Measuring Individual Tree Height and Crown Diameter for Mangrove Trees with Airborne Lidar Data

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Abstract—*Mangroves are unique ecosystems that provide valuable coastal area habitats, protection, and services. Access to observing mangrove forests is typically difficult on the ground. Therefore, it is of interest to develop and evaluate remote sensing methods that enable us to obtain accurate information on the structure of mangrove forests and to monitor their condition in time. The main objective of this study was to develop a methodology for processing airborne lidar data for measuring height and crown diameter for mangrove forests in the north-eastern coastal areas of Brazil. Specific objectives were to: (1) evaluate the most appropriate lidar data processing approach, such as area-based or individual tree methods, (2) investigate the most appropriate parameters for lidar-derived data products when estimating height and crown diameter, such as the spatial resolution of canopy height models and ground elevation models; and (3) compare the accuracy of lidar estimates to field measurements of height and crown diameter. The lidar dataset was acquired over mangrove forest of the northeast of Brazil. The crown diameter was calculated as the average of two values measured along two perpendicular directions from the location of each tree top by fitting a fourth-degree polynomial on both profiles. The lidar-derived tree measurements were used with regression models and cross-validation to estimate plot level field-measured crown diameter. Root mean square error, linear regression and the Nash-Sutcliffe coefficient were also used to compare lidar height and field height. The mean of lidar-estimated tree height was 9,48m and the mean of field tree height was 8.44m. The correlation between lidar tree height and field tree height was r= 0.60, E=-0.06 and RMSE= 2.8. The correlation between height and crown diameter needed to parameterized the individual tree identification software obtained for 32 trees was r= 0.83 and determination coefficient was r^2 = 0.69. The results of the current study show that lidar data could be used to estimate height and average crown diameter of mangrove trees and to improve estimates of other mangrove forest biophysical parameters of interest by focusing at the individual tree level. The research presented in this study contributes to the overall knowledge of using lidar remote sensing to measure and monitor mangrove forests.*

Keywords— Data acquisition, Brazil, Natural resources, Radar altimetry, Variance analysis, Vegetation cover

I. INTRODUCTION

Methods to estimate the amount of biomass of natural forests in the world have been of great interest for the scientific community for many years. This interest has increased in the context of climate change. The Intergovernmental Panel on Climate Change- IPCC has showed in different reports an increase of CO_2 over the last centuries and forecast an increase in CO_2. It is known that forests have an important function in CO_2 sequestration from the atmosphere. The amount of CO_2 sequestered by the forest depends on the amount of biomass that forests have. However, estimates of forest biomass in the world are scarce and often inaccurate. As such, methods to estimate the forest vertical structure and improve estimates of forest biophysical parameters are needed at various scales, from local to global, to better observe climate change effects and design science-based mitigation efforts.

The difficulty of estimating forest vertical structure occurs because such information is obtained with traditional methods that are tedious, laborious and very expensive to collect for large geographic areas. According to Simard et al. (2008), remotely sensed images provide an efficient and cost-effective way to gain insight into mangrove areas that are often difficult to access and survey by field methods. Both optical and active remote sensing techniques have been commonly used to study mangrove forests, and in the past years the combination of radar (RAdio Detection And

Ranging) and lidar (Light Detection And Ranging) has yielded interesting results that reach further than determining mangrove cover alone. Generally, optical remote sensing instruments such as Landsat, MODIS, and SPOT observe the spectral properties of forests but provide limited information on the vertical structure. To this day, mangrove forests have also been studied using polarimetric and interferometric radar and airborne and space-borne lidar systems. Several studies were carried out using radar data for mangrove mapping and monitoring. In addition, three-dimensional (3D) modeling of mangrove forests was made possible by the Shuttle Radar Topography Mission (SRTM) data. The 3D rendition was validated with airborne and space-borne LiDAR and field data to provide large-scale height and biomass estimates of mangrove forests.

More recently, with airborne lidar data becoming more affordable and available in coastal areas, the opportunity has emerged to obtain structural information of mangrove forests with lidar data. Different studies have been conducted to enable the use of lidar data for vertical structure characterization of temperate forest, (Srinivasan et al., 2014), (Zhao et al., 2013), (Kaartinen et al., 2012), (Popescu, 2007), (Popescu & Wynne, 2004), (Popescu et al., 2004) (Popescu et al., 2003), (Popescu et al., 2002). The studies have shown that lidar remote sensing provides highly accurate methods to obtain structural data of forest with the potential to decrease field work and increase accuracy of estimates in areas with difficult field access, such as mangrove forests.

In addition, management of forests for multiple uses, such as timber harvesting and protection of biological diversity, is challenging. Effective management often requires either information about the presence and abundance of organisms – which is not available for many species – or the development of indicators of habitat quality that correlate with species distributions. At the landscape scale, the structure of forests can be quantified and used to predict the occurrence of some species. These structural attributes include the height of the forest canopy, the amount of canopy cover, and biomass. Field measurements of canopy height and canopy cover are conceptually simple. Direct measurements of biomass are somewhat more problematic because they require destructive sampling, although indirect methods, e.g., allometric equations relating Diameter at Breast Height - DBH and/or height to biomass, suffice for most applications (Hyde et al., 2005).

Lidar studies have been conducted in various forest biomes of the world to derive information on the vertical structure of forests (Agca et al., 2011), (Popescu et al., 2003) and also in mangrove forest (Fatoyinbo, 2013), (Wannasiri et al., 2013) (Simard et al., 2008), (Simard et al., 2006), but such studies are yet scarce in Brazil.

