Improving Aboveground Biomass Estimates with 3D Tree Crown Parameters from UAV-LS in Beech Forests

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Abstract

Accurate estimates of aboveground biomass (AGB) are essential for forest policies to reduce carbon emissions. Unmanned aerial laser scanning (UAV-LS) offers unprecedented millimetric detail but is underutilized in monitoring broadleaf Mediterranean forests compared to coniferous ones. This study aims to design and evaluate a procedure for AGB estimates based on the predictive power of crown features. In a first phase, we manually defined Quantitative Structure Models (QSMs) for 320 trees using UAV-LS, ALS, and co-registered terrestrial laser scanning (TLS) data, providing the best non-destructive AGB reference in the absence of destructive measurements. For each reference tree we also measured crown projection and crown volume to build two separated models relating AGB to such crown features. In a second phase we evaluated the potential of UAV-LS for quantifying AGB in a pure European beech (Fagus sylvatica) forest and compared it with traditional ALS estimates, using full automatic procedures. The two obtained tree-level AGB models were then tested using three datasets derived from 35 sampling plots over the same study area: (a) 1130 trees manually segmented (phase-2 reference); (b) trees automatically extracted from ALS data; and (c) trees automatically extracted from UAV-LS data. Results demonstrate that detailed UAV-LS data improve model sensitivity compared to ALS data (RMSE = 45.6 Mg ha^{-1}, RMSE% = 13.4%, R^2 = 0.65, for the best ALS model; RMSE = 44.0 Mg ha^{-1}, RMSE% = 12.9%, R^2 = 0.67, for the best UAV-LS model), allowing for the detection of AGB differences even in quite homogenous forest structures. Overall, this study demonstrates that combining different laser scanner data can foster non-destructive AGB estimation in forested areas across hectare scales (1 to 100 ha).

Keywords: Biomass, LiDAR, Tree allometric scaling rules, Temperate forests, Forest mensuration

1. Introduction

Forests are fundamental natural carbon sinks, actively contributing to mitigating climate change (Verkerk et al. 2019). In recent decades, the demand for accurate methods to estimate aboveground biomass (AGB) in forest ecosystems has grown due to its crucial role in the carbon cycle and in assessing forest health status, habitat quality, forest disturbance and restoration (Heinrich et al. 2021). Carbon stock estimates in forest ecosystems are strictly linked to AGB, which varies with eco-physiological, environmental, and management stand-based factors.

General scaling rules for metabolic and structural plant allometry, such as the theory of Euclidean geometric scaling or metabolic scaling theory (MST (Owen, Flynn, and Lines 2021)), provide valuable insights into biomass patterns at broad scales. However, these theories assume a constant tree crown-volume relation for all the trees of a given species, even though the variability in crown structure, rather than constancy, is crucial for a tree's success in crowded conditions (Pretzsch and Dieler 2012). Therefore, developing models tailored to specific local conditions is essential for managers and practitioners to address site-specific management challenges and achieve their objectives (Ploton et al. 2020; Xu et al. 2021).

One of the major limitations affecting local allometric model accuracy is the reduced number of calibration samples, which typically require destructive harvesting. This process can be costly when used through traditional tools like chainsaws, callipers, and measuring tape, and it often prevents large trees from being harvested (Calders et al. 2022). In addition, during the felling phase, the tree crown is subjected to breakages, leading to inaccurate measurements.

Terrestrial Laser Scanning (TLS) is widely recognized as one of the most accurate and non-destructive methods for estimating individual tree AGB (Brede et al. 2019; Calders et al. 2015, 2022; N. Puletti et al. 2020; Pretzsch 2021). However, its application across large areas faces considerable logistical challenges. TLS campaigns are time-intensive, requiring up to 3–7 days per hectare (Brede et al. 2022), and demand substantial manual effort for individual tree segmentation, particularly in dense and complex forest canopies. These constraints significantly limit its feasibility for calibrating and validating AGB models over broad and heterogeneous landscapes.

Generating wall-to-wall AGB maps requires the integration of field-surveyed data with metrics obtained from Laser Scanning devices, such as Airborne Laser Scanning (ALS) (Brosofske et al. 2014; G. Shao et al. 2018). Although ALS data have been extensively tested in forest ecosystems and are today an integral part of many national-scale environmental monitoring programs (Chirici et al. 2020), challenges remain in their application for AGB assessment. In particular, estimating AGB for deciduous trees is more difficult than for conifers, likely due to differences in growth patterns (Næsset 2004). For example, Beech (*Fagus sylvatica* L.) trees, which have deliquescent tree forms, allocate a great amount of biomass into lateral branches, introducing noise into the relationship between height and volume/biomass. Recent studies have demonstrated that ALS data can be profitably used in such stands when forest structure and species mixture have great variability, particularly if specific variables like site productivity are included (G. Shao et al. 2018). Without such ancillary data, ALS models for pure deciduous forests remain inaccurate (J. Shao et al. 2022; G. Shao, Fei, and Shao 2023; Cao et al. 2023). Despite the widespread use of ALS for AGB estimation, its application in deciduous forests, such as pure beech stands, remains challenging due to the unique structural variability of these forests, characterized by deliquescent branching and lateral biomass allocation.

