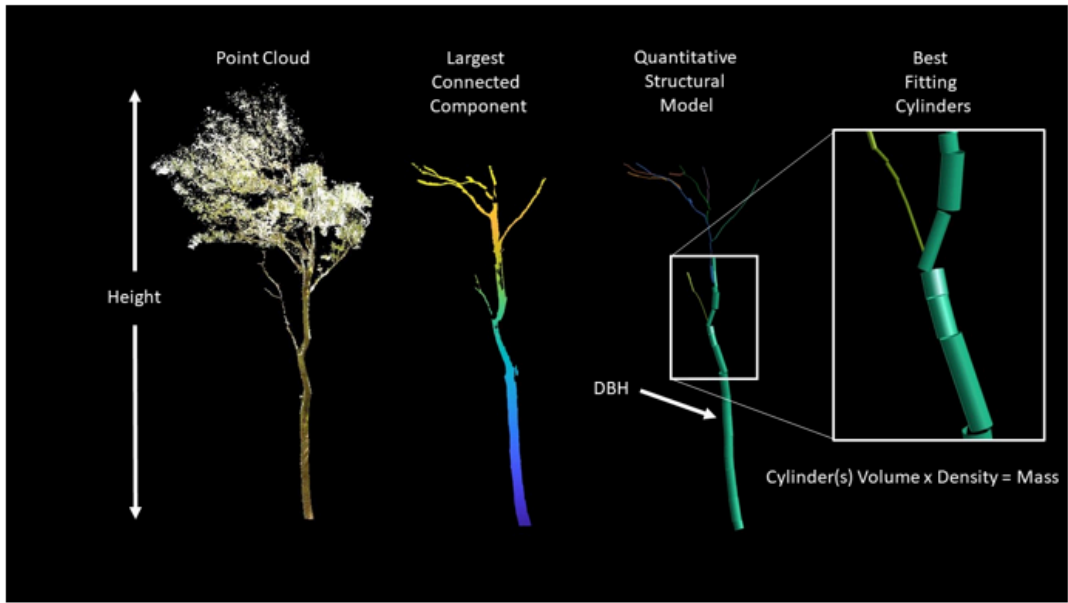


Figure 1

Graphic illustrating some of the steps in our workflow. The largest connected component from the point cloud is segmented and then fit with a quantitative structural model, composed of the best fitting cylinders for each section. Tree height is taken from the raw point cloud and DBH from the QSM. The mass of the tree represented by the QSM is estimated by multiplying the QSM volume times reported density for *A. germinans*.

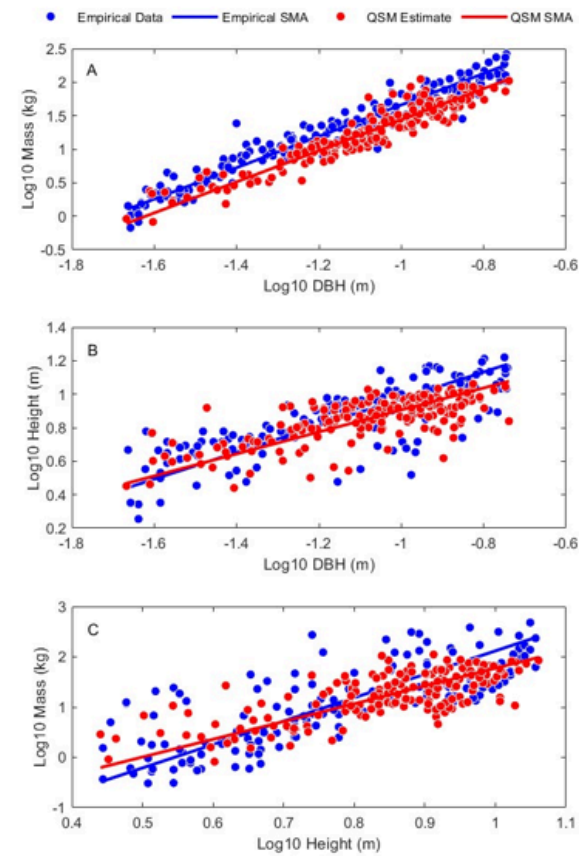


Figure 2

Bivariate relationships between Mass (empirical mass or $Mass_{QSM}$), DBH (empirical DBH or DBH_{QSM}) and Height (empirical height or $Height_{QSM}$) for both the empirical data and the estimates derived from the QSMs. Fitted lines are from SMA regression. Note the slopes for the mass-DBH relationship (Panel A) are statistically indistinguishable, but there is a change in point location in the ordinate axis, with the empirical data higher. This is consistent with the idea that QSMs capture a constant fraction of the tree volume, on average.

