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Comparing efficiency, timing, and costs of different walking paths in HMLS LIDAR survey

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Abstract The technological innovation of terrestrial LIDAR systems has recently given forest planners greater access to key features on forest structure. The Hand Held Mobile Laser Scanner (HMLS) is a recently developed LIDAR tool that is particularly user-friendly and reliable. It is especially useful in the mapping of forest stands, thanks to its implementation of the Simultaneous Location and Mapping Algorithms (SLAM) algorithm. Thus, the present study investigates the ideal walking path to follow during HMLS scanning to survey trees and estimates the biometric parameters of forest stands by testing three distinct schemes. Specifically, two different forest ecosystems are considered in experimental HMLS LIDAR surveys, a beech-dominated deciduous forest and an oak-dominated deciduous forest. Finally, a cost/benefit analysis of each laser survey is analysed according to three walking path models (STAR, GRID, BORDER). A control analysis is also performed of the traditional method without LIDAR. This study contributes to the advancement of a growing body of research on Precision Forestry by considering different characteristics of the forest environment. Regarding practical application, the resulting evaluation of field survey technology can help foresters integrate these techniques into their basic tool kit for forest planning and management processes.

Keywords: LIDAR applications; forest management; natural resources; remote sensing; mobile laser scanner, SLAM algorithm.

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Introduction

Local forest inventories are considered the main way of deriving information for forest management plans since they provide stand characteristics using forest variables derived by simple measures. In fact, the measures that allow to acquire biometric data can be used to evaluate different types of indicators

(Goodbody *et al*. 2021) dealing with different forest ecosystem services (Raši et al. 2020).

The possibilities to derive different Sustainable Forest Management (SFM) indicators related with different ecosystem services are considered pivotal to develop multi-objectives forest management plans (Raihan 2023). In this sense, for forest management plans at local level, generally many forest inventories plots are measured in the field using traditional instruments (i.e., hypsometer and callipers) (Åkerblom & Kaitaniemi 2021, Vandendaele et al. 2022), especially in EU Mediterranean and Apennine forests where the forest structure is complex (Giannetti et al. 2018).

As European and Italian Forest Strategies have pointed out (Raši et al. 2020, MIPAF 2021), the forest sector is dealing with sustainable forest management and is planning need to push up the adaptations of new digital and technological solutions that can help forest technicians, forest engineering and forest managers in acquiring precise data of forest stands (Puletti et al. 2021, Suarez et al. 2005, Shiba et al. 2006, Holopainen et al. 2014, Fardusi et al. 2017, Wulder et al. 2012, Fu et al. 2021, Sferlazza et al. 2022, Giannetti et al. 2023). In this sense, new cutting-edge solutions and tools have arisen to meet the demands of forestry companies to improve productivity and support decision-making in forest planning.

Nowadays the literature review deal with Precision Forestry and Forestry 4.0 (Corona et al. 2017, Singh et al. 2022, 2023) suggest that many digital and technology innovations are being adopted to measures forest plots that can support the developing of multi-objectives forest management plans (Nitoslawski et al. 2021, Giannetti et al. 2023). In this sense, it is mandatory that complex forest data need to be carried out with simply and cost-effectively instruments that will ensure the transparency of forest management operations (Corona et al. 2017), and replicability of data collections (Calders et al. 2020, Campos et al. 2021).

During the last decade, terrestrial and mobile laser scanning for forest inventories have been extensively studied to collect data, thereby replacing laborious manual field measurements using traditional instruments (Åkerblom & Kaitaniemi 2021, Vandendaele et al. 2022).

The use of such instruments can produce accurate measures of traditional forest inventory variables (e.g. diameter and height) (Ducey et al. 2013, Holopainen et al. 2014, Pierzchała et al. 2018, Liang et al. 2018, Giannetti et al. 2018, Sofia et al. 2021, 2022), but also to estimate valuable data regarding stem (Puletti et al. 2019), crown area (Giannetti et al. 2018, Bogdanovich et al. 2021, Chianucci et al. 2021), branch architecture (Wang et al. 2022, Donata Sarti et al. 2022), habitat assessment (Hasan et al. 2019, Puletti et al. 2021, Galluzzi et al. 2022), and fuel types (Forbes et al. 2022).

