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Comparing Mobile Laser Scanner and manual measurements for dendrometric variables estimation in a black pine (*Pinus nigra* Arn.) plantation

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ABSTRACT

The growing demand of ecosystem services provided by forests increased the need for fast and accurate field survey. The recent technological innovations fostered the application of geomatic tools and processes to different fields of the forestry sector. In this study we compared the efficiency and the accuracy of Mobile Laser Scanner (MLS), combined with Simultaneous Localization and Mapping (SLAM) technology, and traditional field survey for the mensuration of main forest dendrometric variables like stem diameter at breast height (DBH), individual tree height (H), crown base height (CBH) and branch-free stem volume (VOL). With ground truth measurements taken from 50 felled trees, we tested the applicability of MLS technology for individual tree parameters estimation in a conifer plantation in central Italy. Our results showed no bias of DBH estimates and the corresponding RMSE was equal to 10.8% (2.7 cm). H and CBH measured with MLS were underestimated compared to the ground truth (bias of −8.6% for H and −13.3% for CBH). VOL values showed a bias and a RMSE of −4.1% (−0.01 m^3) and 12.4% (0.04 m^3) respectively. Tree height is not perfectly estimated due to laser obstruction by crowns layer, but the acquisition speed of this survey, joined with a suitable accuracy of parameters extraction, suggests sufficient suitability of the method for operational applications in simple forest structures (e.g. one-layered stands).

1. Introduction

The accurate measurement of forest stand features is not only a scientific value *per se* but a fundamental step in silvicultural management and forest planning. There is an increasing need for accurate and fast forest field inventories, due also to the growing demand for the assessment of the multiple ecosystem services (Müller et al., 2020). Besides the widespread use, in the last decades, of remote sensing techniques in forest inventories, the operational surveys still require manual measurements of field plots (Hyyppä et al., 2020). Diameter at breast height (DBH), individual tree height (H) and crown base height (CBH) are the tree parameters most frequently measured in the field. Although traditional field measurements are as yet broadly practised, they present some bottlenecks being time consuming and limited in their spatial extent (Bauwens et al., 2016).

1.1. *Geomatic meets forestry: 3D data acquisition and processing*

Current forestry management practices, can benefit from different surveying approaches: Terrestrial Laser Scanning (TLS), Airborne Laser Scanning (ALS), Mobile Laser Scanning (MLS) and Personal Laser Scanning (PLS, a subcategory of MLS). DBH, H, CBH and other tree variables can be estimated using either the ALS system (Luo et al., 2018; Maguya et al., 2015; Sibona et al., 2017), the TLS survey (de Conto et al., 2017; Liu et al., 2018a) or the MLS technology (Čerňava et al., 2017; Forsman et al., 2016). In this scenario, the increasing consciousness and the availability of technological innovations have made possible a stronger bond between geomatic and forestry disciplines. Forest

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inventory at different scales and levels of detail plays a key role for the management choices and the geomatic techniques can increase the automation level during the field measurements (Pierzchała et al., 2018). Indeed, over the last decades, technological development in data collection and computational processes have opened up new fields of research, also in forest data analysis, using remote and proximal sensing approaches (Tao et al., 2015). Then, the forestry point cloud data analysis and management can be conducted using different softwares, as argued by several studies in the literature: CloudCompare (Girardeau-Montaut, 2021), FUSION/LDT (Karna et al., 2019; Moe et al., 2020), LiDAR 360 (Chen et al., 2019; Luo et al., 2018), “3D Forest” (Trochta et al., 2017), Computree (Del Perugia et al., 2019), MATLAB (Itakura and Hosoi, 2020; Zhang et al., 2019), Python (Holmgren et al., 2019; Srinivasan et al., 2015), R packages such as “lidR” (Tompalski et al., 2019; Zaforemska et al., 2019), “TreeLS” (Dalla Corte et al., 2020; Puliti et al., 2020) and “rLiDAR” (Mohan et al., 2017).

1.2. The need for ground-based mobile proximal sensing

The rapid development of acquisition systems able to collect 3D point clouds, allowed the automation of forest inventory procedures. Several platforms have been developed to reduce time and cost of traditional measurements held with optical or electronic instruments and to improve their precision and accuracy (Luoma et al., 2017; Wang et al., 2019). Light detection and ranging (LiDAR) techniques is boosting ecological and forest research, and researchers in various fields began to apply it for modelling analysis (Zhou et al., 2019). TLS is a ground based LiDAR scanning system able to offer data to analyze, improving significantly Above-Ground Biomass (AGB) estimation (Stovall et al., 2017). The 3D model derived by TLS application are treated as ground truth validation of forest biomass models (Momo Takoudjou et al., 2018; Brede et al., 2019). From these data is possible to extract and storing different metric data, such as DBH (Liu et al., 2018b; Dassot et al., 2012), H (Panagiotidis et al., 2016; Cabo et al., 2018), stem volume (Iizuka et al., 2020; Panagiotidis and Abdollahnejad, 2021a; Panagiotidis and Abdollahnejad, 2021b), AGB (Momo Takoudjou et al., 2018; Gonzalez de Tanago et al., 2018) and branch architecture (Lau et al., 2018). Unfortunately, due to the static nature of TLS, it requires multiple scanning stations to ensure the effective detection of the trees. This task is time-consuming and requires manpower (Kunz et al., 2019). The most significant problems are the effects of the occlusion by trunks, crown and the understory vegetation (Bauwens et al., 2016; Gollob et al., 2020; Holopainen et al., 2013). The limitation listed on TLS have boosted researchers to move up technologies able to produce 3D point clouds in a ready to use manner.