It is known that the mangrove ecosystem has very important economic, environmental and climatic functions for the coastal region, where the mangrove forests contribute to biodiversity and act as major biogeochemical links between upland and coastal regions. Mangrove forests have high biodiversity, with more than 1300 species of animals, including many economically important fish and shrimp species. The mangroves have among the most productive ecosystems on Earth with 2.5gCm^{-2} per day, with 25% accumulating in mangrove sediments, 25% is recycled, 50% is exported to oceans and about 10% of C to Global Dissolved Organic Carbon. Mangrove forests protect the shoreline against tropical storms, hurricanes and tidal surges (Fatoyinbo, 2013).

Mangroves are among the most carbon-rich forests in the tropics, containing on average 1,023Mg carbon per hectare in above and belowground C. Organic-rich soils range from 0.5m to more that 3m in depth and account for 49-98% of carbon storage in these systems. The estimated economical mangrove services value varies between $200k to $900k per km^2 per year (UNEP report 2006). New initiatives such as the Reduced Emissions from Desforestation and Degradation (REDD+) and the United Nations Blue Carbon Initiative are developing frameworks to compensate states for their C storage. But as a result of their location and economic value, mangrove forests are among the most rapidly changing ecosystems. The impacts on mangrove forest had been estimated to be very high, since 35% to 50% of mangrove forests have disappeared in the past 60 years, although no systematic baseline data is available (Donato et al., 2011). The greatest current threats derive from human activities: aquaculture, freshwater diversions, overharvesting and urban and industrial development. The effects of climate change, such as sea level rise and increased extreme climatic events, may also increase the vulnerability of mangrove ecosystems.

Mangroves are present on four continents and six geographical regions of the planet, mostly occurring in Central America and the Caribbean, India, the Indochina Peninsula, Brazil and Australia (Barbosa, 2010). Mangroves occupy a significant fraction of the Brazilian coast, about 92% of the coast (± 6800 km) line, extending from the northern end in Oyapock, Amapá (4^{o}30'N) to its southern limit at the Sonho beach in Santa Catarina (28^{o}53'S) (Barbosa, 2010), with its structural maximum development near the equator.

Coastal areas represent the portion of the planet where most of the population lives on Earth. More than half of the world's population lives within 60 km of the coast. In Brazil, 13 of the 17 coastal states capitals are located by the sea. So, not coincidentally, the coastal areas are under greater environmental stress and distributed among the various ecosystems in these areas, mangroves have suffered most from a disorderly urban expansion.

Simard et al. (2008) shown that a recent United Nations Environment Programme report (UNEP, 2006) estimates that their economical value varies geographically between \$200 k and \$900 k per km2 per year. The primary drivers of mangrove conversion are related to human impacts: urban expansion, shrimp farming, water management practices, charcoal cut as well as natural hazards such as sea level rise, hurricanes, severe storms and tsunamis. Among the major impacts of mangrove loss are decline in biodiversity, degradation of clean water supplies, siltation of coral reefs and acidification of coastal soils, erosion, loss of shoreline stability, release of more carbon into the atmosphere, and reduction (or disappearance) of important commercial fish stocks (Sanchez-Ramirez & Rueda, 1999; Rueda & Defeo, 2001). It is estimated that the loss of original mangrove forests is as high as 35% and may reach 60% by 2030 (Valiela et al., 2001; UNEP, 2006; Alongi, 2002). These are, however, gross estimates and do not rely on accurate landscape analyses, which can only be improved through remote sensing landscape scale assessment. Both radar and optical remote sensing have been used extensively to map mangroves with varying degrees of success (e.g. Kovacs et al., 2005; Laba et al., 1997, Ramsey et al., 1996; Rasolofoharinoro et al., 1998; Wang et al., 2004; Held et al., 2003; Simard et al., 2000; Mougin et al., 1999). Recently, structural (tree height) and functional (biomass) attributes of mangroves have been estimated using radar interferometry (Simard et al., 2006). In February of 2000, Space Shuttle Endeavour collected nearly global coverage of Earth's topography using radar interferometry (SRTM, Shuttle Radar Topography Mission). And because of limited penetration of microwaves within vegetation, the SRTM topographic maps contain information related to vegetation height (Kellndorfer et al., 2004). Mangrove forests are located within the intertidal zone (i.e. at sea level), which particularly simplifies the canopy height estimation technique since the ground topography is as flat as the tidal range. SRTM data are distributed with a 90 m spatial resolution around the Earth, reduced from the original 30 m through averaging and subsampling. In a previous paper, Simard et al. (2006) used an airborne lidar (i.e. light detection and ranging) to calibrate SRTM elevation. Lidar measures the time of return of a light pulse reflected off a target and thus measures the relative distance. Recent results using space-borne lidar showed that these data could also be used to estimate vegetation height and correlate it with biomass (Lefsky et al., 2005; Drake et al., 2002a,b). GLAS (ICEsat Geoscience Laser Altimeter System) is the first space-borne lidar instrument for global observations of Earth (Schutz et al., 2005) which has been collecting data since early 2003 and is the benchmark Earth Observing System mission for measuring ice sheet mass balance, cloud and aerosol heights, as well as land topography and vegetation characteristics. Carabajal and Harding (2006) showed that the GLAS waveform (laser return as a function of time) centroid is highly correlated to the SRTM phase center elevation over densely vegetated regions. In this paper, we present a methodology based on SRTM elevation, ICEsat/GLAS, and field data to map mangrove forest height and aboveground biomass. We focus on the Cienaga Grande de Santa Marta (CGSM), Colombia, a large wetland complex where one of the largest mangrove rehabilitation projects in Latin America is currently underway (Botero & Salzwedel, 1999; Rivera-Monroy et al., 2004; Rivera-Monroy et al., 2006). Large man-made hydrological modifications in the region caused hypersaline soil conditions (N90 g kg−1) since the 1960s triggering a large dieback of mangrove wetlands (~ 247 km2). Thus, remote sensing tools are needed to evaluate if current freshwater diversions initiated in 1995 will be successful in restoring mangrove wetlands at the landscape scale. Our objective is to build a baseline map to quantitatively estimate the extent, height and biomass of the mangrove forests in CGSM. We describe how to use ICEsat/GLAS data to systematically calibrate SRTM elevation data, potentially providing a robust method to extend 3D mapping of mangrove forests to other parts of the World. In addition, we collected field data on structural attributes along four mangrove transects in CGSM to calibrate SRTM and to derive a site-specific relationship between mean canopy height and aboveground biomass. The GLAS and field data do not overlap since we were unable to obtain accurate geolocation for our sampling points because of weak GPS signal under the dense canopy. We relied on distance and orientation using a measuring tape and a compass to locate the sampling points on the SRTM maps. The height–biomass relationship enables mapping of biomass in CGSM by extrapolating with the calibrated SRTM canopy height estimates. Biomass estimates in this ecoregion are badly needed to evaluate the impact of mangrove mortality on nutrient cycling (i.e. carbon, nitrogen, phosphorus) and to understand how the loss of above- and belowground biomass affect the role of mangroves as carbon sinks.