However, from a technical point of view, to guarantee a real adaptation of such instruments it is important to provide to forest stakeholders (e.g. forest engineering, managers, and technicians) concrete experiments on how such instruments can quickly provide forest data in response to their needs. In fact, providing such information is considered mandatory when digital/technological changes are applied in daily work. If this information is not provided, technicians can see such instruments as an increase complexity of the works, additional working time, and additional costs, so that such innovations are not embraced and just remain at research level (Weiss *et al*. 2021, Giannetti et al. 2022). These happen especially in those countries, such as Italy, where forests are complex biomes and the forest planning sector needs to be overcame the problems related with fragmentation of forest proprieties and value chains are not well developed (Giannetti *et al*. 2023, Cadez *et al*. 2023).

Belanda et al. (2019) have already showed the dual advantages that terrestrial laser scanning platforms can offers for the forest management plans: firstly, they furnish valuable information unattainable through traditional field surveys, such as stem maps, stem density, basal area, vertical profiles, Leaf Area Index, and crown roughness. Secondly, these platforms efficiently acquire data with highly accurate laser pulse returns. On the variety of Terrestrial LiDAR platforms, the most promising is the Handheld Mobile Laser Scanner (HMLS) showing a good potential to get precise forest variables measures within plots (Giannetti et al. 2018, Del Perugia et al. 2019, Belanda et al. 2019, Jurjević et al. 2020, Tockner et al. 2021, Proudman et al. 2021, Sofia et al. 2022, Vatandaşlar et al. 2022, Chiappini et al. 2022, Qi et al. 2022, Vandendaele et al. 2022), surpassing occluded areas commonly encountered in traditional fixed terrestrial laser scanning (TLS) methods (Chen et al. 2019). Moreover, recent advancements in experimental technological research significantly improved HMLS systems. Specifically, the development of lightweight, structured miniaturized HMLS instruments utilizing Simultaneous Localization and Mapping (SLAM) revolutionized data acquisition in forest environments. These advancements eliminate the reliance on GNSS navigation (Hyyppä et al. 2013, Liang et al. 2014, Kukko et al. 2017), allowing HLMS surveys even in under-canopy forest environments where GNSS signals weaken.

However, when utilizing HLMS, the complexity of forest structures significantly impacts the time needed to automatically analyse the point cloud for deriving forest inventory variables (Giannetti et al. 2018). This aspect could pose a challenge when integrating this technology into the daily work of forest managers or engineers involved in forest planning activities. Moreover, the path that is followed to acquire HLMS can impact the timing of data acquisition, analysis, and the accuracy of data obtained (Del Perugia et al. 2019, Chirici et al. 2023). In fact, some authors (Del Perugia et al. 2019, Chirici et al. 2023), emphasize the importance of conducting studies to test the performance of various survey paths to collect data on increasingly complex forest types.

To the best of our knowledge, some recent studies have shown that the walking scan path of an HMLS system influences the time required to acquire data and the cost of forest field operations. However, previous studies have not explored the accuracy of these walking scan paths within complex forest ecosystems that differ in slopes, tree density, and tree dimensions. Our study aims to investigate the influence of walking scan paths on deriving single-tree attributes using HMLS within the framework of forest management plans and to assess the associated costs to evaluate the efficiency. The research was conducted in two distinct forest types, typical of the Italian landscape: a pure even aged high beech forest and a natural Mediterranean holm oak forest.

Materials and Methods

Study area

The study was carried out in two distinct study areas in Italy that well represent the Apennine and Mediterranean Italian context (Figure 1 - Panel A).