A solution is given by mobile laser scanner (MLS) (Mokroš et al., 2021). These systems combine a laser scanner with an inertial measurement unit (IMU), exploiting the so called SLAM (Simultaneous Localization and Mapping). The accuracy of measurements mainly depends by the synchronization of these components. Moreover, thanks to the moving platform, the occlusion effect is reduced (Bauwens et al., 2016). MLS applications are divided in two categories: handheld laser scanning (HMLS) and backpack personal laser scanning (BMLS). Early scientific publications with MLS date back 2013, and the first system prototype was large in size and weighed approximately 30 kg, which limited its operability and mobility (Kukko et al., 2012). More recent *out-of-the-shelves* products are lighter and more compact than more complex MLS systems, and can be easily held by a single operator even in challenging scenario. Several studies evaluate the accuracy of these different scanning systems in forestry settings. Comparative studies between TLS and MLS revealed that MLS got more accuracy than TLS rate (Gollob et al., 2020), and took less time to collect the data. The use of TLS requires multiple scanning bases to ensure the effective detection of the trees, and the most significant problems are the effects of shade or concealment by trees (Bauwens et al., 2016; Gollob et al., 2019). Conversely, some studies on the quality of the point cloud obtained by MLS report a problem in the model due to noise (Bauwens et al., 2016) or errors in fitting the geometric shapes (Nurunnabi et al., 2017). In order to achieve high accuracy, several factors must be taken into account, such as a small research plot, the best environmental conditions, the instrument used and visibility of the surrounding environment during real-time mapping (Van Brummelen et al., 2018).

1.3. Paper contribution

Given the above-mentioned aspects and in line with the recent literature, in this study we tested the applicability of MLS technology to measure individual tree parameters in a black pine (*Pinus nigra*Arn.) plantation. Specifically, we first compared three methodologies of MLS point cloud processing to obtain DBH, H, CBH and brach-free stem VOL on standing trees and estimated their accuracy. Then, we compared the best MLS-derived and traditional manual-measured values with the ground truth data collected from selected felled trees. From the experiments, we hypothesized that DBH estimation could be affected by less error than total height and crown base height, due to the limitation of crown shielding.

2. Materials and methods

2.1. Study area

The study area is included in the “Cesane Regional Forest” (43°42’N 12°45’E), a large forest area of approximately 1500 ha located on the homonymous mountain system in the norther part of the Marche region in Central Italy. The orographic system is ranging from 200 to 600 m a.s.l. featuring smooth hills and some steep slopes, with an extended top plateau. The forest became state owned a century ago to be restored with reafforestation after intensive agro-pastoral exploitation causing extended slope erosion. Forest plantation, often along man-made stone terraces, started in the early ‘900 but continued especially after World War II using mainly a very resilient conifer species such as *Pinus nigra* var. *nigra*, well adapted even to bare rocky soils. Pine is by far the dominant species (Fig. 1) with a mean stand density equal to 800 n/ha, but manna ash (*Fraxinus ornus* L.) was also frequently planted along the rows. In addition we found a very sporadic occurrence of downy oak (*Quercus pubescens* Willd., 1805), sycamore maple (*Acer pseudoplatanus* L., 1753) and European smoke tree (*Cotinus coggygria* Scop.) that have probably entered naturally in the forest area.

2.2. MLS survey

The survey was conducted in early February 2020 to reduce the occlusion effect caused by deciduous species of the understory, with a Mobile Mapping System device Kaarta Stencil 2.[1] This instrumentation is equipped with a LiDAR Velodyne VLP-16 sensor mounted on top of an aluminum platform, an IMU (Internal MEMS) and an internal processor (Intel-7) for real-time localization and mapping. This instrument scans the environment around the device, quickly and automatically, in 'handheld' mode. It is a light weight (1730 grams) device, with battery life of around 2 h and internal 1 Tb SSD memory. It provides a very dense point detection (300000 maximum number of points to read from the logged up to 10 Hz). The LiDAR has a beam ($\lambda = 903$ nm) with 16 laser profiles and a vertical field of view of $+15^{\circ}$ to -15°, while the horizontal view is 360°. The scanning path was performed considering the following issues: i) avoiding occlusions among trees, maximizing the best coverage for the trees; ii) reducing the drift error, which may occur in repetitive environments where the alignment is harder; iii) avoiding the noise in the point cloud data. For the above-mentioned reasons, we

[1] \https:/www.kaarta.com/products/stencil-2-for-rapid-long-range-mobile-mapping.

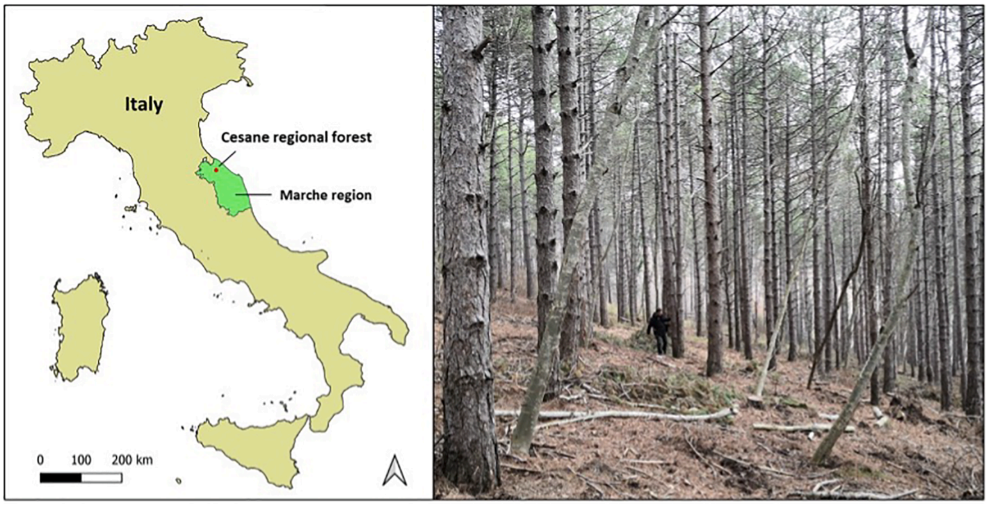

Fig. 1. The location of the study area (left) and a view of the black pine plantation (right).

adopted the following settings (Table 1).

The scan survey covered approximately 0.5 ha of the forest stand and it was conducted walking through the forest plantation rows. The study area was surveyed in 75 min collecting 276 millions of points with a registration radius value of 100 meters (Fig. 2a). During the MLS survey, it also has been possible to view the operations carried out by the tracker camera on an external monitor. Concluded these steps, the system created and currently dated a folder with files describing the configuration settings, 3D cloud characteristics and trajectory estimation. Since the Kaarta is not equipped with an internal GNSS, it has been necessary to manually perform the georeferencing post-process of the point cloud using CloudCompare tools (Kruček et al., 2020). We then collected the coordinates (x,y) of three Ground Control Points (GCPs) with a HiPer VR Topcon GNSS antenna[2] in the centre of three reflective targets placed on the ground at a considerable distance, projected in the WGS 84-UTM33N coordinate reference system.