The recent miniaturisation of LiDAR instruments (Z. Wang and Menenti 2021) has paved the way to integrate more detailed data above the canopy (Brede et al. 2019). Laser scanners mounted on Unmanned Aerial Vehicles (UAV-LS) offer a promising solution to enhance the quality of ALS-based statistical allometric models in temperate and boreal forests (Nicola Puletti, Innocenti, and Guasti 2024), particularly in pure-broadleaved forests (Brede et al. 2019; N. Puletti et al. 2020; J. Shao et al. 2022, Table–A1). UAV-LS offers several advantages over traditional ALS systems (Torresan et al. 2017; Alvites et al. 2022). First, it provides a much higher point density (>1000 points m^{-2}), enabling detailed crown reconstruction. Second, UAV-LS is highly flexible, with faster flight planning (10-20 ha $hour^{-1}$) and lower costs, making it suitable for covering large forest areas efficiently.

To address these limitations, this study evaluates how detailed crown metrics derived from UAV-LS can improve the accuracy of AGB estimates in pure beech forests, leveraging precise crown feature measurements and automated individual tree segmentation (ITS). This study aims to assess the potential of UAV-LS in improving AGB estimates in pure beech forests by leveraging precise crown feature measurements. The analysis combines TLS reference data, manually extracted crown metrics, and an automated ITS algorithm to evaluate UAV-LS's effectiveness compared to ALS-based methods. The experiment was conducted in managed pure beech forests characterized by homogeneous, dense canopy cover and minimal differences in vertical structure, but a wide range of three diameters (i.e., diameter at breast height, dbh, ranging from 4 to 85 cm). TLS data were used as input reference data for variables like tree position, dbh, and tree volume derived from quantitative structure models (QSMs, Georgi et al. 2018). In the first phase, UAV-LS data were manually processed to obtain a precise measure of crown features and tree volume for over 300 trees used as reference. Then, AGB was derived as the product of tree volume, Biomass Expansion Factor (BEF), and Wood Basal Density (WBD). Based on this, an *AGB~crown* model was developed. In the second phase, the *AGB~crown* model was applied using crown features derived from an automatic ITS algorithm as predictor. Finally, plot-level products obtained by ALS and UAV-LS point clouds were compared with reference data to assess their performance.

2. Material and methods

2.1. Study area and data collection

This study was conducted in Alpe di Catenaia, Italy (Figure 1). Terrestrial (TLS) and UAV LiDAR (UAV-LS) data were collected in October-December 2023 across 12 circular sampling plots (15 m radius) in pure beech forest stands with similar climate conditions, soil types, forest structure, and management history (Nicola Puletti, Innocenti, and Guasti 2024).

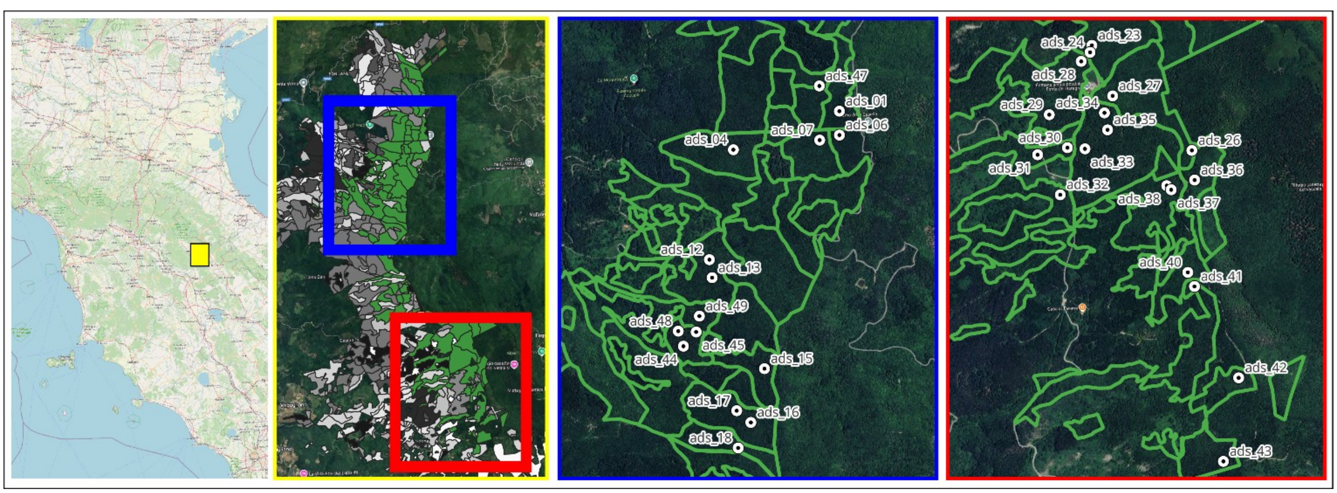

Figure 1: Study area and sampling sites location.

TLS-inventory measurements were conducted by GeoSLAM ZEB-REVO (GeoSLAM Ltd., Ruddington, England) lightweight mobile laser scanner. It features a rotating 2D scanning device and an inertial measurement unit in the handle body. The system acquires 3D information of the surrounding area using the motion provided by the scanning head on the motor drive, enabling the application of 3D simultaneous location and mapping algorithms (N. Puletti et al. 2020). This TLS requires the starting and ending points of the scan process to coincide with some overlaps during the scan path. The centre of each plot was georeferenced using an RTK GPS. Using TLS data, 320 sampling trees were measured following the procedure described in Section 2.2. Forest stand characteristics are summarized in Table 1.