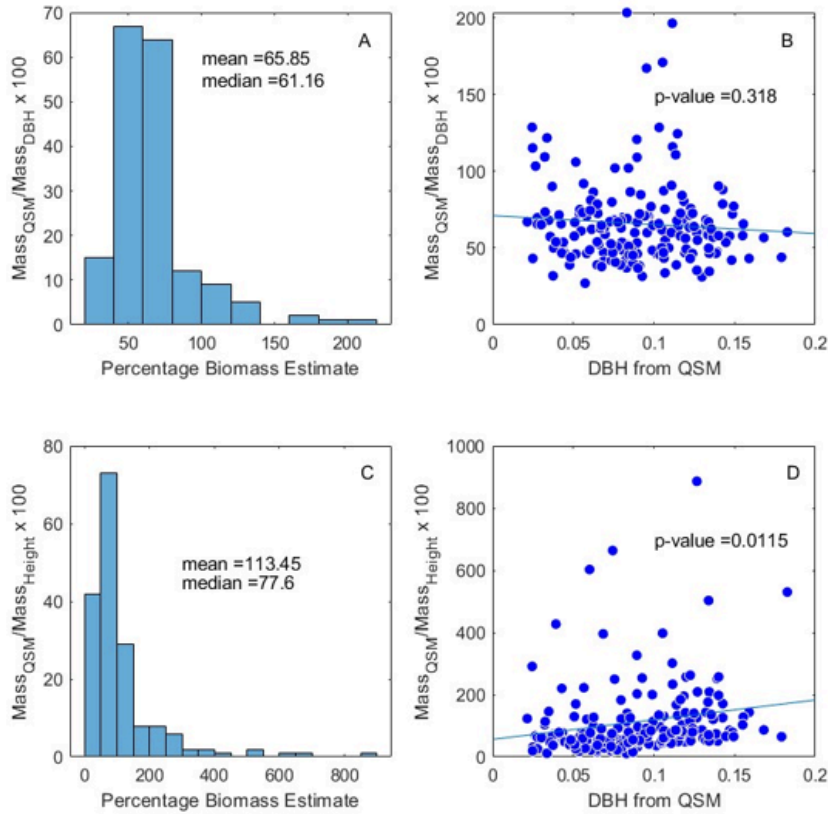


Figure 3

Estimated mass percentages, which are simply $Mass_{QSM}/Mass_{DBH} \times 100$ and $Mass_{QSM}/Mass_{Height} \times 100$, plotted as a histogram (Panels A and C) and as a function of the DBH obtained from each trees QSM (Panels B and D). There is no significant relationship in Panel B, and a slight positive relationship in Panel D.

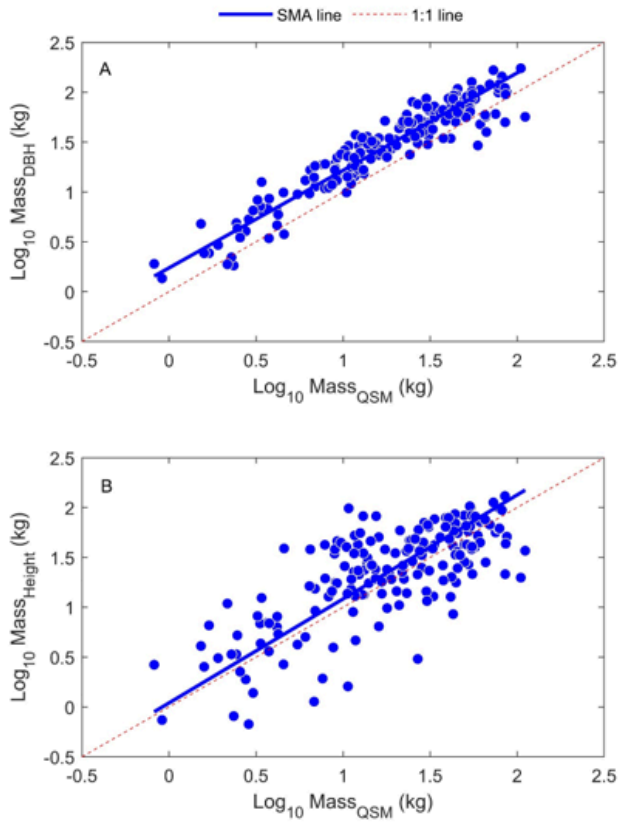


Figure 4

Bivariate plots of Mass_{QSM} vs Mass_{DBH} (Panel A) and Mass_{QSM} vs $\text{Mass}_{\text{Height}}$ (Panel B) with SMA regression functions (blue lines) and a 1:1 line (red dashes) as a reference. There is a fairly tight relationship between in Panel A, with an R^2 of 0.894. The relationship in Panel B is not as strong, with an R^2 of 0.545.

Supplementary Files

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