Tree height in tropical forest as measured by different ground, proximal, and remote sensing instruments, and impacts on above ground biomass estimates.

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Abstract

Tree height is an important structural trait, critical in forest ecology and for above ground biomass estimate, and difficult to accurately measure in the field especially in dense forests, such as the tropical ones. The accuracy of height measurements depend on several factors including forest status, the experience of the observer, and the equipment used, with large subjectivity, heterogeneity and uncertainty in results, that can propagate when tree height is used in models. A comparison of Terrestrial Laser Scanning, Airborne Lidar Scanning, and stereo-photogrammetry (with imagery acquired by a RGB camera mounted on Unmanned Aerial Vehicle) approaches for estimating tree height was here performed, also with reference to ground methods. In fact, all those technique may increase the possibility of precise tree height measures, while reducing manual effort in comparison to more traditional ground techniques. The research was carried out in a dense tropical forest in Ghana; differences in measured heights as well as their impact on above ground biomass estimation were analyzed. All the different methods were characterized by pros and cons: the obtained results indicate that in dense forests, where sight occlusion problems occur, ground traditional techniques can lead to overestimation, while with the other mentioned techniques underestimation can occur, but in variable amount according to the considered instrument. The different height measures caused a remarkable variation in the estimated biomass of this tropical forest: more accurate height measurements are needed to reduce the uncertainty in biomass mapping efforts at any scale. Possibly, the simultaneous use of different methods can help in correctly estimate height uncertainty and reach a convergent and accurate result.

Keyworkds: tree height; forests; biomass; UAV lidar; ALS, photogrammetry; TLS

The authors have no competing interests to declare.

1. Introduction

Tree height is an important ecological trait, and part of many natural resource data collections, being the most widely used indicator of a site's fertility and suitability for a variety of stand management uses, ranging from wildlife habitat to timber production. Tree height can also provide indications on forest health conditions, as climate-induced events can alter growth processes, and disturbance can impact the height of selected individuals and stands. Tree heights are often measured in ecological and biodiversity studies or modeled to characterize life histories of species and populations (Banin et al. 2012, Kruger et al. 1997). In computing above ground biomass (AGB) this information is crucial, with previous work demonstrating that the incorporation of height into allometric models in addition to the diameter variable significantly improves AGB estimates, especially in tropical forests (Feldpaush et al. 2012). At present, most of the widely adopted models include the height variable.

Tree heights can be however difficult to accurately measure in the field, especially in tropical forests where tall, closed canopies, and dense understory occur, limiting the sight of tree tops (Rennie 1979). The accuracy of height measurements thus depend on forest conditions, but also on the experience of the observer, and the equipment used, leading to a large subjectivity and heterogeneity. In the ground, the various methods adopted to measure individual tree height can produce different results, as illustrated by Larjavaara and Muller-Landau (2013) who compared the sine and the tangent methods. Hunter et al. (2013) identified five sources of uncertainty that contribute to the precision of tropical field height measurements, including the offset between measured distance and crown-top position, tree-top occlusion, ground slope, obstacles for distance measurements, and clinometer operator error.

Even when using the same technique, differences in the way the instrument is set or the data are acquired can impact the results. Yu et al. (2004) in a lidar-based study showed that differences in airplane flight altitude produced variations in the tree heights estimated from the lidar point clouds. When height is used as input to calculate AGB, inaccuracy in measures can lead to large errors in biomass estimates (Molto et al. 2013). Also large scale AGB maps derived using remote sensing or models are calibrated and validated using on site level biomass data, computed through allometric models based on diameters and heights (Avitabile et al. 2016, Saatchi et al. 2001).

Among the different techniques that can be used to measure tree heights, here the focus is on Terrestrial Laser Scanning (TLS), Airborne Lidar Scanning (ALS), and stereo-photogrammetry with imagery acquired by a RGB camera mounted on Unmanned Aerial Vehicle (UAV). All these approaches increase the possibility of precise tree height measures while reducing manual effort in comparison to more traditional techniques, such as manual laser distance meter or clinometer.

TLS is a laser-based instrument used in the field to acquire precise range and angular measurements by means of the optical beam deflection mechanism. From TLS, a 3D point cloud of the scanned volume is obtained, and information on forest structure, including trees diameter and height, can be derived (Liang et al. 2016). The highest point over the ground close to the tree stem is collected, and then the value of the corresponding highest cloud point is considered as the tree height. TLS allows to scan a forest stand faster than traditional methods, and its use in forest resource surveys has recently increased (Srinivasan et al. 2015). However, similarly to other field-based techniques, due to occlusion problems the heights extracted from TLS point cloud can result lower than the actual values (Brede et al. 2017, Liu et al. 2016).

With ALS the distance from the sensor on an airplane to a target can be measured through pulsed laser light: the differences in laser returns time can then be used to make a digital 3-D representation of the target thanks to the laser penetration capability (Rosca et al., 2018). In ALS surveys covering forests, the point cloud is classified and interpolated to obtain a Digital Surface Model and a Digital Elevation Model, and by subtraction a Canopy Height Model (CHM) which contains the real height from the ground. The CHM is then filtered, usually with local maxima algorithms, to identify single trees metrics. With airborne surveys, the detection of top canopy is not affected by occlusion issues, but the capability to precisely hit the tree tops and map the ground level is influenced by various factors, including forest structure, lidar pulse density, scan angle, platform altitude, and beam size, among others. Different studies reported underestimation of tree heights with ALS, especially in old growth forests (Andersen et al. 2006, Clark et al. 2004, Goodwin et al. 2006). While many countries already conducted large lidar surveys covering forested areas, ALS data are unfortunately still not always open access, and surveys are in general expensive.

Low cost UAVs systems equipped with a consumer-grade RGB camera can acquire stereo imagery, from which a high resolution point cloud can be generated and processed to obtain a DSM. Using a local maxima algorithm the identification of tree tops is possible, and then by means of ground level subtraction, tree heights can be estimated. However, interpolating the terrain with only the few points obtained by stereo optical imagery, which differently from lidar does not penetrate the canopy, can be a problem (Wallace et al. 2014, Rosca et al., 2018). A high resolution Digital Elevation Model (DEM) obtained from other sources is therefore necessary to estimate individual tree level metrics. When ground information is available or the forest terrain is flat, UAVs can represent a cost-effective approach.