Research studies have been conducted in Brazil for ecosystem horizontal characterization using remote sensing, (Moura et al., 2012), (Pontailler et al., 2003), (Wang et al., 2005), (Galvincio, 2011), (Galvíncio et al., 2012), (Galvíncio et al., 2011), (Giongo et al., 2011), (Silva et al., 2013) for mangrove forest, (Silva, 2012), (Franca et al., 2012), but for vertical characterization of mangrove forest with lidar data, no studies have been conducted yet in Brazil.

The main objective of this study was to develop a methodology for processing airborne lidar data for measuring height and crown diameter for mangrove forests in the north-eastern coastal areas of Brazil. Specific objectives were to: (1) evaluate the most appropriate lidar data processing approach, such as area-based or individual tree methods, (2) investigate the most appropriate parameters for lidar-derived data products when estimating height and crown diameter, such as the spatial resolution of canopy height models and ground elevation models; and (3) compare the accuracy of lidar estimates to field measurements of height and crown diameter.

II. MATERIAL AND METHODS

Study area

The spatial location of the mangrove forests in this study is in the Recife municipalities, Pernambuco state, Brazil, Figure 1.

Lidar data

The airborne lidar data were obtained in April 2013. The aircraft equipment on board included the following: Trimble Aerial Camera aerial camera X4, with four bodies with integrated camera P65 + four sensors and Apo-DigiTar and an Optech laser sensor Airbone Laser Terrain Mapper Model (ALTM) Gemini 167. Moreover, planes were equipped with navigation systems consisting of autopilot and GPS guidance receivers.

In this study the aerial photographs were utilized for visualization of the area. In implementing the aerial surveys the following parameters were used: Flight altitude: 600 meters Opening angle (FOV): 20; Overlap side (between groups): 30% Min Number of tracks: 137; Average point density: 5.51 / m².

The horizontal reference datum used was the Geocentric Reference System for the Americas - SIRGAS 2000 was adopted as Vertical Datum, the Network of National Reference Level (RRNN) - Imbituba (SC). The Projection System used was Universal Transverse Mercator (UTM).

Field data

Data were collected on nine plots shown in Figure 1 (A1, A2, A3, B1, B2, B3, C1, C2 and C3), each being a square of 20x20m, Figure 2a. Each areas denoted by A, B, and C include a cluster of three plots of 20x20m. For delimitation of plots, we used nylon rope, calibrated metric tape and bamboo stakes. In each plot, heights of 10 representative trees were measured, giving a total of 90 measurements of tree height. The tree heights were measured with a telescopic pole and a hypsometer. The mean height of the plots was calculated as the mean of all 10 measured tree heights in each plot, and the area height was computed as the mean of three clustered plots. The field data used in this study were also described in Barbosa (2010). The A area has central UTM coordinates x=290998 and y= 9104376, the B area has central UTM coordinates x = 290998 and y =9104974 and C area has x= 291537 and y = 9104338. The coordinates were obtained with a recreational grade Garmin GPS, with an estimated average accuracy of 12m. The field data were collected for the A area on 07/25/2009 and 06/26/2009, for the B area on 08/20/2009 and for the C area on 09/18/2009. The time discrepancy between the lidar data acquisition and field data collection was nearly 3.5 years. Table 1 shows the descriptive statistics of the field data and percentage of species per area.

