An Acad Bras Cienc (2023) 95(1): e20201503 DOI 10.1590/0001-3765202320201503
Anais da Academia Brasileira de Ciências | *Annals of the Brazilian Academy of Sciences*
Printed ISSN 0001-3765 I Online ISSN 1678-2690
www.scielo.br/aabc | www.fb.com/aabcjournal

FORESTRY SCIENCE

Combining ALS and UAV to derive the height of *Araucaria angustifolia* in the Brazilian Atlantic Rain Forest

ERNANDES M. DA CUNHA NETO, HUDSON F.P. VERAS, MARKS M. MOURA, ANDRÉ L. BERTI, CARLOS R. SANQUETTA, ALLAN L. PELISSARI & ANA PAULA D. CORTE

Abstract: Quantitative data obtained from native forests is costly and time-consuming. Thus, alternative measurement methods need to be developed to provide reliable information, especially in Atlantic Rain Forests. In this study we evaluated the hypothesis that the combination of an Airborne Laser Scanner (ALS) and an Unmanned Aerial Vehicle (UAV) can provide accurate quantitative information on tree height, volume, and aboveground biomass of the Araucaria angustifolia species. The study was carried out in Atlantic Rain forest fragments in southern Brazil. We tested and evaluated 3 digital canopy height model (CHM) scenarios: 1) CHM derived from ALS models; 2) CHM derived from UAV models; and 3) CHM from a combined ALS digital terrain model and UAV digital surface model. The height value at each tree coordinate was extracted from the pixel in the three evaluated scenarios and compared with the field measured values. ALS and UAV+ALS obtained RMSE% of 6.38 and 12.82 for height estimates, while UAV was 49.91%. Volume and aboveground biomass predictions are more accurate by ALS and UAV+ALS, while the UAV produced biased estimates. Since the ALS is currently used, periodic monitoring can be carried out by a combination of active (ALS) and passive (UAV) sensors.

Key words: forest inventory, Lidar, photogrammetry, remote sensing, sustainable management.

INTRODUCTION

Forest monitoring is an essential operation to assess the regeneration and dynamics of native tree species (Kwak et al. 2007, Strigul 2012), for which height and volume are the main indicators for biological and commercial purposes (Panagiotidis et al. 2016). However, continuous data obtention by traditional forest inventories involve expensive and time-consuming activities (Gardner et al. 2008, Chave et al. 2014, Tang & Shao 2015), and is susceptible to non-sampling errors such as indirect height measurements, mainly in native forests (Larjavaara & Muller-Landau 2013).

It is challenging to quantify the tree metrics in the Atlantic Rain Forest biome due to the relief, vegetation density, and forest understory. These factors directly influence the tree height measurements and cause inaccurate values (Southworth & Tucker 2001, Munroe et al. 2007, Teixeira et al. 2009). The height of some species, such as *Araucaria angustifolia* (Bertol.) Kuntze, is an important variable which cannot be directly obtained by tree's cut, since they are protected by law due to the intense past exploitation (IBAMA 1976, Brasil 2006, Orellana et al. 2017).

However, the legal restriction does not ensure the future conservation of *A. angustifolia* (Hess et al. 2016). In addition, the reduction of rain forests is mainly due to unawareness about the species' economic and ecological benefits, as their trunk provide quality wood and the fruits produce revenues for the community, thus encouraging the use of this species in reforestation and restoration programs (Eisfeld et al. 2008, Orellana et al. 2017). However, remote measurement methods are essential to ensure rain forests conservation without breaking the law.

The use of remote sensing techniques such as the airborne light detection and ranging (Lidar) have been recommended for this purpose since this active sensor applies a laser pulse which penetrates surfaces and makes it possible to map three-dimensional structures (Wulder et al. 2008, Su & Guo 2014, Su et al. 2016, White et al. 2016). However, the cost of acquiring Lidar data is one of the main problems to inventory a forest (Hird et al. 2017). The use of unmanned aerial vehicle (UAV) photogrammetry is an alternative and cheaper technology than ALS to acquire 3D point clouds to capture forest attributes with similar accuracy to Lidar, especially tree canopy height (Snavely et al. 2008, Fonstad et al. 2013, Salamí et al. 2014, Stepper et al. 2014, Matese et al. 2015, Goodbody et al. 2017).

Despite of point clouds' ability to estimate forest variables, those derived from passive sensors in UAVs have difficulty to generate the digital terrain model (DTM), especially in densely vegetated forests. Thus, combining UAV and Lidar has potential to measure forest attributes using a single Lidar flight to design the DTM and then UAV to construct the Canopy High Model (Dandois & Ellis 2013, Vastaranta et al. 2013, White et al. 2013, Ota et al. 2015, Corte et al. 2020). Some studies have shown the association of these techniques, but only in forests with less complex structures (Jayathunga et al. 2018, Corte et al. 2020, Silva et al. 2020), for example in forests in Sweden in which the predominant species are conifers such as *Pinus sylvestris* (Persson et al. 2013), and only in areas smaller than three hectares (Zhang et al. 2019). Consequently, it is necessary to evaluate the efficiency of combining these sensors in larger areas and more complex forests such as the Atlantic Rain Forest.

