Trending applications of Phase Change Materials in sustainable thermal engineering: An up-to-date review

A FULLY AUTOMATIC FOREST PARAMETERS EXTRACTION AT SINGLE-TREE LEVEL: A COMPARISON OF MLS AND TLS APPLICATIONS

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KEY WORDS: Mobile Mapping, Remote Sensing, Forest Parameters Extraction, MLS, SLAM, ITD.

ABSTRACT

Forests are vital for ecological, economic, and social reasons, and adopting sustainable forest management practices is necessary. While traditional forest monitoring techniques provide detailed data, they are time-consuming; conversely, geomatic techniques can provide more detailed data for forest resource management. This study aims to assess the suitability of Mobile Mapping Systems (MMS) with simultaneous localisation and mapping (SLAM) technology for precision forestry purposes in challenging environments. We compared the performance of MMS data with Terrestrial Laser Scanning (TLS) data and evaluated the Forest Structural Complexity Tool (FSCT), which was developed for TLS datasets, on MMS data. The case study area is a highly sloped coniferous forest in the Italian Alps affected by a severe fire in 2017. Data were processed using a fully automated open-source Python tool that detects each tree's position, Diameter at Breast Height (DBH), and height. The validation procedure was conducted with respect to the TLS point cloud manually segmented. The results show that using MMS with SLAM technology is suitable for precision forestry purposes in challenging environments and that FSCT performs well on MMS data.

1. INTRODUCTION

Forests are essential resources for ecological, economic, and social reasons, and their protection and management can benefit from a complete understanding of tree distribution and composition. Forests (i) play a crucial role in regulating the Earth's climate by absorbing carbon dioxide from the atmosphere through the photosynthesis of chlorophyll; (ii) regulate the Earth's water supply through transpiration; (iii) protect the soil by reducing erosion, preventing landslides, and offering natural protection against rockslides; (iv) provide diverse ecosystems and guaranteeing biodiversity; (v) provide economic benefits both directly (e.g. timber production) and indirectly (e.g. tourism). These reasons lead to the primary need to adopt a sustainable forest management approach to improve risk prevention, production, protection, and preservation (Siry et al., 2005). For this purpose, deepening and innovating monitoring, data collection, and processing techniques are necessary.

Traditional forest monitoring techniques are considered reliable, provide detailed data on forest conditions, and can be performed by surveyors relatively quickly; however, such methods are often time-consuming and require extensive in-situ work. Traditional monitoring is mainly carried out through visual inspection and the manual collection of data on the field, such as tree density, canopy size, trunk diameter (Diameter at Breast Height, DBH), tree height, health status (through the identification of any presence of disease and insect infestation).

Developing practical tools for forest resource management, such as adopting geomatic techniques and producing innovative cartographic products, is necessary for achieving future sustainable development goals (Pirotti, 2012). The acquisition methodologies can be terrestrial or aerial. While the use of Uncrewed Aerial Systems (UASs) is efficient for rapid data acquisition and 3D modelling with Aerial Laser Scanning (ALS) or through photogrammetric acquisitions, it is also costly and requires careful survey planning and operator expertise; moreover, the models obtained from aerial surveys often do not guarantee a complete description of the lower part of the trunk of the trees and the undergrowth. This phenomenon is even more limiting in the case of aerial images. At the same time, as regards point clouds, the penetrating power of laser scanning technology allows the acquisition of points of the lower part partially covered by the vegetation above. On the other hand, terrestrial acquisitions can be static, commonly referred to as Terrestrial Laser Scanning (TLS), or mobile, using Mobile Laser Scanning (MLS). Static terrestrial scans can reach an accuracy of less than one centimeter, but at the same time, it is a more expensive technique; moreover, several acquisitions from different observation points are necessary to guarantee a wide distribution of points to describe the object under investigation fully. On the other hand, mobile laser scanners facilitate survey activities. It can work without a Global Navigation Satellite System (GNSS), which enables the use of a mobile laser scanner in environments that do not have satellite coverage; at the same time, the acquired point cloud has a lower point density, a higher noise, and an accuracy at the centimeter level (Hyyppä et al., 2020). Mobile Mapping System (MMS) with a simultaneous localisation and mapping (SLAM) technology has been employed in several forestry studies (Liang et al., 2018; Mokroš et al., 2021; Pierzchała et al., 2018) conducted in different scenarios and a comparison and performance assessing of several acquisition techniques were also deepened (Hyyppä et al., 2020). However, to the best of our knowledge, no studies have yet been conducted on the accuracy of MMS in particularly challenging scenarios. Moreover, the forest environment can be challenging to detect using a Mobile Mapping System. In fact, in these scenarios, only a few features help the SLAM algorithm improve the alignment (Mokroš et al., 2021).