The first study area namely “Camaldoli” is a beech forests (Lon. 11.831969, Lat. 43.811521; WGS84 EPSG:4326) located at 1270 m a.s.l. in Tuscany in the Foreste Casentinesi, Monte Falterona, and Campigna National Park. The beech forests (*Fagus sylvatica*) cover 95% of the wall area. Beside beech, other species include rowan (*Sorbus aucuparia*), common whitebeam (*Aria edulis*), sycamore maple (*Acer pseudoplatanus*), goat willow (*Salix caprea*), and silver fir (*Abies alba*), with a sparse shrub layer of 5% cover are present (Ubaldi 1988, Arrigoni et al. 1998, Casini et al. 1999). According to the European Forest Types (EFTs) classification the area is a “Beech Mountain Forests – Apennine and Corsican mountainous beech Forest” (Barbati et al. 2014, Giannetti et al. 2018) (Figure 1 - Panel B(a)).

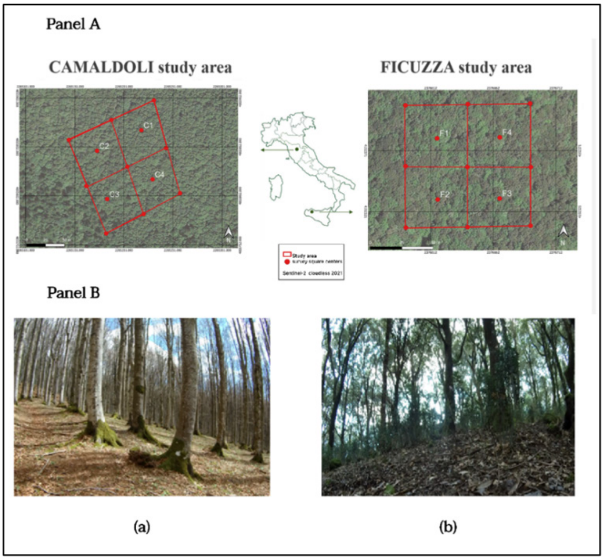


Figure 1 Location of study areas and field plot (Panel A), and overview of the forest stands in the two study areas (Panel B) – (a) beech forest in Camaldoli; (b) Holm oaks forest in Fairuza.

Climatic data from the nearby 'Camaldoli' station shows an average annual temperature of 8.7°C and annual precipitation of 1641.6 mm. Temperature peaks in July while rainfall peaks in October (179.0 mm), with the least in July (60.0 mm), but no pronounced dry summer period on average (https://www.cfr.toscana.it/index.php).

The second study area namely "Ficuzza" (Lon. 13.370163, Lat. 37.867241, WGS84 EPSG:4326), is a holm oak natural Mediterranean forest located at 681 m a.s.l. in Sicily in the nature reserve of "Bosco della Ficuzza, Rocca Busambra, Bosco del Cappelliere, and Gorgo del Drago". In this area, oaks dominates (holm oak, *Quercus ilex*, 60%, and downy oak, *Quercus pubescens*, 35%) covering 95% of the wall area, accompanied by occasional manna ash (*Fraxinus ornus*, 0.5%) and hedge maple (*Acer campestre*, 0,5%), and a sparse shrub layer (4%) (Figure 1 - Panel A). Following the EFTs the area is classified as "Broadleaved evergreen oak-Mediterranean evergreen oak forest" (Barbati et al. 2014, Giannetti et al. 2018) (Figure 1-Panel B(b)). Climate data from 'Ficuzza' station (681m) reported an annual temperature of 15.1°C, peaking in July (20.5°C) and lowest in January (9.8°C), with annual precipitation at 752 mm. Rainfall peaks in December (130 mm) and dips in July (4.8 mm) (http://www.sias.regione.sicilia.it/).

Field plots

To perform the analysis and to compare traditional and HLMS measures, 4 fixed area square plots of 2500 m^2 were identified in each study area, differentiated by slope (%) and trees density. The plots were distributed according to the systematic aligned sampling scheme to optimize sampling efficiency (Figure 2). For each plot, two types of measures were carried out: a traditional measure (conducted using traditional instruments such as tree calliper and hypsometer) and the HMLS scans. The details description of measures done in each plot will be described in the next sections.

For the analysis in the Camaldoli forests, we selected an area at an altitude of 1250 m a.s.l., primarily characterized by pure beech stands (Figure 2, Panel A). In Ficuzza, the chosen area is located to the southwest of Rocca Busambra, at an altitude of 950 m a.s.l., featuring a Holm oak deciduous forest.