On the other hand, it is also necessary to develop research with *A. angustifolia*, since management prohibition results in reduced growth, lower regeneration, and profit losses (Hess et al. 2014). Scientific research can assist in species' sustainable management, promoting their conservation and the survival of remnants (Hess et al. 2016). Our hypothesis is that the combination of Airborne Laser Scanner (ALS) and UAV can provide accurate information on complex native forests. Therefore, the objectives of this study were to: i) to evaluate the accuracy of the UAV (passive sensor) application to estimate the total height of *A. angustifolia*; ii) to evaluate the accuracy of combining UAV (passive sensor) + ALS (active sensor) to estimate the total height; and iii) to evaluate the results for estimating the volume and biomass stocks of *A. angustifolia*.

MATERIALS AND METHODS

Description of the area and inventory

This study was carried out on an urban fragment of Mixed Ombrophilous Forest located in the Atlantic Rain Forest. The location coordinates are: 25°26'52.93" S and 49°14'25.42" W, and the total area is 7.51 hectares. This forest is situated on the Federal University of Paraná, Jardim Botânico campus, in

Curitiba, Paraná (Figure 1). The region's climate can be classified as subtropical humid mesothermal without a defined dry season (Cfb by the Köppen-Geiger classification), with an average temperature of 18 ºC, annual average precipitation of 124 mm (Alvares et al. 2013), and an altitude equal to 900 m above sea level.

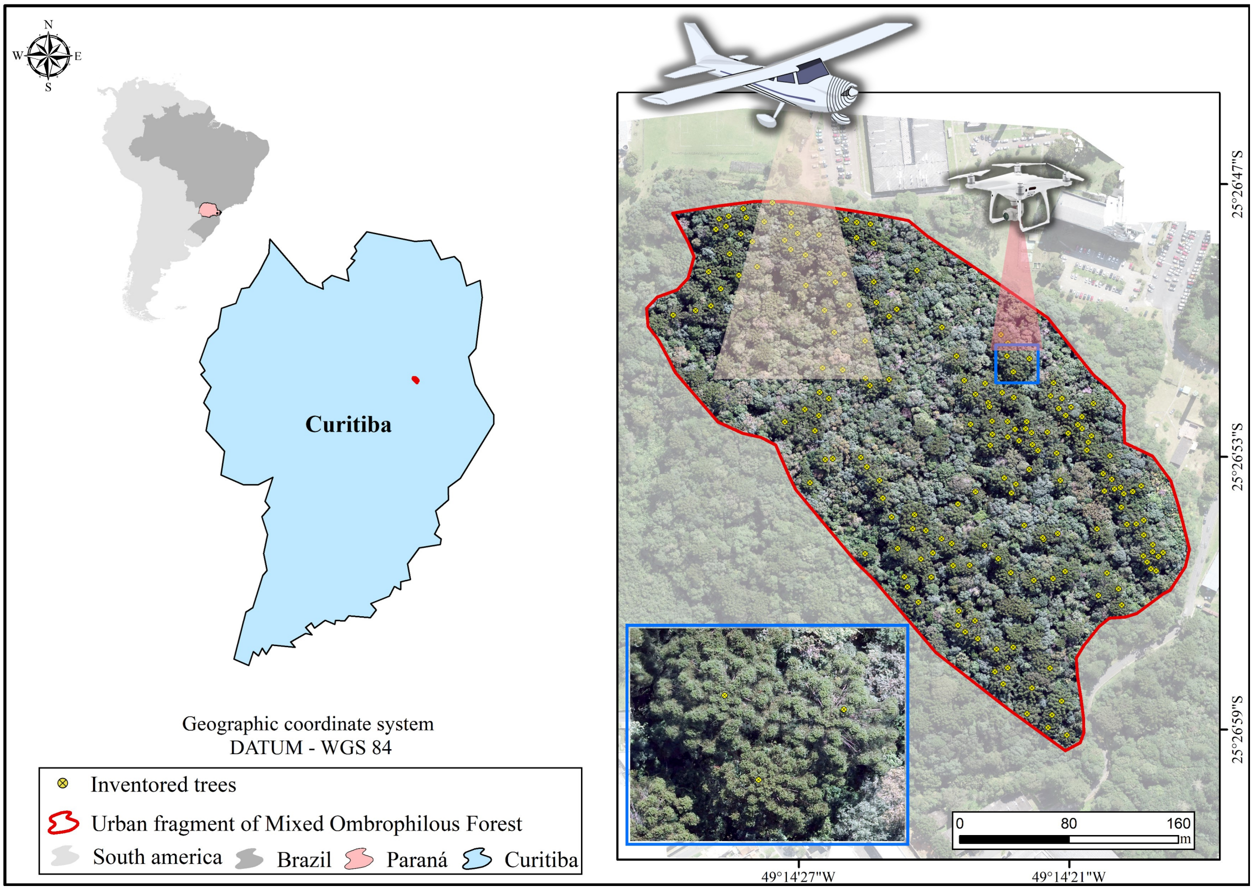

Figure 1. Urban Fragment of Mixed Ombrophilous Forest located in the Atlantic Rain Forest in Curitiba, Paraná.