Only limited information is available on the accuracy of tree heights as measured by different techniques or sensors over the same forest (Fowler and Kadatskiy 2011, Rosca et al., 2018), in particular in tropical forests. Considering the high economic costs of forest surveys, independently by the adopted instrument or technique, a comparative analysis over a single site can be useful, as it provides valuable information to help decision making in forest resources management and planning. The objective of this research is to comparatively analyze tree numbers and tree heights as derived by: i) a ground-based traditional technique, ii) a TLS system, iii) a set of stereo-photogrammetry with imagery from a UAV, and iv) an ALS acquisition. Specifically, for tree number estimation the ground data were considered as the reference. For tree height, we present a comparison of different techniques, evaluating their agreement, due to the uncertainty reported when using ground –based techniques (Hunter et al. 2013; Larjavaara and Muller-Landau 2013; Ronnie, 1979). The impact of different height estimates on the computation of above ground biomass estimation using allometric equation was also analyzed. The research was realized in a dense tropical forest in Ghana, in the Ankasa Conservation Area, where occlusion problems are highly relevant.

2. Materials and methods

2.1 Study area

The study site (Fig.1) is the Ankasa Conservation Area located in southwestern Ghana and composed by the Ankasa Game Reserve and the Nin-Suhien National Park. Ankasa extends over approximately 509 km^2: protected since 1976, it includes a National Park and a Resource Reserve, and represents a remnant spot of the Upper Guinean forest belt, that once covered all the west African coasts. The area has gentle topography, with low hills (90 m average elevation) and presence of small swamps, a mean temperature ranging from 24°C to 28°C, high humidity all year round, and average annual rainfall in the 2000-2200 mm range. The vegetation is wet and moist evergreen forest, with very high floristic and structural diversity, that provides protection to rare wildlife, including forest elephants, chimpanzees, and leopards. Species typical of this forest area include: *Cynometra ananta* Hutch. & Dalz., *Lophira alata* Banks ex C.F.Gaertn., *Heritiera utilis* Sprague , and *Protomegabaria stapfiana* Beille (Hall & Swaine 1981; Vaglio Laurin et al. 2016a, 2016b). Prior to 1976, in Ankasa borders some logging activities were carried out, and illegal forest disturbance can still occur (Damnyag et al. 2013). The data collection was realized in the core of the conservation area, in a 0.7 ha research plot of lowland mature moist forest far from past or present disturbance.

Figure 1. The Ankasa Conservation Area (in red) located at the Ghana – Ivory Coast border.

2.2 Datasets

Terrestrial Laser Scanning (TLS) data were collected in March 2016 (dry season) using two Riegl VZ-400 instruments, operating at a wavelength of 1550 nm. Horizontally, the instrument can scan 360° in azimuth direction and vertically it has a field of view of 100°: 70° above, and 30° below the horizontal plane. 88 scan positions were set up, in correspondence of the grid nodes resulting from the division of the 0.7 ha plot in 70 10x10 m subplots; 6 reflectors were placed for co-registration purposes in each scan position. 176 TLS point clouds were collected, and then merged and co-registered using Riegl RiscanPro (Riegl). The accuracy of the final point cloud was < 1 cm; the dataset was divided into 20 tiles to facilitate data handle; the plot boundaries as scanned by TLS were used to subset airborne lidar and photogrammetric data.
Photogrammetric data were also collected in March 2016 using a Phantom 3 Professional UAV equipped with a 4K camera. The Pix4Dcapture software (Pix4D) guided the flight plan: 215 RGB images were collected at 5 cm spatial resolution. Using Agisoft Photoscan Professional software (Agisoft LLC) a point cloud and orthophotos were produced.
Airborne lidar (ALS) data were collected in March 2012 with a Optech GEMINI sensor, having a 1064 nm wavelength laser, emitting at 167 kHz max pulse repetition frequency and with 0.25-mrad (1/e) beam divergence, collecting up to 4 range measurements. Mean laser point density ranged between 12 and 20 points per square meter; maximum scan angle of the laser beam was < 11°; positional errors in horizontal and vertical dimensions were < 0.27 m. The point cloud was classified using Terrascan software (Terrasolid) into ground and vegetation returns.
A botanical survey was realized in March 2016 collecting species, diameter at breast height (DBH), and height information for trees having DBH above or equal to 10 cm. The height of the trees was measured with a transponder and vertex meter. Wood density values at species level were extracted from the Global Wood Density Database (Dryad; Chave et al. 2009); for species not present in the database the genus or family value was adopted. Above ground biomass (AGB) was computed according to Chave et al. (2014) equation.

2.3 Data analysis

The data analysis workflow included different steps. First, the three point clouds derived by ALS, TLS, and photogrammetric surveys were co-registered. Three canopy height models (CHM) were then derived from each of the co-registered point clouds, using the lidar-derived DEM for ALS and the photogrammetry dataset, and TLS-derived DEM for the TLS datasets. The visible crowns were delineated in the CHMs, extracting tree-level information using an inverted watershed procedure, and thus deriving heights.
A stem map was produced using the fine scale TLS point cloud, manually detecting DBHs of larger trees and corresponding heights. A univocal match between ground data and selected trees in the stem map was then established, according to correspondence in positional, DBH and height values. For these selected trees, height values as measured with different instruments were compared. Above ground biomass was also calculated using as input into the allometric equation the DBHs from ground database and the heights as measured by different instruments, to evaluate the impact in carbon stocks estimates at tree and plot level. All the steps were realized using CloudCompare and ArcGIS software.

2.3.1 Point clouds co-registration

A manual exclusion of few outliers found in each dataset was initially performed (Fig. 2). The ALS point cloud (LPC) was set as the reference dataset for co-registration purposes. The photogrammetric point cloud (PPC) was firstly co-registered to the ALS one, and then the process was repeated for the TLS point cloud (TPC).

Figure 2. Detection and exclusion of outliers (red circles) from the PPC dataset over the plot.