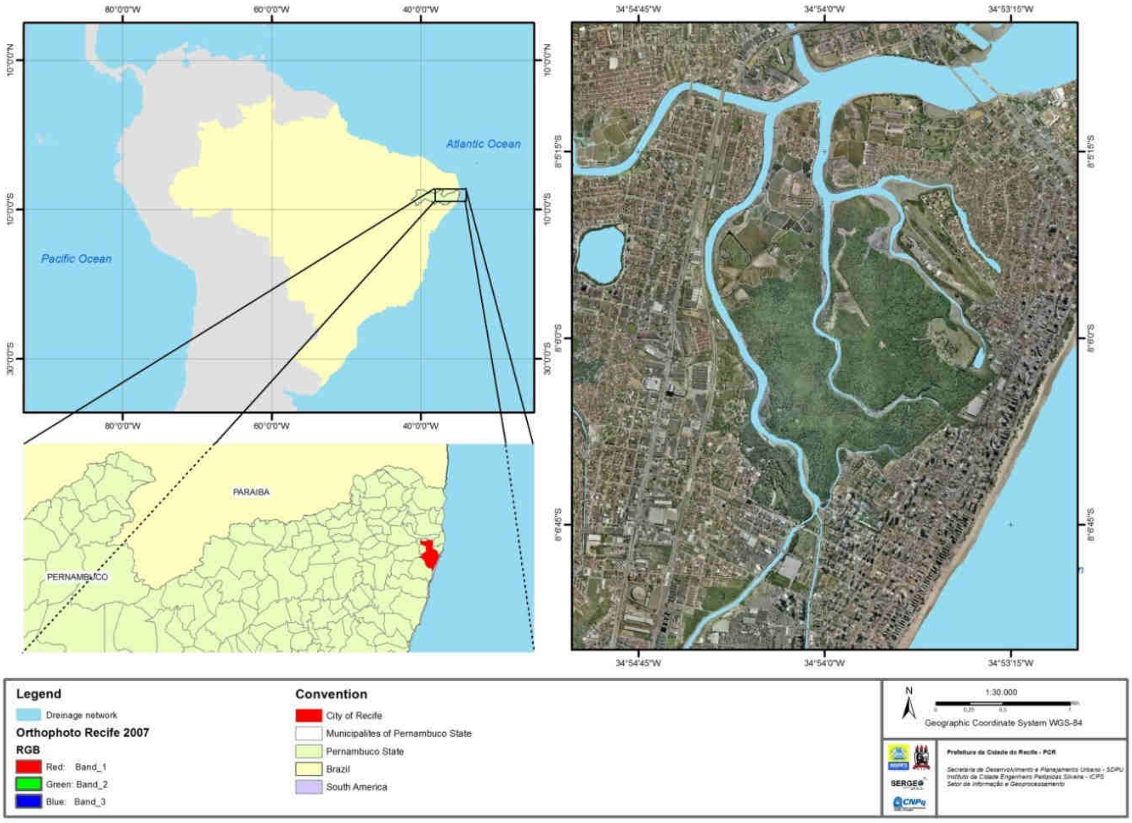


Fig.1: Spatial location of the Pina mangrove, municipalities Recife, Pernambuco state, Brazil, and field plots.

While the number of plots may seem low, we would argue that field measurements in mangrove forests are very difficult to obtain, given the problematic access through the coastal environment with little firm ground, mangrove roots, tidal waters, complexity of the root system above ground or water, and marshy areas. Moreso, the lidar technology has been proven to have centimeter accuracy, therefore we consider that the limited number of plots we worked with is sufficient to provide significant statistical evaluation of lidar's capability of estimating the vertical structure of mangrove forests.

Table 1 – Descriptive statistics of the field data for mangrove.

Area	Number of trees/1200m^2 in field	Mean height (m)	Standard deviation for height (m)	dbh (cm)
A	186	8.30	3.64	11.83
B	243	6.81	2.03	11.81
C	154	9.17	3.74	12.33
Percentage of species per area.				
Area	R. Mangle (%)	L. Racemosa (%)	A. schaueriana (%)	
A1	72	19	9	
A2	26	52	22	
A3	6	63	31	
B1	46	51	3	
B2	28	67	5	
B3	58	42	0	

C1	9.5	75.5	9.5	
C2	2.5	59	38.5	
C3	24	74	2	
Mean	**30.2**	**55.83**	**13.33**	

III. METHODS

The first specific objective of our study was to investigate the most suitable approach for processing lidar data to extract tree measurements, such as the point cloud area based approach and the individual tree approach. The individual tree approach is based on deriving interpolated surfaces of the ground and canopy top. Individual trees are then identified and measured on the canopy height model (CHM), as described below.

Canopy height model

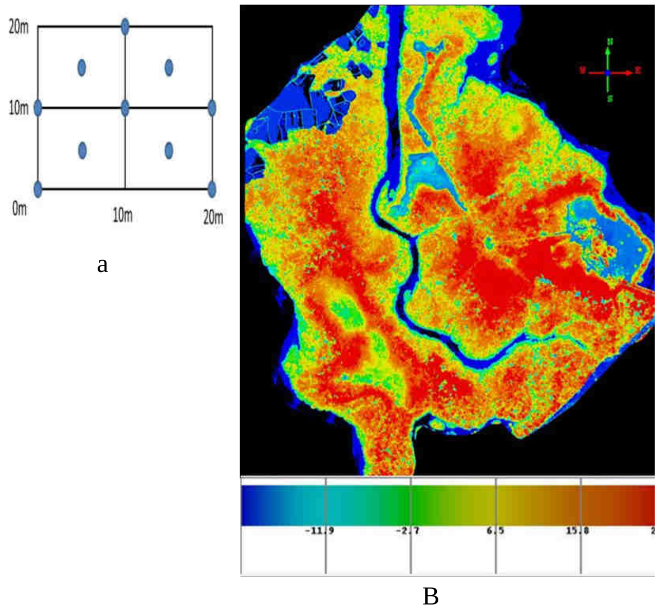


Fig.2 a) Design of field data collection; b) Resulting CHM at 0.5m spatial resolution.