The Mixed Ombrophilous Forest originates from the interaction between Austral-Andean and tropical Afro-Brazilian floras, which is considered one of the most biodiverse forests (Myers et al. 2000, Laurance 2009). Myrtaceae and Lauraceae are the predominant families, which represent 24.75% of the total families, with *A. angustifolia*, *Casearia sylvestris* Sw, *Luehea divaricata* Mart. & Zucc, *Ocotea puberula* (Rich.) Nees and *Symplocos tetrandra* Mart. as the main species (Orso et al. 2020).

A. angustifolia (Araucariaceae) is popularly known as Parana pine, being one of the most important species of the southern Brazil, with height between 10 and 35 m, and diameter at breast height over 50 cm (Aquino 2005, Wendling & Zanette 2017). It produces high quality and strong wood, which can be used for cellulose, civil building, and veneer, while its fruit is important for human and fauna nutrition (Lorenzi 1998).

The *A. angustifolia*'s crown is cone-shaped when young, while in the adult stage, the crown is umbrella/cup-shaped. The species first flowering happens between 12 and 15 years, and the reproductive organs are modified leaves, composed by many carpeled leaves. The female's strobilus contains the fruit, which is used for animal and human nutrition, and for the species' regeneration (Wendling & Zanette 2017). The natural regeneration and establishment of this trees is problematic, because the farmers fear losing their property for the species' preservation, so they usually retire the plants at the young stage (Wendling & Zanette 2017).

We carried out a 100% inventory of *A. angustifolia* trees in 2019. This species was selected due to its importance for forest dynamics and restoration, as well as its easy identification of its canopy in aerial mapping (Rex et al. 2018). A total of 177 trees were identified, in which the diameter at breast height (1.30 m) (d) and total height (h) were measured using diameter tape and a Haglöf Vertex® IV hypsometer. In addition, spatial coordinates were collected using Garmin® Geomap 62S GPS.

Aerial data collection

Airborne Laser Scanner (ALS) data were collected in 2012 in which a point cloud with a density of 4 points.m^{-2}, altimeter accuracy of 10 cm, and ground sample distance (GSD) of 18 cm were obtained. The digital terrain model (DTM) was created from this point cloud (ALS).

UAV mapping was performed in 2019 with DJI Phantom 4 Pro equipment with a 1" 20-megapixel camera (RGB) and a Complementary Metal Oxide Semiconductor (CMOS) sensor with a mechanical shutter and FOV lens. The UAV flight was performed at 120 m above the ground at a speed of 6 m.s^{-1}, a camera angle of 90°, side overlap of 79%, front overlap of 84%, and three photographs per second, resulting in a 3.34 cm GSD.

Four control points collected with GPS RTK (Real-Time Kinematic) were used to correct positioning errors, with an altimeter accuracy less than 10 cm. The point cloud from the passive UAV sensor was produced by Pix4Dmapper® version 4.4.1 software (Pix4D SA 2020) with a total of 34.58 million points and a density of 83.2 points.m^{-2}. Next, the Digital Surface Model (DSM) and the DTM were obtained from this cloud in R® version 3.6.1 software, with the lidR, rLIDAR, raster, and rgdal packages (R Core Team 2019).

Three scenarios of digital canopy height models (CHM) were subsequently tested: 1) ALS Scenario – CHM derived from ALS models; 2) UAV Scenario – CHM derived from UAV models; and 3) UAV+ALS Scenario – CHM from combined ALS digital terrain model (DTM) and UAV digital surface model (DSM). The height value at each tree coordinate was extracted from the pixel in the three evaluated scenarios. These values were compared with the values measured in the field (Figure 2).

Assessment of estimated heights

Root Mean Square Error - *RMSE* (1), *bias* (2) and Pearson linear correlation - *r* (3) statistics were applied to compare height estimates. The Chi-squared test - χ^2 (4) was applied at 0.05 significance level, considering the hypotheses: H_0 = heights measured in the field are statistically similar to the heights estimated by remote techniques; and H_1 = heights measured in the field are statistically different from the heights estimated by remote techniques.

$$RMSE\ (\%) = \frac{100}{\bar{y}} \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \tag{1}$$

