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RESEARCH

Combining hand-held and drone-based lidar for forest carbon monitoring: insights from a Mediterranean mixed forest in central Portugal

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Abstract

The adoption of novel methods in forest management planning requires the incorporation of precise forest and tree data to improve scheduling and meet multi-objective criteria principles. This study evaluates advanced methods for mapping tree structural attributes to create detailed baselines for forest carbon biomass, a key indicator in environmental policies. We specifically investigate the combined use of mobile sensors (hand-held laser scanning, HLS) and airborne (unmanned laser scanning, ULS), to estimate biomass and carbon stocks in a Mediterranean mixed forest. The novelty of our study lies in the synergistic application of HLS and ULS technologies and the evaluation of different ULS flight altitudes (50, 70, 90, 110 m) and scanning modes to optimize data accuracy and coverage. The main questions addressed are: (1) How do different flight altitudes and scanning modes of ULS affect the accuracy of biomass and carbon stock estimations? (2) What is the impact of merging HLS and ULS data on the precision of tree structural attribute measurements? (3) Can the combined use of HLS and ULS overcome the limitations of individual systems, particularly in complex forest structures? Our case study is conducted in a 1-ha plot in a complex, terraced forest region in Central Portugal, chosen for its high species diversity and structural complexity, which present significant challenges for remote sensing technologies. This site represents a typical Mediterranean mixed forest, allowing us to test methods in conditions that are both typical and challenging for forest monitoring. The distribution of HLS estimates was aligned with reference DBH measurement, though systematically lower (~ 2–3 cm bias). The impact of these measurement errors on total biomass estimation was around 13%. In contrast, major discrepancies were observed in tree height estimations when comparing HLS, ULS, fused ULS-HLS point clouds, with field reference data. ULS operated effectively at heights up to 110 m, increasing coverage without compromising result quality. However, merging point cloud datasets did not significantly improve the accuracy of tree height estimates due to the complexity and high species mingling of the forest stand. We recommend caution in using field measurements for validating tree height estimates with laser sensors under these conditions.

Keywords Precision forestry · Forest monitoring · Mobile laser scanning · Forest inventory

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Introduction

Qualitative and quantitative indicators describe crucial forest structural metrics to quantify aboveground biomass density (AGBD) and forest carbon sequestration potential and monitor fluxes over time (McElhinny et al. 2005; Pretzsch and Zenner 2017; Pascual 2021; Dubayah et al. 2022). The estimation of forest structure based on remote sensing—fundamentally through and active laser scanning or radar—is now solid at global scales (Dubayah et al. 2020), for landscape applications (Maltamo et al. 2014; Lindberg and Holmgren 2017; Beland et al. 2019; Guerra-Hernández et al. 2022) and for the sensing of individual tree features and components (Disney et al. 2018; Hyyppä et al. 2020). Laser scanning have contributed to a change of paradigm in tree mapping and questioned whether field height measurements are suitable to calibrate/validate laser-derived estimates (Zhao et al. 2018; Laurin et al. 2019). Overestimation in sparse conditions and underestimation in dense, old-growth environments are frequently reported supported with field measurements (Wang et al. 2019; Persson et al. 2022; Calders et al. 2022). The operationalization of these 3D sensing advances in the close-range domain is evolving fast to enhance forest management planning (Ehbrecht et al. 2017; Lindberg and Holmgren 2017; Pascual 2019).

Close-range sensing observes targets at a target-to-sensor distance reaching up to several hundred meters. It is a rapidly evolving arena in the 3D forest remote sensing that provides unprecedented means to understand physical (Jucker et al. 2015) and ecological processes (Calders et al. 2020, Maeda et al. 2022) or tackling critical challenges in in-situ sampling designs (Persson et al. 2022, Calders et al. 2022). Portable hand-held Laser Scanning (HLS) is particularly well suited to close-range environments (Giannetti et al. 2018; Fan et al. 2021; Keefe et al. 2022; Tupinambá-Simões et al. 2023). The quality of HLS data, collected on the move and with portable sensors, is lower for close-ranged applications compared to terrestrial laser scanning systems (TLS) capable to use quantitative structure models (QSMs) at time-consuming efforts (Wilkes et al. 2017; Calders et al. 2022). However, HLS is fast (i.e., it takes minutes to scan one ha), accurate in tree positioning and tree diameter estimation (Cabo et al. 2018; Fan et al. 2021; Tupinambá-Simões et al. 2023), but the detection capabilities towards forest canopies is not as precise as in TLS (Vandendaele et al. 2024). One promising approach to improve HLS tree height estimates is to fuse HLS data to above-canopy 3D-scans from Unmanned Aerial Vehicles (UAVs) (Wallace et al. 2016, Fekry et al. 2022). Combining Unmanned Laser Scanning (ULS) and HLS can improve the precision of tree structural metrics (Wallace et al. 2016; Shimizu et al. 2022; Štroner et al. 2023). Alone, HLS and ULS can support forest carbon monitoring in local areas scales or for research purposes, as its application at regional or national scales poses significant challenges, but a fused HLS-ULS point clouds could potentially overcome limitations on occlusion and phenological impacts (Brede et al. 2019; Shimizu et al. 2022). The latter is especially relevant in mixed Mediterranean forests (Bravo-Oviedo et al. 2014; del Río et al. 2016; Pretzsch and Zenner 2017). Bringing the best of HLS and ULS is relevant for Mediterranean mixed forests where species mingling is prone for high uncertainties in the retrieval of vegetation profiles (Tupinambá-Simões et al. 2023).

In this study, the accuracies of two laser scanning technologies were evaluated, as well as the impact of estimated structural properties on above- and below-ground carbon stocks (Pascual et al. 2023). We evaluated the influence of flight altitude and scanning mode in unmanned laser scanning (ULS) data acquisition on biomass and carbon stock estimates. Additionally, we assessed the improvement from merging point cloud data from ULS and HLS to improve the estimation of dominated trees adding geolocated tree height data to the assessment. Finally, we evaluate the cost of error propagation from tree structure estimation into biomass stock estimation at area level. The potential applications and limitations of integrating HLS and ULS data for operational forest monitoring in complex mixed-species environments were also discussed.

Material and methods

Experiment site

The study site was selected in the Ourem Council in the district of Santarém, Portugal, due to its high species diversity and structural complexity, which present significant challenges for remote sensing technologies. This 1-hectare plot (Fig. 1) includes a mix of deciduous and evergreen species such as *Pinus pinea*, *Pinus pinaster*, *Quercus suber, Quercus faginea*, *Crataegus monogyna*, *Fraxinus spp*., and *Eucalyptus spp.* The site's varied topography and species composition offer a comprehensive testing ground for evaluating the performance of mobile laser scanning in a complex, mixed-species environment.