Table 1: Stand characteristics based on trees manually isolated in the Terrestrial Laser Scanning (TLS) point cloud. Volume was derived from Quantitative Structure Models (QSMs).

	min	mean (st.dev.)	max
N ha^{-1}	141.5	443.4 (239.1)	1174.2
dbh (cm)	4.0	34.9 (6.6)	85.0
TH (m)	2.9	14.1 (4.0)	26.4
tree volume (m^3)	152.4	282.1 (90.7)	474.8

Airborne LiDar data were acquired over a 42 km^2 area surrounding the surveyed plots using a Riegl Q680i discrete-return sensor mounted on a Partenavia/Vulcanair P68-Victor aeroplane. The flight, performed on July 15, 2021 at an altitude of 915 m above the ground, used a 400-kHz pulse repetition rate, resulting in an average density of 25 pulses per m^2. LiDAR points were first classified into ground and non-ground (vegetation) using the lidR package (Roussel et al. 2020). A 1-m resolution digital terrain model raster layer was obtained by interpolating ground points to normalize the point cloud.

We simultaneously collected UAV-LS data and field measurements over the sampling plots. The UAV-LS LiDAR platform consisted of a DJI Matrice 350 quadcopter integrated with a Zenmuse L1 LiDAR sensor (DJI Inc. in Shenzhen, China), an advanced scanning sensor designed for aerial surveying applications. It integrates a LiDAR module, an RGB camera with a non-full-frame configuration, and an inertial measurement unit (IMU). With a detection range of 450 m under 80% reflectivity conditions, a high point rate of up to 240,000 points per second and ranging accuracy of 3 cm at a range of 100 m (Diara and Roggero 2022; Štroner, Urban, and Línková 2021), the system provides high-quality data. Flights were conducted approximately 55 m above the digital terrain model uploaded to the UAV-LS at a speed of approximately 13 h^{-1}, resulting in a mean point cloud density of more than 1500 points m^{-2}. Data processing was carried out in Terra® which allowed the import and the alignment of drone flight trajectory data. From Terra® the complete point cloud was exported in LAS format.

TLS, UAV-LS, and ALS data were aligned by assigning RTK GPS positions to TLS data and using Cloud Compare software (GPL software 2021; Nicola Puletti et al. 2024). The aligned three-point cloud data (TLS, UAV-LS, ALS) collected over the 12 sampling plots were clipped to the corresponding 15 m radius circles, producing a separate point cloud for each sampling plot.

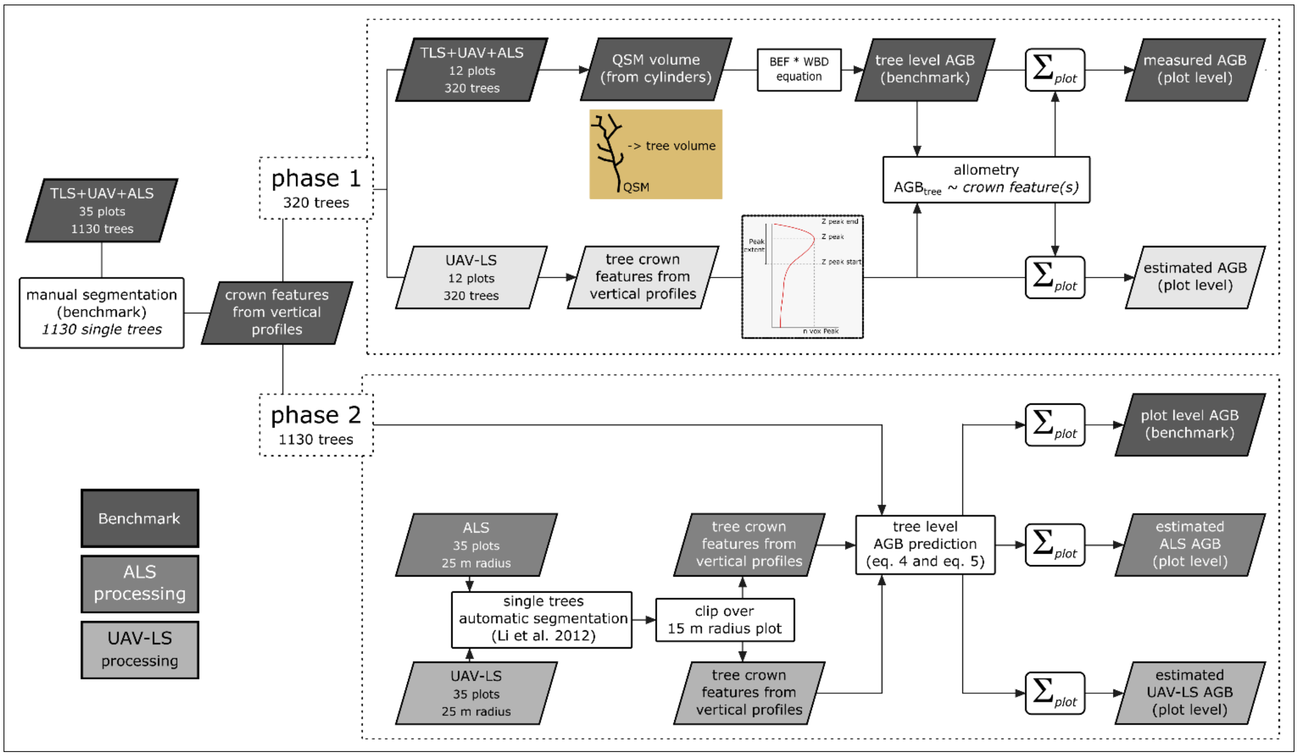

Figure 2: Processing workflow. In the first phase (upper panel) 12 sampling plots among 35 measured were processed. QSMs for more than 300 trees were obtained from manual segmentation. Vertical Profiles Features (VPFs) were derived from voxelised point clouds of each sampled tree. The outputs of this first phase are: (i) plot level AGB, used as reference for phase 2, and (ii) AGB~VPFs model. In the second phase (right panel), two fully automatic procedures were compared using UAV-LS and ALS data from all 35 sampling plots measured over the study area. Single trees were automatically identified and segmented using a well-established approach. AGB was estimated using the AGB~VPFs model created in phase 1. Finally, the estimated values of different procedures were compared for evaluation.