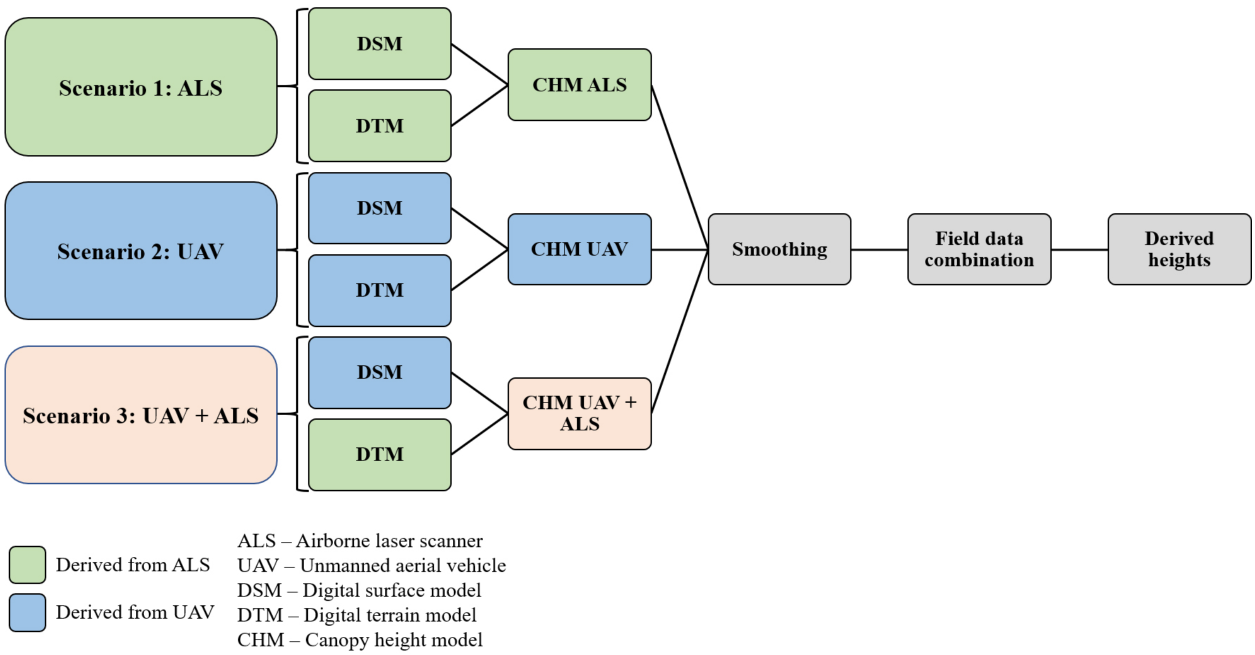

Figure 2. Flowchart of UAV point cloud processing steps for estimating total height of *Araucaria angustifolia* trees in Atlantic Rain Forest.

$$bias\ (\%) = \frac{100}{\bar{y}} \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)}{n} \tag{2}$$

$$r = \frac{\sum_{i=1}^{n} (yi - \bar{y}) \left(\hat{yi} - \bar{\hat{y}}\right)}{\sqrt{\sum_{i=1}^{n} (yi - \bar{y})^2 \sum_{i=1}^{n} \left(\hat{yi} - \bar{\hat{y}}\right)^2}} \tag{3}$$

$$\chi^2 = \frac{{}_{i=1}^{n}(\hat{y}_i - yi)^2}{yi} \tag{4}$$

$\bar{y}$ is the mean of measured variable, y_i is the measured variable, $\hat{y}_i$ is the estimated variable, n is the number of trees, and $\bar{\hat{y}}$ is the mean of estimated variable.

Volume and biomass estimations

A. angustifolia tree volumes (v) were estimated considering the equation (5) proposed by Eisfeld et al. (2008), with coefficient of determination (R^2) equal to 0.989 and standard error of estimates (*SEE*) of 8.9%. Aboveground biomass stock (c) was estimated using the equation (6) fitted by Sanquetta et al. (2014), with R^2 of 0.860 and *SEE* of 19.75%. Heights obtained with Vertex IV and remote techniques were applied in these equations aiming to compare the volume and biomass estimates by means of *RMSE* and *bias* statistics.

$$v = 0.039817 + 0.000042\ (d^2\ h) \tag{5}$$

$$log\ (c) = -1.5232 + 2.1400\ log\ (d) + 0.4559 \log\ (h) \tag{6}$$

RESULTS

The UAV point cloud allowed us to identify the *A. angustifolia* trees and visualize their stems (Figure 3a) and canopies (Figure 3b). However, the estimated heights in scenario 2 were different from the field measures and influenced by the low quality of the DTM produced in this scenario. Scenarios 1 and 3 resulted in similar estimated heights to the field measurements in the 100% inventory (Table I).

Figure 3. Estimated height (a) and canopy visualization (b) of *A. angustifolia* tree by means of combined UAV+ALS.

Table I. Descriptive statistics of *A. angustifolia* heights measured by 100% inventory, ALS, UAV, and combined UAV+ALS.

Method	Minimum (m)	Mean (m)	Maximum (m)	Standard deviation (m)
Forest inventory	16.10	19.45	24.00	1.57
ALS	14.54	19.60	24.54	2.15
UAV	4.11	9.93	15.75	2.35
UAV/ALS	17.00	21.53	26.57	2.16

The heights measured in the 100% inventory showed a smaller amplitude between minimum and maximum values than those estimated by remote techniques (Table I). On the other hand, there was a greater standard deviation from UAV estimates, as well as underestimation of mean heights. The ALS and UAV+ALS height distributions were similar to the 100% inventory, while UAV underestimated the heights (Figure 4).