Recent management history in the plot, abandoned over the last decades, included fuel treatments to trim the dense understory and to ease the accessibility to the study from the boundary access points. The plot was systematically divided into 25-m squares (16 subplots) to better capture the spatial variation in species distribution and structure. During the inventory conducted in February 2023 (leaf-off season), field

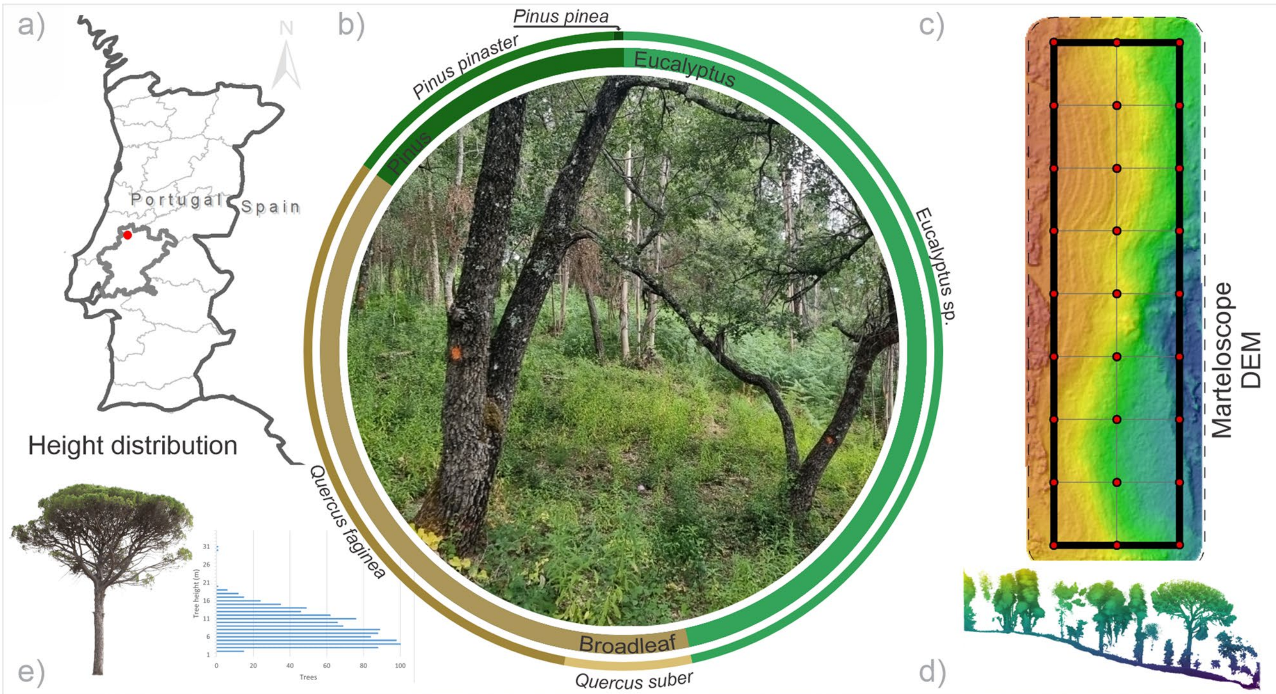

Fig. 1 Overview of the study site in Central Portugal. **a** Location sketch showing the position of the 1-ha plot. **b** Histogram of tree height distribution within the plot. **c** Plot map with sub-plots and the digital elevation model (DEM). **d** Profile of the point cloud obtained from HLS. **e** Central image showing the understored vegetation inside the plot and the species distribution

measurements of diameter at breast height (DBH, 1.3 m) and tree height (TH) were collected for every tree exceeding 7 cm in DBH. The plot contained a total of 348 trees, 216 of which had sprouted more than one shoot, with up to 10 shoots on a single stump. The tree density within each sub-plot varied from 64 to 896 trees per hectare. The maximum recorded diameter was 123 cm, and there was a high density of trees with diameters less than 10 cm. Tree height was measured for each tree using a Nikon Forestry Pro II laser rangefinder/hypsometer (Nikon, www.nikon.com). Additionally, TH measurements were collected for a subsample of 108 trees using Vertex III hypsometer (Haglöf, www.haglof.se). TH for all trees was estimated using a regression model to correct the bias from the Nikon instrument, based on the Vertex measurements. A total station (Topcon OS 100 model, accuracy: ±3 arc seconds for angular measurements and 2 mm + 2 ppm for distance measurements) was used to map stem locations.

Hand-held laser scanning (HLS) for terrestrial scanning

The study area was scanned on February 14th during the 2023 leaf-off season. The HLS was performed with a hand-held GeoSLAM ZEB-Horizon scanner, which can emit hundreds of thousands of laser pulses per second with a relative accuracy of 6 mm over a range of 100 m. This HLS system is equipped with a LiDAR Velodyne VLP-16 sensor, mounted in a spinning head. More details of the instrument can be found in (GeoSLAM Ltd., Nottingham, UK). To georeferencing the HLS point cloud, a topographic polygonal survey was carried out with the assistance of a Topcon OS-100 total station. A set of 28 boundary points were used to set study area boundaries. Along the 1-km length track scanned in 31 min, 15 Ground Control Points (GCPs) were used to enhance the geolocation of the laser point cloud. For the topographic survey, two reference points using was measured with Topcon SR GNSS receiver. The HLS data post-processing was done in the manufacturer's software. The HLS point cloud was then clipped using a 10-m buffer to match the plot boundaries (Fig. 2).

Laser scanning using unmanned aerial vehicles

The quadcopter DJI Matrice 300 RTK equipped with a GNSS RTK receiver was used to mount the DJI Zenmuse L1 LiDAR sensor composed of a LIVOX module and the RGB camera. The UAV-LiDAR system (ULS) was set to operate at 4 m s^{-1}, 66 and 80% in lateral and frontal overlap, respectively, and off-nadir scan angles of 30°. Four flight altitudes and two scanning modes (maximum of two or three echoes per emitted laser pulse) were tested. The dual-echo mode increases point cloud density while the triple echo increases the proportion of echoes between ground and top-of-canopy.

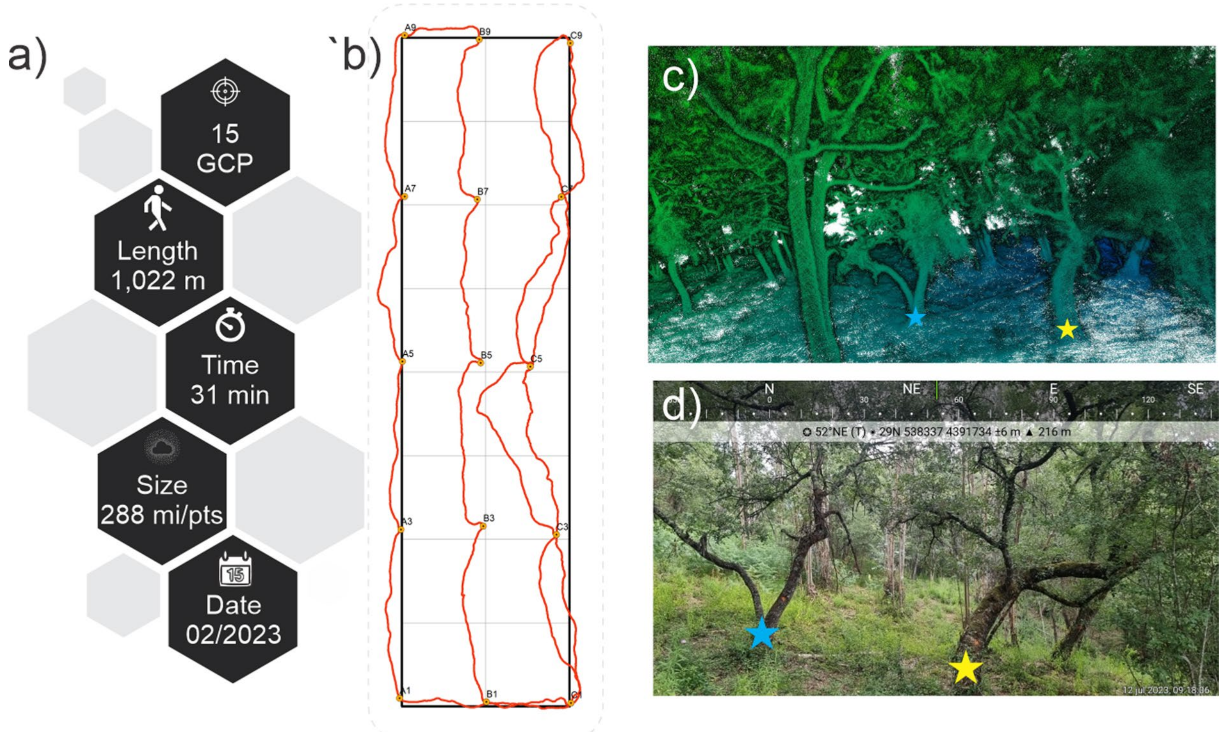

Fig. 2 **a** Infographic illustrating the HLS scanning processed data. **b** Scanning path with ground control points. **c** View of the raw point cloud of the area represented in the photograph (**d**)