Several approaches for an automatic Individual Tree Detection (ITD) have been proposed in the literature. These methods have

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been developed starting from different types of data (aerial images from drones (Belcore et al., 2020; Ferreira et al., 2020; Santos et al., 2019), helicopters or satellites (Lassalle et al., 2022; Wagner et al., 2018); aerial or terrestrial point clouds (Hui et al., 2021; B. Yang et al., 2016; J. Yang et al., 2020), for different scenarios and forest types (coniferous or deciduous forests) and based on different approaches (point cloud-based (Krisanski et al., 2021; Latella et al., 2021; Ma et al., 2020)) or raster-based (Yuchu Qin et al., 2014; Zörner et al., 2018)). Regarding the most common and recent open-source algorithms for ITD, **Table 1** summarises the most important ones.

Tool	Data type	Approach	Language
Tree detection evo (Mäyrä et al., 2021)	Airborne hyperspectral images and LiDAR data	Raster-based	Python
PyCrown (Zörner et al., 2018)	LiDAR point clouds	Raster-based	Python
FSCT (Krisanski et al., 2021)	LiDAR (sensor-agnostic)	Point-based	Python
Forest Metrics (Shendryk et al., 2016)	LiDAR point clouds	Point-based	C++
Individual Tree Extraction (Luo et al., 2021)	MLS point clouds	Point-based	Python
Treeseg (Burt et al., 2018)	LiDAR point clouds	Point-based	C++

Table 1. Open-source algorithms developed for Individual Tree Detection.

In this study, we performed a forest parameter extraction using a TLS-borne fully automated open-source algorithm at a single-tree level with SLAM-based MMS data and compared the results with TLS data. The case study is located in a highly sloped coniferous forest in the Italian Alps, whose extension is approximately 70 hectares. Moreover, the study area has different tree densities, as the upper portion was thinned out just before the forest fire. Data were processed with the innovative fully-automated open-source Python tool FSCT (Forest Structural Complexity Tool) (Krisanski et al., 2021) developed for high-resolution TLS point clouds. The goal of this contribution is (i) to define whether the use of MMS is suitable for precision forestry purposes in challenging environments; (ii) to evaluate the performance of the FSCT tool on MMS data.

The MMS acquisition was conducted with a KAARTA Stencil 2, while the reference point cloud was acquired with a Riegl VZ 400i terrestrial laser scanner. The output of the processing on the MMS point cloud was validated with respect to the TLS point cloud manually segmented and deepening the accuracy in the Individual Tree Detection (ITD), in the assessment of the Diameter at Breast Height (DBH), and the tree height (H).

2. MATERIALS AND METHODS

The case study (**Figure 1**) is located in a highly sloped coniferous forest in the north-west Italian Alps in the municipality of Mompantero (Turin), 45.162344N, 7.037318E, which was affected by a severe fire in 2017 (De Petris et al., 2020; Vacha et al., 2023). The extension of the area is approximately 70 hectares. The tree vegetation consists almost solely of dense, even-aged *P. sylvestris* stands, which present different tree densities as the upper portion was thinned out just before the forest fire.

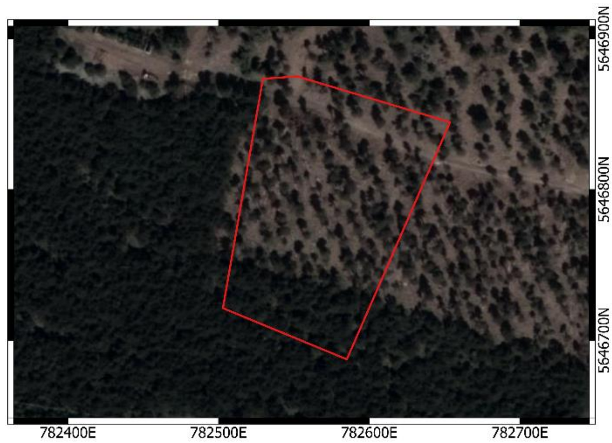

Figure 1. Study area (EPSG: 32632).