2.2. Benchmark: single tree QSM to quantify volume and AGB

The workflow combines both manual and automatic steps. In the first phase (see Figure 2), Trimble Real Works software (TRW) was used for tree segmentation and QSM production. Each segmented tree was then reconstructed through a semi-automatic cylinder-fitting procedure, resembling the traditional approach based on Smalian method for stem volume estimates, using virtual cylinders of about 1 m in length. The total tree volume (V_{tree}, in m^3) was computed by summing all the cylinders and then converted to biomass using Equation 1:

$$AGB_{tree} = V_{tree} \cdot BEF \cdot WBD \quad (1)$$

where BEF is the Biomass Expansion Factor, used to expand growing stock volume to the aboveground woody biomass volume, and WBD is the Wood Basal Density, used to convert fresh volume to dry weight (Mg m^{-3}). For beech trees in central Italy BEF_{Beech} = 1.36 and WBD_{Beech} = 0.61 (Marino et al. 2021, Table A2).

For each tree, different architectural traits were also measured: (1) total tree height (TH); (2) the surface of the crown at its maximum extension, considered as the crown projection (*CrPrj*); (3) and the crown volume (*CrVol*). A set of algorithms was developed using functions from lidR package (Roussel et al. 2020) to characterize crown features from the xyz-data of each focal tree and its neighbors. First, the original point cloud of each tree was voxelised at a resolution of 25 cm, for a balance between achieving suitable results and minimising computation time. To avoid residual noise in the original point cloud, only voxels containing at least three points were classified as "vegetation" and used to compute single-tree vertical profiles. From the smoothed curve (red-line in Figure 2), the height of the maximum crown projection (Z-peak, in meters), crown base height (Z-peak-start, in meters) and total tree height (Z-peak-end, in meters) were derived. Crown volume (*CrVol*) was computed as the sum of all vegetation voxels between Z-peak-start and Z-peak-end, while crown projected area (*CrPrj*) was determined using a 2D convex hull at the maximum crown projection. All these features were identified by analysing the single-tree vertical profile with the findpeaks function from the pracma R-package.

2.3. AGB allometric modelling approach

Following a strengthened procedure (He et al. 2018), the general biomass equation for each tree is defined as:

$$Y = \alpha X^{\beta} \quad (2)$$

where *Y* represents AGB and *X* is a correlated tree attribute, typically the dbh. In this study, *X* corresponds to one of the considered crown features (i.e. crown projection or crown volume). To address the heteroscedasticity often present in nonlinear regressions with original scales of measurements (Packard, Birchard, and Boardman 2010), the Equation 2 was log transformed:

$$\ln(Y) = \alpha_1 + \beta_1 \ln(X) \quad (3)$$

AGB of an individual tree was modeled as a function of both crown projected area (*CrPrj*) and crown volume (*CrVol*) of the tree, expressed as:

$$\ln(AGB_{CrPrj}) = \alpha_{CrPrj} + \beta_{CrPrj} \ln(CrPrj) \quad (4)$$

$$\ln(AGB_{CrVol}) = \alpha_{CrVol} + \beta_{CrVol} \ln(CrVol) \quad (5)$$

The log-transformation, however, introduced a systematic bias, tipically corrected using the following correction factor (CF):

$$CF = \exp(SEE^2/2) \quad (6)$$

where CF is the correction factor, and SEE is the standard error of the estimate, calculated as follows:

$$SEE = \sqrt{\sum_{i=1}^{n} \left(\ln(Y_i) - \ln(\hat{Y}_i)\right)^2 / (n-2)} \quad (7)$$

The final equation for estimating AGB is:

$$AGB = e^{\alpha} X^{\beta} CF \quad (8)$$

where X is either crown projection or crown volume.

2.4. Automatic ITS from ALS and UAV-LS point clouds

After the first phase focused on the calibration of AGB modelling using manually measured trees, the second phase tested the performance of automatic algorithms for Individual Tree Segmentation (ITS) in structurally homogeneous broadleaf temperate forests. Cao et al. (2023) recently reviewed ITS methods for broadleaf tropical forests - with a heterogeneous forest structure, from which Li et al. (2012) method was selected for this study. This rule-based ITS algorithm, integrated into the lidR processing packages (Roussel et al. 2020) offers a low cost-benefit ratio in the forest stands measured. Moreover, rather than relying on raster CHM, which limits detection to dominant trees, Li et al. (2012) analyses point cloud structures and has shown a detection accuracy rate of up to 90% in mixed forests. The same workflow was applied to both UAV-LS and ALS data for comparison (Figure 2). To avoid time-consuming procedures, specific and fixed parameters were established in the ITS algorithm.

2.5. Statistical analysis

In the first phase (Figure 2), the two previously presented models (Equation 4 and Equation 5) were evaluated using data from 320 manually segmented beech trees, from the 12 sampling plots (Figure FS1). AIC was used as a validation technique to assess model performance with new data. Finally, to evaluate the accuracy of AGB estimates at the plot level, observed and modelled results from the same 12 sampling plots were compared. Model assessment metrics included R^2 and *RMSE* computed using Equation 9 as follows:

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}\left[\ln\left(Y_i\right)-\ln\left(\widehat{Y}_i\right)\right]^2}{n}} \quad (9)$$

The second phase (Figure 2) evaluated the performance of the selected ITS algorithm (Li et al. 2012) for individual tree identification and crown feature extraction aimed at AGB estimation, using ALS or UAV-LS data separately. Tree mapping evaluation was also conducted using completeness and correctness (Laino et al. 2024). Finally, the performance of the proposed models was assessed using data extrapolated from the fully automated ITC and crown featuring methods.