2.3. Traditional field survey and ground truth assessment with felled trees

Within the MLS scanned area, we selected 50 pines of representative tree diameter and height within the pine stand (Fig. 2b). We first traditionally measured the 50 standing trees: DBH with a dendrometric caliper, H and CBH (the height from the tree stem base up to the first living tree branch) with a Haglöf Hypsometer (Vertext III). We also registered the relative tree positions measuring with sub-metric precision their horizontal distance and azimuth with a TruPulse 360B rangefinder (Laser Technology Inc.) from five GCP recorded with the HiPer VR Topcon GNSS receiver. The DBH of the selected trees ranged from 13.5 to 37.0 cm, with a mean and median value of 24.9 cm and 25.3 cm respectively.

Table 1
Kaarta Stencil 2 parameters setting used for field survey.

Parameters	Value [m]
VoxelSize	0.4
registrationRadius	100
cornerVoxelSize	0.2
surfVoxelSize	0.4
surroundVoxelSize	0.6
blindRadius	1.0

In a second step, the selected 50 trees were cut down in September 2020 after authorization from the regional authority. We measured the stems total length (equal to the tree height) of felled trees with a measuring tape and the length from the stem base to the first living branch (corresponding to CBH). Stem diameter was measured at the stem base, at 1.30 m (corresponding to DBH) and at the median line of every 1 m long virtual sections from the base to the tapering diameter of 7 cm. The branch-free stem height was determined by visual interpretation of the stem profile, until a mean cut off height of 8 m. The branch-free volume (VOL) of single felled stems was computed applying the Heyer's formula (Eq. 1):

$$V = S_1 + S_2 + S_3 + \cdots S_{n-1} + S_n \tag{1}$$

where V is the volume up to 8 meters above the ground and S_1, S_2, S_{n-1} are the transversal surface areas of each 1 m long log. We assumed that collected measures on felled trees were error free and we used them as reference data for the comparison with traditional measurements and with remote sensed records.

2.4. Point cloud processing

For better comprehension we outlined the data processing workflow in Fig. 3.

We analyzed the points cloud by developing a semi-automatic approach for the extraction of metric data. The first phase concerns importing and visualising the raw data in CloudCompare (Girardeau-Montaut, 2021); then, we filtered the raw cloud by removing unnecessary detected areas to make its management easier. After having delimited the test area, we performed data filtering using the "Statistical outlier remover" SOR function (Rusu and Cousins, 2011) which allows to discard outliers and noise points produced on the trunks surface during the acquisition phase. Then, we carried out the classification between the ground and above ground points, using the Cloth Simulation Filter (CSF). CSF filters the terrain points, ensuring significant time savings and accurate reliability of the final data. The values adopted to set the parameters, optimized after several tests, were 0.3 m cloth resolution and 0.6 m distance threshold, with a maximum of 50 iterations for the analysed sample. Since some portions of the trunk were classified as ground points (Fig. 4) it required further filtering using the "Features Geometric" tool which classifies all point verticality concerning the nearest neighbours point, based on the local orientation and curvature of the stem point cloud (Hackel et al., 2016). For this project, "TreeLS" package (de Conto et al., 2017) was used to segment the whole point cloud forest and to get a point cloud for each individual tree, which

[2] https://www.topconpositioning.com/it/support/products/hiper-vr.

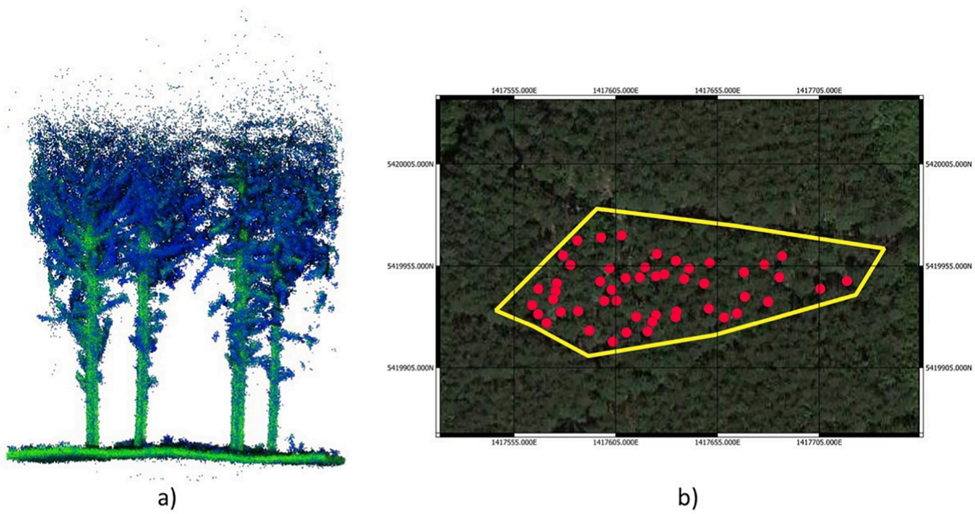

Fig. 2. a) an example of the tree point cloud view by Kaarta Stencil 2; b) distribution of the 50 selected trees (red dots) within the yellow boundary of the forest plot.

calculates the vertical area and enables visual detection of surfaces that extend perpendicularly to the ground. After normalizing the points cloud, we automatically extracted a set of metric data belonging to each of the 50 felled pines for statistical evaluation. We manually matched the coordinates of the extracted trees with those collected in the field with the laser rangefinder, both data were registered in the same reference system (WGS84-UTM33N).