For the purposes of this study, an integrated sensor system based on SLAM (Simultaneous Localisation and Mapping) technology and capable of efficiently acquiring geospatial data was used. The KAARTA Stencil 2 survey system is an integrated mobile mapping platform; it combines a portable laser scanner with a video camera to automatically generate 3D point clouds. The merits of this platform consist in its low cost and light weight, which enhance its manageability. The technology is versatile and can be adapted for use in any environment, particularly in closed and complex spaces or forested areas with limited or absent satellite visibility. The survey system includes a laser scanner, data processor, and camera, allowing for accurate data acquisition while in motion.

The integrated laser scanner has a maximum range of 100 meters, a horizontal and vertical field of view of 360° and 30°, respectively, and an accuracy of ± 30mm. The feature tracker acquires images at a resolution of 640x360 pixels and a frame rate of 50 Hz. Using LiDAR and IMU data through an odometry and mapping algorithm, the system can produce real-time 3D maps of the surveyed environment. Furthermore, the SLAM algorithm leverages the acquired images to solve the localisation problem, optimise the estimated trajectory, and produce a 3D point cloud of the examined area. The KAARTA Stencil 2 has a tool specifically designed for post-processing acquired data, which can be done at a slower speed than the original acquisition speed. This can help improve point clouds' registration in cases where real-time acquisition may have failed. The software also allows configuration parameter modifications to adapt to specific survey environments. The instrument also includes a Loop Closure tool which uses various functions to improve scan registration and trajectory estimation coherence, correcting global drift errors by matching trajectory paths and enforcing overlap between the initial and ending points.

To evaluate the accuracy of the MMS outcome, five LiDAR scans were acquired with the high-performance terrestrial laser scanner RIEGL VZ-400i. This time-of-flight laser scanner can capture information up to 800 meters. Thanks to its ability to record multiple echoes, it is particularly suitable for use in forest environments, as it can penetrate through the vegetation. The scans were then registered and georeferenced using reflective markers whose position was previously measured through the support of a topographic network.

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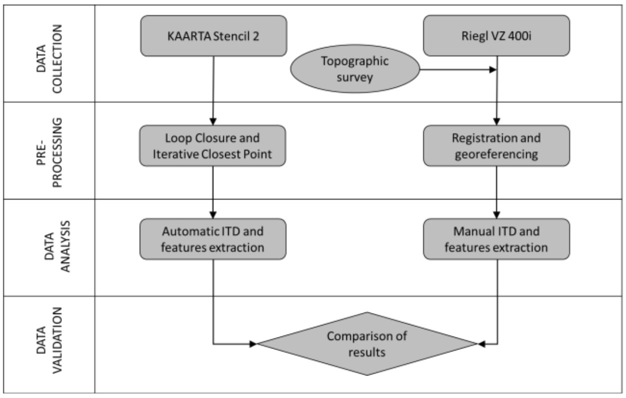

Figure 2. Workflow of the paper.

The workflow of the paper is illustrated in **Figure 2**. Section 3.1 describes the operations adopted during the data acquisition phase; Section 3.2 elaborates on the pre-processing procedures of the point clouds; in Section 3.3, the central data processing is explored; finally, the strategies adopted to validate the results are described in Section 3.4.

2.1 Data collection and pre-processing

The surveyor followed a closed acquisition path to ensure a comprehensive understanding of the area under investigation. The acquisition process began upstream of the area and followed a winding path downstream until reaching the lowest point. The operator then retraced his steps, intersecting the outward route multiple times until reaching the starting point. The acquisition took approximately 13 minutes, covering a trajectory of around 550 meters. Specific configuration parameters were used for data acquisitions optimised for vegetated environments. These settings include values for voxel size (0.4), point cloud resolution in the map file, point cloud resolution for scan matching and display (cornerVoxelSize equal to 0.4m, surfVoxelSize equal to 0.8m, surroundingVoxelSize equal to 0.6m), minimum point-to-point distance for mapping (1 m), and no restrictions on the planarity of motion.