Table 1 Configuration and details on the eight unmanned laser scanning (ULS) datasets collected for the analyses

Flight elevation (m)	Scan rate (kHz)	Max laser echoes per pulse	Scanning density. All laser returns/last returns (scale: m^2)	Point spacing (cm). All laser returns/last returns (scale: m^2)
50	240	2	2955/2071	0.02/0.02
50	160	3	2163/1389	0.02/0.03
70	240	2	1788/1379	0.02/0.03
70	160	3	1280/927	0.03/0.03
90	240	2	1105/953	0.03/0.03
90	160	3	793/647	0.04/0.04
110	240	2	701/647	0.04/0.04
110	160	3	476/436	0.05/0.05

Four flight altitudes and two scanning modes were tested. Density and spacing statistics of the resulting point cloud generated during the flights is shown with the total acquisition time—from take-off to landing—to complete the ULS surveys

The timing and density of ULS surveys collected on February 23th, 2023, were controlled to measure the trade-off between density, altitude and laser penetration (Table 1).

The set of eight ULS point clouds were processed using the *lidR* package in the R programming environment (Roussel et al. 2020; R Core Team 2023). Laser echoes classified as ground to produce a digital terrain model (DTM) with a grid cell of 25 cm, which was later used to normalize the height of laser echoes classified as vegetation to above-ground height. A fine-grained rasterized Canopy Height Model (CHM) was used to detect tree locations and delineate canopy crown properties. A 50 cm resolution for the CHM was selected as it provided a balance between computational efficiency and the level of detail needed to accurately represent the canopy structure, according to Dai et al (2022) a variation between 0.07 and 1.2 has a marginal influence on the results. Higher and lower resolutions were tested, and 50 cm was found to be optimal for this study, using for all cases the pit-free algorithm implemented in the *lidR* package, with a 20 cm sub-circle to fill in the gaps (Fig. 3).

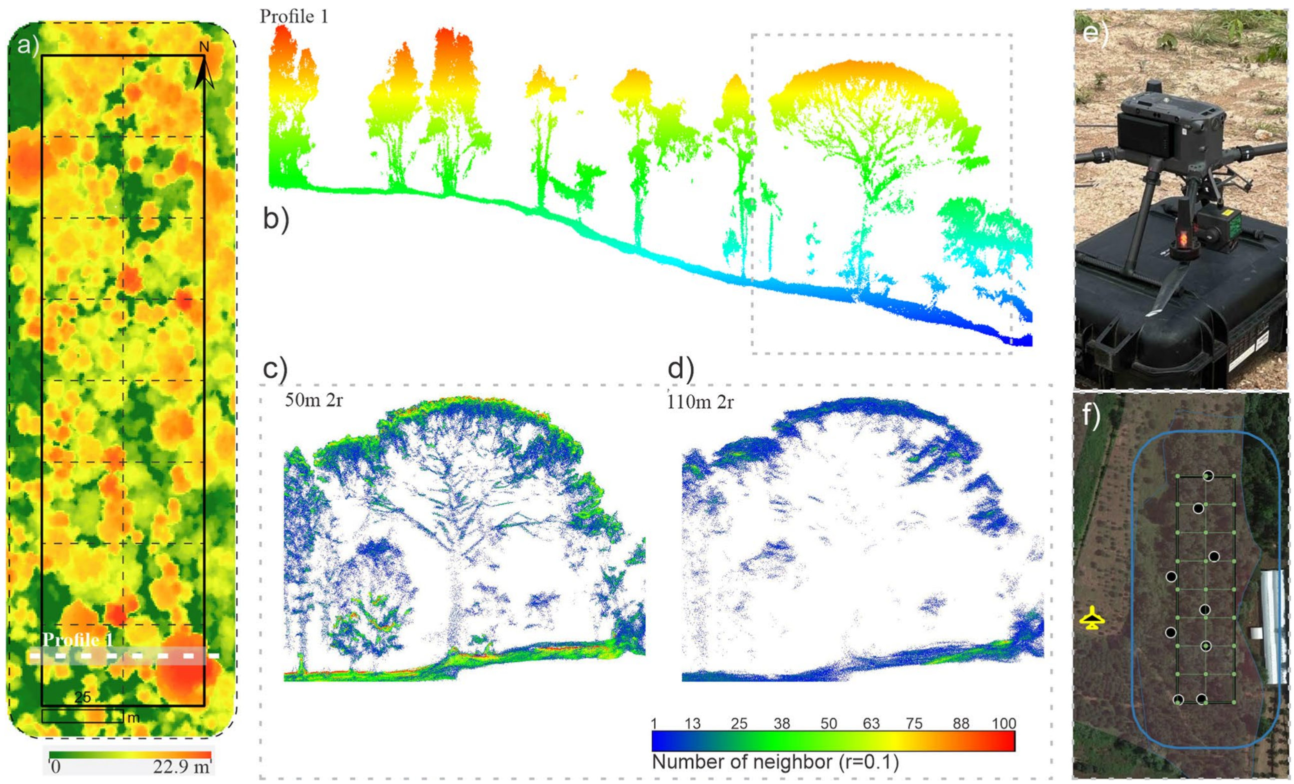

Fig. 3 Overview of the study site and data from ULS. **a** Location sketch with Canopy Height Model. **b** Profile of the point cloud illustrating tree heights and structure at 50 m altitude and 2 returns. **c**, **d** Point cloud profiles at 50 m and 110 m altitudes with two returns, colored by density of points in a 10 cm neighborhood. **e** Image of the UAV used for scanning. **f** Flight plan for the study area with black dots indicating the check points

The individual tree detection (ITD) algorithm by Popescu et al. (2002), available in the lidR package, was employed to identify the tops of the trees. This process utilized a local maximum filtering approach with a variable window size parameter ranging from 3 to 5 m. Subsequently, the point cloud was segmented into individual trees using the Dalponte2016 algorithm (Dalponte and Coomes 2016) implemented in the *segment_trees* function. This segmentation leveraged the CHM and the identified tree tops as input parameters, along with a seed threshold of 0.45, a canopy threshold of 0.65, and a maximum canopy radius of 30 m.

Fusion of HLS and ULS surveys

Fused point clouds provide an enriched representation of the 3D space, potentially expanding mapping abilities merging several scanning sources. The 50-m altitude 2-return ULS survey was merged to HLS survey. The Iterative Closest Point (ICP) algorithm available in the CloudCompare software (CloudCompare 2023), was used to align and fuse HLS and ULS data. The ICP algorithm efficiently reduces the variance between candidate paired points for matching (Du 2011), enhancing spatial registration with each iteration (Khazari et al. 2020; Wang and Zha 2023). To visually check the quality of the fused point cloud 8 spheres were installed during field operations (Fig. 4).