For this scope, we analysed several data extraction methodologies. More in deep, for the detection of forest metrics we exploited the “3D Forest” open source application (Trochta et al., 2017), “VoxR” package and the combination of “TreeLS-rLiDAR-lidr” packages inside R language (R Core Team, 2021). Afterward, we compared these methods with ground truth data. The first method is “3D Forest” application, based on the C++ language and widely used to analyze points clouds from Terrestrial Laser Scanning. This is based on clustering points according to their relative distance, minimum number, corner and distance between centroids of each cluster (Kruček et al., 2020). This application is suitable for processing trees with simple crown structure, reason why it has severely limited the extraction of further data. In fact, the irregular crown shape and dense foliage limited a correct investigation, such as the segmentation and volume of branches, leading to discordant results. Therefore in this case we calculated DBH, H and branch-free stem VOL (Fig. 5a). The tool allows the extraction of two different DBH, the first Randomized Hough transformation (RHT) according to the circle detected in the point analysis, whereas the second one, based on Least Square Regression, with an algebraic estimate of the geometry calculation of the detected circle (Chernov and Lesort, 2005). Next, we defined H as the calculation of the maximum distance between the two points along the Z axis. Finally, we computed the branch-free stem volume using the Convex hull algorithm. At the end of this procedure, a denoising operation was used to filter out those points not belonging to the trees. Noise reduction and cleaning operations are included in CloudCompare. The second test consisted on running the “VoxR” package (Lecigne et al., 2018), a library written with the R language (Team et al., 2013) which is based on a voxelization algorithm that has allowed the classification of points in a regular three-dimensional grid of voxels (Fernández-Sarría et al., 2013). The file, imported in.txt format, was subjected to metric analysis, using the “tree_metrics” function and setting the voxel size as 0.05 m; DBH, H and VOL values were extracted (cylinder), such as diameter, height, and volume (Fig. 5b). This function makes the metric data extraction easy and intuitive. The third method tested is a set of R-packages allowing the extraction of the whole metric data. TreeLS (de Conto et al., 2017) permits the users to customize the parameters according to the tree characteristics and the points clouds, using algorithms with various functions. The most important one allows the stem mapping through the automatic detection of individual trunk points. We carried out the correct identification of the trunk’s points, separating it from the branches and leaves by means of the Hough transformation and consequently exploiting the RANSAC algorithm (de Conto et al., 2017). The latter subdivides the cloud into several subsets, providing the inventory of each calculated geometric primitive (cylinder), such as diameter, height, and volume (Fig. 5c). The last step generates a series of geometric primitives of cylindrical shape along the vertical axis of the trunk. Before being reconstructed by using the geometrical primitive, in particular the circular cylinders (Markku et al., 2015), the stem point cloud tree was sliced into three subclasses.This necessary because of stem tapering as also addressed by Panagiotidis and Abdollahnejad (2021b). The slicing step has carried out along the z-axis from up to the maximum height of 8 metres for each investigated tree. We calculated a cylinder primitive geometrical by Ransanc algorithm. It was filtered on vertical point cloud slice with high accuracy. Thus, the output a high details and accuracy concerning the metric data, such as DBH, H and branch-free stem volume.

This choice derived from LiDAR data that provide an incomplete representation of the trunk surface, due to physical obstacles (fallen trees, shrubs or saplings) or shaded areas. In particular, denoising operations tend to poorly filter out even heterogeneous or unshaded portions of point clouds, compromising the correct data analysis. An interpolation of the two diameter values closest to the breast height (1.30 m) allowed to calculate each stem DBH. Furthermore, in this set, the barycentric coordinates of each point cloud tree and the DBH were extracted. Again, using the inventory data, we achieved the volumes of the cylinders, estimating them up to a height of 8 m above the ground. The maximum height was then extracted using the lidR package (Roussel et al., 2020). Finally, the “rLiDAR” package (Silva et al., 2016) was used for the calculation of the CBH. This package enables to find a set number classes of point clustered along the z-axis tree by “kmeans” algorithm. Thereby, for each subset was computed “Convex Hull” algorithm which had facilitated the distinction of the crown from the trunk (Fig. 6).

2.5. Comparison analysis

We evaluated the bias and root-mean-square error (RMSE) of selected variables (DBH, H) comparing first the results gained with the three different algorithms (“3D Forest”, “VoxR” and the combination of “TreeLS-lidr-rLiDAR” packages) with ground-truth measures on felled