Height estimates by ALS (scenario 1) and UAV+ALS (scenario 3) compared to the 100% inventory resulted a *RMSE* of 1.24 m and 2.49 m, *RMSE%* of 6.38% and 12.82%, respectively, while the *RMSE%* for individual use of UAV (scenario 2) was equal to 49.91% (Table II). In addition, ALS (scenario 1)

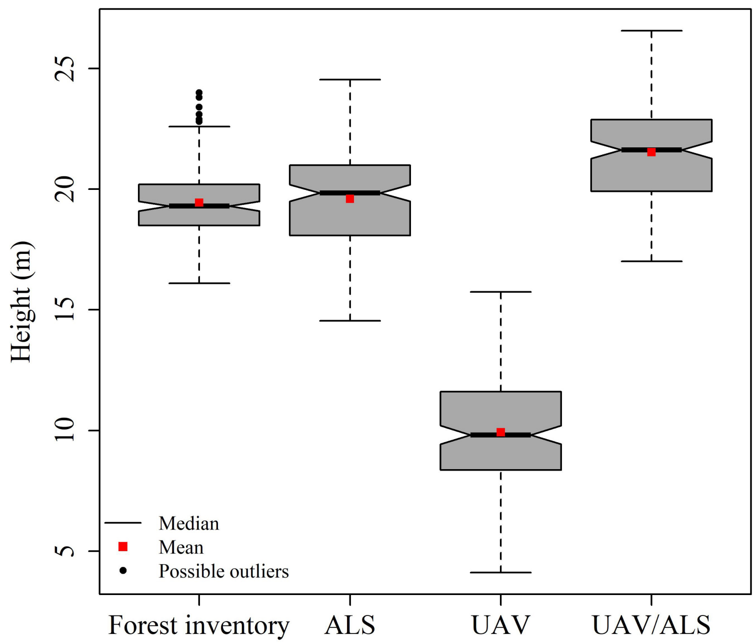

Figure 4. ***A. angustifolia*** **height distributions by forest inventory, ALS, UAV and combined UAV+ALS.**

Table II. ***A. angustifolia*** **height statistics by ALS, UAV and combined UAV+ALS.**

Method	*RMSE* (m)	*RMSE* (%)	*bias* (m)	*bias* (%)	*r*	χ^2
ALS	1.24	6.38	0.16	0.80	0.82	14.35^{ns}
UAV	9.70	49.91	9.52	48.94	0.59	860.33*
UAV/ALS	2.49	12.82	-2.09	-10.73	0.78	56.36^{ns}

* is significance by the Chi-square test at 0.05 of significance level, and ns is non-significance.

underestimated heights (*bias*) by 0.80%. UAV+ALS (scenario 3) overestimated by 10.73%, while UAV underestimated by 48.94%, resulting in a strong correlation (*r*) for ALS and UAV+ALS, but moderate for UAV (Table II).

Heights estimated by scenario 2 resulted in statistically different values from the 100% inventory by the χ^2 at 0.05 of significance level, while the heights from the scenarios 1 and 3 were statistically equal (Table III). Additionally, scenarios 1 and 3 provided more accurate estimates of *A. angustifolia* heights than scenario 2 (Figure 5).

The digital terrain model (DTM) derived from the ALS point cloud showed higher values (Figure 6a) which the DTM from the UAV point cloud did not identify (Figure 6b), such as the drainage area located in the West (magenta color) and terrain elevations in the South (green color). These results influenced the differences between the ALS canopy height model (CHM) (Figure 6c), UAV CHM (Figure 6d) and the UAV+ALS CHM (Figure 6e). The ALS CHM and UAV CHM showed gaps due to the low density of the Lidar point cloud, as well the inability of the UAV DTM to identify the soil correctly.

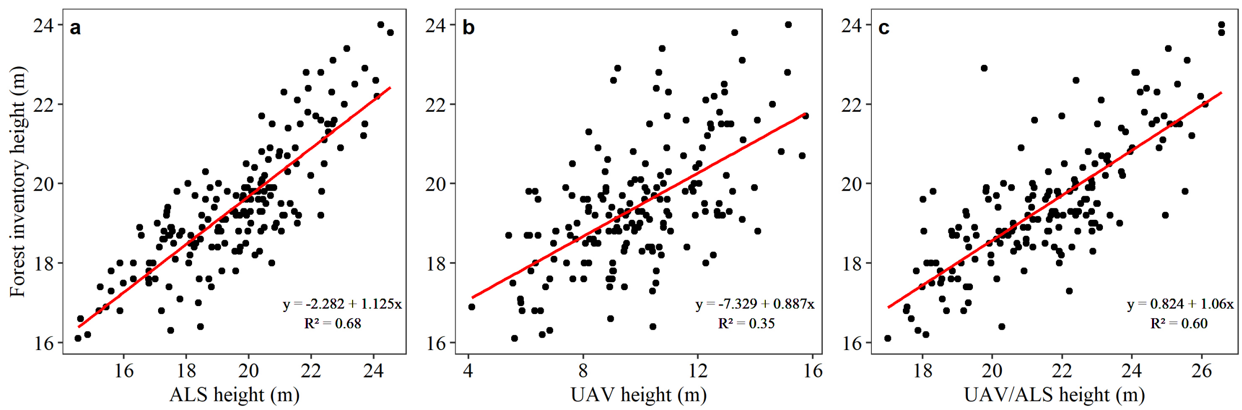

Figure 5. ***A. angustifolia*** **forest inventory heights by ALS (a), UAV (b) and combined UAV+ALS (c) height estimates.**