3. Results

3.1. Phase 1: Crown features

The process of crown feature extraction (projection and volume) was effective over the 320 manually segmented reference trees. The beta coefficient ($\beta_{CrVol}=0.78$) obtained from the best model (Equation 5) representing the metabolic scaling coefficient aligns closely with the theoretical value equal to 0.75. The 12 sampling plots show significant variability in the crown sizes of the trees. The average crown area is 15.4 m^2 (min = 0.2, max = 75.7) with a standard deviation of 13.5 m2, while crown volume has an average of 39.9 m^3 (min = 1.8, max = 194.2) with a standard deviation of 36.4 (Figure FS2). Pearson correlation coefficients (*r*) between crown features and traditional tree attributes, such as dbh and total tree height, are consistently below 0.45. However, correlations increase significantly to 0.88 and 0.90 when comparing tree volume with crown projection and crown volume, respectively.

3.2. Phase 1: AGB model assessment

The AIC used for tree-level model assessment indicates that the model from Equation 5 (AIC=364.4) performs slightly better than that from Equation 4 (AIC=397.9). Although a lower AIC (92.3) is achievable using both *CrPrj* and *CrVol*, the model with *CrVol* as the sole predictor was preferred for simplicity. Using *CrVol* as the predictor (Equation 5) we obtained the best result (R^2 = 0.74, RMSE = 0.41, RMSE% = 2.9 %, Figure 3).

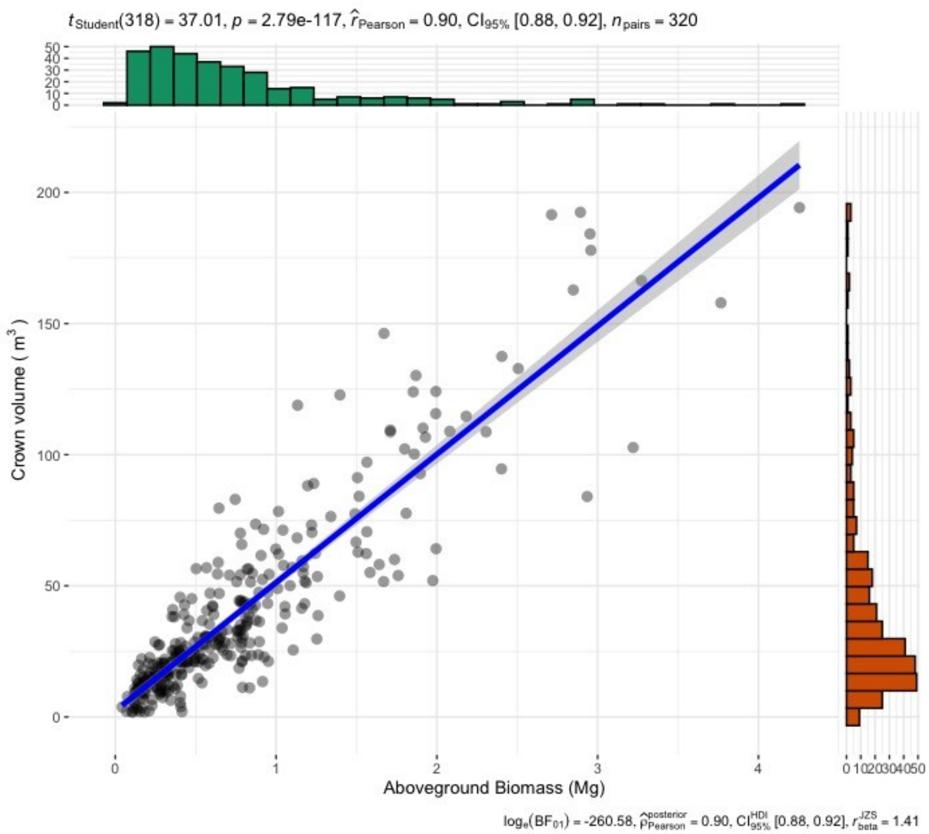

Figure 3: Scatterplot and relations between crown volume and aboveground biomass of the 320 sampled trees.

3.3. Phase 2: individual tree detection

Figure 4 (together with Table TS1 and Figure FS3, see supplementary materials) displays results for both ALS and UAV-LS individual tree detection. Under the given conditions, ALS proved to be less effective, consistently performing worse than UAV-LS. ALS fails to detect many trees in several cases (3 out of 35 plots). On the other hand, UAV-LS tends to overestimate tree numbers in less dense forests and underestimate in denser forest conditions (Figure 4). The indices used for ITD assessment (completeness and correctness) exhibit similar patterns, with UAV-LS also showing better performances (Figure 5).