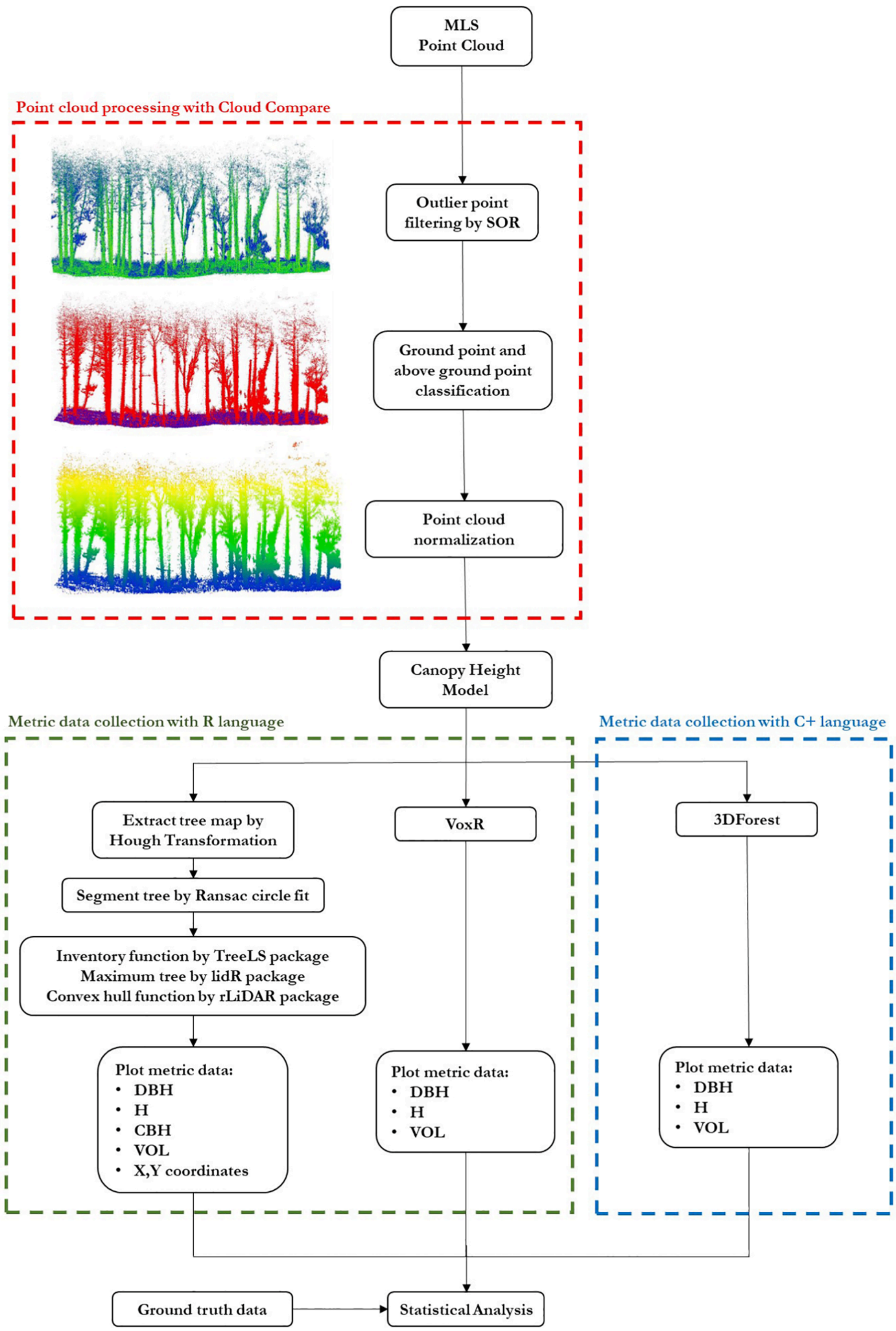

Fig. 3. Research Workflow (Diameter at breast heigh (DBH), individual tree height (H), crown base height (CBH), branch-free stem volume(VOL), barycentric coordinates (X,Y)).

trees; then, comparing traditional field surveys and the best MLS method with ground truth (adding CBH). We used the following equations:

$$bias = \sum_{i=1}^{N} \frac{x_i - x_{i,ref}}{N} \tag{2}$$

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(x_i - x_{i,ref})^2}{N}} \tag{3}$$

where N is the number of felled trees, x_i refers to the estimates achieved with the algorithms and with traditional survey, and $x_{i,ref}$ refers to the corresponding ground truth value. Additionally, we used the following definitions for the relative bias and RMSE:

$$bias\% = \frac{bias}{x_{ref}} \times 100\% \tag{4}$$

$$RMSE\% = \frac{RMSE}{x_{ref}} \times 100\% \tag{5}$$

where x_{ref} is the mean of the reference values. For the comparison among the three MLS methods with ground truth measurement, we also evaluated the bias and RMSE for stem volume extraction up to 8 meters above the ground. We fitted regression lines of DBH and H values dis-

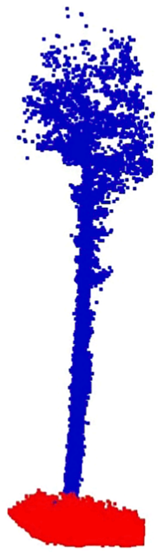

Fig. 4. The individual output from Cloth Simulated Filter (CFS) algorithm. The ground points are red and off-ground points blue.

tribution derived by laser survey, traditional field operation and ground truth assessment data. Finally, we plotted all parameters distribution using boxplot charts and tested the differences of means using paired two-sided *t-test* with 95% of confidence level ($\alpha = 0.05$).

3. Results

3.1. Comparison of the three MLS methods for feature extraction

Exploiting the object 3D reconstruction, we obtained the score with most accuracy, with the identification of the closest geometric primitive of its original shape. With this first analysis we wanted to discard the less accurate method for a better comparison in the following step. The best accuracy is reached with the "TreeLs-lidR-rLiDAR" packages combination (Table 2), through the Hough transformation. We then performed a stem modelling with the RANSAC algorithm, which allowed the more accurate estimation. The use of MLS has produced zones with low density and high noise point clouds (Fig. 7).

3.2. Comparison of traditional and MLS methods with ground truth

Bias and RMSE values of traditional field sampling compared to ground truth measurements are very low for DBH: 0.8% (0.2 cm) and < 5% (1.1 cm) respectively (see Table 3). Similar gaps occur in tree sub-samples with DBH below and above 25 cm (RMSE of 0.8 cm and 1.3 cm respectively). Manual measured tree height was slightly under-estimated compared to the ground truth (% bias = −0.7 and % RMSE = 10.2) as well as in trees sub-sample with heights below 17.5 m (bias % = −1.3 and RMSE % = 11.2) (Table 3). Diversely, the RMSE of H estimates of trees higher than 17.5 m indicated a minor overestimation (1.6 m and 8.9%) compared to the ground truth. CBH showed a bias of 0.1 m (0.6%) and a higher RMSE (15.8%) (Table 3).

Comparing MLS values with ground truth measurements (Table 4), the bias of DBH estimates was equal to 0 for both absolute and percent values and the RMSE 10.8% (2.7 cm). For DBH sub-groups, we found opposite estimates: positive for DBH below 25 cm (0.8 cm and 4.1%) and negative for DBH above 25 cm (-0.8 cm and −2.8%); % RMSE was equal for both classes (10.6%). H and CBH measured with MLS were under-estimated compared to the ground truth (bias of −8.6% for H and −13.3% for CBH) but CBH estimate had the highest percent RMSE value (19.5%). Splitting the analysis by H classes (below and above 17.5 m), both SLAM measures confirmed an overall underestimation compared to the ground truth (bias % of −7.6 for H below 17.5 m and −9.8 for H above 17.5 m). Branch-free stem volume (up to 8 meters) values showed a bias and a RMSE of −4.1% (−0.01m^3) and 12.4% (0.04 m^3) respectively.