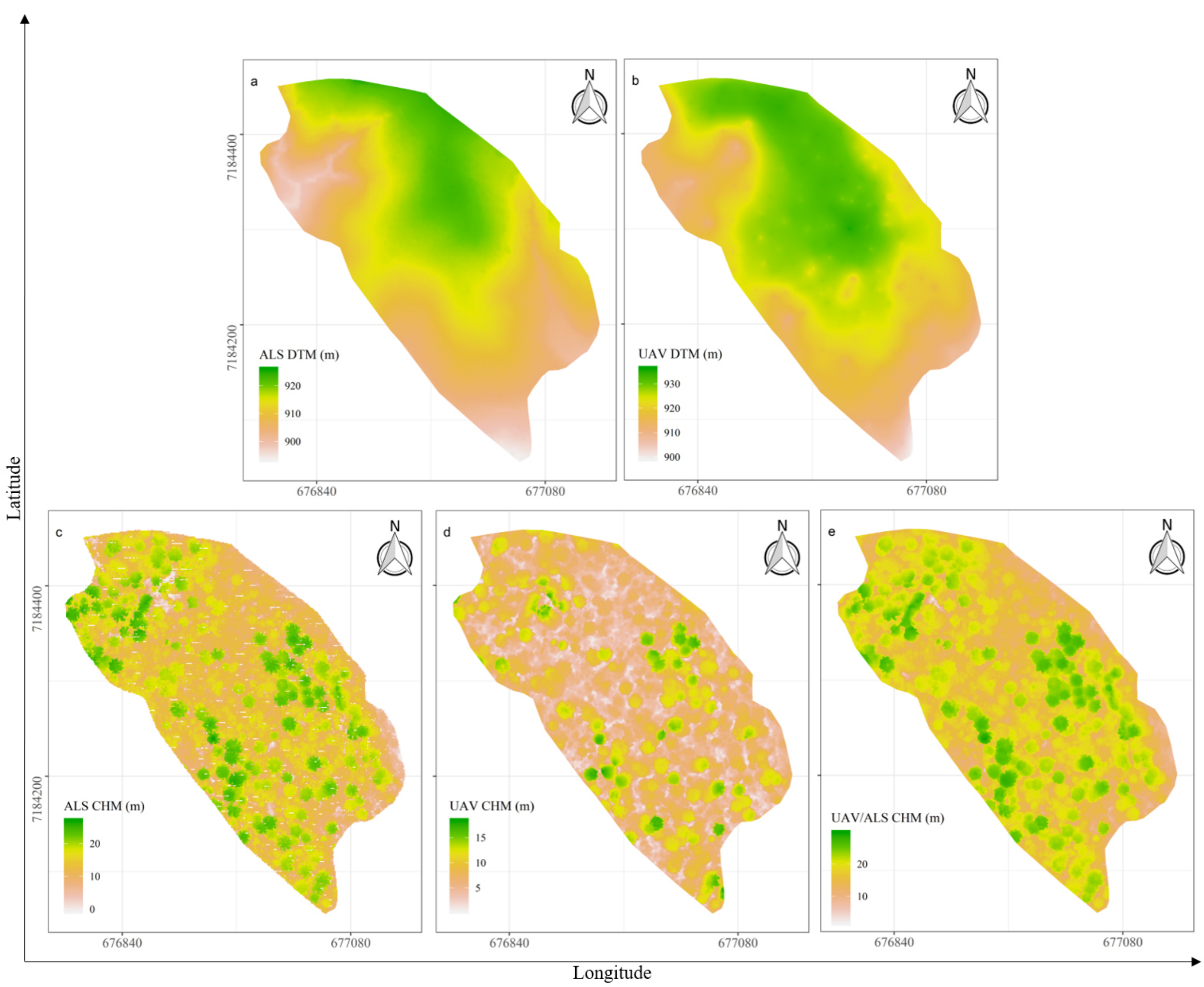

Figure 6. **Digital Terrain Model (DTM) and Canopy Height Model (CHM) by ALS, UAV and combined UAV+ALS.**

Heights estimated by ALS and combined UAV+ALS did not have an expressive negative impact on the volume estimates, nor on the aboveground biomass stock of *A. angustifolia*. ALS resulted in *RMSE* of 0.22 m³ for volume and 25.24 kg for aboveground biomass stock, while the UAV showed 1.73 m³ and 239.70 kg. In addition, the UAV+ALS showed a *RMSE* of 0.49 m³ for volume and 54.23 kg for biomass (Table III). However, ALS and UAV+ALS overestimated volume by 1.28 and 10.87% (*bias*), while UAV underestimated volume by 46.82%. Furthermore, the ALS and UAV+ALS overestimated biomass stock by 0.54 and 4.83%, while UAV underestimated it by 25.75% (Table III). Scenarios 1 (Figures 7a and 7d) and 3 (Figures 7c and 7f) presented more accurate total heights than scenario 2 (Figures 7b and 7e). Consequently, scenarios 1 and 3 better represented the volume and aboveground biomass realities.