Tree inventory using the FSCT tool and comparisons to field data

Forest Structural Complexity Tool (FSCT), an open-source software designed for analyzing laser scanning data in forestry applications (Krisanski et al. 2021a) was used to process the data. The FSCT has a history of effective use in broad-area surveys and individual tree mapping, as demonstrated in various research projects (Krisanski et al. 2021b). FSCT was used over the HLS survey before testing it on the HLS-ULS fused point cloud. We were particularly interested in how the integration of laser echoes from canopy tops, captured by ULS scans at different altitudes, could enhance tree height measurements beyond the baseline provided by HLS data alone. The outcomes from FSCT processing offered valuable insights, including the diameter, height, and trees' location. These findings played an important role in correlating field-collected data with traditional forest inventory methods. A subset of 38 well-geolocated trees were used

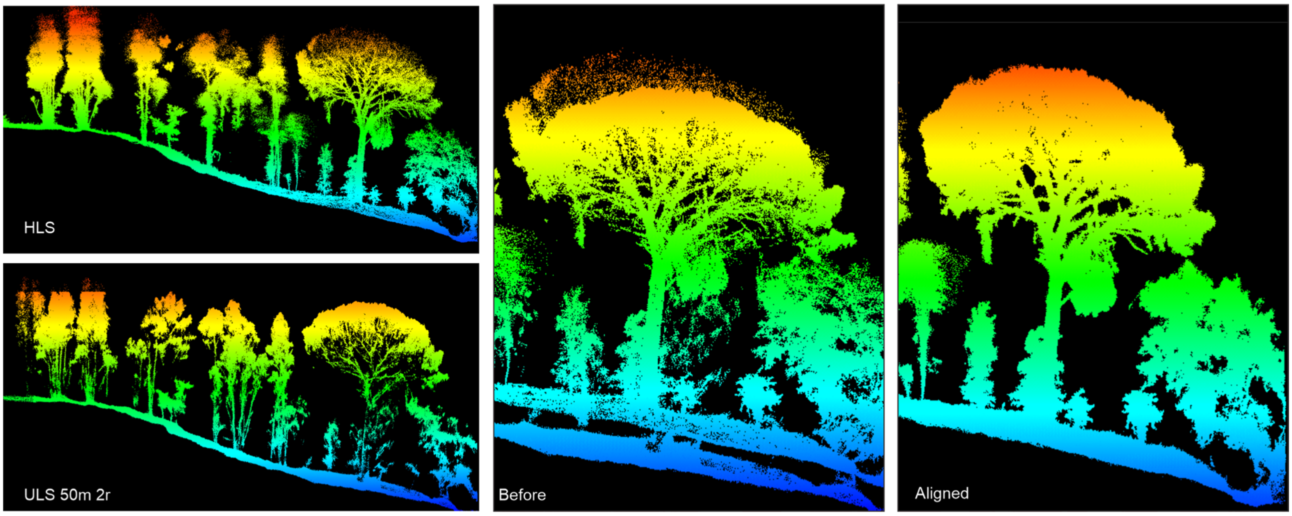

Fig. 4 Example of fused point cloud data combining hand-held laser scanning (HLS) and unmanned laser scanning (ULS). The showcase point cloud alignment between ULS and HLS, and for the fused point cloud

for tree height validation. FSCT results were used to match detected tree to these reference trees also identified from ULS surveys. The *lidR* package was used to establish a 2-m buffer around these locations and retrieve tree height from one ULS survey for the comparison to field height and to FSCT-estimated values using HLS and the fused HLS-ULS data.

Allometries to estimate tree aboveground biomass

The estimation of tree biomass and carbon stocks in forest inventory traditionally relies of allometric equations using DBH and/or tree height as predictors. The equations from the National Forest Inventories of Spain and Portugal are well-suited to our geographical scope. Species-specific allometric equations were applied for the six species to estimate individual tree stem biomass, bark, branch and foliage biomass, and aboveground biomass of each tree for *Pinus pinea* (Correia et al. 2018), *Pinus pinaster* (Tomé et al. 2007), *Quercus faginea* (Ruiz-Peinado et al. 2012), *Crataegus monogyna* (Montero et al. 2005), *Quercus suber* (Paulo and Tomé 2006, Tomé et al. 2007) and *Eucalytus spp*. (Tomé et al. 2007). Model equations are presented in the Supplementary. These models have DBH as predictor from the different biomass components while tree height is used for *Pinus pinea*, *Pinus pinaster, Eucalyptus spp.* and *Quercus faginea* but not for *Quercus suber* and *Crataegus monogyna*. Errors in the estimation of DBH influence all measured trees but not for tree height. After accounting for errors in the estimation of DBH and tree height using reference data and laser scanning surveys, we aimed to evaluate the variability in biomass and carbon stocks estimates by species when accounting for sensing errors on tree structural attributes.

Statistical analyses and models applied

Statistical analyses were carried out to assess the accuracy of different tree's structural attributes derived from LiDAR, evaluate the influence of flight altitude on ULS data and quantify the impact of measurement errors on biomass and carbon stock estimates. All statistical analyses were carried out using R software (R Core Team 2023).

To assess the effects of flight altitude on the CHM derived from the ULS data, quantile distributions were used to summarize the CHM estimates at flight altitudes. The variability of the CHM products was statistically analyzed by comparing the two- and three-return scan modes. Kruskal-Wallis test was applied to data sets that do not assume a non-normal distribution to determine whether there were significant differences between CHM products at different flight altitudes. The Wilcoxon signed-rank test was used to determine whether two dependent groups differed significantly, ranking the groups instead of comparing mean values. The accuracy of tree's structural estimates (DBH, TH) derived from the HLS, ULS and HLS-ULS merged scan datasets was assessed using quantile-quantile comparisons with field reference data. To compare distributions, we used the total explained variance (R^2) to quantify the proportion of variation explained, the Root Mean Square Error (RMSE) to assess the magnitude of estimation errors, and both bias and model deviation to examine systematic trends of overestimation or underestimation.

The impact of measurement errors on biomass and carbon stocks was analysed by simulating systematic and random errors in DBH and TH values. Biomass estimates were calculated using species-specific allometric equations from the National Forest Inventories of Spain and Portugal. The sensitivity of biomass calculations to DBH and TH errors was examined using error propagation analysis, quantifying the reduction in above-ground biomass density (AGBD) and estimated carbon stocks under different error scenarios.

Results

Effect of flight altitude and scanning mode on ULS data

Repeated ULS surveys at different altitudes exhibited strong agreement in the CHM products, with deviations increasing as flight altitude increased. Using the 50-m CHM as a baseline (Fig. 5), RMSE progressively ranged from 6.4 cm (70-m flight) to 52.0 cm (110-m flight) for two-return scanning and from 19.2 to 80.7 cm for three-return scanning. In both cases, a negative bias increased with altitude.

The Shapiro-Wilk normality test was conducted separately for datasets with two and three returns across the four flight heights (50 m, 70 m, 90 m, and 110 m). In both cases, the test yielded p-values of 2.12e-16, indicating a non-normal distribution of Z-values. Consequently, the Kruskal-Wallis test was applied, the results indicated no statistically significant differences among flight heights for both the two-return dataset (p = 0.57) and the three-return