To co-register LPC and PPC, a mesh model was used to covert the points from PPC, having lower density with respect to LPC, into a surface made by triangular (or quadrilateral) contiguous and non-overlapping faces joined along their edges. The vertical displacement observed between the LPC and PPC was manually reduced, using the matching bounding box centers procedure. These initial two steps helped in the identification of control points. An horizontal and vertical coarse alignment was conducted using four crown tops pairs as ground control points, clearly detected in LPC and PPC for being very tall trees with characteristic crown shapes, and evident tree tops that facilitate the vertical alignment. Fine alignment followed, based on the iterative closest point (ICP) algorithm, which iteratively minimizes the mean square error between points in a point set and the closest points in the other one (Chen and Medioni 1992; Besl and McKay 1992); iterations number was set to 20.
The co-registration of the LPC and TPC started with a data resampling: the TPC reached 20.6 gigabytes in size, organized in 20 tiles. To handle such a large dataset the procedure suggested by Theiler (2014) was followed, subsampling each TPC tile to obtain points spaced by a distance equal to 0.1 m, thus reducing the data to a sparser set before seeking for correspondent features in LPC. The 20 tiles were merged in one dataset and four crown tops were identified in TPC and LPC, again selecting tall trees with characteristic shape. The point clouds for these crowns were extracted from both TPC and LPC, also repeating the co-registration procedure at finer crown scale. The transformation matrices were recorded and then applied to the full TPC.
To evaluate the alignment result, the cloud to cloud distance was calculated: for each point in the source cloud, a 'nearest neighbor' is searched in the reference one computing the Euclidean distance.

2.3.2 Canopy Height Model generation

Three DSMs were generated from LPC, TPC and PPC. For the classified LPC (ground and vegetation points), only first returns were converted into a raster using a 'local maxima' interpolation procedure, thus using the points of maximum height as raster pixel values. For TPC, and PPC the whole point clouds were used to generate the DSMs.
Two DTMs were also generated. For LPC, the interpolation procedure was based on ground returns only and the selection of 'local minimum'; for TPC, given the high density of points at ground level, no interpolation procedure was applied, and the minimum value of point height in each pixel was selected as pixel value in the raster.
CHMs, representing the difference between the top canopy surface and the underlying ground topography, were obtained subtracting the digital terrain model (DTM) from the digital surface model (DSM), both available from LPC and TPC. From PPC, given the lack of penetration capability, only the DSM was computed and for CHM generation the DTM derived from LPC was used.
To test impact of spatial resolution on tree detection capabilities in tree top detection and for crown delineation, all the layers were generated at 1m and 0.5m spatial resolution.

2.3.3 Tree crown segmentation crown delineation

The variable window filter algorithm (Popescu & Wynne, 2004), as implemented in the ForestTools R package (Plowright, 2018), was used to detect tree tops from the canopy height models. For the 1m CHM's the variable window size was determined using a linear function with a=0.05 and b=0.6, while for the 0.5m CHM's a=0.05 and b=0.5 were used. Those values were empirically determined for the specific datasets, by

systematically increasing both the a and b values with steps of 0.01 and 0.01 respectively. First the b parameter was optimized, where the plot of detected number of trees for each b-value shows a clear jump at the ideal b value. Using this b-value the optimal value for a was determined. Again, the value was selected where number of detected trees plotted against the a-values showed consistent outputs. This was cross-checked against the number of emergent trees as described in the field-survey.
Next the watershed function (Meyer & Beucher,1990) was applied to segment crowns from the canopy height model, where the segmentation is guided by the point locations of the individual tree tops. For the individually detected trees summary statistics of the crown dimensions and tree height were calculated.

2.3.4 Stem map and DBH from TLS data

To create a stem map, the TPC was segmented at 1.3 m above the ground. Next, a height ramp color was applied, which made it possible to distinguish the stems from surrounding lower vegetation. The stem map thus obtained showed several circular or semi-circular shapes corresponding to the tree stems: each stem was manually segmented. To calculate DBH longest and shortest axis were averaged. For large trees with buttress structure, the cross section was gradually moved upward until it was regular in shape and the DBH could be determined. For tilted trees or those growing on slopes, the DBH was measured along the stem direction. To find the height of trees for which DBH was measured, the stem map was converted into a raster and superimposed on the CHM. The maximum pixel value around the stem was manually identified also considering slope direction, and considered as the tree top with correspondent height.

2.3.5 Matching trees from remote and ground databases

TLS and botanical ground survey were conducted collecting tree information at subplot level. The stem map was firstly overlapped to the georeferenced ground data grid. A mismatch between datasets (due to the imprecise geolocation often occurring under dense forest coverage) was observed, as corresponding subplots in TLS and ground survey did not include same DBHs and height values. Therefore, a manual search of corresponding trees in the two dataset was performed: for trees having DBH > 30 cm in the ground database, the correspondence with a tree in the same subplot or in the surrounding ones was searched in the stem map and in PPC, allowing a maximum difference of 10% in DBH. Only unequivocally identified pairs were considered as matched trees. The previous co-registration of all point clouds allowed to establish a match for those selected trees among the different datasets. Analysis of Variance (ANOVA) was used to determine if the height of the selected trees, estimated using the different acquisition methods, was significantly different.

2.3.6 Above ground biomass estimate

For the selected trees, above ground biomass (AGB) was estimated using the equation from Chave et al. (2005, 2014); the equation has DBH, wood density, and height as inputs. For DBH, ground collected values were always used as input in the equation; for height, measures from the different datasets were used.

3. Results

A total of 331 trees belonging to 82 different species with DBH > 10 cm were recorded in the botanical survey; Fig. 3 shows the histogram of height obtained from ground survey, with a recorded maximum height of 55.5 m and a mean height equal to 20.6 m. The TLS survey recorded 188 trees with DBH> 20 cm.

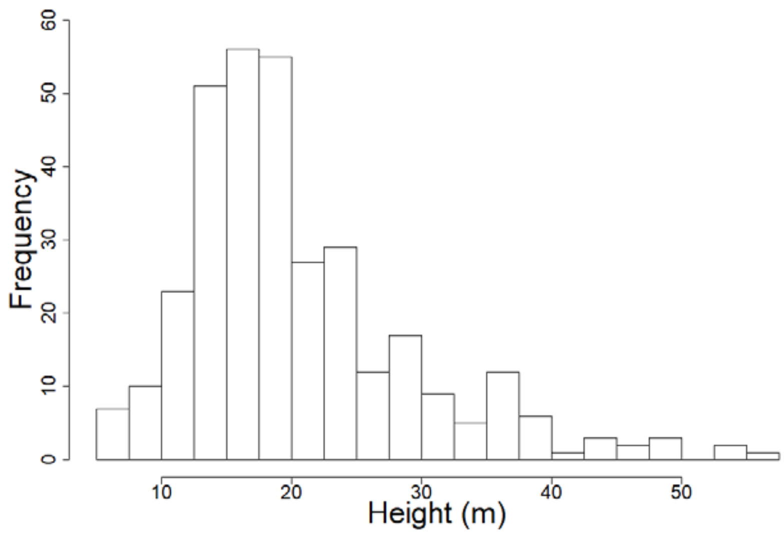

Figure 3. Distribution of tree heights from ground survey in the 0.7 ha field plot.

