



Using Terrestrial Laser Scanning and Empirical Allometries to Develop Biomass Error Estimates for Black Mangrove Trees

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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. Because of the many 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 aboveground volume and biomass in monospecific *Avicennia germinans* stands in Cedar Key, FL using high density terrestrial laser scanning (TLS). Following merging, cleaning, and segmentation of the TLS point clouds, quantitative structure models (QSM) were fit to estimate the volume and mass (volume multiplied by wood density (ρ)) of the main trunk and lower branches of 176 individual trees. By comparing QSM-based mass estimates to mass predicted from empirical allometric relationships, we show that TLS captures, on average, approximately 65% of the tree volume, and thus mass. We also show that the average proportion of tree biomass estimated by the fitted QSMs 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 which can improve biomass estimation for blue carbon accounting. We also provide error estimates to aid similar research efforts and identify areas in need of methodological improvements for future work.

Keywords Terrestrial laser scanning (TLS) · Quantitative structural models (QSM) · *Avicennia germinans* · Biomass · Mangrove

Introduction

Mangrove forests are recognized as recruitment zones and critical habitats for diverse marine and terrestrial species (Nagelkerken et al. 2000; Mumby et al. 2004). They have also been highlighted for their capacity to attenuate storm damage from hurricanes and tropical cyclones (Alongi 2008;

Zhang et al. 2012). With average production levels of $2.5 \text{ g C m}^{-2} \text{ day}^{-1}$ (Jennerjahn and Ittekkot 2002), mangroves are amongst the most productive forests on Earth and their importance in blue carbon economics has been widely recognized (McLeod et al. 2011; Bertram et al. 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 et al. 2003). In fact, the soils in mangrove forests contain carbon levels that are among the highest in the tropics (Donato et al. 2011). This 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 blue-carbon accounting efforts (measurement, reporting, verification) (Howard et al. 2014; Bertram et al. 2021) and further understand their role and influence on forest community structure, resilience, and resource flux (Alongi 2008; Danielson et al. 2017).

Traditional forest mensuration approaches in mangroves are logistically difficult, time-consuming, and thus costly. Coastal mangrove forests are adapted to peat, muck, sandy,

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and silty loam soils that are subject to regular tidal inundation which can make them difficult to access and traverse (Cooray et al. 2024). Red mangrove (*Rhizophora mangle*) stands have numerous, strong prop roots that provide stability in soft soils but also make walking among them quite challenging. Mangroves in many regions are also home to potentially dangerous fauna such as the American crocodile (*Crocodylus acutus*) in southern 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 such as tree height or diameter at breast height (DBH) (Golley et al. 1962; Day et al. 1987; Soares and Schaeffer-Novelli 2005; Smith and Whelan 2006). However, such approaches are labor intensive, typically limited in spatial scale, and often require harvesting of trees to develop site- or region-specific allometric equations. Moreover, mangrove harvesting is currently prohibited in many locations due to conservation concerns and recent analyses suggest that global allometric equations may be adequate for some investigations (Price et al. 2024, 2025).

To explore alternatives to harvesting, scientists are increasingly relying on active remote sensing approaches to measure tree dimensions (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 sensed tree dimensions, one can then estimate stand or landscape level biomass (Heumann 2011; Kuenzer et al. 2011; Feliciano et al. 2017) using previously published empirical allometric equations (Golley et al. 1962; Imbert and Rollet 1989; Fromard et al. 1998; Ross et al. 2001; Smith and Whelan 2006; Osland et al. 2014). 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 the canopy (Fromard et al. 2004; Simard et al. 2006).

While quantitative structure models (QSM) fit to TLS point clouds have been used to estimate tree volume and biomass in many terrestrial forests, mangroves have seen much less activity due in part to the various challenges associated with scanning in these forest types (Feliciano et al. 2014; Olagoke et al. 2016; Warfield and Leon 2019; Kargar et al. 2020). In contrast to some forest types 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 by wind or flooding which results in canopy openings that facilitate new growth in the understory. The use of TLS in such forests

is difficult due to the high levels of occlusion that occurs when laser beams are intercepted by the numerous leaves, branches, and small trees, resulting in incomplete scans. 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 accurately 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 or structure of the scanned tree?* Without painstakingly collecting hand measurements of the entire tree, the missing fraction of tree volume is difficult to quantify. 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 et al. 2018); however, since mangroves are a protected species in many areas, harvesting them is usually not an option.