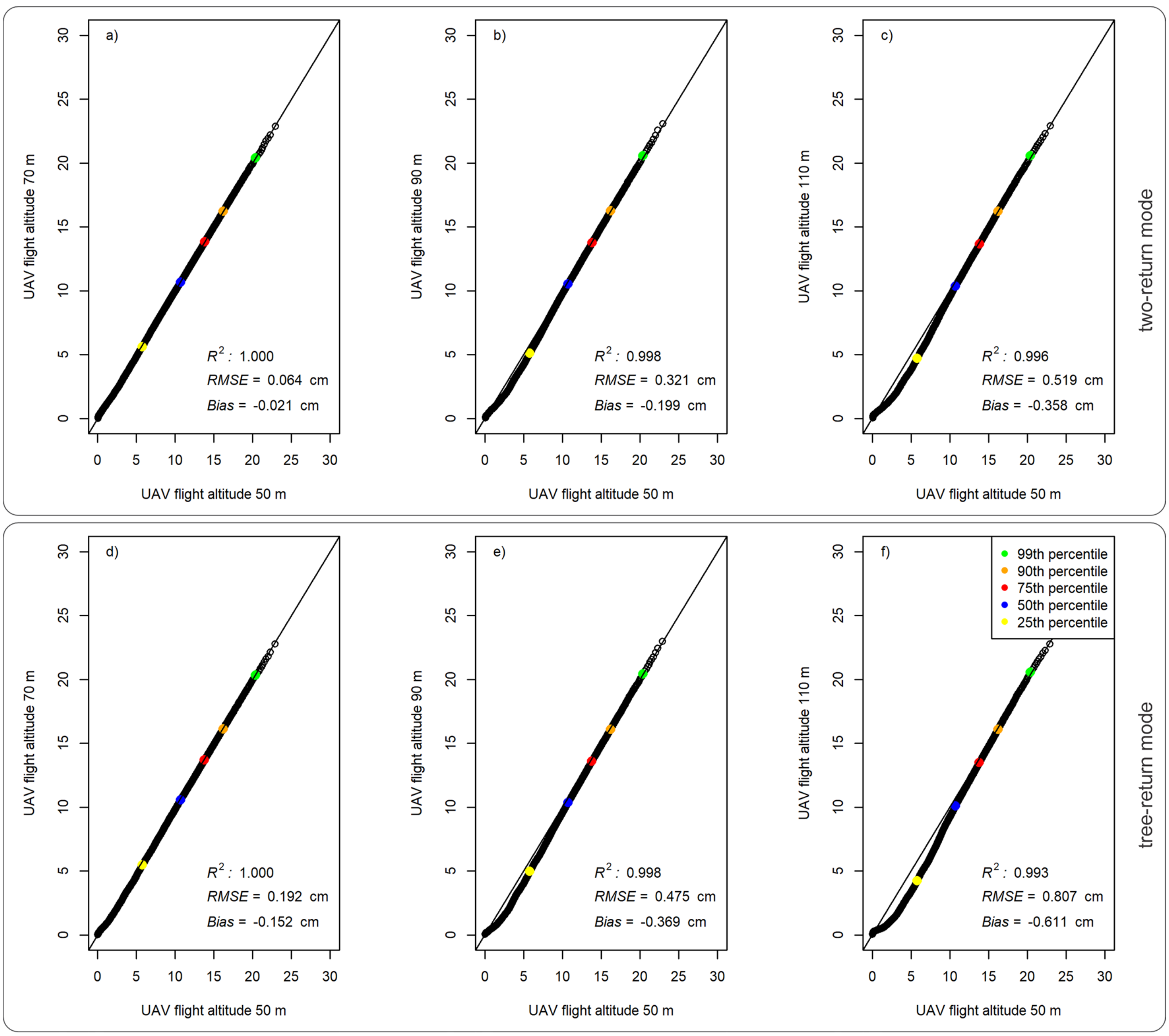

Fig. 5 Quantile distribution of canopy height model products derived from unmanned laser scanning (ULS). Panels **a**, **b**, **c** show results using two-return mode for data acquisition, with four flight altitudes: 110 m, 90 m, 70 m, and 50 m (baseline). Panels **d**, **e**, **f** show the results using three-return mode with the same flight altitudes

dataset ($p = 0.13$), suggesting that canopy height distributions remained consistent regardless of flight altitude. To further investigate potential differences, pairwise Wilcoxon tests were performed. The results confirmed that no significant pairwise differences were present in either dataset, as all Wilcoxon p-values were closed to 1.000, except for the 50 m vs. 110 m (three returns) comparisons that showed the value of 0.148 as p-value.

Detailed CHM products were used with standard tree detection algorithms framed for CHM products (Fig. 6). Tree tops are detected first before CHM-supported growing region algorithms delineate canopies extent. In the first phase, over 95% of the trees were retained across all four CHM products for a given scanning mode. While tree locations persisted, changes in the delineation of tree canopies were visible especially over isolated trees and not much in dense patches. Here, large spatially continuous clusters of detected trees were observed for all flights.

Outputs from the ULS individual tree inventory showed balanced tendencies between scanning modes and slightly more sensing ability for detecting short trees below 10 m using the 50-m survey (Fig. 7). The range of tree density in the 1-ha plot using HLS-based outcomes ranged from 304 to 326 trees (Table 2).

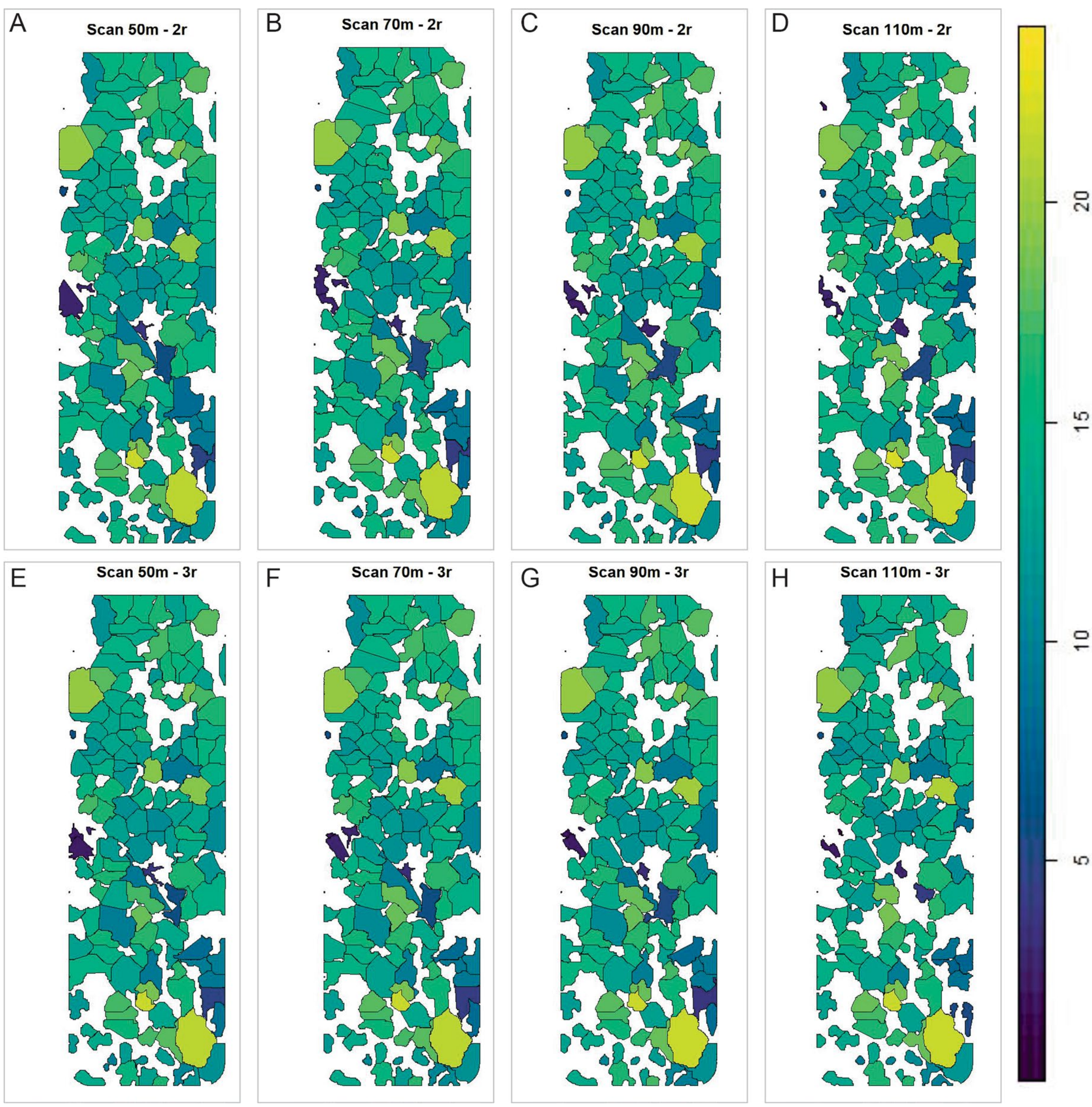

Fig. 6 Spatial layout of tree canopies detected with unmanned laser scanning (ULS) and coloured by aboveground height. Results are presented for four flight altitudes; 110, 90, 70 and 50 m (baseline) and two scanning modes (two and three returns)