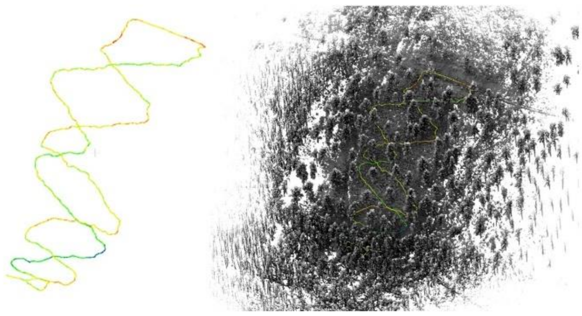

Figure 3. Point cloud acquired with the KAARTA Stencil 2 (on the right) and trajectory covered (on the left).

Data were then post-processed with the specific tool, simulating a lower acquisition speed according to an adaptive procedure considering the registration's reliability. The Loop Closure tool optimised the result and ensured that the initial and ending points overlapped. This process took approximately 40 minutes for the first phase and an additional 30 minutes to optimise the result, ultimately generating a point cloud of roughly 160 million points. The resulting point cloud and trajectory are shown in **Figure 3**. A preliminary registration was carried out using the Iterative Closest Point (ICP) algorithm (Li et al., 2020) available in the software 3D Reshaper, based on pairs of equivalent points identified in both the point cloud and reference model; this procedure allows to harmonise the models from mobile mapping tools with reference data

The reference TLS point cloud was acquired with a resolution of one point every 6 millimetres at a distance of 10 meters, and it consists of approximately 750 million points.

2.2 Data analysis

The KAARTA point cloud thus obtained was subsequently processed through the open-access point cloud processing algorithm FSCT (Forest Structural Complexity Tool) (Krisanski et al., 2021). The algorithm was developed using a database based on terrestrial laser-scanned point clouds. Still, it is declared effective with any type of forest point cloud regardless of the data acquisition methodology, as long as a high point density characterises it. In this study, it was decided to use the FSCT tool (previously introduced in **Table 1**) as it is one of the most recent and increasingly popular algorithms; moreover, some studies have already used it to process forest data at single-tree level with encouraging results (Tupinambá-Simões et al., 2023).
The FSCT processing algorithm performs a semantic segmentation of the point cloud with a deep learning technique based on the Pointnet++ architecture; subsequently, the points describing the terrain are used to create a digital terrain model (DTM) used to perform point cloud filtering after segmentation. Then, the point cloud is subdivided into slices clustered using a hierarchical density-based spatial clustering to detect stems and branches whose points are fitted inside cylinders. In the end, the sorting cylinder measurements procedure into individual trees is performed. Please refer to the reference article (Krisanski et al., 2021) and the Github repository (https://github.com/SKrisanski/FSCT) for a more detailed description of the method. This algorithm provides several outputs in addition to the Individual Tree Detection; specifically, we mainly focused on the position, the DBH, and the height of each tree.

The high computational demand necessary for the execution of the algorithm made it necessary to divide the area into five sub-areas, which were subsequently merged again. During the subdivision phase, particular attention was paid to selecting the areas so that the trees on the edge were entirely considered in one of the two areas.

2.3 Data validation

In order to evaluate the performance and accuracy resulting from a forest survey using a mobile mapping system, the point cloud acquired with the KAARTA Stencil 2 system was compared with the reference point cloud. The two products were compared by calculating the Euclidean distance between the points using the 3D data management software 3D Reshaper. The analysis was conducted both on the entire point cloud and a limited portion, filtered to eliminate the points related to the undergrowth and highlight the accuracies on individual trees.

Data validation of the analysis procedure was performed with respect to the TLS point cloud, which has been manually processed according to this workflow: single trees were manually individuated and segmented by visual interpretation of the point cloud; the height of the tree (expressed in terms of the elevation of the ground) was obtained by normalising the point cloud with respect to the elevation of the terrain obtained from the DTM; the single trees were then imported into the commercial 3D Reshaper software and the DBHs were measured using a circular fitting of the cloud points between 1.10 m and 1.50 m. Although the DBH is traditionally calculated at a height of 1.3 m from the ground, it was decided to consider the portion mentioned above of the trunk to include a greater quantity of points and perform a circle fitting with greater reliability. The reference trees were compared with those automatically identified using the FSCT tool. The validation of the point cloud segmentation at the single tree level was performed with respect to the treetop coordinates, carrying out a spatial search for each point and matching them with the closest reference point within a pre-set search radius. Each matched tree's DBH and height values were compared, and the RMSE values were calculated.