To address this limitation, Feliciano et al. (2014) obtained TLS data for 40 individuals from two mangrove species (*R. mangle* and *Avicennia germinans*) in Everglades National Park, Florida, and used published mass estimates for canopy branches (Clough et al. 1998; Fromard et al. 1998; Komiya et al. 2005) to arrive at a canopy correction factor of $20 \pm 10\%$. Unfortunately, only one of the three papers they cited contained mass estimates for their two target species. Moreover, the demarcation between canopy branches and non-canopy within these studies is subjective. Similarly, Olagoke et al. (2016) scanned 36 *A. germinans* trees in French Guiana and compared them to allometric data (Fromard et al. 1998) from 25 locally harvested trees and estimated a root mean squared error of 13.5% for their QSM mass estimates, albeit for a range of tree sizes considerably larger than our current study. While these studies are an important starting point for establishing correction factors which can account for the unresolved biomass, the small number of trees and species represented by these studies point toward the need for additional analysis.

Here we adopt a complementary approach where measurements from QSMs derived from TLS data from 176 trees are combined with recently compiled allometric data for *A. germinans* to derive tree-level biomass estimates. In an analysis of mangrove allometric data from nine sites spread across the Atlantic/East Pacific biogeographic region (Price et al. 2024), it was shown that the best single predictor of aboveground 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. Similarly, using height as a predictor across sites, the R^2 was 0.896 and the mean site specific R^2 was 0.845. Thus, in mangroves, as is true in many tree species, DBH

and height are strong and reliable predictors of aboveground biomass.

Our TLS data was collected at three 168 m² plots in Cedar Key, Florida comprised solely of *A. germinans* individuals. We used the scans to determine DBH or height for each tree to predict its allometric-based, aboveground biomass. We then took the volume obtained from QSM fitting and multiplied it by published wood density (ρ) values to arrive at a QSM-mass estimate. The difference between the two mass estimates from each approach is taken to be an estimate of the fraction of the canopy volume missing from the QSM fitting.

These combined approaches allowed us to test the following three hypotheses:

- 1) QSMs derived from TLS scans of individual trees capture a majority of the aboveground volume and thus biomass.
- 2) The fraction of volume captured does not depend systematically on tree size.
- 3) The mass predicted by tree DBH is more accurate than that predicted by tree height.

Methods

Here we use tree measurements from a recent study compiling allometric data from nine mangrove sites across the Atlantic/East Pacific biogeographic region for three common species *A. germinans*, *R. mangle*, and *Laguncularia racemosa* (Price et al. 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.

The mangrove trees were scanned in three plots in the Cedar Key area of Florida, USA. Plot 1 (29.142384, -83.031444) was located along the Cedar Key Railroad Trestle Nature trail, within a lagoon-like geomorphological setting. Plots 2 (29.102487, -83.070206) and 3 (29.102523, -83.070490) were on Seahorse Key, a carbonate reef island. Tree growth was similar across all three plots thus they are combined here to increase statistical power.

Palynological studies indicate the presence of *A. germinans* in the Cedar Key area for over 800 years before present (Yao et al. 2023). *A. germinans* is the most cold tolerant of the three true mangrove species growing regionally (Osland et al. 2017) and expansion/contraction cycles due to extreme freezing events have been documented in the area (Stevens et al. 2006).

The Cedar Key area experiences a semi-diurnal tidal pattern, with a mean range of 0.86 m and diurnal range of

Table 1 Regression results. Each row contains the y-variable, x-variable, axes (log10 or linear), regression method (SMA or OLS), group, number of trees (n), R², 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 ($p < 0.05$)

Y-variable	X-variable	Axes	Method	Group	n	R ²	Slope	LowCI	UppCI	Intercept	LowCI	UppCI	Figure
Mass	DBH	Log ₁₀	SMA	Empirical	160	0.937	2.343	2.253	2.438	4.005	3.891	4.119	2 A
Mass _{QSM}	DBH _{QSM}	Log ₁₀	SMA	QSM	176	0.894	2.32	2.209	2.435	3.76	3.636	3.885	2 A
Height	DBH	Log ₁₀	SMA	Empirical	132	0.631	0.7995	0.7197	0.8881	1.772	1.672	1.873	2B
Height _{CC}	DBH _{QSM}	Log ₁₀	SMA	QSM	176	0.514	0.6564	0.5915	0.7285	1.562	1.487	1.638	2B
Mass	Height	Log ₁₀	SMA	Empirical	154	0.626	4.66	4.225	5.139	-2.541	-2.9	-2.181	2 C
Mass _{Height}	Height _{CC}	Log ₁₀	SMA	QSM	176	0.545	3.534	3.195	3.908	-1.76	-2.068	-1.453	2 C
Mass _{DBH}	Mass _{QSM}	Log ₁₀	OLS	-	176	0.894	0.9246	0.877	0.9721	0.3044	0.2413	0.3676	4 A
Mass _{Height}	Mass _{QSM}	Log ₁₀	OLS	-	176	0.545	0.7701	0.6648	0.8754	0.3798	0.24	0.5196	4B
Mass _{DBH}	Mass _{QSM}	Linear	OLS	-	176	0.724	1.234	1.12	1.348	8.999	4.854	13.144	4 C
Mass _{Height}	Mass _{QSM}	Linear	OLS	-	176	0.345	0.6642	0.5273	0.8011	15.57	10.58	20.55	4D

1.16 m (tidesandcurrents.noaa.gov). The climate is humid and subtropical, with rainfall patterns strongly influenced by the Atlantic hurricane season. The average annual precipitation is ~ 1500 mm and the average winter daily temperature is 11°C . Pore water salinity of 20–25 ppt was reported on Seahorse Key in 2018 (Yao et al. 2023). The area is dominated by *A. germinans*, with sparse clusters of *R. mangle* and *L. racemosa*.