In the horizontal dimension, the co-registration between LPC and PPC was characterized by a mean point distance of 0.44 m, a standard deviation equal to 0.52 m, and root mean squared error (RMSE) of 0.62 m. The co-registration between LPC and TPC showed a mean distance of 0.45 m, a standard deviation of 0.62 m, and an RMSE equal to 0.33 m. In the vertical dimension the cloud to cloud comparison values resulted in mean differences of only several centimeters (Table 1).
The TLS and photogrammetry surveys were both realized in 2016,: the derived DSMs show similar features. Instead, ALS survey was done in 2012, and the four-year difference in time with respect to other datasets has to be taken into account. In fact, the ALS-derived DSM shows differences, like the one evidenced in red rectangle area in Fig. 4, due to changes occurred in the canopy along time.

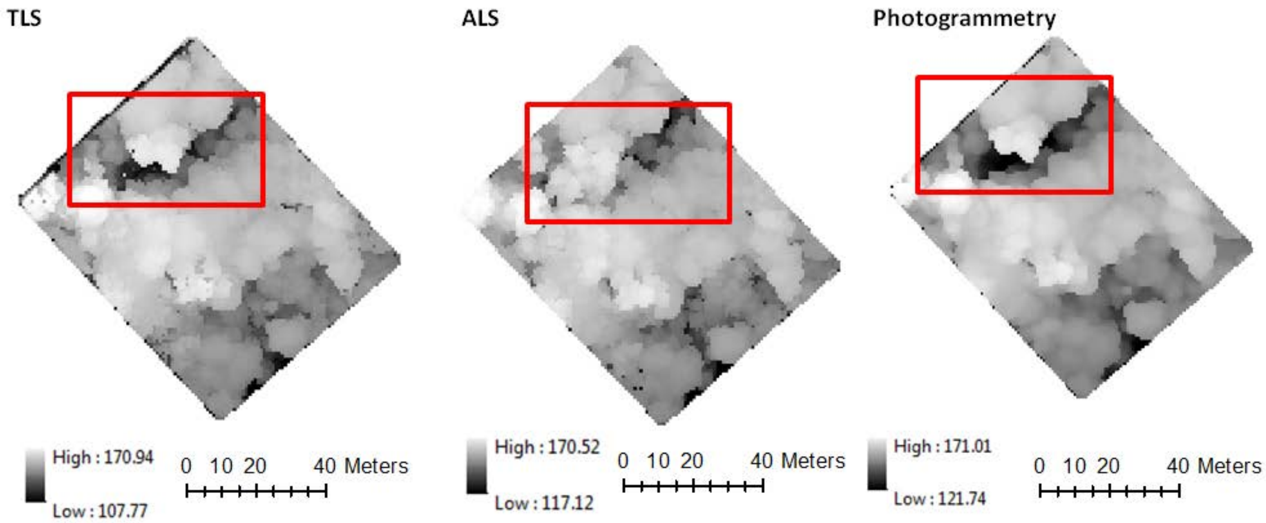

Figure 4. DSMs retrieved from TLS, ALS and Stereo Photogrammetry datasets at 1m spatial resolution

Table 1: statistics of cloud to cloud distances in the z direction

Cloud to cloud	Mean(m)	Std. dev(m)	Min(m)	Max(m)
TLS to ALS	0.09	0.66	-4.03	3.82
PPC to ALS	-0.02	0.49	-3.48	3.67
PPC toTLS	0.00	0.34	-3.74	2.91

The two DTM derived from TLS and ALS showed similar features (Fig. 5), with a flat ground and a downward slope toward the southeastern corner. The DTM generated with TPC without interpolating ground points resulted less smooth with respect to the LPC one.

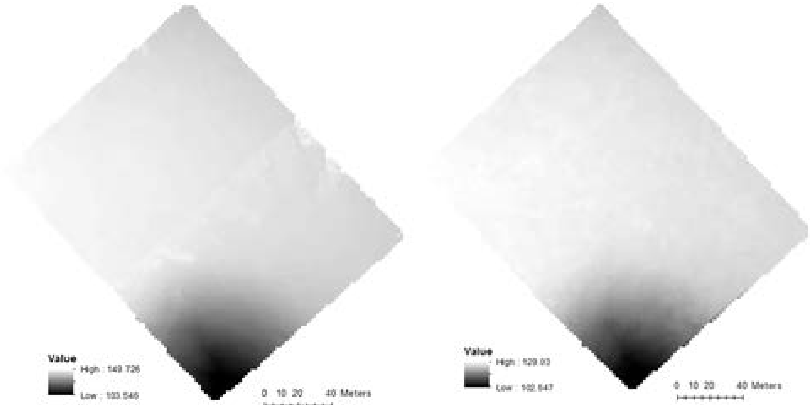

Figure 5. DTMs retrieved from ALS (left) and TLS (right) datasets at 1m spatial resolution

The histograms of the three CHMs illustrate the distribution of canopy height model values (Fig. 6). Two peaks are visible; the first peak at approximately 33 m for ALS CHM, and at 32 m for TLS and photogrammetry CHMs; the second peak is approximately at 28 m, 26 m and 25 m for ALS, TLS and photogrammetry data, respectively.