Fig. 8a shows the overestimation of smaller DBH values and the underestimation of greater values (red line) using MLS. The comparison of tree height (Fig. 8b) reveals the same pattern of underestimation of MLS data for the heighest trees. We did not detect statistical differences in mean DBH ($\alpha = 0.05$) between the two estimation methods (MLS and TRAD) compared to the direct measurement on felled trees (Fig. 9a), but we found them in mean H (MLS vs FELLED) both for the whole sample (15.6 m vs 17.1 m respectively) and splitting it by H classes (15.1 m vs 16.3 m for H<17.5 m and 16.3 m vs 18.1 m for H >17.5 m) (Fig. 9b). We also detected significant statistical differences in comparison of mean

Fig. 5. DBH extraction phases: a) DBH and Tree Height data extracted by 3D Forest; b) Voxelization by "VoxR" package; c) Reconstruction of the geometrical primitives with RANSAC on the points classified as stem.

Fig. 6. CBH estimated by Convex Hull function.

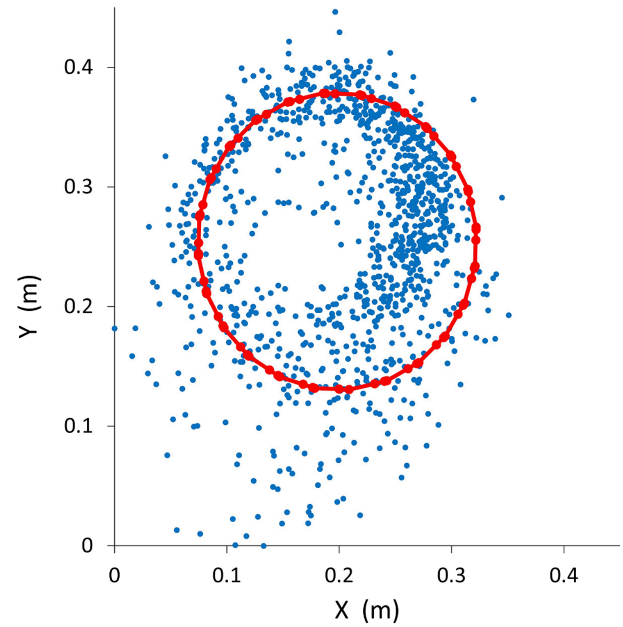

Fig. 7. DBH points extracted and plotted on a 2D graph. Red dots are the ones used to interpolate with a suitable circle, while blue dots are the discarded ones.

Table 2
Comparison of DBH (diameter at breast height), H (tree height) and VOL (branch-free stem volume up to 8 meters) measures collected from the 50 felled trees and parameters estimated by different algorithms. In brackets standard deviation is reported for felled trees measures and percentage values for bias and RMSE.

	DBH (σ) [cm]		H (σ) [m]		VOL (σ) [m^3]	
FELLED	24.7 (5.2)		17.1 (1.2)		11.2 (1.5)	
Platform	Bias (%)	RMSE (%)	Bias (%)	RMSE (%)	Bias (%)	RMSE (%)
3D Forest	0.9 (3.8)	4.1 (16.3)	−2.4 (−14.4)	3.1 (18.3)	0.0 (−11.5)	0.1 (31.7)
VoxR	2.6 (10.4)	6.8 (27.0)	−1.7 (−9.9)	2.4) 14.0)	0.0 (−11.1)	0.1 (39.6)
TreeLS-lidr-rLiDAR	0.0 (0.0)	2.7 (10.8)	−1.5 (−8.6)	2.4 (13.9)	0.0 (−4.1)	0.0 (12.4)

CBH (9.7 m for MLS vs 11.2 m for felled trees) and for stem volume (0.31 $m^3$for MLS vs 0.32 $m^3$for felled trees) (Fig. 10).

4. Discussion

Forest structure and yield measurements are essential not only for computing timber productivity but also for calibrating any kind of multi-functional forest management (e.g. biodiversity conservation, carbon sequestration and other ecosystem services). Nonetheless, accurate forestry measurements are not straightforward due to forests complexity and to the characteristics of the traditional instruments used in forest field measurements (e.g., calipers and clinometers). They are easy to use but they require several operational steps, becoming time consuming, laborious and expensive when repeated in inventory survey (Shao et al., 2020). MLS can provide very fast data collection of large areas, reducing the efforts for surface area and the measurement error. Holopainen et al. (2013) compared the accuracy and the efficiency of TLS, ALS and MLS systems on 438 trees in an urban forest area in Finland. The study proves that TLS and MLS outperform ALS for the parameters detection, as the canopy effect hampers the achievement of trustful results. Vatandaşlar and Zeybek (2021) evaluated the efficiency and reliable of Zeb-Revo

Table 3
Tree variables values reached with traditional manual measurements on standing trees (TRAD) and from cut down trees (FELLED). Abs: absolute values; %: percent values.

Variable	N	Mean (σ)		Bias		RMSE	
		TRAD	FELLED	Abs	%	Abs	%
DBH [cm]	50	24.9 (5.4)	24.7 (5.2)	0.2	0.8	1.1	4.5
H [m]	50	17.0 (2.1)	17.1 (1.2)	−0.1	−0.7	1.7	10.2
CBH [m]	50	11.2 (1.4)	11.2 (1.5)	0.1	0.6	1.8	15.8
DBH ⩽25 [cm]	25	20.7 (3.4)	20.6 (3.4)	0.1	0.4	0.8	4.1
DBH >25 [cm]	25	29.2 (3.4)	28.9 (3.1)	0.3	1.1	1.3	4.6
H ⩽17.5 [m]	28	16.1 (2.0)	16.3 (1.0)	−0.2	−1.3	1.8	11.2
H >17.5 [m]	22	18.1 (1.8)	18.1 (0.5)	0.0	0.0	1.6	8.9
CBH ⩽17.5 [m]	28	11.2 (1.4)	11.1 (1.9)	0.1	0.7	1.9	17.5
CBH >17.5 [m]	22	11.2 (1.3)	11.2 (1.0)	0.05	0.5	1.5	13.2

Table 4
Tree parameters values measured with SLAM (MLS) and on the ground (FELLED). Abs: absolute values; %: percent values.