A handful of studies have examined how the number of scans, the spatial arrangement, and distance from one another have influenced tree detection rates and measurement accuracy (Heinzel and Huber 2018; Liu et al. 2018; Reddy et al. 2018; Gollob et al. 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, most of these studies were performed in closed canopy forests where tree boles are large and more spaced out compared to typical mangrove forests. Of these previous studies, Heinzel and Huber (2018) examined forests with structural properties most similar to ours and used five scan positions, one central and four perimeter forming a square with 25 m sides (625 m^2 total area). However, the trees in their study were larger than the trees in our plots, thus we adopted a modified sampling design with one central scan and four perimeter scans each at an approximate distance of 7.32 m from the central scan, forming a circular plot with a total area of 168.33 m^2 . We chose this radius value because it is equivalent to the radius of the phase 2 subplot used by the Forest Inventory and Analysis program of the US Forest Service, for which there are comparable mangrove census data (Woudenberg et al. 2010).

The plots were scanned between 10/10/22 and 10/13/22, during the hours closest to low tide each day to make walking through the plots easier and reduce the risk of damage to

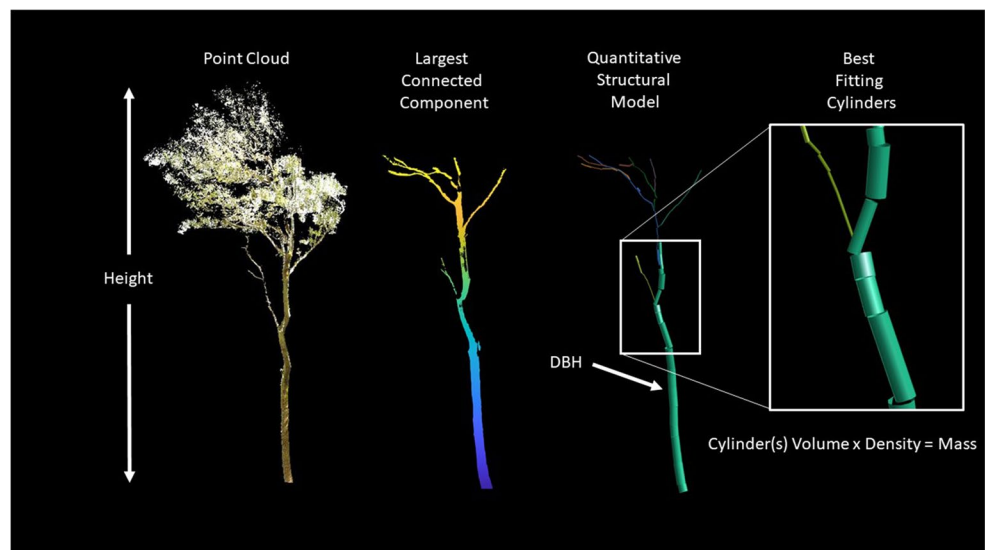
the scanner. Light winds that occurred on a nearly persistent basis, did affect scan quality, particularly in the highest and smallest tree branches.

We used a FARO Focus S350 HDR lidar scanner. Twelve target spheres were placed around the perimeter of each plot to facilitate subsequent merging of the point clouds corresponding to the five scan positions. Each scan was 360 degrees horizontally and 300 degrees vertically, at a range of 613 m. Scan times were roughly 12 min per scan position. Following collection in the field, the five scans were co-registered and processed in FARO SCENE software 2019.2 (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 package (CloudCompare 2023). Point clouds were cleaned using the Statistical Outlier Removal (SOR) filter which calculates the mean distance from each point to its k nearest neighbors and removes points that are farther than the mean distance times a user set parameter ($nSigma$) times the standard deviation in point distance. We used the default settings of $k=6$ and $nSigma=1$. Clouds were also cleaned using the ‘Noise filter’ tool, which removes points that are greater than a certain radius from a locally fitted plane around each point. We used the default radius of 0.009996 m . Point clouds were normalized relative to the ground level, and the height for each tree ($Height_{CC}$) was measured in CloudCompare 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. Each segmented tree was visually inspected and

Fig. 1 Graphic illustrating the main steps of our TLS processing 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 ρ for *A. germinans*



any remaining leaves or noisy branch sections were manually removed using the cutting tool within CloudCompare.