The latitude and longitude of the centre of each square plot (Figure 2) and the four angles of the square were recorded by a GNSS receiver Trimble R8s GNSS System, which lasted for approximately 2 h with a 2 s logging rate. The post-processed centre coordinates revealed standard deviations of 0.9, 0.6 and 1.8 cm, respectively, for x, y and z.

Traditional field measures

Since the aim of the work is to compare traditional and HMLS measures in the context of sustainable forest management planning, we utilized the same approach for the traditional field measures as done by Italian forest

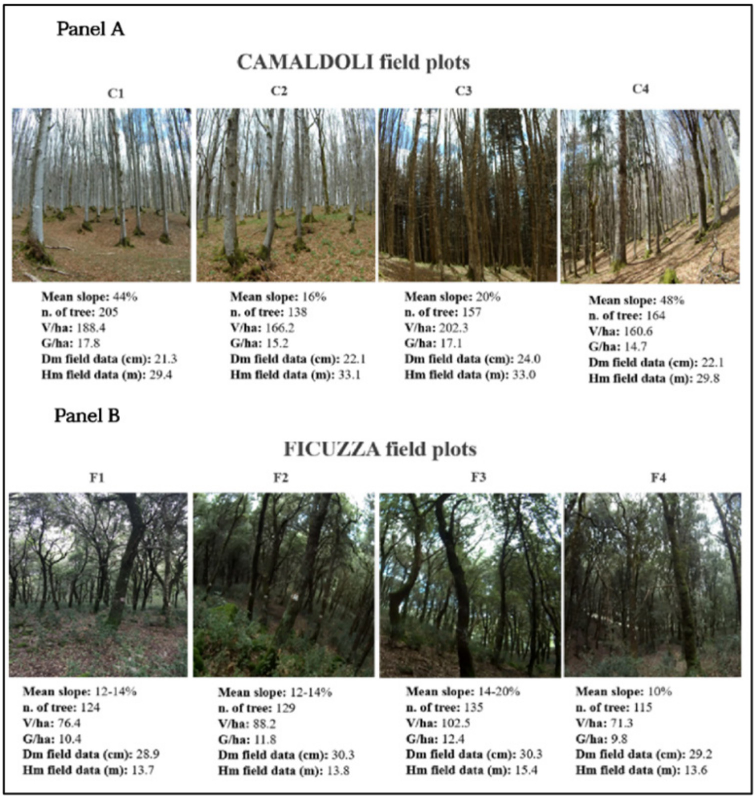


Figure 2 Main characteristics of Camaldoli (Panel A) and Ficuzza (Panel B) forest plots. Mean slope: medium value of field plot's slope, n. of tree: the number of trees per ha, V/ha: growing stock volume (m^3 ha^{-1}), G/ha: basal area (m^2 ha^{-1}), Dm: the m G/ha: basal area (m^2 ha^{-1}), Dm: the medium value of DBH measured in the field, Hm: represents the medium value of Height measured in the field.

managers and engineers. This approach can be divided in four main phases, which can be summarized as follow:

1) *Preliminary site analysis* – this phase involves identifying the forest area to be surveyed, choosing the size of the survey area, and organizing the necessary means, instruments, and personal for the survey.

2) *Collection of forest plot qualitative data* – in this step quantitative data related to forest plots are gathered. This may include information about species composition, forest structure, ecological features, and others relevant factors.

3) *Forest inventory measures in the field* – this phase involves conducting forestry inventory measurements on-site. It includes the delimitation of the plot area and the measurement of all the tree within a plot, in accordance with the field protocol of a sustainable forest management plan. The plot measurements were done by the D.R.E.Am, an Italian company, through the Life GOPROFOR project. Only trees with a diameter at breast height (DBH) ≥ 9.5 cm were measured and for each tree the following data were collect: species, DBH and tree height (H). DBH was measured with a calliper from two directions perpendicular to each other at approximately 1.3 m, while TH were measured with a Haglöf Vertex laser hypsometer (Vertex IV Hypsometer/ Transponder 360 Package; Haglöf Sweden AB, Långsele, Sweden). The Vertex Laser Geo 360 has a precision of 0.01 m, with a nominal accuracy of 0.04 m over a range of 700 m.