Variable	N	Mean (σ)		Bias		RMSE	
		MLS	FELLED	Abs	%	Abs	%
DBH [cm]	50	24.7 (5.1)	24.7 (5.2)	0.01	0.04	2.7	10.8
H [m]	50	15.6 (1.7)	17.1 (1.2)	−1.48	−8.64	2.4	13.9
CBH [m]	50	9.7 (1.1)	11.2 (1.5)	−1.48	−13.3	2.2	19.5
VOL [m^3]	50	0.31 (0.1)	0.32 (0.1)	−0.01	−4.1	0.04	12.4
DBH ⩽25 [cm]	25	21.4 (3.3)	20.6 (3.4)	0.8	4.1	2.2	10.6
DBH >25 [cm]	25	28.0 (4.3)	28.9 (3.1)	−0.8	−2.8	3.1	10.6
H ⩽17.5 [m]	28	15.1 (1.7)	16.3 (1.0)	−1.2	−7.6	2.4	14.7
H >17.5 [m]	22	16.3 (1.6)	18.1 (0.5)	−1.8	−9.8	2.3	12.9
CBH ⩽17.5 [m]	28	9.4 (1.2)	11.1 (1.9)	−1.7	−15.5	2.5	22.4
CBH >17.5 [m]	22	10.0 (1.0)	11.2 (1.0)	−1.2	−10.4	1.7	14.9

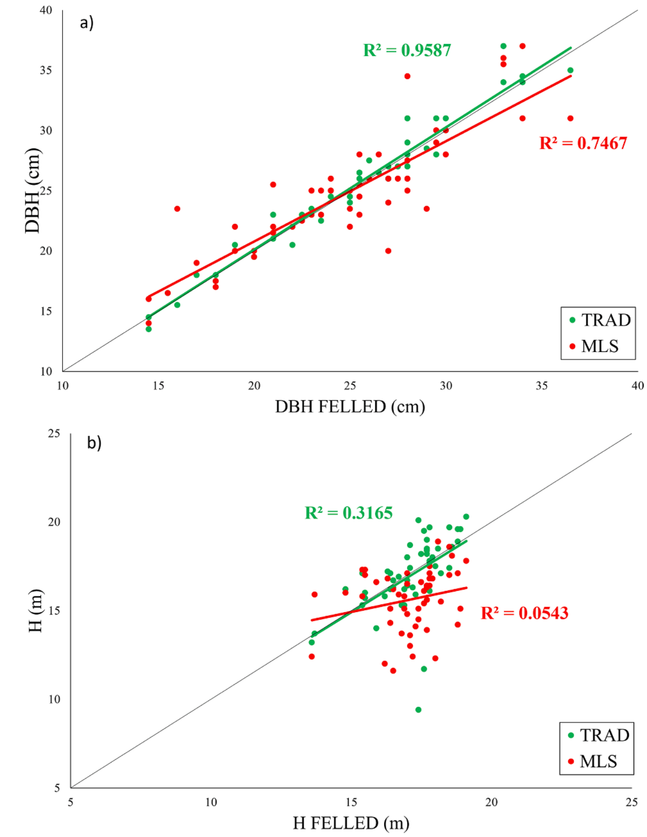

Fig. 8. Regression analysis between DBH (a) and H (b) values derived by laser survey (MLS, red dots), traditional field operation (TRAD, green dots) and ground truth assessment data (FELLED).

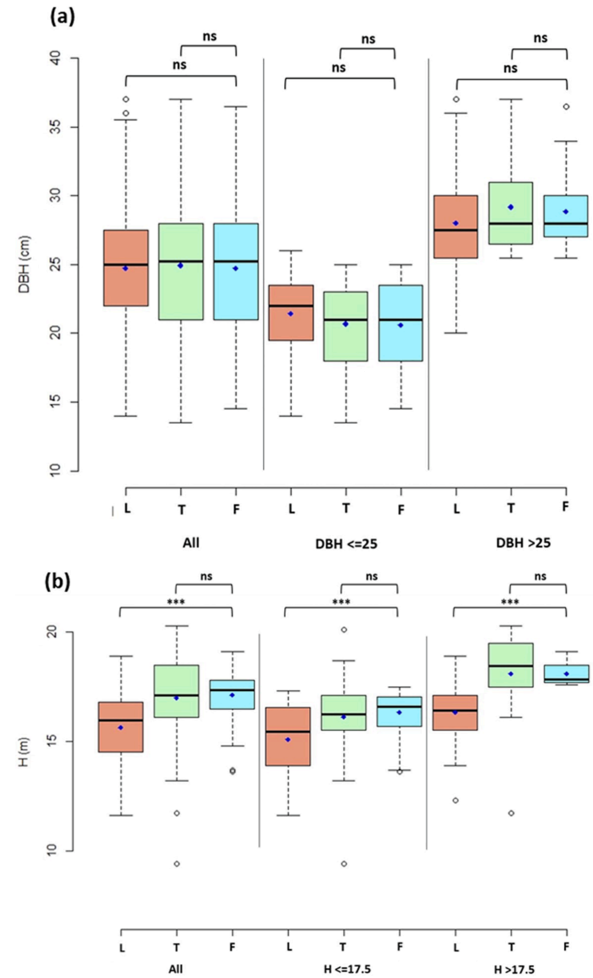

Fig. 9. Boxplots of the DBH distribution (a) and tree height H (b) from MLS (L - red), TRADitional (T - green) and FELLED trees measurement (F - blue) for the whole sample (All) and sub-samples (DBH below/above 25 cm and H below/above 17.5 m). Horizontal bold lines are medians, blue dots are the means. Whiskers are minimum and maximum values and circles are outliers. Significance of differences in DBH and H between MLS, TRAD and FELLED are marked by "ns" (not significant, p-value > 0.1) or "***" (p-value < 0.001) tested with paired two-sided Student's t-Test.