To create quantitative structural models for each tree branching structure, we utilized the TreeQSM software version 2.4.1 (Raumonen et al. 2013; Calders et al. 2015; Markku et al. 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 analysis here used trees that also had smaller *DBH* values. Thus, for consistency, we utilized the *DBH* estimated by TreeQSM for all trees.

TreeQSM uses several parameters to fit QSMs, however as per software documentation (<https://github.com/InverseTampere/TreeQSM/tree/master/Manual>), 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 in the 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 individual tree point cloud, from which we calculated the mean and standard deviation of tree volume estimates. All other values were left as the default values populated by the software developers.

We also recorded a series of other output parameters returned by the TreeQSM software including: trunk volume (*L*), branch volume (*L*), height (*m*), trunk length (*m*), branch length (*m*), total length (*m*), the number of branches, maximum branch order, trunk surface area (m^2), branch surface area (m^2), *DBHqsm* (*m*), and *DBHcyl* (*m*). Detailed explanations of how TreeQSM determines the values of these parameters can be found in the TreeQSM manual. From these values we calculated two additional derived parameters: the branch length to trunk length ratio and the branch volume to trunk volume ratio.

Most of the parameters returned by TreeQSM will be intuitive to readers, however the difference between *DBHqsm* and *DBHcyl* may not be. *DBHqsm* is the diameter of the cylinder fit to the trunk at a height of 1.3 m. *DBHcyl* is the diameter of a cylinder fit to the trunk point cloud from 1.1 m to 1.5 m heights. These two values are slightly different ways of measuring tree *DBH* and are strongly correlated with one another.

We found five published estimates of ρ (0.67, 0.792, 0.9, 0.77 0.75, g/cm^3) for *A. germinans* contained within a global compilation (Chave et al. 2009) and used the mean, minimum, and maximum of these values (0.776, 0.67 and 0.9) to create three different biomass estimates. Our mean ρ

value is close to the mean values utilized by Feliciano et al. (0.770, 2014) and Olagoke et al. (0.728, 2016). To estimate biomass for each tree we multiplied the ρ values by the volume derived from the QSM fitting (Eq. 1).

$$Mass_{QSM} = Volume_{QSM} \times \rho \quad (1)$$

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 et al. 2006). We fit OLS regression equations to data for the following two relationships, *Mass* vs. *DBH* (*MvD*) and *Mass* vs. *Height* (*MvH*).

We then used the OLS allometric models to 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).

$$Mass_{DBH} = MvD_{slope} \times \log_{10}(DBH_{QSM}) + MvD_{intercept} \quad (2)$$

$$Mass_{Height} = MvH_{slope} \times \log_{10}(Height_{CloudCompare}) + MvH_{intercept} \quad (3)$$

Analyze differences between mass predicted from the empirical regression equations (Eqs. 2 and 3) and mass from QSM fitting (Eq. 1). Regression exponents were estimated using the software package Standardized Major Axis Tests and Routines (SMATR, Warton et al. 2006). Data were $\log_{10}$ transformed before regression fitting to meet the regression assumption of homogeneity of variance. OLS regression equations were also fit to untransformed data.

To compare the mass estimated using Eq. 1 to that using Eqs. 2 and 3, we calculated mass ratio percentages, which are simply $Mass_{QSM}/Mass_{DBH} \times 100$ and $Mass_{QSM}/Mass_{Height} \times 100$. We examined the mass ratio percentages in several ways, first by looking at a histogram of their values to understand the central tendency and dispersion, second by plotting the mass ratios as a function of tree size (indexed using *DBH*) to detect any systematic change as a function of tree size, and third, by plotting mass ratios as a function of the branch to trunk volume ratio (for $Mass_{QSM}/Mass_{DBH}$), and as a function of tree height (for $Mass_{QSM}/Mass_{Height}$). We also examined the mass ratios resulting from the $Mass_{QSM}$ values calculated using the lowest and highest reported wood ρ values.

We also plotted $Mass_{QSM}$ vs. $Mass_{DBH}$ and $Mass_{QSM}$ vs. $Mass_{Height}$ on logarithmic axes (log base 10) and fit SMA regression slopes to each bivariate relationship to examine the scaling strength of each relationship and compare it to a reference 1:1 line. The same two relationships were also

plotted on linear axes to make the spread of the data easier to understand.