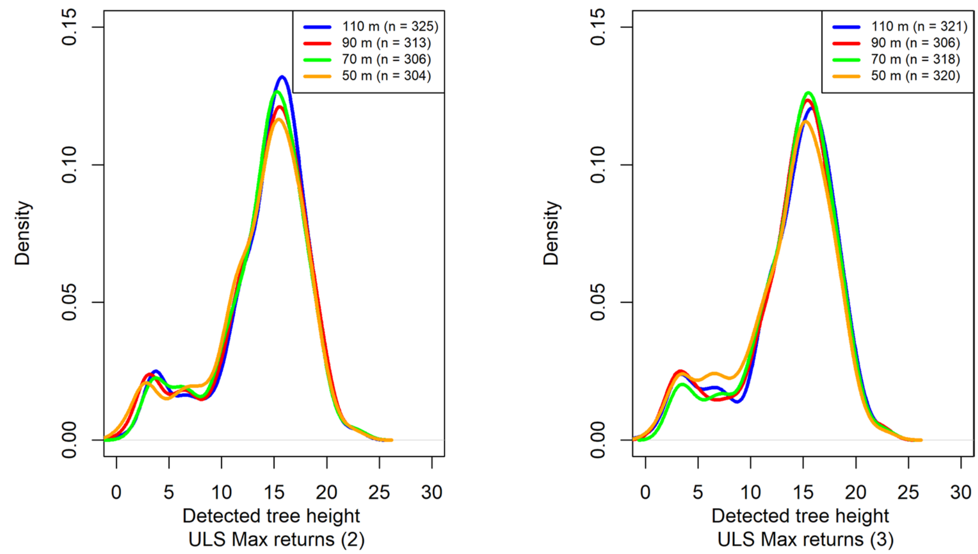

Fig. 7 Tree height estimates derived from Unmanned Laser Scanning using four flight altitudes (50–110 m) and two scanning modes regarding the maximum possible returns by laser pulse

Table 2 Individual tree mapping results using Unmanned Laser Scanning under four flight altitudes and two scanning modes

Flight elevation (m)	Max laser echoes	Detected trees	Lowest height (m)	Tallest height (m)	Mean tree height (m)	SD laser echoes (m)
50	2	304	0.814	23.0	14,0	4.28
50	3	320	0.112	23,0	13.9	4.54
70	1	333	0.241	22.8	13.4	4.36
70	2	306	0.446	23,0	13.8	4.48
70	3	318	0.891	22.8	13.7	4.53
90	2	313	1.730	23.2	13.8	4.25
90	3	306	2.320	23.1	14.0	4.20
110	2	325	0.356	22.9	13.6	4.51
110	3	321	0.705	22.9	13.4	4.57

The range of tree height estimates and the number of detected trees is presented

Diameter estimation using HLS and fused point clouds

The retrieval of DBH estimates using HLS showed a consistent overestimation compared to field measurements. One important result is the lack of FSCT results for the ULS survey due to insufficient pulse density between terrain and forest canopies. The coverage of laser points between canopies and ground was below minimum thresholds to produce tree mapping outputs. The fusion of HLS and ULS surveys minimally corrected the bias towards DBH measurements as shown in the quantile-quantile distributions (Fig. 8). Note, we compare distribution trends in Fig. 8 using all detected trees and all reference trees. The taller the tree height, the larger the discrepancy between measured and laser-based estimates DBH. The comparison to field data showed HLS and the fused point cloud ranged within the domain of most field measurements corresponding to *Eucalyptus spp*. and *Quercus faginea*. Most of the underestimation occurred for dominant pine trees.

Assessment of geolocated tree height data

Conditions in the understory and the presence of multi-layered forest conditions make it difficult to assess tree height estimates. Using a subset of 80 dominant trees, we compared field height estimates to estimated height from FSCT using HLS the fused point cloud and to ULS data. For the later, we used measured tree positions to retrieve the elevation values from the set of ULS surveys. The results showed the large error between field and sensed height estimates (RMSE > 4 m) and the strong consistency better HLS and the fused point cloud (HLS + ULS, RMSE ~ 1 m). Results from laser surveys excluded several trees below 10 m height from the sensed ranged. The 5 out of 80 trees meeting this condition highly explained the RMSE values and biases. Paired tree height values between HLS and the fused data showed consistency along the tree height domain, mostly ranging above 10 m (Fig. 9).

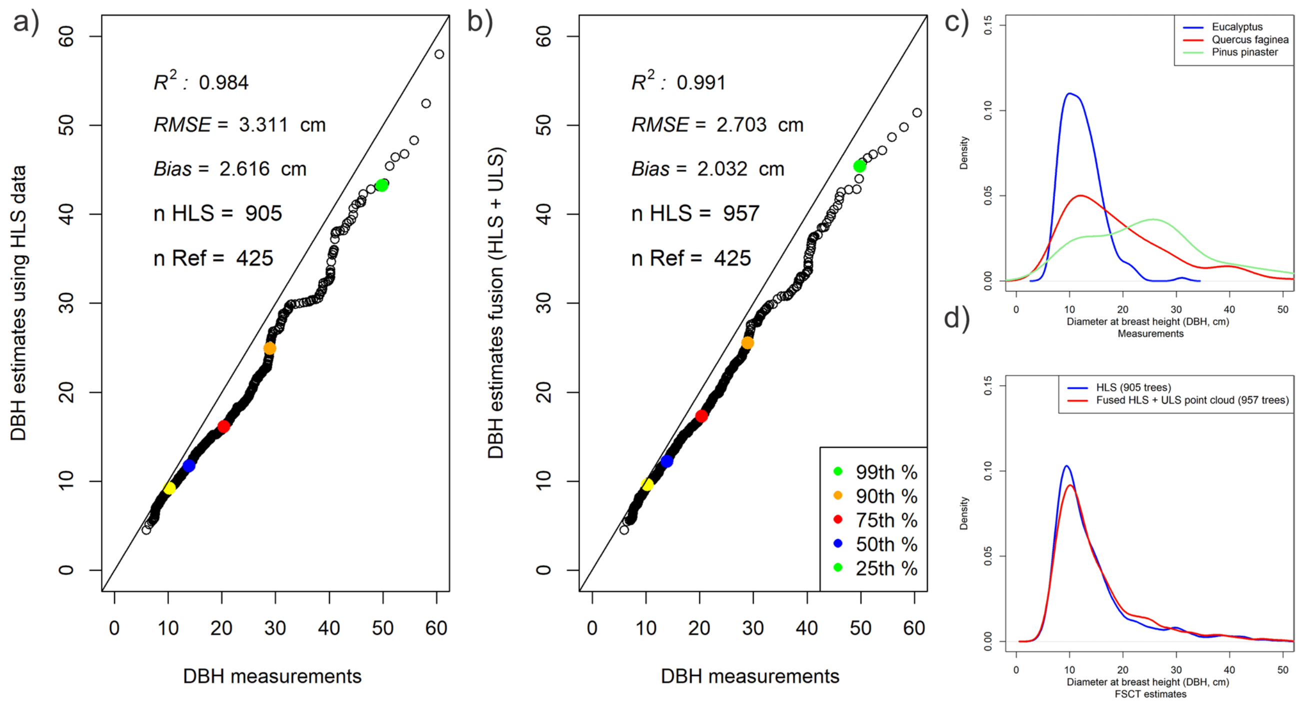

Fig. 8 Quantile-quantile relationship between measurements and estimates of diameter at breast height from hand-held (HLS), and fused hand-held and airborne unmanned laser scanning. Diameter histograms are presented for laser surveys and for reference data by species using field inventory information