3. RESULTS

3.1 Data acquisition

Figure 4 shows the comparison results between the KAARTA cloud and the reference TLS cloud. 70% of the points have an accuracy of less than 6.3 cm, and 85% have an accuracy of less than 12.5 cm. The figure also shows that the points with the least accuracy are mainly located in the area with the most significant forest density.

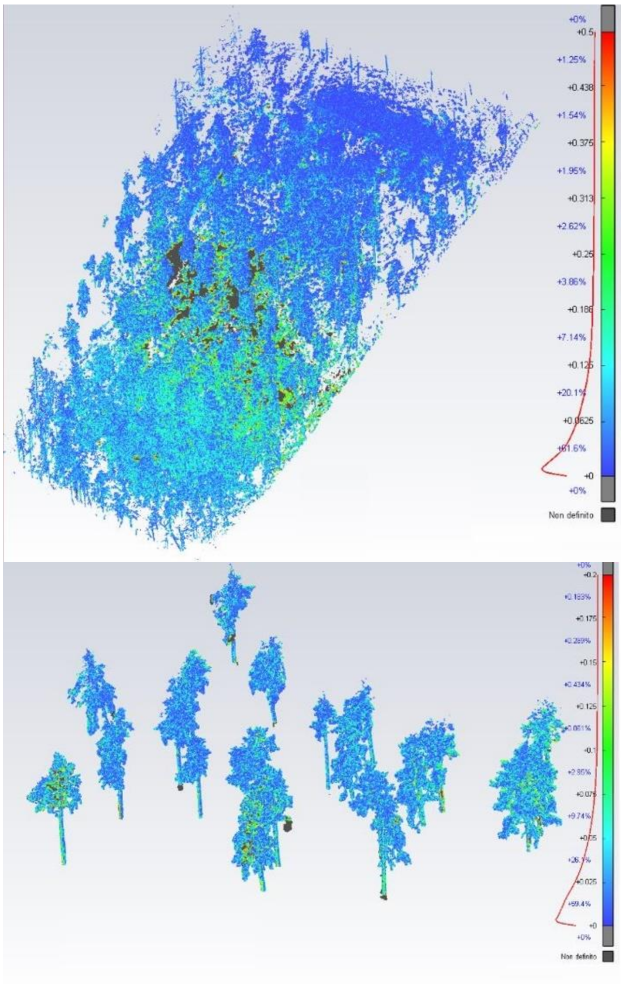

Figure 4. Complete KAARTA Stencil 2-point cloud (on the top) and a portion of individual trees (on the bottom).

3.2 ITD and forest parameters

Figure 5 shows the segmented MLS point cloud. Following validation, 86% of the trees are correctly identified and segmented (166 trees out of 192). Trees that were not correctly identified automatically (26 specimens) were excluded from further validations on DBH and height.

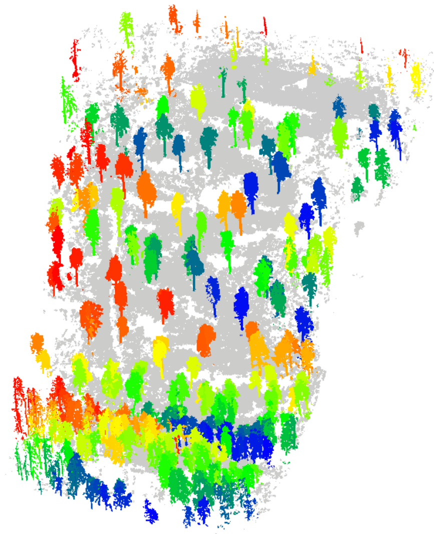

Figure 5. Segmented MLS point cloud at the single-tree level.

The distribution of the DBH and the heights is illustrated in **Figure 6**.