Results

Following cleaning and segmentation, we obtained point clouds for 176 individual trees (available here: <https://doi.org/10.6084/m9.figshare.31324393>). Eight different QSMs were fit to each point cloud from which we calculated mean QSM statistics (Table S1) and $Mass_{QSM}$ estimates for the mean, minimum and maximum density values (Table S2). In total there were 1408 individual QSMs ($8 \times 176 = 1408$, SI Figs. 4–1411). The smallest point cloud had 10,316 points, the largest 1,278,252, and the mean was 127,852 points. TreeQSM estimates of tree dimensions for each of the eight different fits per tree (1408 in total) are included in Table S3.

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 were 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) were 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 ($Mass_{QSM}/Mass_{DBH} \times 100$) is slightly right skewed (Fig. 3A), but the mean (65.85) and median (61.16) are close to each other. The mean mass ratio percentage ($Mass_{QSM}/Mass_{DBH} \times 100$) using the lowest and highest reported ρ values was 56.85 and 76.37, respectively (Fig. S2). The distribution of $Mass_{QSM}/Mass_{Height} \times 100$ is more strongly skewed (Fig. 3C), with a mean value of 113.45 and median value of 77.60. The mean mass ratio percentage ($Mass_{QSM}/Mass_{Height} \times 100$) using the lowest and highest reported ρ values was 98 and 1.32, respectively.

OLS regression fits indicate 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).

OLS regression statistics for the relationships between $Mass_{DBH}$, $Mass_{Height}$ and $Mass_{QSM}$ are provided in Table 1 and the relationships for these variables on $\log_{10}$ and untransformed axes are in Fig. 4. Data on non-transformed axes (Fig. 4) show that most points in Panel C are above the 1:1 line. Panel D shows the high variance in the data.

Figure S1 shows the empirical relationship between $Mass$ and DBH together with the relationship between

$Mass_{QSM}$ and DBH_{QSM} , with error bars corresponding to the 95% confidence intervals for each $Mass_{QSM}$ estimate, which were generated from the eight different QSM fits (Table S2). Panel A shows the relationship using the mean reported ρ in Eq. 1, and Panels B and C, the minimum and maximum ρ values, respectively.

Figure S2 has histograms for the mass ratio percentages using the mean, low and high ρ estimates (see Methods). Figure S3 plots the mass ratio percentage derived from DBH as a function of the branch volume to trunk volume ratio (Panel A), and the mass ratio percentage derived from height as a function of tree height.