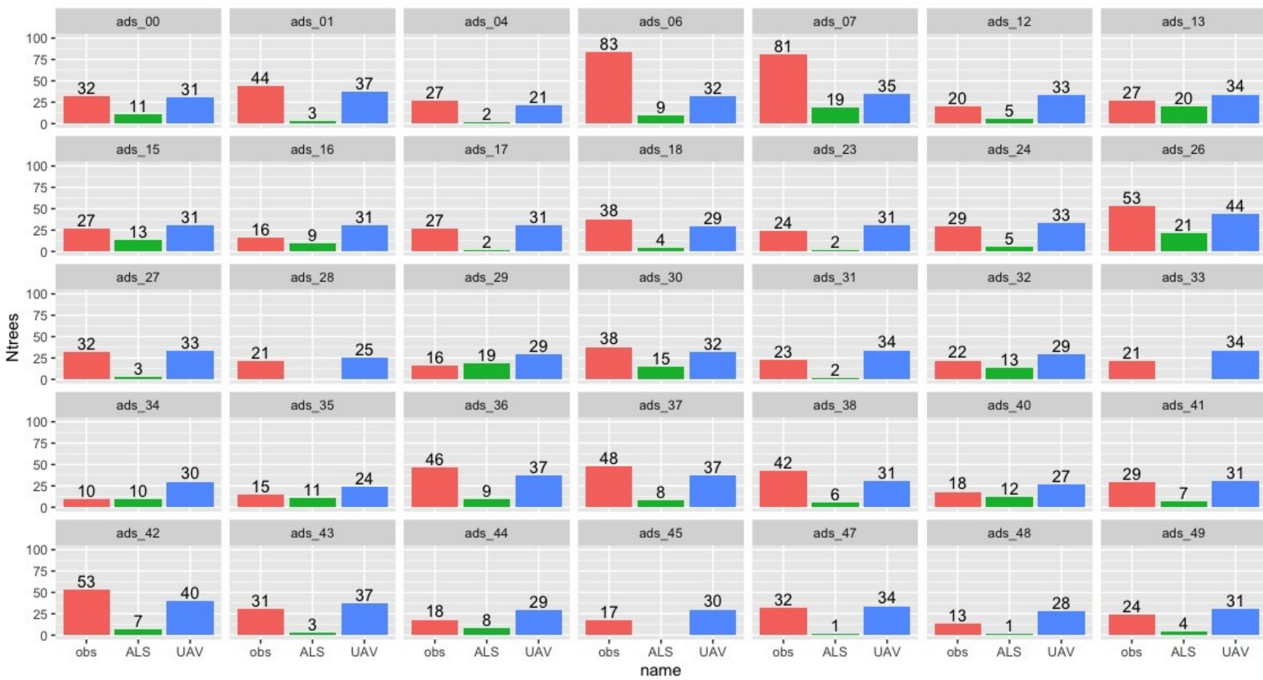

Figure 4: Number of trees observed over 35 plots and estimated using both ALS and UAV point clouds by automatic segmentation.

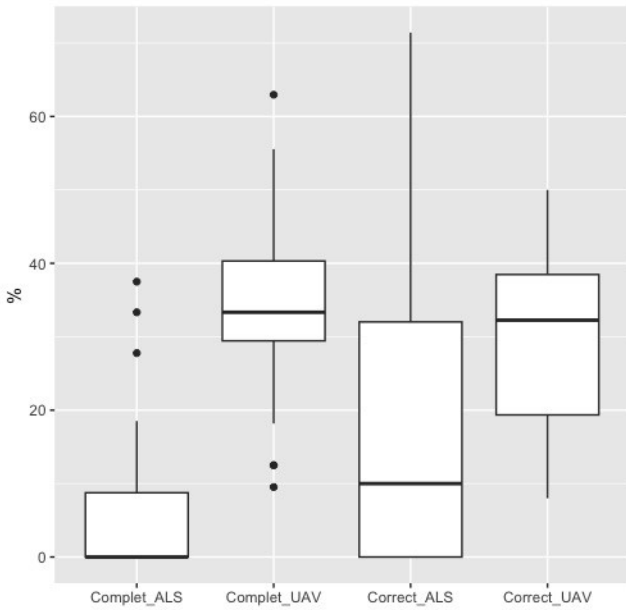

Figure 5: Distributions of completeness and correctness over 35 plots from both ALS and UAV data.

Phase 2: AGB estimates from ALS and UAV-LS

Figure 1 shows the results of the fully automatic procedure in estimating AGB under the given conditions. Using the crown surface area and the model from phase 1 (Equation 4), UAV-LS consistently overestimates AGB with a relatively constant coefficient. On the other hand, ALS always underestimates AGB without any clear pattern. When applying the model from Equation 5, ALS results remain less accurate, while UAV-LS data produced more reliable results Figure 1.

4. Discussion

This study demonstrates that tree architectural traits (Dorji et al. 2019) influence the accuracy of AGB estimates from ALS and UAV-LS, regardless of forest mixture or structure, as previously noted in ground-based studies (Penanhoat et al. 2024; Pretzsch 2021).

Despite the homogeneous nature of the beech forests studied, there was significant variability in the crown sizes of the trees we examined, with standard deviations of 13.5 m^2 for crown area and 36.4 m^3 for crown volume. Reference tree crown dimensions from TLS and UAV-LS are manually defined in CloudCompare, ensuring a realistic representation of 320 standing trees for TLS and 1000 for UAV-LS systems (Barbeito et al. 2017). These segmented trees were modelled using MST allometries (Li et al. 2012; Pretzsch and Dieler 2012).