Impact of errors from forest structural on forest biomass

Using field measures are reference error-free data, we simulated systematic and random errors on DBH and tree height measurements in the observed error range from HLS and ULS surveys. The reference inventory sets a benchmark for biomass and carbon densities, which are observed to be markedly sensitive to inaccuracies in DBH measurements. The estimated total AGBD was 90.25 Mg ha^{-1} and the belowground component accrues 28% of the aboveground component. A systematic reduction of DBH estimates - in the range observed for HLS, 2 cm—reduced the AGBD stock in 14%. We quantify in ~ 6.5–7 Mg ha^{-1} cm the impact of under-predicting DBH keeping tree height invariant. We simulated DBH errors using 5 cm as upper bound. By randomizing the error in the simulated range and computing it proportionally to DBH estimates, we found similar values to the 2-cm case simulation (~78 Mg ha^{-1}). The marginal cost per measurement scale of lowering DBH had more impact than lowering three heights. Simulating combined errors in DBH and tree height showed similar values as DBH-only simulations showing the substantial influence of DBH into tree biomass allometries, both above and belowground biomass pools, compared to tree height. A systematic reduction of tree height by 1 and 2 m lowered the total AGBD stock by 0.38% and 0.64%, respectively, while for the case of DBH, an underestimation of 1 cm decreased the stock by 7% (Table 3).

Discussion

The study synergized the use of two sources of mobile laser scanning to accurately and efficiently map from above and below canopy forest stocks in the Mediterranean: Specifically, it utilized (i) HLS below the canopies, (ii) ULS to describe top-of-canopy conditions and (iii) a fused point cloud approach to combine laser measurements. Monitoring using HLS data proved fast and effective at sensing tree positions, capable of detecting small-diameter trees. However, it lacked accuracy at retrieving tree height, especially when using field height measurements as the baseline for benchmarking, an approach that is discouraged in forest with intense multi-layering and species mingling.

Impact of ULS flight altitudes

The ULS point cloud data concentrated laser pulses in dominant trees and upper canopy sections but poorly represented the understory in the study area. Consequently, estimating DBH using ULS survey was not feasible, regardless of flight altitude and scanning mode. Nonetheless, consistency was observed in CHM maps, with minor differences between

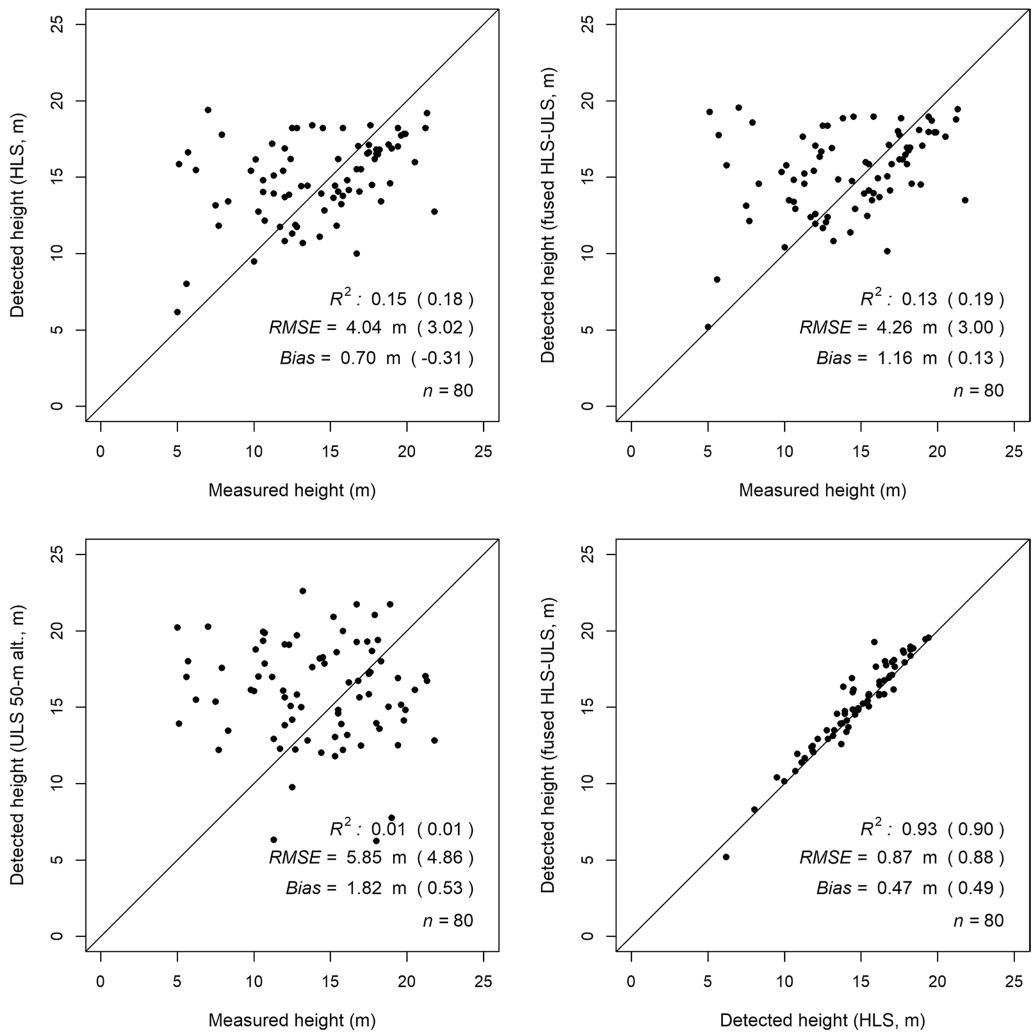

Fig. 9 Comparison of tree height measurements to estimates from hand-held (HLS), unmanned lidar (ULS) and fused HLS-ULS using 80 reference trees. Accuracies above 10 m in tree height are reported between brackets

Table 3 Total biomass and carbon estimates in the plot by component: aboveground and belowground

Error	Variable	Scale (unit)	Aboveground biomass density (Mg ha^{-1})	Belowground biomass density (Mg ha^{-1})	Aboveground carbon density (Mg C ha^{-1})	Belowground carbon density (Mg C ha^{-1})
Reference inventory			90.25	25.76	45.12	12.88
Syst	DBH	1 (cm)	83.95	23.78	41.97	11.89
Syst	DBH	2 (cm)	77.96	21.91	38.98	10.95
Syst	DBH	3 (cm)	72.30	20.13	36.15	10.07
Syst	DBH	5 (cm)	61.90	16.90	30.95	8.45
Rand	DBH	0–5 (cm)	75.56	21.31	37.78	10.65
Syst	TH	1 (m)	89.90	25.55	44.95	12.78
Syst	TH	2 (m)	89.68	25.35	44.84	12.67
Syst	DBH	1 (cm)	83.68	23.60	41.84	11.80
	TH	1 (m)				
Syst	DBH	5 (cm)	61.97	16.71	30.99	8.35
	TH	2 (m)				

Results for the error-free field inventory represent the baseline. Systematic and random errors on diameter at breast height (DBH), tree height (TH) and simultaneously on both were simulated. Biomass and carbon estimates are based on open-access National Forest Inventory allometries used in Spain and Portugal

ULS flights at 50–110 m. This confirmed the potential of fine-grained ULS mapping outputs to detect disturbances and changes in carbon sinks and to map the height of dominant trees, although it fell short in estimating overall forest structure.