4) *Data plot analysis* – the collected data from the forest plots were analyzed to estimate key forest variables such as basal area (G, m^2 ha^{-1}), number of trees (N, ha^{-1}), and growing stock volume (V, m^3 ha^{-1}). These variables are commonly used to assess the overall condition of the forest and are essential for sustainable forest management planning (Giannetti et al. 2020). V of each callipered tree was calculated based on the equations developed by Tabacchi et al. (2011) in the framework of the 2nd Italian National Forest Inventory based on tree DBH and height. The results of the plot level variables are summarized in Figure 2.

The time needed for each phase was collected to compare it with HLMS derived measures. Moreover, the data derived by the traditional field measures at plot and tree levels were assumed to be error free, since they were used as benchmark to perform the comparison with the data derived by HMLS.

HMLS measures

The work related to HLMS measurements in forest management plans, can also be also divided into four main phases. The first two phases are the same as the ones in traditional field measures and cannot be performed using HLMS. These phases involve the *preliminary analysis of the site* and the *collection of qualitative data from forest plots*. However, HLMS completely transforms the other two phases, which are the *forest inventory measures* and the *data plot analysis*. In the following sections, the HLMS platform used in this study and the process of acquiring field forest inventory scan and automatically extracting of single tree and plot data will be described in detail.

HMLS platform

The scans were carried out using the HMLS GEOSLAM ZEB HORIZON ™ (GEOSLAM ltd., UK) (Figure 3). The main characteristics of the HMLS are reported in Table 1. This instrument uses Simultaneous Localization and Mapping (SLAM) technology developed by the robotics and machine vision community to perform cloud-to-cloud registration. It solves the problem of missing or poor GNSS signals under the forest canopy.

Figure 3 GEOSLAM ZEB HORIZON™ Hand Held Mobile Laser Scanner (HMLS)

(Giannetti et al. 2017, Gollob et al. 2020, Sofia et al. 2022). In addition, this technology allows a union of multiple lidar scans to be performed automatically, thus allowing artificial reference targets not to be used.

Forest inventory scan

●HMLS walking paths

To address the aim of providing forest managers with technical insights on the use of HLMS, a preliminary literature review was conducted. The purpose of this review was to identify the types of walking paths to follow in data acquisition for forest plot using HLMS. According to previous studies, three walk paths (i.e. Star, Grid, Border) were chosen (Figure 4) to be tested in the field to compare their operability for forest management purposes (Gollob et al. 2020, Bauwens et al. 2016, Del Perugia et al. 2019, Liang et al. 2018, Sofia et al. 2021, Tupinambá-Simões et al. 2023). Two walking paths (i.e. *Star walking path* (STAR) and *Grid walking path* (GRID)) were chosen according to a literature review of previous studies, while one was designed for the present

Table 1 Characteristics of GEOSLAM ZEB HORIZON™ Handheld Mobile Laser Scanner (HMLS).

Characteristic	Description
Data acquisition speed	300,000 measurements per second
3-D measurement accuracy	1-3 cm
Maximum range	100 m
Laser safety class	Class 1 / λ 903nm
Angular field of view	360◦ × 270◦
Weight of scanner head	3.7 kg
Dimension of scanner head weight	100mm x 200mm x 240mm

study (i.e. *Border walking path* (BORDER)) (Figure 4). The *STAR* walking scan path begins at the centre of the plot and is based on the concept of walking along paths that radiate outward from the centre, like the rays of a star, ensuring a complete and detailed scan of the area. At the end of each ray, the operator returns to the centre by following an adjacent ray path before starting the next outward scan (Figure 4).

The *STAR* (Figure 4) has been widely used in recent studies, including those that utilized the GEOSLAM ZEB HORIZON ™ (Gollob et al. 2020, Hyyppä et al. 2020, Sofia et al. 2021, Tockner et al. 2021, Vatandaşlar et al. 2021). *STAR* is considered an effective method for acquiring HLMS data due to its ability to reduce noise in point clouds and minimizing the number of missing trees by enabling the acquisition of dense LiDAR point clouds.