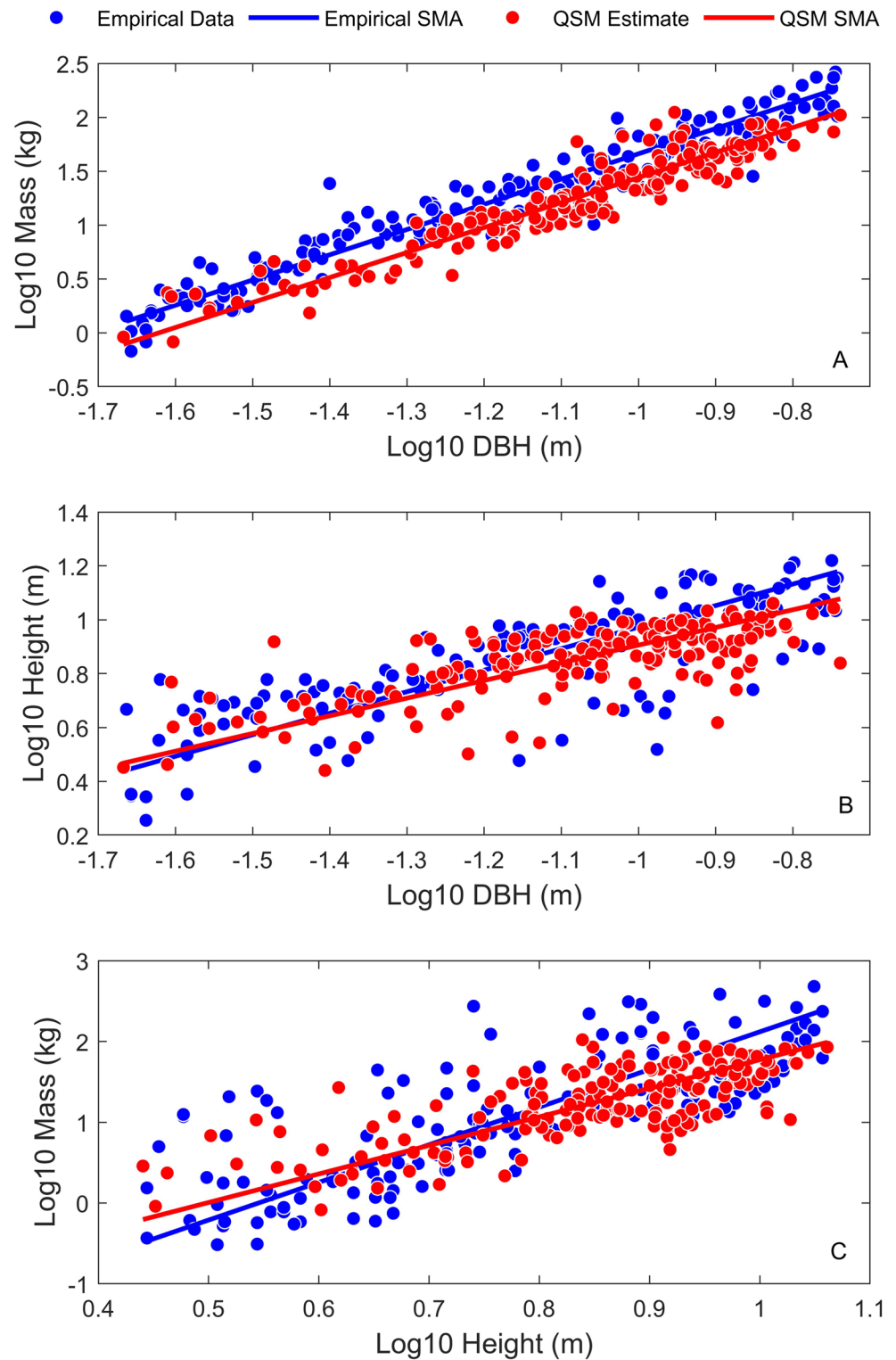
Discussion

Given the importance of mangroves in the blue carbon economy and their protected status in many regions (Bertram et al. 2021), developing non-destructive methods for biomass estimation is of broad interest (Heumann 2011; Kuenzer et al. 2011). Lidar technology has emerged as a promising, non-destructive approach to plot scale estimation of aboveground biomass (Feliciano et al. 2017; Owers et al. 2018; Kargar et al. 2020; Asmath et al. 2025; Dunlop et al. 2025; Matta et al. 2025). However, without scanning followed by destructive harvesting of trees, estimating the error associated with such approaches is difficult. Moreover, whether the magnitude of the error depends on forest structural characteristics such as tree size and/or canopy complexity is also unknown.

We have shown that the slope of 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, the slopes from these two relationships 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 scans consistently 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, either using an estimate from linear regression (Table 1; Fig. 4), or as a fixed percentage as done in previous work (Feliciano et al. 2014; Olagoke et al. 2016). Our results indicate a correction factor of about 35% (range 23.6%–43.1%) which is just above the upper bound of the 20% ($\pm 10\%$) correction factor reported by Feliciano et al. (2017). Our correction factor is also higher

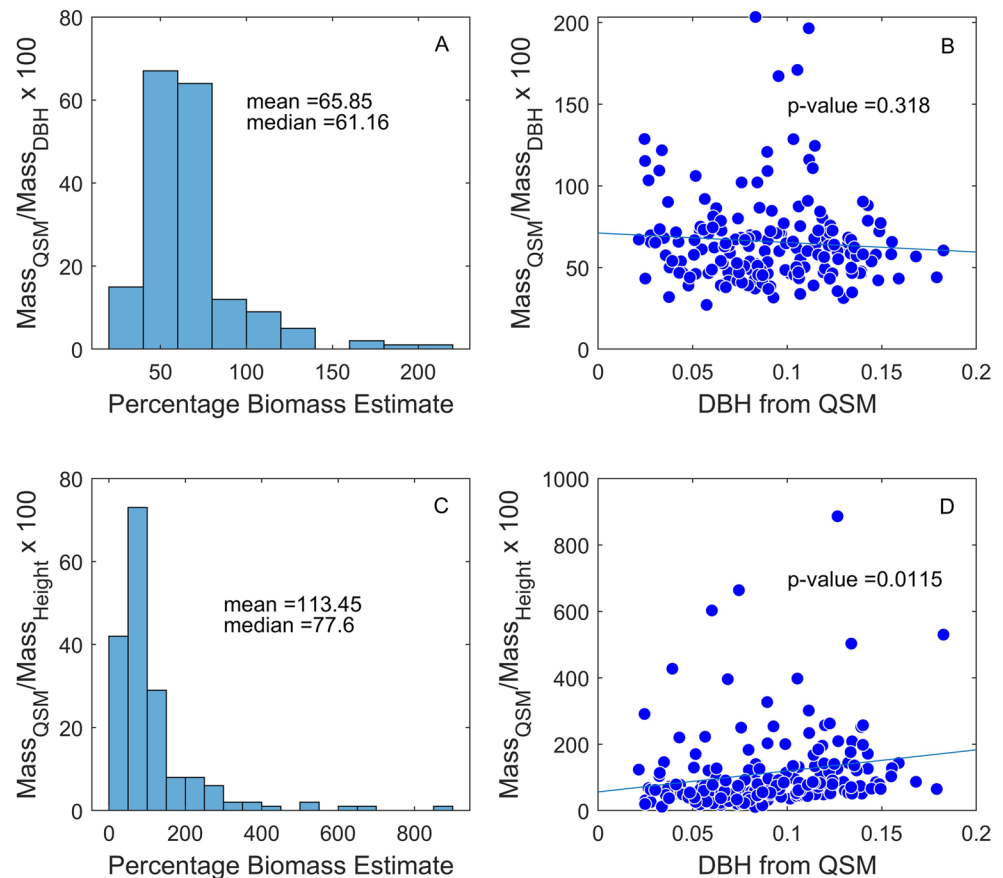
Fig. 2 Bivariate relationships between Mass (empirical mass or $Mass_{QSM}$), DBH (empirical DBH or DBH_{QSM}) and Height (empirical height or $Height_{QSM}$) for both the empirical data and the estimates derived from the QSMs. Fitted lines are from SMA regression. Note the slopes for the mass-DBH relationship (Panel A) are statistically indistinguishable, but there is a change in point elevation 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