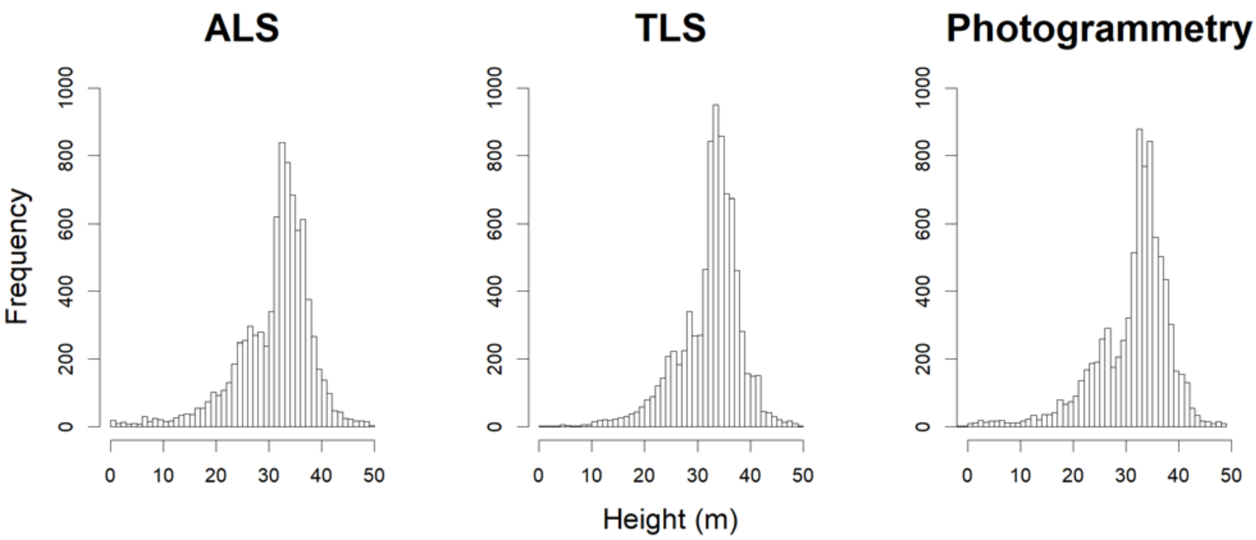

Figure 6. Histograms for CHMs from TLS, ALS, and photogrammetry, at 1m spatial resolution.

Table 2. Statistics for CHM derived tree segmentations at 1m and 0.5m spatial resolution derived from TLS, ALS, and photogrammetry.

	ALS 1m	ALS 0.5m	TLS 1m	TLS 0.5m	PPC 1m	PPC 0.5m
a	0.05	0.05	0.05	0.05	0.05	0.05
b	0.6	0.5	0.6	0.5	0.6	0.5
Trees	162	160	160	159	105	106
Mean crown area (m^2)	51.01	51.39	52.01	51.50	78.25	77.31
Median crown area (m^2)	39	33.5	37	33.5	63	53.38
SD crown area (m^2)	54.90	54.19	46.31	55.94	59.49	68.53
Min crown area (m^2)	5	1.5	8	4.5	10	2.25
Max crown area (m^2)	469	427	288	423.25	328	342

Mean height (m)	33.84	32.25	33.56	32.50	33.39	32.47
Median height (m)	34.57	33.88	34.13	33.63	34.27	33.81
SD height (sd)	4.33	6.65	4.98	6.02	5.82	6.60
Min height (m)	21.02	4.05	13.22	2.76	3.27	2.46
Max height (m)	49.22	49.10	49.27	49.46	48.74	48.22

As a result from tree crown segmentation 105 crowns were detected from the photogrammetry CHM, 162 from ALS CHM, and 160 from TLS CHM at 1m spatial resolution, with mean heights equal to 32.47, 33.56 and 33.84 m, respectively. Photogrammetry provided a smoother point cloud for the canopy top and consequently a smoother CHM, thus resulting in a lower number of detected trees. The number of detected trees with ALS and TLS is close to the number of >20cm DBH trees in the inventory. It has to be noted that the number of segmented tree crowns is highly dependent on the a and b parameters in the function fitting. Those values were optimized visually on the TLS datasets and then applied to the other datasets. For the 0.5m CHMs the b parameter had to be diminished, otherwise the number of estimated crowns would have been much higher. It is worth to stress that the optimal a and b values depend on the used datasets and resolution, and the values empirically found may not be directly transferable to other conditions. Table 2 reports the statistics for CHMs derived height and crown size values (0.5m and 1m spatial resolution). The histograms of heights for the tree groups derived from segmentation show considerable differences in height classes distribution (Fig. 7). Furthermore, large differences are found with respect to ground data (Fig. 3); in the ground survey the small trees are included, while with TLS or remote techniques only larger trees are sampled.

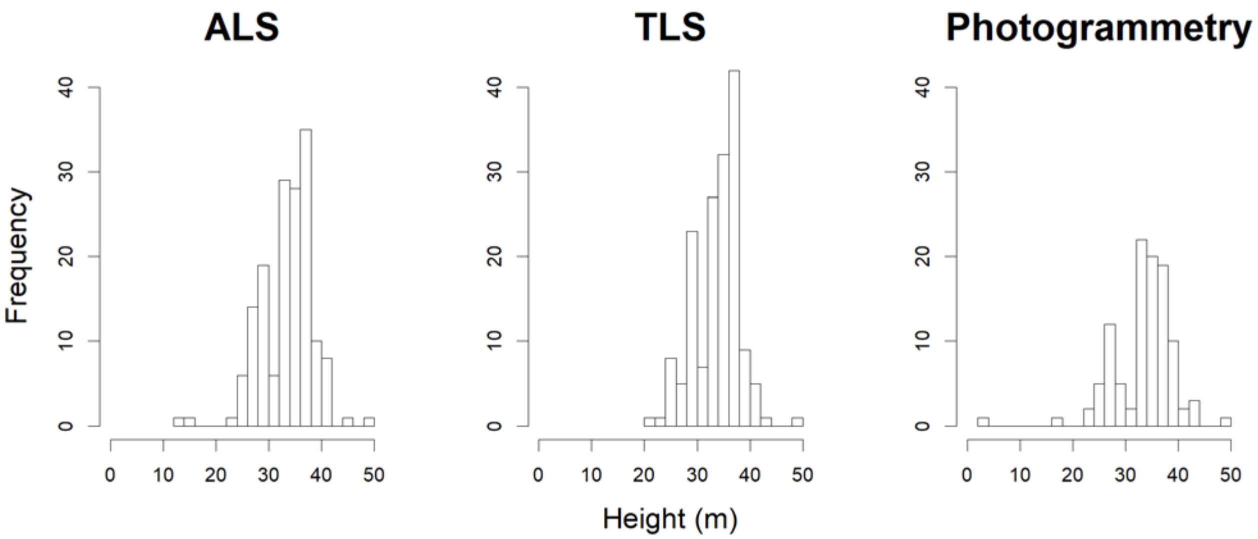

Figure 7. Histograms of height detected from ALS, TLS and photogrammetry tree segmentation based on CHMs at 1m spatial resolution.

The detection of crowns resulted in a lower number of tree crowns from the photogrammetry CHM, which obviously influences the statistics about the crown dimensions.

Fig. 8 shows the individual crowns delineation at the two spatial resolutions for the different acquisition techniques. Although differences are clearly visible, the mean crown size for ALS and TLS are comparable, even for the different CHM resolution when the segmentation parameters are adapted. With photogrammetry the lower number of detected tree tops also results in larger crown segments. The spatial distribution of areas with larger or smaller tree crowns is the same for all three acquisition techniques, but both LiDAR techniques distinguish much more smaller trees than photogrammetry does.