When UAV-LS was analysed using the ITS algorithm developed by Li et al. (2012) dominated trees were barely detected, achieving only moderate correctness and completeness (~30% for UAV-LS compared to <10% for ALS).). For correctly segmented trees, crown height variability is captured by analysing the 3D vertical uniformity distribution (thresholds at the 75th and 95th percentiles) (Nicola Puletti et al. 2024). However, the phenotypic plasticity and deliquescent architecture of beech trees affected the crown-boundary delineation of standing trees in ALS and UAV-LS point clouds, impacting the AGB estimation accuracy, as noted in previous studies (Y. Wang et al. 2016). Secondary factors affecting detection include forest stand characteristics (i.e., tree density: maximum 1,174 trees ha^{-1}) and competition (Barbeito et al. 2017; Nicola Puletti et al. 2024); individual tree architecture (i.e., deliquescent architecture and plasticity in growth forms) (Pretzsch 2021), and technical aspects such as point cloud occlusion (Alvites et al. 2021; Bruggisser et al. 2019). Following previous classifications (Liang et al. 2018; Y. Wang et al. 2016), the selected forest sites fall into the moderate-to-difficult complexity forest category (~443 trees ha^{-1}).

High-resolution TLS point clouds enable accurate tree architectural traits reconstruction (*CrVol*, *CrPrj*), aligning closely with AGB estimates in the MST-based allometry model (RMSE% = 2.9%). The MST model produced an acceptable beta coefficient for AGB estimates (equal to 0.78) (Lin et al. 2013). However, UAV-LS produces more accurate AGB estimates than ALS (Figure 6), likely due to point quality captured by UAV-LS systems, allowing occlusion handling through penetration and closer proximity to the top canopy (Bruggisser et al. 2019). Considering that all forest sites (except ads_26; Figure 7) exhibit mono-layered vertical stratification, the primary factor probably affecting the tree AGB estimation is occlusion caused by large branches overlapping smaller ones, worsened by the incorrect segmentation of nearby crowns. The incorrect tree segmentation in pure stands is implicit in ITS analysis, especially in the closed-canopy broadleaf stands (Barbeito et al. 2017; Cao et al. 2023). Previous studies show that ALS-based crown segmentation algorithms achieve accuracies below 30% for Commission I (extra trees detected within crowns) and less than 40% for Commission II (trees detected outside crowns) (Y. Wang et al. 2016). Nevertheless, the tree detection method we used (Li et al. 2012) achieved an F-score of 0.5 in mixed conifer forests (Pirotti, Paterno, and Pividori 2020) and a 75% detection rate in mixed conifer-broadleaf forests (Torresan et al. 2020), which aligns with our findings. Another challenge in tree detection was the configuration of parameters for 3D forest site analysis, which was time-intensive and site-specific (Li et al. 2012).

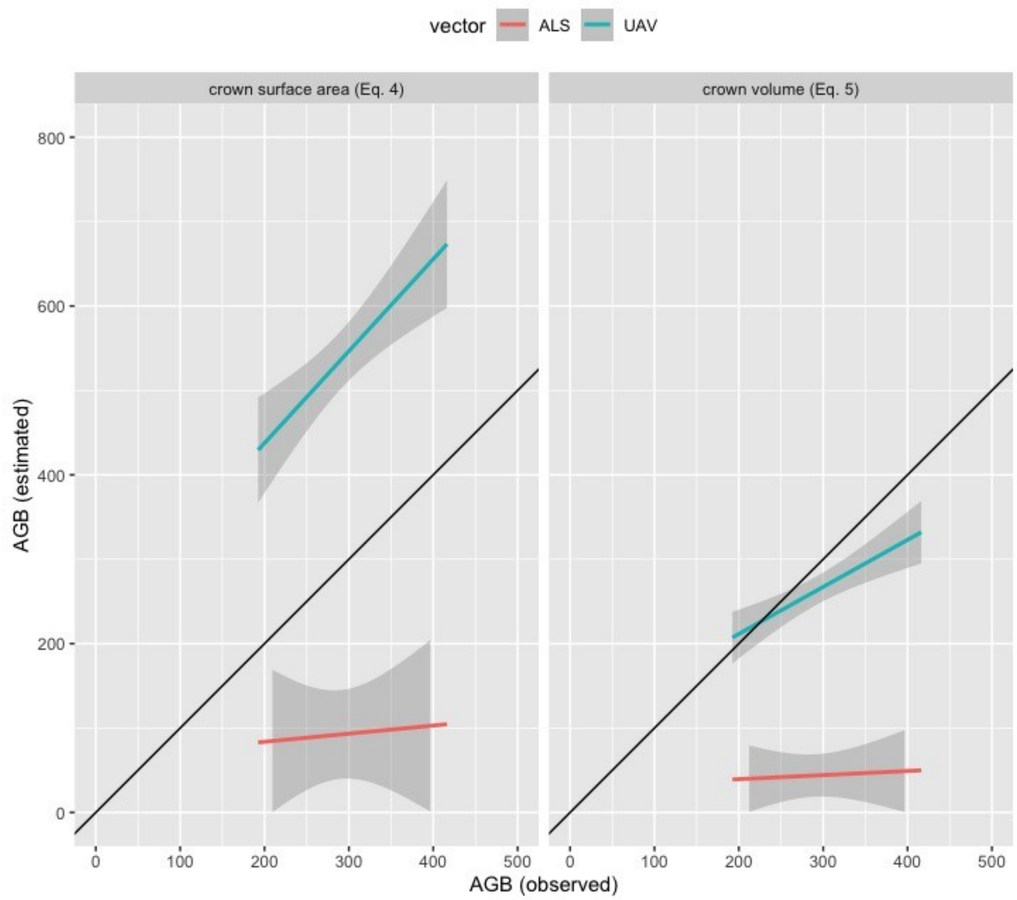

Figure 6: Estimated AGB by both Equation 4 and 5 and with different LiDAR vectors (ALS (red) and UAV-LS (green)).