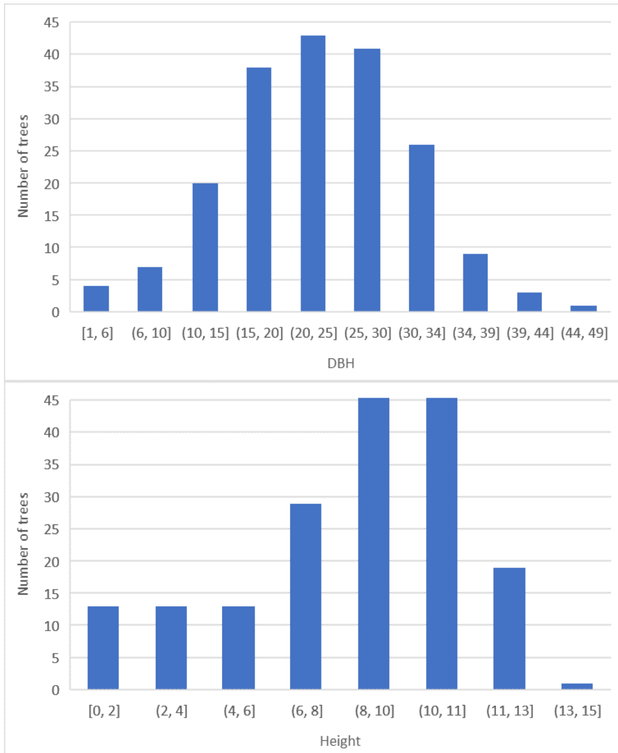

Figure 6. Distribution of the Diameter at Breast Height (on the top) and the height (on the bottom)

Parameter	Value
% Matching	86.5 %
RMSE (DBH)	6.5 cm
RMSE (H)	3.66 m

Table 2. Results of the comparison between MMS and TLS data.

Comparing the automatically estimated values with those obtained from the cloud of reference points, an RMSE relative to the height equal to 6.5 cm and an RMSE relative to the height equal to 3.66 m are obtained (**Table 2**).

4. DISCUSSION

The comparison between the KAARTA cloud and the reference cloud acquired with the terrestrial laser scanner highlights the strengths and weaknesses of a mobile mapping system applied in forest environments. The ease of acquisition in terms of time and effort used to carry out the survey, and the type of post-processing required, means that acquisitions of this type can be widely used in any field, even more so in more complex scenarios in which more operator experience is required. The automation of the procedure for identifying forest parameters at the level of a single tree imposes itself as a necessary and fundamental procedure nowadays to be able to make the best use of the type of data obtained with the laser scanner in an effective and efficient manner.

Although the advent of LiDAR technology has led to greater use of point clouds in various research areas such as the one carried out in this study, we must not forget that radiometric information, on the other hand, provide colour information of objects and can be used to detect trees based on their visual appearance. Machine learning algorithms, such as convolutional neural networks (CNNs), can be trained on RGB images to detect trees based on features such as colour, texture, and shape. KAARTA Stencil 2 does not save images (they are only used to support the SLAM algorithm). Still, other commercial solutions can combine point clouds and image data to provide more robust and accurate results for individual tree detection.

The SLAM algorithms integrated into the KAARTA mobile mapping system allow acquisitions to be made in environments where the GPS signal is poor or absent, still obtaining a good point cloud registration; this is subsequently further improved through post-processing based on the Loop Closure tool and on the ICP algorithm. On the contrary, the terrestrial laser scanner requires markers or recognisable points for the registration of the clouds. This makes this type of acquisition less immediate and more time-consuming in the in-situ survey phase.

The FSCT algorithm is one of the most recent open-source methods developed to automatically process high-density forest point clouds. Even in a complex scenario like the one analysed in this study, the results are outstanding; out of 192 trees, only 26 were not identified (23.5%). From a comparison and visual interpretation of the reference data with the position of the unidentified trees, it is observed that they are mainly located in the lower part of the study area, where no thinning was done, and the forest density is higher. Regardless of the data typology used to generate the cloud, it is widely known that trees of different ages and with different heights present more significant difficulties in the segmentation phase due to multilayering. To this is added the problem intensely discussed in the literature related to the intersection of the crowns of trees when they are located at short distances or in the presence of undergrowth or trees of lower heights and overhung by taller trees. On these aspects, it would be necessary to compare the methodology applied in this study with that of other algorithms to try to identify an approach that can be generic and valid in different forest conditions.