To derive the CHM, lidar elevations were transformed to heights above ground and not the ellipsoid, to reflect vegetation heights, We used the software package Quick Terrain Modeler-QTM and its functions to derive Above Ground Level (AGL) heights rather than absolute elevations. Some of the most common reasons for wanting to work in AGL space are to measure tree and roof heights, to measure the height of potential vertical obstructions (VO's), and to selectively remove vegetation and canopy from a point cloud, thus enabling the user to see and identify objects under foliage or other obstructions. This tool calculates and assigns an AGL elevation value, in addition to an absolute elevation value, to every point in a point cloud or every vertex in a surface model by comparing heights to a bare earth model. The terrain model could be user-derived or available from other sources. We derived the terrain model using QTM, with a spatial resolution of 5m. By interpolating top elevations in the point cloud with heights above ground, we derived the CHM with two grid samplings, 0.5m and 1m. Figure 5 shows the CHM.

Locating individual trees and measuring heights and crown diameters

This study used the TreeVaW software for measuring individual trees with lidar data. Details of the methods used in the software can be seen in Popescu et al. (2003) and Popescu and Wynne (2003). The software implements a variable filter for identifying individual trees which is based on a relationship between crown diameter and tree height derived through a regression model. The parameters (coefficients) of this regression model can be specific to the forest and species measured with lidar data. To derive the window calibration relationship, we developed a regression model between height and crown diameter using on-screen measurements of 32 trees identified by visual analysis of the CHM. When a tree is identified visually on the CHM, the total tree height can be obtained directly on the CHM by reading the elevation value at the top of the tree. The crown diameter were obtained by averaging two crown measurements taken on two perpendicular directions, N-S and E-W using measurement tools available in the Quick Terrain Model software. The parameters that we used with the software Treevaw were Minimum Expected Crown Width of 1.0m and a Maximum Expected Crown Width of 20m.

For analyses of accuracy of lidar data were utilized the following criteria:

Root mean square error (RMSE)

The Root Mean Square Error (RMSE) (also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power.

The RMSE of a model prediction with respect to the estimated variable X_{model} is defined as the square root of the mean squared error, equation (1):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}}$$

equation (1)

where X_{obs} is observed values and X_{model} is modelled values at time/place i.

The calculated RMSE values will have units. However, the RMSE values can be used to distinguish model performance in a calibration period with that of a validation period as well as to compare the individual model performance to that of other predictive models.

Pearson correlation coefficient (r)

Correlation – often measured as a correlation coefficient – indicates the strength and direction of a linear relationship between two variables (for example model output and observed values). A number of different coefficients are used for different situations. The best known is the Pearson product-moment correlation coefficient (also called Pearson correlation coefficient or the sample correlation coefficient), which is obtained by dividing the covariance of the two variables by the product of their standard deviations. If we have a series n observations and n model values, then the Pearson product-moment correlation coefficient can be used to estimate the correlation between model and observations, equation (2).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

equation (2)

The correlation is +1 in the case of a perfect increasing linear relationship, and -1 in case of a decreasing linear relationship, and the values in between indicates the degree of linear relationship between for example model and observations. A correlation coefficient of 0 means the there is no linear relationship between the variables.

The square of the Pearson correlation coefficient (**r^2**), known as the coefficient of determination, describes how much of the variance between the two variables is described by the linear fit.

After obtaining the coefficient for the regression equation for crown as a function of tree height, the coefficients were inserted in TreeVaW to map individual trees first, and then to estimate their height and crown width for the study area. To clarify, the regression coefficients are only used by TreeVaW to calibrate the continuously varying filter size to identify trees, and not to estimate their crown width. Crown width is estimated as the average of two measurements taken on perpendicular profiles of the CHM around the tree tops identified as local maxima.

We mapped individual trees and obtained heights and crown widths estimates for both CHM spacings of 0.5m and 1m. Due the low accuracy of the recreational-grade Garmin GPS used to locate field plots, we report TreeVaW results for two areas sizes, one equal to the field plots of 20x20m and one with a buffer around the field plots, centered on the same GPS plot locations, but covering 40x40m areas.

Point Cloud Metrics

The point cloud statistics were computed for both 20x20m and 40x40m area sizes, in two situations. First, we computed point cloud statistics for all laser points higher than 0.5m above ground, to exclude the effects of low vegetation and aerial roots. This means that all points below 0.5m were excluded when calculating point cloud metrics. Second, we computed point cloud metrics for all laser points above ground, i.e., with a height above 0m.

IV. RESULTS AND DISCUSSION

The correlation between height and crown diameter obtained for the 32 trees was significantly high. These were the trees we visually identified to calibrate the variable window size in TreeVaW. The coefficient of determination was $r^2 = 0.69$ and correlation was r= 0.83, as shown in Figure 3. Popescu et al. (2003) obtained R^2 between 0.62-0.63 and standard error of estimate of 1.36-1.41m for dominant trees in eastern United States forests. Gill et al. (2000) development models of tree crown radius for several conifer species of California and obtained R^2 values in the range of 0.2691 to 0.6077 and RMSE values from 0.6081 to 1.48m. Hyde et al. (2005) examined the ability of a large footprint lidar system to retrieve forest structural attributes in the highly variable terrain and canopy conditions of the Sierra Nevada Mountains in California. The agreement between field and lidar measurements of canopy cover was only fair (r2=0.54, RMSD=19.6%, p <0.00) for plots (n =112) where the limited sampling protocol was used. In contrast, at the 40 plots that were more intensively field sampled, field and lidar estimates were in good agreement (r2=0.81, RMSD=9.4%, n =40, p <0.00). In our study, results showed a relatively high value of R^2 for mangrove forest, in line with other findings in the lidar literature.