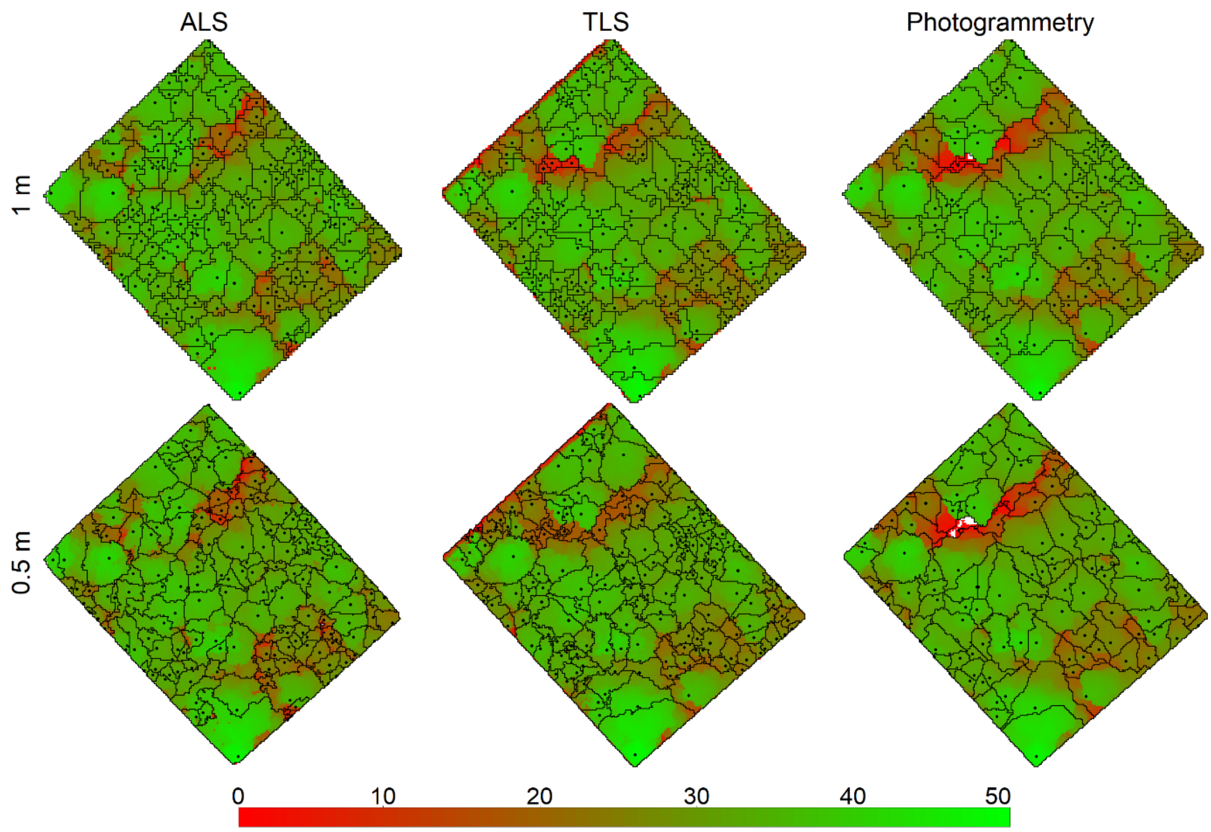

Figure 8. Tree detected using tree crown segmentation at 1 m (top and 0.5m (bottom) spatial resolution for the ALS, TLS, and photogrammetry datasets.

From the stem map derived from TLS data, 38 trees with DBH > 30 cm were clearly detected. However, only 21 tree pairs were univocally identified in ground and TLS databases. The average height of these trees as from TLS data resulted equal to 35.3 m, while from ground data to 37.2 m, almost 2 m higher than the previous. The ANOVA results show that there is no statistically significant difference between the mean heights derived with the different techniques (F-value = 0.367). The RMSE for DBH values resulted equal to 2.38 cm, while RMSE for height to 6.44 cm, with ground measures having higher values with respect to TLS ones. Fig. 9 shows the scatterplots for DBH and height of the 21 trees, as measured by field data collection and TLS.

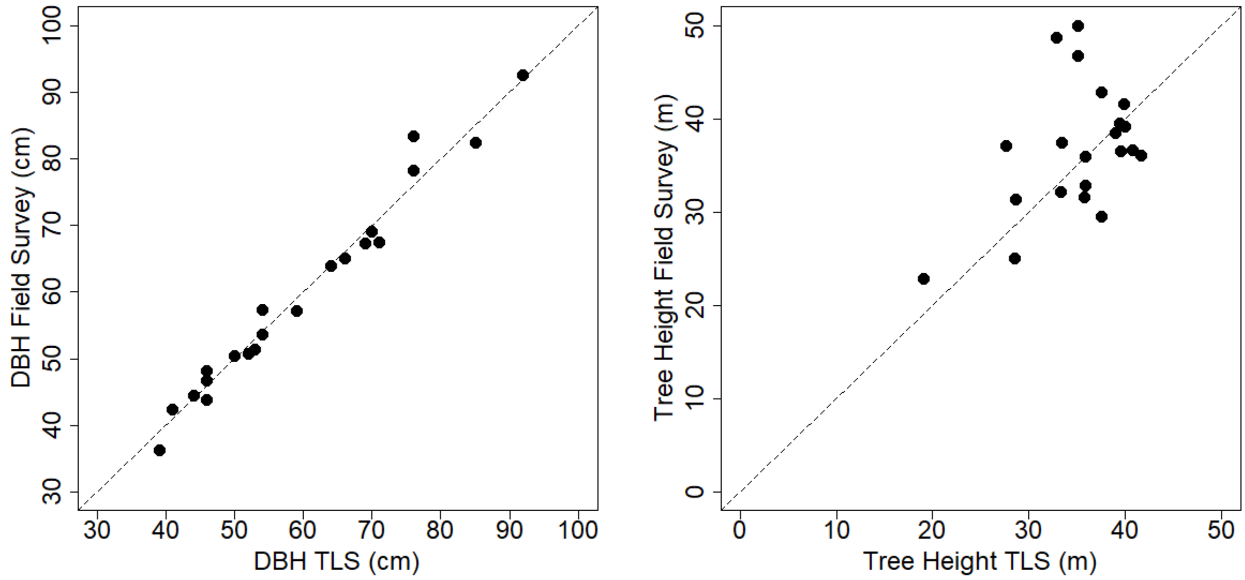

Figure 9. Scatterplots of DBHs (left) and heights (right) for 21 pairs of trees identified in ground and TLS datasets, plotted against the 1:1 line.