About correctly identified trees, The FSCT algorithm achieves RMSE values in line with the reference measurements for height (about 3 meters) and diameter (6 centimetres), which represents 37% of the mean height value and 26% of the mean DBH value, respectively. Concerning the height, 37% is high but expected value because the top of the tree is described in a limited way due to the acquisition range of the KAARTA. This problem is discussed in the literature and is mainly solved by integrating aerial data (drone survey). Moreover, even the TLS reference data must be interpreted with caution because, since it is a terrestrial acquisition, theoretically, we cannot be sure that the identified treetop is actually that of the tree without visual interpretation since we do not have aerial or traditionally collected data (i.e., hypsometer). It should be considered that the mapped specimens have a high canopy insert, which is also scattered due to the passage of fire. In general, the KAARTA data tends to underestimate the heights of the reference. About DBH, the average error is smaller, and 6 cm can be considered acceptable in the forestry field; in fact, most trees have DBH between 15 cm and 34 cm. Another aspect to consider is that working on layers and cylinder fittings, the point cloud must be uniformly dense in the vertical development. Consequently, there should be sufficient points on all sides of the trunk to represent an adequate arc of the circumference for fitting. Therefore, the acquisition was made with a crossed path to collect as much information as possible for each trunk, and the finning on the cylinder is realised on 0.4m portion of the trunk (1.1 m-1.5 m). Similarly to what discussed for the height, also in this case DBH in situ measured with traditional techniques is not available.

The cost of KAARTA's ease of use is paid for point cloud accuracy. Despite the post-processing process, which significantly improves the final result, the accuracy of the final output is affected by an error which, as described in subsection 3.1, is less than 6.3 cm for 70% of the points. From this point of view, it should be emphasised that this type of error is also linked to the fact that the two acquisitions are not precisely contemporary and that the thinnest branches and leaves are subject to the effect of the wind, which modifies their position. Another problem with SLAM systems is the incorrect registration of clouds, particularly in natural and highly vegetated areas, such as the study area. Even if the data is complete, it may not be correctly modelled by the algorithm. However, thanks to the loop closure and ICP algorithm, this application found no significant misalignments.

Evaluated parameters	MLS	TLS
Time of survey	Reduced times	More extended times
Ease of survey	Higher	Lower
Pre-processing	Loop Closure and ICP	Topographic survey and registration
Accuracy of the point cloud	Lower	Higher
Accuracy of the forest parameters	Lower	Higher

Table 3. Comparison between MML and TLS point clouds.

The forest typology (species density and morphology) influences the data quality, whether TLS or MMS. Specifically, it must be noticed that the density of trees in the upper part of the study area is low due to thinning in previous years, and the undergrowth is sparse due to the 2017 fire, making manual segmentation activities easier than in the lower part of the area. In the latter, the density is higher and composed of more layers, making manual operations uncertain. These values align with the results obtained from the automatic procedures described in the literature and comply with the accuracies required in the forestry sector. **Table 3** summarises the pro and cons of MLS and TLS point clouds.

From this first application of the FSCT algorithm for ITD and forest parameter estimation, it performs outstandingly despite being developed for denser and different types of data while applied on a sparser MMS point cloud. This analysis is a first step of a more extensive study. More rigorous and in-depth investigations are needed to compare different segmentation and parameter estimation methods in different scenarios based on various data.

5. CONCLUSIONS

Forest monitoring is a highly debated topic of fundamental importance worldwide. However, traditional techniques are time-consuming and do not allow an efficient estimation of forest parameters on a large scale. This study addresses the use of mobile mapping systems in forestry environments for purposes related to precision forestry in an automatic way. In particular, the validity of MMS systems in a challenging environment, with a high slope, heterogeneous density was investigated.

The point cloud resulting from the acquisition was processed through the FSCT open-source tool that performs Individual Tree Detection and the estimation of forest parameters at the single tree level, and the results were compared with a manually processed TLS point cloud. Results are promising; the IDT procedure is performed with a success rate of 86.5%. Moreover, the values of the root-mean-square deviation on the height and on the DBH confirm that the use of Mobile Mapping Systems assisted by automatic data processing can be considered as an efficient innovative time-saving approach for monitoring forests.

Nevertheless. further tests are needed to investigate the accuracy of other forest parameters (e.g. biomass) and the quality of the processing algorithm. Moreover, additional considerations should be deepened regarding the detection of the tree in its complete elevation extension and particularly of the treetop using terrestrial instruments.

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