The three-return mode in the Zenmuse L1 was expected to provide better coverage of intermediate and lower tree profiles; however, a significant lack of laser penetration was observed (Štroner et al. 2021). Other studies in more homogenous forest types using ULS have reported better results (Puliti et al. 2020; Rodríguez-Puerta et al. 2021; Kuželka et al. 2020). For instance, Kuželka et al. (2020) detected 99–100% of all trees in their research plots. Rodríguez-Puerta et al. (2021) found that all individual tree detection (ITD) algorithms tended to underestimate the number of trees. However, accuracy was lower for trees less than 1 m of height. Puliti et al. (2020) demonstrated that UAV laser scanning data could estimate forest growing stock volume at various scales without field data calibration, achieving the highest accuracy in open pine stands and the lowest in dense birch or spruce stands, with ULS estimates being statistically equivalent to intensive field survey estimates at the forest scale.

Trees species, especially broadleaf trees, are more challenging in tree height estimation due to foliage seasonality (Tupinambá-Simões et al. 2023). Approximately 35% of our trees were measured in leaf-on but scanned in leaf-off. The scenario favored the sensing and measuring of tree diameter below the canopies as observed in the consistency of distributions between measurements and estimates from HLS data (Bienert et al. 2018). The lack of foliage further reduced HLS's ability to detect branches and top-of-canopy components (Wilkes et al. 2017; Laurin et al. 2019; Landry et al. 2020).

From above the canopies, high-density ULS data was robust towards flight altitude changes that minimally impacted high-resolution CHM maps (Hu et al. 2020; Kuželka et al. 2020; Peng et al. 2021). Moreover, ULS detected tree-tops of co-dominant and top-dominant individuals, but a substantial number of understory trees remained undetected from occlusion (Wallace et al. 2016; Puliti et al. 2020). Suppressed trees represent significant challenges when scanned with ULS. These trees are often overshadowed by dominant trees, preventing LiDAR pulses from reaching their crowns or trunks effectively. As a result, their heights are often underestimated or even not detected (Chen et al. 2018). Even when some laser pulses manage to penetrate the canopy, they may not reach the highest points of the suppressed trees, leading to inaccurate height estimates.

The unrealistically large canopies ULS-segmented proved the limitations to tree crown segmentation in leaf-off conditions (Hakula et al. 2023). Leaf-on conditions are usually preferred for biomass estimation and derived foliage-rich canopy indicators (Kellner et al. 2019). However, for this case, the timings were matched to measure the marginal contribution of data fusion between ULS and HLS both in leaf-off. For instance, Brede et al. (2019) showed high accuracies in stem mapping using dense ULS in the beginning of the leaf-on season but the understory was sparse and not as multi-layered and dense as in our mixed forest.

Accuracy of HLS and ULS fusion

We imposed a threshold on tree height to validate tree height estimates, but not to validate DBH as we compared distributions, not paired observations between reference and estimates. Overall, we observed a low marginal improvement in the fused approach to estimate both DBH and tree height as observed by Fekry et al. (2022) in China's subtropical forests. However, better performance on tree height estimation is reported in (RMSE = 1.77 m, Shimizu et al. 2022) but in different conditions: ULS fused approach using more uniform laser data (i.e., TLS instead of HLS) and in coniferous in Japan (i.e., invariant towards seasonality in foliage). In our case, we used no minimum height threshold to compare DBH data as this would have left substantial proportion of young and dominated trees in our Mediterranean forest area out the analyses (Young et al. 2022). The bias in DBH estimates using HLS was in the range of 2–3 cm which can lower total biomass stocks between 13 and 19% when systematically applied to our forest inventory data using NFI-operational models in Spain and Portugal.

Systematic biases and measurement errors

The estimation of biomass and carbon using tree allometries highly depended on accurate DBH measurements rather than accurate tree height measurements. A systematic reduction of tree height by 1 and 2 m lowered the total AGBD stock by 0.38% and 0.64%, respectively, while an underestimation of DBH by 1 cm decreased the stock by 7%. Monitoring approaches using HLS are suitable for matching reference trees and detected trees (Tupinambá-Simões et al. 2023) and estimate DBH. The cost of underestimating tree height is mitigated by the structure and parameter values in tree biomass models. The set of biomass models used both DBH and tree height as biomass predictors, giving substantially more importance to DBH than tree height.

Implications for forest carbon monitoring

Approaches as HLS supports tree-level biomass monitoring—both in leaf-on and leaf-off—when the dependency on DBH in biomass allometries is high. It is not uncommon to exclude tree height in biomass allometries to lower sampling costs (e.g., Giardina et al. 2003). Two-predictor biomass models are more generalized these days although tree-level metrics derivable from remote sensing such as canopy cover can roadmap further efforts in the important task of converting tree structural metrics into biomass and carbon stocks.

The selection of the monitoring technique and associated measurements errors must acknowledge the relative contribution of measurement errors considering the structure and compositions of tree allometries by species. Alternatively, QSMs from high-quality terrestrial laser point clouds remove the uncertainty as woody tree components are derived for each detected tree. The QSMs approach using HLS represents a promising avenue for enhancing the precision, accuracy, and dependability of aboveground biomass estimation. To harness this potential fully, the creation of streamlined algorithms, user-friendly in nature, becomes paramount. These algorithms not only empower users but also hold substantial potential for continuous AGB data monitoring and ensuring its unwavering reliability.

Conclusions

This study demonstrates the complexities and challenges involved in accurately estimating forest biomass and carbon stocks using mobile laser scanning technologies in Mediterranean mixed forests. While hand-held laser scanning (HLS) proves effective in tree positioning and diameter estimation, it faces limitations in accurately retrieving tree height, particularly against the backdrop of intense forest multi-layering and species mingling. Unmanned laser scanning (ULS) contributes valuable data for canopy mapping but shows limitations in understory representation and diameter estimation. The fusion of HLS and ULS data, although innovative, offers marginal improvements in accuracy for both diameter and height estimations. Importantly, the study underscores the significant impact of measurement errors in laser scanning on biomass and carbon stock estimations, particularly regarding diameter at breast height (DBH). These results highlight the critical need for continued advances in remote sensing technologies and methodologies, combining different techniques, for more accurate and reliable monitoring of forest carbon, which is vital for effective environmental policy and forest management planning.

To improve the accuracy and utility of mobile laser scanning technologies, future research should focus on refining algorithms and integrating additional data sources. Combining HLS and ULS can provide valuable information on crown and stand structure, tree vitality, and canopy gaps, which were not fully explored in this study. Moreover, successive inventories using these technologies can enhance the estimation of forest growth, mortality, and other dynamic changes over time, providing a comprehensive understanding of forest ecosystems.

Implementing continuous monitoring systems and improving the synchronization between different laser scanning technologies will be crucial. This approach can lead to more precise measurements and better data integration, ultimately contributing to more effective forest management strategies and environmental policies. Emphasizing the development of user-friendly tools and algorithms for processing and analyzing laser scanning data will further enhance the accessibility and applicability of these advanced remote sensing techniques.

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Declarations

Conflict of interest The authors declare no competing interests.

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