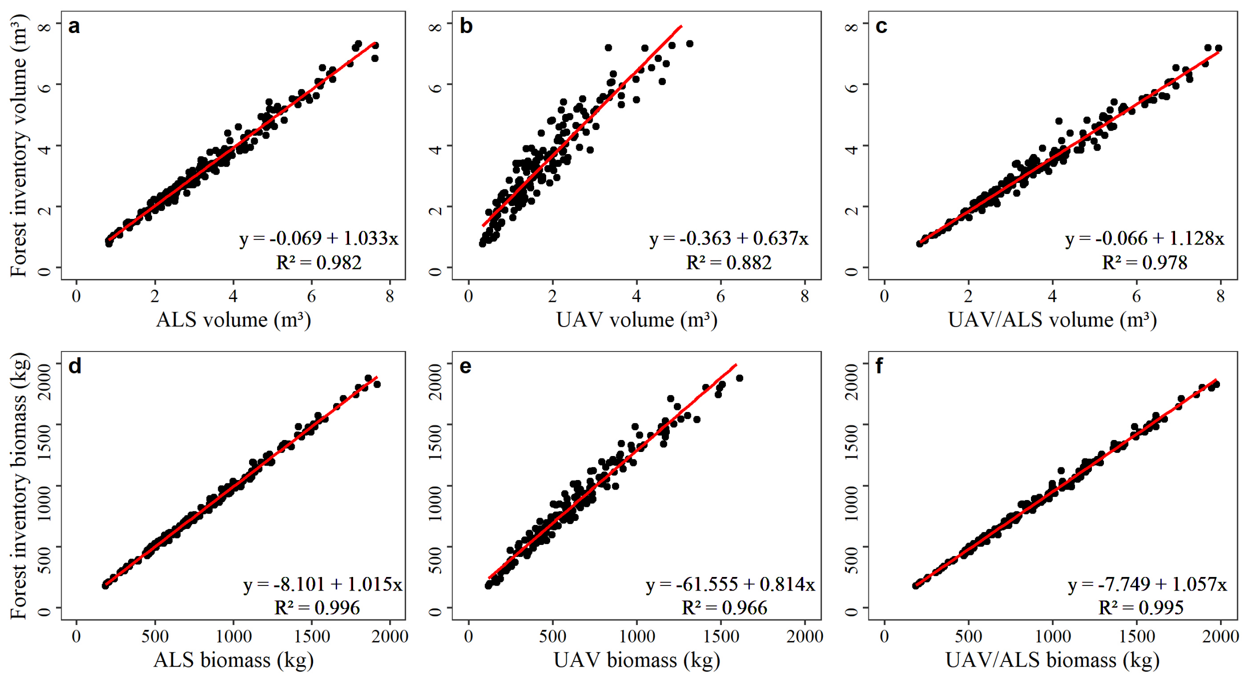

Figure 7. Relationship between *A. angustifolia* volume and aboveground biomass stock estimated by ALS, UAV and combined UAV+ALS.

Values estimated by the individual use of UAV showed greater dispersion, since the volume and aboveground biomass stock behaviors were not correctly characterized by the heights estimated by scenario 3 (Figures 7b and 7e).

DISCUSSION

Scenario 2 (UAV) in this study was not accurate to estimate tree height (Table II), which is contrary to the conclusions from Zarco-Tejada et al. (2014) and Birdal et al. (2017). This result is related to the lower forest structure complexity assessed by these authors with tree heights between 1.16 m and 4.38 m and 1.20 m to 7.10 m, respectively. On the other hand, trees in the present study showed heights between 16.10 m and 24 m (Table I), which makes it difficult to measure this variable.

The largest standard deviation (Table I) and inaccurate height estimates by UAV (Table II) are due to the equipment's low altimeter accuracy because of its infrared sensors and GPS module.

Table III. Statistics of *A. angustifolia* volume and aboveground biomass estimated by 100% inventory, ALS, UAV, and combined UAV+ALS.

Method	Minimum	Mean	Maximum	Standard deviation	Total (hectare)	*RMSE*	*RMSE* (%)	*bias*	*bias* (%)
Volume (m^3)									
Forest inventory	0.77	3.44	7.33	1.48	80.96				
ALS	0.82	3.48	7.62	1.54	82.00	0.22	6.30	-0.04	-1.28
UAV	0.33	1.83	5.26	1.01	43.05	1.73	50.36	1.61	46.82
UAV/ALS	0.83	3.81	8.63	1.69	89.76	0.49	14.15	-0.37	-10.87
Aboveground biomass stock (kg)									
Forest inventory	178.40	861.95	1877.90	377.90	20314.93				
ALS	183.49	866.62	1919.06	384.26	20424.96	25.24	2.93	-4.67	-0.54
UAV	115.94	639.96	1612.72	312.84	15082.90	239.70	27.81	221.99	25.75
UAV/ALS	184.77	903.62	2002.49	400.50	21297.02	54.23	6.29	-41.67	-4.83

On the other hand, aeronautical navigation of ALS (Scenario 1) data is an accurate and efficient equipment, since the radiogoniometry is used in its georeferencing system. This method uses radio waves employing radiological signals between two stations as in RTK systems, which allows high sensor altimeter accuracy and accurate tree height measurements.

The height results show a difference between the scenarios (Tables I and II and Figures 4 and 5), which is mainly evidenced in the Digital Terrain Model (Figure 6), which in turn affected the height estimates by scenario 2 (UAV). On the other hand, although the ALS DTM is influenced by vegetation structures, it collects ground information (Simpson et al. 2017, Cunha Neto et al. 2021). Therefore, only an accurate DTM can provide reliable forest information and enable using remote sensing techniques in forest inventory, in which at least one ALS flight is necessary to design a DTM (Ota et al. 2015, Cunha Neto et al. 2021).