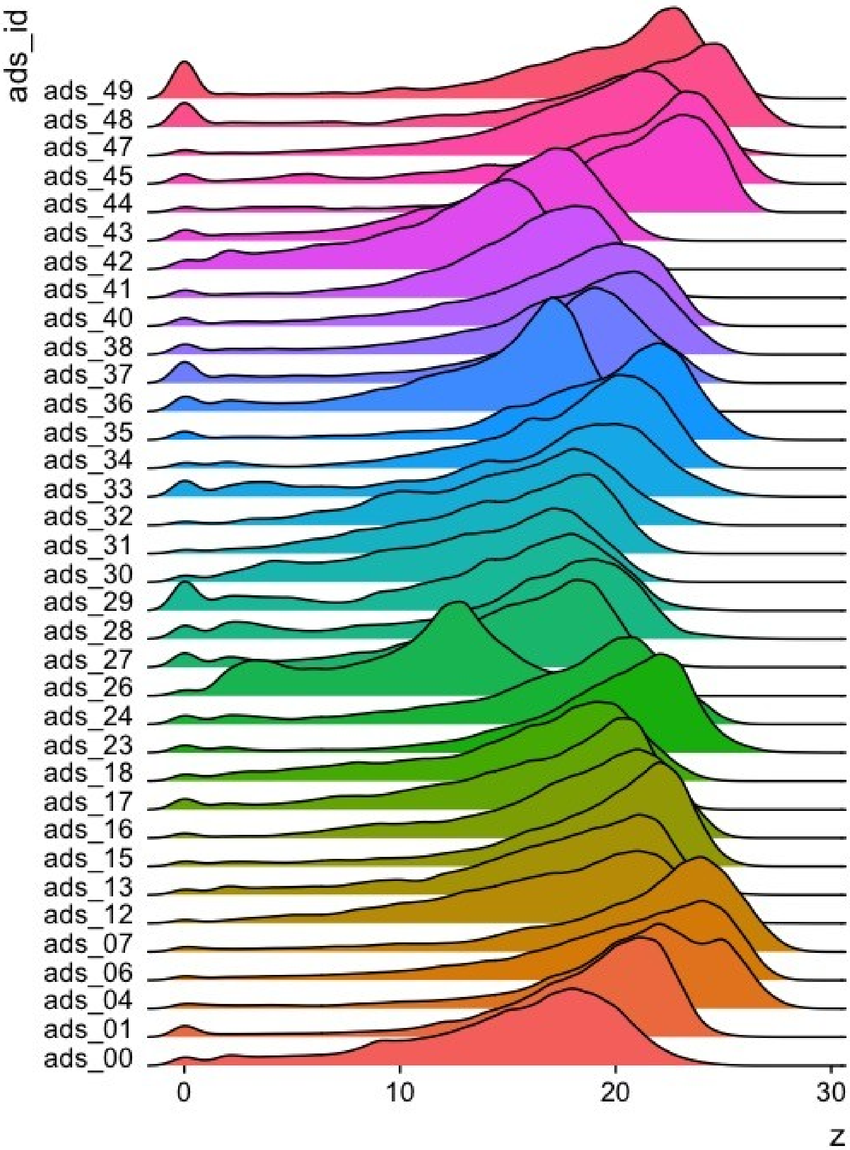

Figure 7: Vertical profiles of 35 sampling plots, as derived from UAV-LS point clouds. With few exceptions (e.g. ads_26), the distribution is unimodal from the ground to the top of the canopy.

In this regard, unsupervised algorithms such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise) (Alvites et al. 2021), hierarchical filtering and clustering (HFC) (Zhang et al. 2024), or learning algorithms (i.e., convolutional neural network) (Straker et al. 2023) could prove more effective in detecting trees. However, the unavailability of these ITC algorithms in R software limits their accessibility for non-expert users. Therefore, developing R packages to integrate these advanced algorithms would be essential for expanding their use in tree detection. AI-based approaches hold promise for future tree detection and segmentation tasks. Once these challenges are addressed, UAV-LS data could enable more frequent, cost-effective updates for AGB monitoring with high resolution (Fassnacht et al. 2024).

Accurately delineating tree architectural traits can significantly affect the accuracy of AGB estimates from aerial LiDAR systems, especially ALS. As expected, segmenting dominated trees remains a primary challenge in our workflow; however, our findings align closely with previous studies (Liang et al. 2018; Y. Wang et al. 2016). Nevertheless, the manually segmented reference trees in Phase 1 provided a robust validation step for the outputs in Phase 2, thanks to the detailed representation of forest plots using point clouds. Integrating aerial with terrestrial LiDAR data may improve detection rates, allowing closer alignment with reference AGB estimates (Alvites et al. 2022). Implementing the MST to beech trees to capture crown irregularities, regardless of purity (Barbeito et al. 2017), requires high-resolution point clouds, which currently limits its application to terrestrial and drone-based LiDAR systems (Barbeito et al. 2017; Owen, Flynn, and Lines 2021; Martin-Ducup et al. 2020).

5. Conclusions

Quantifying forest aboveground biomass is crucial for climate action and forest management policies. This study confirms that UAV-LS systems, with their high-density point clouds, significantly improve local AGB predictions in homogeneous beech forests compared to ALS. Applying the Metabolic Scaling Theory to beech trees effectively requires high-resolution point clouds, ideally from drone-based LiDAR systems. Although segmenting dominated trees remains challenging, traditional crown measurement methods are time-intensive and prone to errors. Integrating terrestrial and UAV-LiDAR data offers an efficient and promising alternative for accurately capturing tree architecture. These findings underscore the value of UAV-LS data for AGB estimation and demonstrate the potential of precise crown measurements to advance climate and forestry goals.

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