lidar (HMLS) by GeoSlam company compared to manual field measurements, considered as ground truth, in a forest stand (79 ha) in Turkey. They reported that DBH RMSE was 2.41% and bias 0.56%, while the timber volume showed a high deviation (21,5%), compared with allometric values. Bauwens et al. (2016) compared TLS with a handheld MLS. These two different systems, compared with the traditional field DBH measurements, provided similar results with a bias < -0.2 cm and a RSME < 1.5 cm. The DBH detection was determined with an accuracy of <3 cm scoring 96% for the TLS and 98% for the MLS. These rates decreased, respectively, to 78% and 73% with < 1 cm accuracy. This confirms that TLS e MLS produce comparable results in terms of accuracy, while the latter may result convenient as it reduces the time spent for performing the survey and the post processing phase of point cloud registration. Our results showed that data collected with MLS survey in an dense even-aged black pine plantation, provides acceptable DBH estimations, featuring a 10.8% RMSE respect to ground truth (4.5% RMSE with traditional measurements). The accuracy of DBH estimation with MLS remains sufficiently high at all size classes. The error slightly increases with height measurements, ranging from 13.9% for H and 19.5% for CBH, where traditional hypsometer survey produced 10.2% and 15.8% respectively. It is worth to note that our study confirms the most recent findings in the literature; the accuracy of H estimations decreases when the tree height increases, highlighting some limitation of the proposed approach. Consistently, the RMSE increases from the ground to the top of the tree for two reasons: i) the crown, being more dense, generally occlude the light beam by LiDAR; ii) the distance from the scanner to the stem decreases both measurement accuracy and points resolution. Both of these effects result in a smaller number of good quality arcs (Hyyppä et al., 2020). The values achieved in this work are not very different from those recorded in a Finland Boreal forest (Hyyppä et al., 2020) where the RMSE for total tree height estimation,

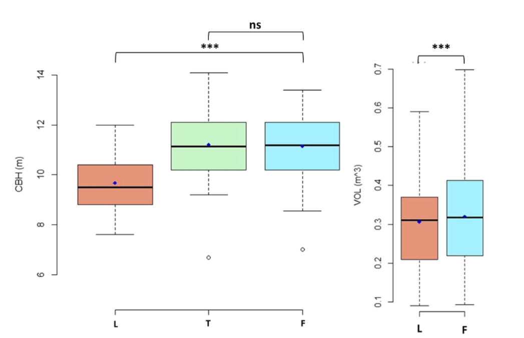

Fig. 10. Boxplots showing the CBH distribution (a) the volume distribution (b) of the tree stems from SLAM laser technology (L - red), traditional (T - green) and field direct measurement of felled trees (F - blue), across the whole sample (n = 50). Horizontal bold lines are medians, blue dots are means. Whiskers are minimum and maximum values and circles are outliers. * = p value < 0.05, ** = p value < 0.01, *** = p value < 0.001; ns, not significant (paired and "two-sided" Student's t-Test for laser and traditional measures with the ground truth).

using a backpack mobile laser scanner, was 8.7%. From the statistical analysis, the authors reported a RMSE of stem Volume computed in two sample plots, ranging from 0.053 m^3 e 0.002 m^3. The tree density in Boreal forests is usually much lower than in scarcely thinned mountain conifer plantations where the standing trees treetops are often hardly detectable. Considering our case with similar characteristics, the RMSE value compared with felled trees is 0.004 m^3. A detection accuracy of 90.9% was reached for the DBH detection from a MLS based point cloud compared with traditional ground data (Chen et al., 2019). This is confirmed even in the article by Cabo et al. (2018), where TLS e ZEB REVO are compared in *Pinus pinea* and *Platanus hispanica* plantations. In those sites, DBH RMSE is 0.011 m e 0.009 m respectively and H RMSE of 1.340 m and 9.440 m. Our approach produces comparable results with those already described in the reviewed literature, despite the authors tested the methodology with trees higher that 15 meters and in sunny conditions that reduce the MLS accuracy. Kaarta Stencil 2 proved to be versatile and featuring higher mobility if compared with TLS. The data processing method proposed in our study provides the most robust denoising method was the Hough transformation, since it maintains stem features up to the tree crown, allowing a better accuracy on the stem modelling phase. It worked out in good combination with the cylinder fit Ransac algorithm for stem modelling. The proposed workflow is linear and replicable to further studies as well the sample used. Dealing with the CBH, the proposed method (Convex Hull) provides a 3D graph showing the differences between the crown and the remaining stem, enabling the CBH visualization. A more efficient approach could be the combination of airborne collected data, for a more realistic detection of the crown shape from the forest canopy top (Luo et al., 2018). Finally, an important aspect that needs further studies is the effect of diameter size (Ryding et al., 2020). In our study we have limited the detection to the dominant and regularly shaped species, the black pine, providing more homogeneous target and facilitating the data processing. The results obtained are encouraging but need to be validated in more heterogeneous structures with mixed species and multilayer stands.

5. Conclusions

This study demonstrates the applicability of the hand held MLS with SLAM algorithm for the estimation of metric parameters of individual trees in a black pine (*Pinus nigra Arn.* plantation). The advantages of the MLS-SLAM application transcend the automatic registration of the scans and the low weight of the device, which favoured a high rate of reliability in retrieving the 3D structure and forest monitoring. Statistical analysis between LiDAR and ground truth data shows an accuracy of about 10% of relative RMSE. The forest environment investigated had very dense and overlapping crowns, and the presence of a consistent number of branches from 8 m height hindered the laser beam in acquiring objects at this height; this limitation reduces the estimate of the maximum tree height and total stem volume calculation. Our method exploited a semi-automatic procedure for the branch-free stem volume estimation, even if few thresholding operations are needed in the loop. Our research paves the way for future experiments, by highlighting limitations that deserve further investigation. Firstly, the sample stand is homogeneous both in terms of tree species and morphology; the same approach should be tested in a more complex contexts. Secondly, the lack of literature benchmarks in the definition of CBH. Indeed, the comparison with ground truth data is left to the operator's subjectivity; a more objective method of CBH extraction should be proposed in future research. Finally, the estimation of H cannot be sufficiently accurate, and integration with aerial data is still mandatory to guarantee a complete mapping of the surveyed area. Nonetheless, remote sensing data will provide new and accurate field data to improve measuring and estimation forest parameters, such as basal area or stand volume.

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CRediT authorship contribution statement

Stefano Chiappini: Data curation, Investigation, Methodology, Software, Writing – original draft. **Roberto Pierdicca:** Data curation, Formal analysis, Methodology, Writing – review & editing. **Francesco Malandra:** Data curation, Formal analysis, Investigation, Writing – review & editing. **Enrico Tonelli:** Data curation, Formal analysis, Investigation, Writing – review & editing. **Eva Savina Malinverni:** Writing – review & editing. **Carlo Urbinati:** Conceptualization, Funding acquisition, Resources, Writing – review & editing. **Alessandro Vitali:** Conceptualization, Investigation, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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