Thanks to co-registration of point clouds, the height values for the 21 trees were extracted also from ALS and photogrammetry datasets at 1m spatial resolution; Fig. 10 shows the comparison of heights values from different remotely sensed datasets and the related coefficients of determination (R^2).

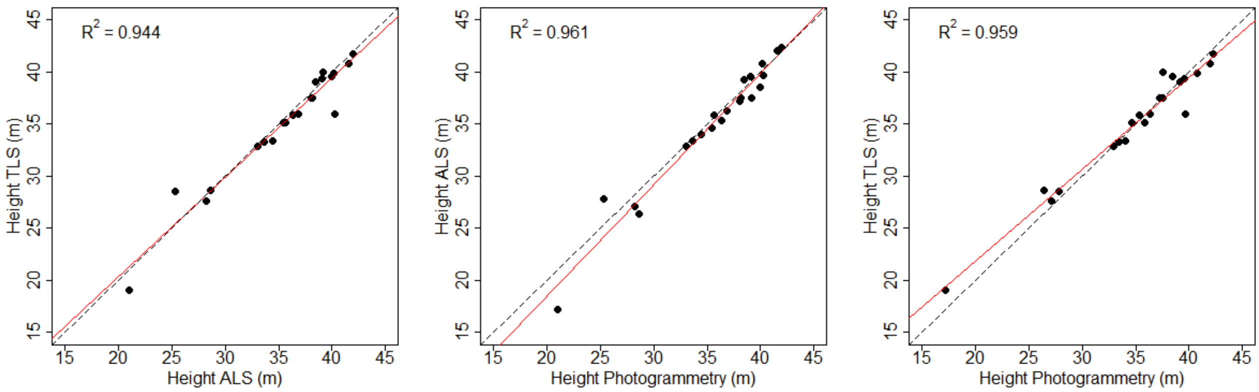

Figure 10. Comparison of heights for 21 trees according to ALS, TLS and photogrammetry measures, with regression line (in red), the 1:1 line (black dashed) and coefficients of determination (R^2).

The total above ground biomass (AGB) for the 21 large trees was computed for each dataset using Chave et al. (2005; 2014) allometric equation, using in input the DBHs collected in ground survey, the species-level wood density values, and heights according to the various datasets (Table 3). As from the botanical ground survey, the AGB for the whole 0.7 ha research plot resulted equal to 264.6 Mg, corresponding to 378 Mg ha^{-1}. The ratio between the AGB of the 21 trees and that of the whole plot from ground data resulted equal to 0.36. Applying this ratio to other datasets, under the assumption that the differences in height as measured for the pairs by different techniques hold for all the trees in the plot, and thus the error in height measure is similar in tree age classes and species, the amount of AGB per hectare was finally computed per each dataset, as well the differences in tons with respect to ground measured AGB (Table 3).

Table 3. Comparison of AGB values obtained using heights measures from different techniques.

	Ground	**TLS**	**ALS**	**Photogrammetry**
Total AGB for 21 trees (Mg)	95.9	88.6	89.9	91.6

Ratio to ground AGB for 21 trees (%)	100	92.3	93.7	95.5
AGB per hectare	378.0	349.1	354.2	360.8
Difference to ground AGB (264.6 tons)	0	28.9	23.8	17.2

4. Discussion and conclusions

The data collected in the botanical ground survey illustrate that this mature Ghana forest is very diverse in species composition and highly dense, and the height distribution evidences a multi-layered canopy.

A good agreement between the lidar-derived point cloud and terrestrial lidar and photogrammetric point clouds was obtained in the co-registration procedure, with mean point distance below 0.5 m in all cases for the horizontal plane, and below 0.1 m for the vertical plane. The co-registration step is important when evaluating height as measured from different instruments, as large errors can affect the evaluation.

The DSMs derived from lidar, terrestrial lidar and photogrammetric point clouds evidenced the changes occurred in the forest in the 4-year period, as in the more recent 2016 datasets (TLS and photogrammetry) a gap in the canopy was visible, while it was not evident in 2012 ALS data.

The DTMs derived from ALS and TLS appeared very similar, with negligible differences, partly possibly caused by the difference of four year in datasets acquisition and partly due to the interpolation procedure applied to ALS data. With photogrammetry data it was not possible to produce a quality DTM due to the dense canopy cover and thus the poor ground information included in this dataset (Rosca et al., 2018). A limit to the use of this technique for deriving tree individual metrics is thus represented by the availability of a high resolution DTM, that should be available or collected from other sources. Birdal et al. (2017) obtained individual tree heights from a coniferous urban open forest using UAV-based imager, generating the CHM entirely from photogrammetry data with a 94% correlation and a root-mean-square error of 28 cm with respect to ground data. However, the authors remarked that this approach is suitable only in open forest. Further, the co-registration of the PPC with the other datasets relied on feature matching. This means that either a CHM should be available for (at least part of) the study area, or the absolute positioning of the PPC should be improved when no reference CHM is available. The UAV used in this study carried a simple GPS system, resulting in a possible offset of 2-5 m. This can be improved using an RTK-GPS system for the positioning of the UAV. So when a detailed DTM is present, UAV-based photogrammetry represents a cost-effective method to frequently detect changes in canopy horizontal structure, but it cannot be operated stand alone in a tropical forest setting.

On the other hand, with TLS technique accurate DBH information can be obtained in addition to height data: this represents an advantage when exploring structural changes below the top canopy level, as the DBH information cannot be captured by ALS or photogrammetric techniques.