than the 13.5% mean error reported by 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. The mean DBH and height of trees in Olagoke et al. is 45.4 cm and 27.5 m, respectively (see Table 2 in 2016). In contrast, the mean DBH and height of our measured trees is 9.1 cm and 5.23 m,

respectively. It is likely that in forests with large trees, the bole and lower branches, those most likely to be captured by TLS, constitute a greater fraction of the total biomass of the tree. Our plots occur toward the northern range limit for *A. germinans*, thus they are considerably smaller than trees growing at lower latitudes (Osland et al. 2022).

Fig. 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 tree's QSM (Panels B and D). There is no significant relationship in Panel B, and a slight positive relationship in Panel D



Further, our sample plots occur in an area that is subject to semi-periodic disturbance in the form of tropical storms or hurricanes which are known to affect forest structure (Simard et al. 2019; Rovai et al. 2021). Northwestern Florida is one of the more hurricane prone areas in southeastern US. Such disturbances can strip leaves and branches from trees, leading to gaps with dense understory growth which can cause significant occlusions in lidar scans and hampers the ability to resolve canopy branches. These limitations are counterbalanced by our larger sample size, which is over four times higher than those used in Feliciano et al. (2014) and Olagoke et al. (2016).

Should the opportunity arise to scan mangrove trees and then harvest them, to directly measure aboveground 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. However, as mentioned, the fact that these mangrove species are protected throughout much of their range makes the possibility of tree harvesting less likely.

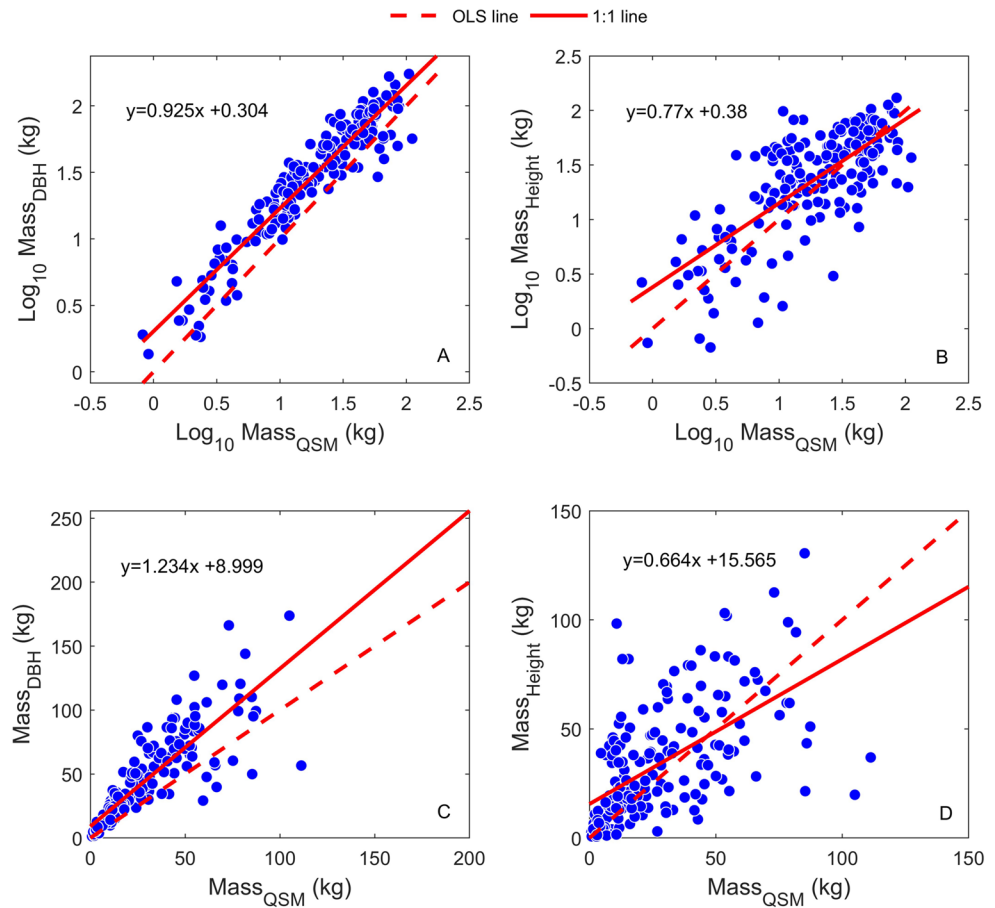
Unfortunately, there appears to be high variance in the mass ratio percentage estimates ($Mass_{QSM}/Mass_{DBH} \times 100$ or $Mass_{QSM}/Mass_{Height} \times 100$) in Fig. 3 (Panels A and B). While a majority of the $Mass_{QSM}$ estimates (122/176) capture 50%