The correlation of height values between UAV+ALS and 100% inventory (Table II) indicates the accuracy obtained by combining these sensors. Ota et al. (2015) and Jayathunga et al. (2018) also obtained a higher correlation between heights measured in the field and UAV+ALS (scenario 3) than UAV (scenario 2). On the other hand, the correlation between height values by UAV and 100% inventory often resulted in values below 0.50 (Wallace et al. 2014, Zarco-tejada et al. 2014, Dempewolf et al. 2017).

Combined UAV+ALS has achieved positive results in other studies with *RMSE* of 16.7% for volume and 18.9% for biomass stock in a Mixed Conifer–Broadleaf Forest (Jayathunga et al. 2018). Persson et al. (2013) found an *RMSE* of 22.4% for biomass and 12.9% for tree height in forest stands. Ota et al. (2015) obtained *RMSE* of 9.68% for Seasonal Tropical Forest biomass. Such studies emphasize the accuracy of the results, since UAV+ALS obtained *RMSE* of 12.82%, 14.15% and 6.29% for height, volume and aboveground biomass stock, respectively.

Furthermore, these results may be more accurate in denser UAV point clouds and larger overlaps (cross-flight), such as those found by Guerra-Hernández et al. (2018) with a UAV point cloud of 96.63 points m^{-2} and a *RMSE* equal to 9.79% for height measurement. In a similar condition to this study, Larjavaara & Muller-Landau (2013) obtained an *RMSE* of 13.4% for height with a laser clinometer in a tropical forest, while UAV+ALS provides an *RMSE* of 12.8%, thus allowing more accurate estimates with reduced employees and field time.

Scenario 2 (ALS) obtained a higher correlation and lower RMSE in comparison to the other scenarios (Table II). However, due to the high data acquisition cost and the difficulty of periodic monitoring with ALS sensor, the combination of ALS (first moment) and UAV (subsequent moments) in scenario 3 can be an effective and less expensive alternative. Thus, only one Lidar flight makes it possible to obtain a digital terrain model, while other data collections can be carried out with UAV (cheaper technology) for forest characterization.

In Atlantic Rain Forest where harvesting trees is forbidden by law, we believe that forest inventories in the future will only collect the tree diameters, while the tree heights will be collected by remote sensors, thus the volume and carbon stock will be determined by allometric equations (Table III and Figure 7).

CONCLUSIONS

Scenario 3 (UAV+ALS) provided accurate (r = 0.78) estimates of *A. angustifolia* heights, enabling statistically accurate estimates of volume and aboveground biomass stock in the Atlantic Rain Forest. Therefore, since the ALS is currently used, periodic monitoring can be carried out with an active (ALS) and passive (UAV) sensor combination for forest characterization.

Acknowledgments

The authors are grateful to the Conselho Nacional de Desenvolvimento Científico e Tecnológico - CNPq, Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - CAPES, and graduate Program in Forest Engineering of the Federal University of Paraná (UFPR) for providing the resources for this study. This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brazil (CAPES) - Finance Code 001 (A. Corte # 88887.373249/2019-00).

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How to cite

CUNHA NETO EM, VERAS HFP, MOURA MM, BERTI AL, SANQUETTA CR, PELISSARI AL & CORTE APD. 2023. Combining ALS and UAV to derive the height of *Araucaria angustifolia* in the Brazilian Atlantic Rain Forest. An Acad Bras Cienc 95: e20201503. DOI 10.1590/0001-3765202320201503.

Manuscript received on September 18, 2020;
accepted for publication on April 17, 2022

ERNANDES M. DA CUNHA NETO[1]
https://orcid.org/0000-0001-6775-0365

HUDSON F.P. VERAS[1]
https://orcid.org/0000-0002-0203-1914

MARKS M. MOURA[1]
https://orcid.org/0000-0002-2964-8527

ANDRÉ L. BERTI[2]
https://orcid.org/0000-0003-4086-1529

CARLOS R. SANQUETTA[1]
https://orcid.org/0000-0001-6277-6371

ALLAN L. PELISSARI[1]
https://orcid.org/0000-0002-0915-0238

ANA PAULA D. CORTE[1]
https://orcid.org/0000-0001-8529-5554

[1]Departamento de Engenharia Florestal, Universidade Federal do Paraná, Av. Prefeito Lothário Meissner, 632, Jardim Botânico, 80210-170 Curitiba, PR,, Brazil
[2]Departamento de Engenharia Florestal, Universidade Federal Tecnológica do Paraná, Estr. p/ Boa Esperança, km 04 - Zona Rural, 85660-000 Dois Vizinhos, PR, Brazil

Correspondence to: **Ernandes M. da Cunha Neto**

E-mail: netomacedo878@gmail.com

Author contributions

EMCN.: forest inventory, conceptualization, formal analysis, investigation, methodology, software; writing-original draft; HFPV.: data curation, formal analysis, investigation, methodology, software; writing-original draft; MMM.: investigation, methodology, software; writing-original draft; ALB.: forest inventory; CRS., ALP, APDC.: conceptualization, investigation, methodology, supervision, writing-review and editing.