The comparison of CHMs at 1 m spatial resolution showed lower maximum and mean height values for photogrammetry data with respect to the other two datasets. More important, the crown detection with watershed crown segmentation produced very different results in number of identified trees, with much lower amount of individuals detected when using photogrammetric data, with respect to ALS and TLS, with the latter recording the higher number of individuals. Overall the number of detected trees is much less than what is reported by ground survey, but the difference is reduced when only trees with DBH > 20 cm are counted. This indicates that ALS and Photogrammetry techniques are not suited for the detection of small trees, such as the newly recruited ones, a fact also noted using airborne lidar by Dalponte and Coomes (2016). With TLS those smaller trees can be detected, but this requires a very different approach than presented here. The mean heights of trees resulted similar among the different datasets, but the histogram of tree heights from photogrammetric data showed not only less individuals but also a different distribution in heights compared to the other histograms. At 1 m resolution, the mean trees height resulted slightly higher with ALS data, followed by TLS and then photogrammetry; at 0.5m the mean heights were generally a bit lower but comparable for all three techniques. In the result evaluation, the four-year time difference of the ALS dataset should be considered. In this period, mortality and recruitment of new trees as well as growth can occur. However, the first two events usually are counterbalanced in old-growth forest leading to minor changes in tree population, while for large old trees the hydraulic limit reduces the growth in height (Ryan and Yoder 1997).

These results first indicate that the number of trees that can be detected with the watershed procedure is much lower than the trees recorded by ground surveys, as expected. However, the number of trees detected from the CHM acquired with ALS and TLS is close to the number of >20 cm DBH trees as recorded in the ground survey. Ground surveys, either with traditional techniques or TLS remains fundamental for full inventory purposes. Results from the watershed analysis also indicate that when possible the higher spatial resolution is not essential, but tree detection parameter settings have to be adapted to suit the right resolution. For the tree pairs having DBH > 30 cm, a large difference was found between TLS and ground survey measured heights, almost reaching 2 m. Instead, the agreement between the ALS, TLS and photogrammetric height for these pairs was very good, with a coefficient of determination around 0.95; this agreement suggests that overestimation of tree height occurred when collecting data with traditional technique.

Differences in height measurements from field and airborne lidar data were relevant in four Brazilian Amazon sites, especially for larger trees: ground based measurements of height exceeded airborne lidar measurements of height by an average of 1.4 m, possibly due to a combination of overestimation by field measures and underestimation by lidar (Hunter et al. 2013). Instead, a comparison of field vs. lidar measured height for two commercially significant species in western North America, the Douglas-fir (*Pseudotsuga menziesii*) and the ponderosa pine (*Pinus ponderosa*) evidenced that the field conventional measured were more accurate than the lidar ones, with the latter also depending on laser beam size (Andersen et al. 2006). In a United Stated Pacific Northwest forest, ground survey height data were compared to lidar height data from leaf-on and leaf-off airborne acquisitions, for > 1000 trees from 45 plots. Overall, lidar error resulted higher than what estimated by other studies, exceeding 10% of tree height for 60% of the trees and 43% of the plots at leaf-on and 55% of the trees and 38% of the plots at leaf-off, possibly due to suboptimal performance of standard preprocessing lidar algorithms (Gatziolis et al. 2010). The contrasting findings of these studies evidence that the accuracy of height estimated in the ground or by ALS largely depends on specific site conditions, instruments settings, and the ability of the operators; however measuring tree heights of cone-shaped species can be easier from the ground, as the tree top can be more evident.

Height data derived from photogrammetry, through a stereomodel combined with a digital terrain model (DTM) obtained by airborne lidar, were compared to field measured height for 202 *Thuja occidentalis* individuals, reveling a mean negative bias of 0.88m from photogrammetry (St-Onge et al. 2004).

Underestimation of tree height was also reported by a research comparing Canopy Height Models (CHM) derived from terrestrial laser scanning (TLS) with the one from UAV-borne laser scanning data, collected over Netherland forested plots, which showed that TLS could not always detect the top of the canopy (Brede et al. 2017).

When the AGB for the 21 unequivocally matched pairs was computed, using as input same DBHs (from ground data) but heights from different techniques, differences emerged as the higher height values recorded in the ground survey lead to higher AGB. The AGB estimated using ground height values was 7.6 %, 6.3 %, and 4.5 % higher than that estimated using TLS, ALS photogrammetric heights, respectively. If the ratio between AGB from 21 trees to that of the entire plot was assumed as constant, the biomass computed using ground heights resulted 10 %, 9 %, and 6.5 % higher than that estimated using TLS, ALS, and photogrammetric heights, respectively. These values are similar to those found in other studies: Hunter et al. (2013) evaluated that the impact of height error on AGB estimation in four Brazilian forest sites caused a 5-6% uncertainty in the overall plot biomass.

Previous research suggests that in dense forests, where sight occlusion problems occur, ground traditional techniques can lead to overestimation of tree heights, unless the tree tops are clearly visible and distinguishable, such as in the case of cone-shaped trees or open forests. On the other hand, with ALS, TLS and photogrammetry techniques underestimation can occur, in variable amount according to local and instruments conditions (Wang et al. 2019). We found that same effects in our study area. In comparison, although limited to smaller areas of maximum few hectares, TLS estimates are most promising since they provide more robust estimations for DBH, height and volume variables compared to ground instruments (Gonzales et al., 2018), and provide the full reconstruction of forest in 3D, allowing for additional research and analysis. Furthermore, advantages were obtained integrating ALS and TLS in assessing single tree attributes (Giannetti et al. 2018).

Forest density and tree tops visibility represent important characteristics to be initially evaluated. When enough resources are available, the ALS technique may represent an advantage, as it can cover relatively large areas in a reduced time, and allows the generation of a DEM. Increasing as much as possible the number of laser pulses per meter can minimize the chance that the tree tops are missed. TLS is more time-consuming and data acquisition can be almost as expensive as with ALS over larger areas, with the disadvantage that from the ground the visibility of tree tops can be reduced, but at the advantage of precise ground information and DBHs collection. In this study the TLS-derived heights were similar to those obtained by ALS; possibly, this technique is preferable when accurate data on growth or stem density are needed. From photogrammetric data lower heights were obtained in this research, however the economic convenience of this techniques supports its use when a DEM is available and for repeated canopy monitoring. A promising new opportunity is provided by low flying drone-based lidar systems with wide viewing angles that also record point clouds looking side-ways into forests allowing estimations stem characteristics such as DBH (Brede et al., 2017).

In conclusion, different methods to estimate tree height can be adopted, each with pros and cons, with the selection of the most appropriate method depending on resources and opportunities. As in other studies, the different measures caused a remarkable variation in the estimated AGB of this tropical forest. Height is certainly responsible for a part of the uncertainty associated to AGB estimates: more accurate height measurements can help to reduce the uncertainty in AGB mapping efforts at any scale. Possibly, the simultaneous use of different methods can help in correctly estimate height uncertainty and reach a convergent and accurate result.

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