After we obtained the parameter for regression equation, we used the coefficients to parameterize TreeVaW. We used a minimum tree height of 1m, median filtering 3x3 pixels.

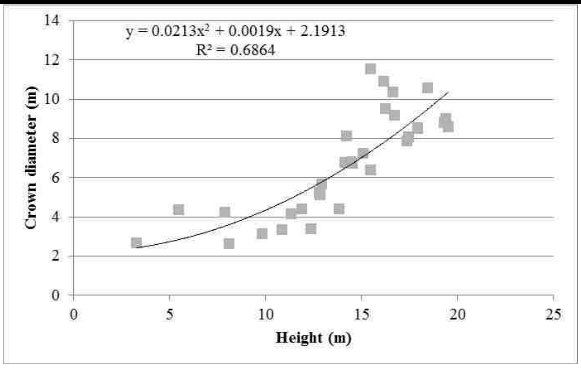


Fig.3: Relationship between Height and Crown diameter for 30 trees.

Wannasiri et al. (2013) studying the mangrove individual tree detection showed a kappa coefficient of agreement (K) value of 0.78. In their study, the estimation of crown diameter produced a coefficient of determination (R^2) value of 0.75, a Root Mean Square Error of the Estimate (RMSE) value of 1.65 m, and a Relative Error (RE) value of 19.7%. Tree height determination from lidar yielded an R2 value of 0.80, an RMSE value of 1.42 m, and an RE value of 19.2%. Similar results were obtained in our study. But, according to Wannasiri et al. (2013), an increase in the percentage of crown overlap results in an accuracy decrease of the mangrove parameters extracted from the lidar-derived CHM, particularly for crown measurements.

Sherrill et al (2008) evaluated the relative ability of simple light detection and ranging (lidar) indices (i.e., mean and maximum heights) and statistically derived canonical correlation analysis (CCA) variables attained from discrete-return lidar to estimate forest structure and forest biomass variables for three temperate subalpine forest sites. Both lidar and CCA explanatory variables performed well with lidar models having slightly higher explained variance and lower root mean square error. Adjusted R2 values were 0.93 and 0.93 for mean height, for the lidar and CCA explanatory regression models, respectively. The CCA results indicate that the primary source of variability in canopy structure is related to forest height.

The height of mangrove trees estimated with lidar and Treevaw was compared to field-measured height. As the field data were obtained in 2009, the difference between lidar data acquisition and field data collection was 3.5 year, therefore we used the work of Gorforth Jr. And Thomas (1980) in analyzing tree growth of red mangrove (Rhizophora Mangle L.) in Florida, United States, which reports an average growth of 10cm/year. The field data used in our study were collected in 2009 with 30.2% of R. Mangle, Table 1. Considering that the increase in tree height is 10cm/year, in 3.5 year the mangrove trees in our study area increased their height by approximately 35cm. Therefore, the mean field-measured height would be 8.44m when projected for 2013, to coincide with the timing of the lidar data acquisition, Table 2.

An interesting finding was to see that the grid sampling of 0.5m was a better option for processing lidar data for mangrove forests, because when using the grid sampling of 1m, the lidar data overestimated the tree height. The mean Treevaw-estimated height with a 0.5m CHM was 10.63m for 2013, mean height field was 8.44m and mean height CHM 0.5m was 9.48m, Table 2. The correlation coefficient was r=0.60 between field data and 0.5m CHM, with RMSE=2.8. As explained before, due to the fact that the coordinates were obtained with a recreational-grade Garmin GPS with an estimated average accuracy of 12m, it is possible that the lidar area used to derive measurements does not coincide with the field plot. Therefore, we analyzed the lidar-derived measurements over both 20x20m and 40x40m areas, for both TreeVaW and area-based methods. The larger 40x40m plot should compensate for the GPS error when averaging estimates over this larger area. The correlation coefficient was 0.70 and RMSE=2.2, for both areas 20x20m and 40x40m.

Coops et al. (2007) used lidar to measured foliage height and to estimate several stand and canopy structure attributes. The study focused on six Douglas-fir [Pseudotsuga menziesii spp. Menziesii (Mirb.) Franco] and western hemlock [Tsuga heterophylla (Raf.) Sarg.] stands located on the east coast of Vancouver Island, British Columbia, Canada, with each stand representing a different structural stage of stand development for forests within this biogeoclimatic zone. Tree height, crown dimensions, cover, and vertical foliage distributions were measured in 20m x 20 m plots and correlated to the lidar data. The design of data collection was similar to our study, Figure 2. Coops et al. (2007) showed that measured stand attributes such as mean stand height, and basal area were significantly correlated with lidar estimates (R^2 = 0.85, P < 0.001, SE = 1.8 m and R^2 = 0.65, P < 0.05, SE = 14.8 m2 ha–1, respectively). Therefore, this study demonstrates that lidar data can provide quantitative information on stand and tree height, which can be successfully modelled, providing detailed descriptions of canopy structure.

Table 2 – Statistical data of the field data and lidar data for mangrove.