of the tree volume 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%.

Branching structure, specifically the ratio of branch volume to trunk volume, influences the likelihood of overestimating mass (Fig S3, Panel A), with high ratios associated with overestimates. Similarly, shorter trees are also more likely to lead to overestimating tree mass (Fig S3, Panel B). It is likely that shorter, more highly branched trees lead to noisier QSM fits due to increased occlusion. Moreover, even under moderately windy conditions, smaller trees and branches are more likely to sway, leading to higher variance in local point densities along tree branches. These factors may contribute to over-fitting and thus higher volume and mass estimates than estimates derived from point clouds obtained under ideal conditions.

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.

Fig. 4 Bivariate plots of $Mass_{QSM}$ vs. $Mass_{DBH}$ (Panel A) and $Mass_{QSM}$ vs. $Mass_{Height}$ (Panel B) on Log_{10} axes with OLS regression functions (solid red lines) and a 1:1 line (red dashes) as a reference. The same two relationships are depicted in Panels C and D on linear (non-transformed) axes. Equations for the best fit OLS line are provided in the upper left of each panel with full statistics for all four relationships are contained in Table 1. There is a fairly tight relationship 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



Figs S972-979 or S988-995). Figure 3, Panel C displays results from trees that have lots of branches but did not grow very tall (e.g. see Figs S1052-1059 or S1108-1115), or trees for which our segmentation pipeline captured a large bole, but not much of the tree height (see Figs S884-891, or S1020-1027).

There are numerous challenges to gathering TLS data in mangrove forests (Feliciano et al. 2014; Olagoke et al. 2016; Matta et al. 2025). Mangroves occur in areas that are tidally inundated with thick mud and so walking amongst them is challenging. Many species have abundant pneumatophores (Dunlop et al. 2025), 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 branches and roots to a specific tree within QSMs extremely challenging (Asmath et al. 2025). 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 (Raumonen et al. 2013; Calders et al. 2015; Markku et al. 2015).

Mangroves also frequently occur in areas of high disturbance due to wind, waves, and storms that strip leaves and branches from trees (Alongi 2008; Krauss and Osland 2019). 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 (Feliciano et al. 2014; Olagoke et al. 2016). 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 volume/mass in smaller *A. germinans* stands. This confirms a similar range of canopy correction used previously in other studies in Florida (Feliciano et al. 2014), but is greater than that found in French Guiana where trees were considerably larger (Olagoke et al. 2016). Until more specific corrections are developed, this factor can likely be generalized for use with other similarly sized mangrove trees.

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 et al. 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 plot level TLS. Furthermore, such drones could potentially scan at multiple elevations, increasing point coverage in the upper canopy, 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 rapidly progressing, thus solutions such as this are likely to emerge in the near future.

Conclusion

For investigators wanting to use nondestructive, remote sensing-based approaches such as TLS to estimate biomass for mangrove trees to underpin conservation or blue carbon assessments, the cost and benefits of such approaches should be given careful consideration. In principle, QSMs derived from TLS could approach true aboveground biomass measures, particularly with more scan positions, larger trees, ideal field conditions, and with improvements in the underlying algorithms used to create QSMs (Raumonen et al. 2013; Hackenberg et al. 2015; Yang et al. 2024) and minimize known sources of error (Demol et al. 2022; Morales and MacFarlane 2024, 2025). However, the time required to complete all steps of this workflow and its relatively small footprint size and resource intensive nature, must be weighed against alternative approaches such as simply measuring tree DBH and/or tree height for a much larger number of trees and utilizing regional/global allometries (Price et al. 2024, 2025) to rapidly estimate biomass.

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Data Availability Point clouds corresponding to each segmented tree have been deposited in an online repository (<https://doi.org/10.6084/m9.figshare.31324393>).

Declarations

Competing interests The authors have no competing interests to declare.

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