	N				Height (m)								Crown diameter (m)	
Area	Field	L 0.5m (1600/4 area)	L. 0.5m (20x20m)	L. 1m (20x20m)	Field average (20x20m)		CHM 0.5m Average (20x20m)	CHM 0.5m Average (40x40m)	Treevaw 0.5m (20x20m)	Treevaw 0.5m (40x40m)	Treevaw 1.0m (40x40m)	Treevaw 1.0m (20x20m)	0.5m	1.0m
					2009	2013								
A1	67	9	12	3	8.83	9.18	8.44	9.73	10.32	10.32	11.26	10.82	1.84	1.25
A2	31	11	7	2	8.32	8.67	13.80	12.08	12.23	12.23	13.96	13.78	2.82	1.00
A3	88	17	18	2	7.76	8.11	9.26	8.73	9.49	9.49	10.59	12.09	1.74	1.50
Total	**186**	**37**	**37**	**9**	**8.3**	**8.65**	**10.5**	**10.18**	**10.68**	**10.68**	**11.94**	**12.23**	**2.13**	**1.25**
B1	114	13	21	0	7.32	7.67	6.88	5.47	7.55	7.55	8.92	-	1.01	-
B2	36	22	32	3	6.37	6.72	4.62	5.72	6.79	6.79	7.96	6.7	0.99	0.66
B3	93	19	32	4	6.75	7.1	7.9	7.94	9.41	9.41	10	9.52	1.37	0
Total	**243**	**54**	**85**	**7**	**6.81**	**7.16**	**6.47**	**6.38**	**7.92**	**7.92**	**8.96**	**8.11**	**1.12**	**0.33**
C1	53	8	7	0	9.2	9.55	12.77	11.53	11.66	11.66	13.11	-	2.5	-
C2	39	12	8	1	8.89	9.24	13.94	13.62	13.66	13.66	16.88	15.96	3.07	2.25
C3	62	18	11	1	9.42	9.77	7.71	8.39	9.67	9.67	10.4	10.11	1.48	2.00
Total	**154**	**48**	**26**	**3**	**9.17**	**9.52**	**11.47**	**11.18**	**11.66**	**11.66**	**13.46**	**13.03**	**2.35**	**2.13**
Mean	**194**	**46**	**49**	**6**	**8.09**	**8.44**	**9.48**	**9.25**	**10.08**	**10.08**	**11.45**	**11.12**	**1.86**	**1.24**

Figure 4 shows the comparison between the number of individual trees in the field data and the number of trees identified on lidar data by using Treevaw, with a CHM of 0.5m. On average, TreeVaW was only able to identify 24% of the number of individual trees in the field. Kin (2007) studying individual tree species using lidar obtained an average of 48% of the number of individual trees in the field data. The lower number of trees identified by lidar in mangrove forests could be explained by the fact that TreeVaW identifies local maxima as tree tops. When trees crowns are well delineated for individual stems, TreeVaW should identify trees visible on the CHM, i.e., dominant and co-dominant trees, but not suppressed trees. Given that mangroves stems are clustered together, their crowns are intricately overlapped and multiple stems appear to have one crown. As such, TreeVaW only counts crowns that are individually separable on the CHM, but there may be multiple stems counted in the field that compose such crowns.

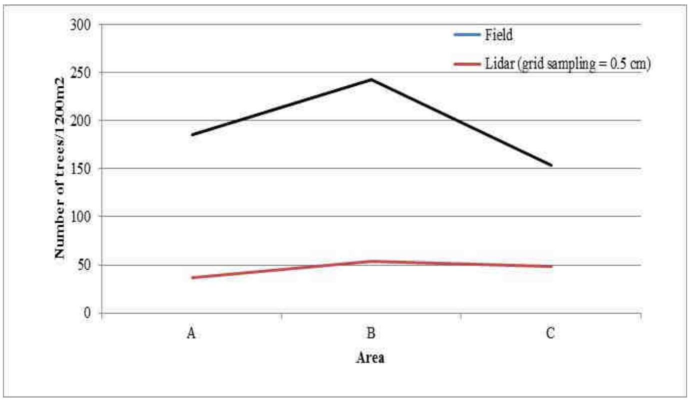
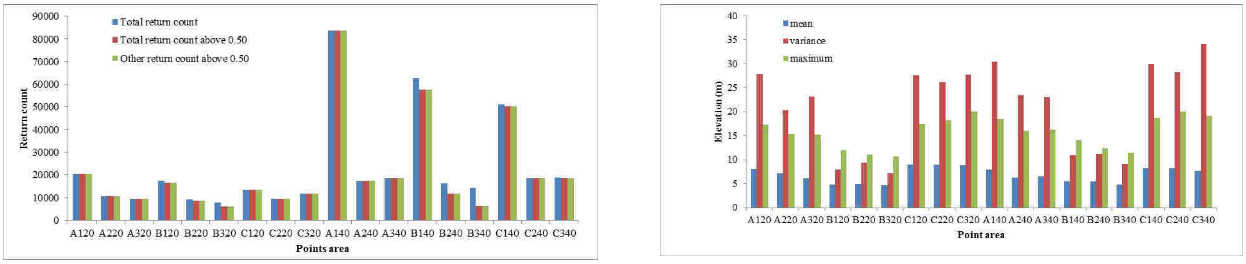


Fig. 4: The number of individual tree for mangrove species after isolating lidar point clouds with grid sampling 0.5m and comparison with field data.

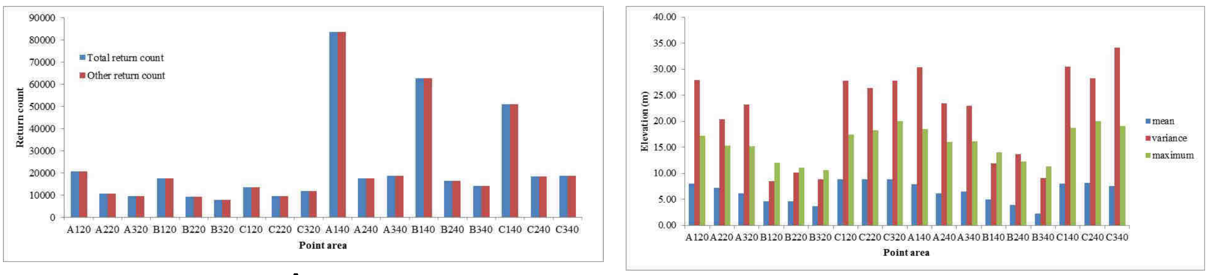
Area-based method - Point Cloud Metrics

Figure 5 (a and b) and 6 (a and b) show statistics for the A, B and C plot areas for point cloud metrics of 0.5m and 0m, respectively. Note that the difference between point clouds metrics of 0.5 and 0m was small.



A **b**

Fig.5: Statistics of A, B and C area for point cloud metrics of 0.5m.



A **b**

Fig.6: Statistics of A, B and C area for point cloud metrics of 0m.

We analyzed the CHM of 0.5m and 1m for all area of Pina mangrove. For a grid sampling of 0.5m and 1m size to estimate AGL, descriptive statistics are shown in Table 3. In this table showed statistical differences when processing the lidar data with CHM derived at 0.5m and 1m spacings. Based on our findings, we recommend using 0.5m CHMs for mangrove forests when processing lidar data because the Std. Error was minor 0.03. Given the multiple mangrove stems grown into a single crown, a higher-resolution CHM would be recommended for mangrove forest as processing methods such as TreeVaW could identify more trees on higher-resolution CHMs, as more local maxima could be identifiable in such situations. Lower-resolution CHM, such as 1.0m or even larger grid spacing, will present fewer local maxima for tree top identification.

Table 3 - Sample grid for AGL.

Variable	**N**	**Minimum (m)**	**Maximum (m)**	**Sum**	**Mean (m)**	**Std. Error (m)**	**Std (m)**	**Variance**
				(0.5 cm)				
Crown diameter (m)	66,963	0.5	8.5	120573.06	1.80	0.003	0.84	0.61
Height (m)	66,963	1.36	24.34	696651.55	10.40	0.014	3.67	13.54
				(1m)				
Crown diameter (m)	12,613	1	9	29048.75	2.30	0.007	0.85	0.72
Height (m)	12,613	1.3	24.09	160539.77	12.72	0.034	3.91	15.31

When comparing the results of CHM 0.5m, points clouds metrics of 0.5m and points clouds metrics of 0m note that the method of point cloud metrics of 0.5m was the better choice to estimate mangrove height with lidar data.

V. CONCLUSIONS

Lidar data can provide quantitative information on stand and tree height, which can be successfully modelled, providing detail descriptions of canopy structure. Treevaw was only able to identify trees visible on the canopy height model, i.e., dominant and co-dominant trees, but not suppressed trees.

The results of the current study show that lidar data could be used to estimate the height and average crown diameter and to improve estimates of others mangrove forest biophysical parameters of interest by focusing at the individual tree level. The crown diameter estimated with lidar at the individual tree level and its use for biomass assessment have been well document by Popescu et al. (2003). The method of point cloud metrics of 0.5m provided better results for estimating mangrove height with lidar data.

The research presented in this study contributes to the overall knowledge of lidar measurements of canopy structure and tree dimensions in complex ecosystems such as the mangrove forests. The utility of the LiDAR data collected over forest canopies and the processing methodologies developed in this study and the extended lidar literature show the ability of lidar remote sensing to extract variables, which directly correlate to mangrove tree structures, for a better understanding of complex mangrove ecosystems ecology.

The use of remote sensing data to obtain vertical structural of mangrove plant is important because reduce very expensive and hard work related to the hydrodynamic of high variation in the field. Under high tide is difficult the human access in this area. The remote sensing lidar data can be obtained independently of the water level in this ecosystem.

In order, the remote sensing data are advantageous because permit evaluate the spatial and temporal variation in a shorter time of a huge amount of information. In different world areas, the mangrove monitoring is not efficient, neither accurate, because the knowledge of physical, natural and human action characterization of this ecosystem is unclear. The improvement of the remote sensing technology can to contribute to monitoring of mangrove on four continents and six geographical regions of the planet, mostly occurring in Central America (Caribbean), India, the Indochina Peninsula, Brazil, and Australia. In Brazil, 13 of the 17 coastal states capitals are located near the sea. Therefore, not coincidentally, the coastal areas are under greater environmental stress and distributed among the various ecosystems in these areas, mangroves have suffered most from a disorderly urban expansion. Is necessary to know the actual situation and the human impacts to improve the monitoring and contribute to the public polices of these ecosystems.

The results suggest that further studies must be developed using new techniques, for example drones, to improve the data and promote advanced in knowledge of the mangrove ecosystem in the world. It is important to develop adjusted equation specific to the mangrove ecosystem under different environmental conditions.

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