The GRID walking scan path, like the *STAR* path, begins at the centre of the plot. However, in this case, the operator moves to one corner of the plot and scans the area by following parallel lines that are equally spaced. At the end of the acquisition from the opposite corner, compared to the starting point, the operator returns to the centre of the plot to conclude the scan (Figure 4). The *GRID* (Figure 4) was chosen because previous studies using the first generation of ZEB (ZEB 1 GEOSLAM with a laser range of 15-30 m and data acquisition speed of 43200 point/sec) with lower accuracy have suggested that walking along straight lines yields accurate results in measuring DBH and H (Ryding et al. 2015, Giannetti et al. 2018, Oveland et al. 2018, Del Perugia et al. 2019) which are the focus of our work.

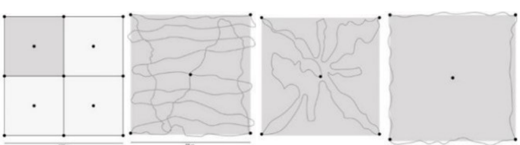


Figure 4 Schemes of walking path during HMLS scanning.

However, in comparison to the previous studies, we decided to include perpendicular straight lines rather than solely using parallel lines (Del Perugia et al 2019). This choice was made because capturing the same object from multiple directions allow for obtaining more precise and less noisy point clouds (Chiappini et al. 2022).

The BORDER (Figure 4) was designed specifically for this study. In this case, the scan was performed starting from one corner of the plot, and the acquisition was conducted by walking along the border of the plot. The scan concludes at the starting corner of the plot.

Considering the instrument we used, the GOSLAM ZEB HORIZON ™, which has a maximum laser range of 100 m, we aimed to test it efficiency by walking along the border of the plots without entering them. The BORDER was chosen because it may allow to reduce the time of acquisition.

●HMLS scan

To perform the scans, the plot area and the walking path were marked on the ground. Subsequently, when acquiring data with the HLMS GEOSLAM ZEB HORIZON™, it is mandatory that the start and end points of the acquisition are identical. This point also corresponds to the switching on and off the instrument.

For the STAR and GRID, the scans were initiated and concluded in the centre of the plot (Figure 4) while for BORDER in the upper-left corner of the plot (Figure 4). Once the HLMS was ready, the operators performing the scan held the laser in his hand and waited 10s to ensure the stability for the IMU system. The operator then proceeded with the acquisition following the designated and maintaining a slow walking speed (2 km/h). Moreover, as it mandatory to record the coordinates of field plot for forest management plans, the operators made a stop of 15s at the four corners of the plots for the paths. This allowed for the automatic acquisition of a reference point in the point cloud, which was used to georeferenced the 3D point cloud into a geographic system (Figure 4).

In this study, all scans were conducted by a single operator to maintain consistency in data acquisition. The operator, approximately 1.70 m tall, held the scanner at a height of about 1.20-1.30 m, similar to that of a traditional calliper. This consistent positioning ensured uniformity in the measurements taken across different walking paths and plots.

The scanner was held at elbow height throughout the acquisition process, which helped maintain a stable scanning angle. By keeping these parameters constant, we aimed to minimize variability in measurements related to scanner positioning and operator differences, focusing instead on the variance in accuracy associated with the walking paths followed and the occlusion caused by the differing structures of the plots.

As previously mentioned, walking speed was also kept constant, although it may have varied slightly in more challenging plots characterized by steeper slopes or dense shrubbery.

The time required to perform the acquisition of each plot using the different paths was recorded for the purpose of comparing it with the traditional measures.

HLMS point cloud forest inventory plot data processing

A total of 24 HLMS scans were acquired (i.e. 3 scan x 8 plots). The data of each one of the scans were processed using the GeoSLAM Hub 6.1 (GeoSLAM Hub 6.1 Development Team 2021) to obtain a 3D point cloud (Figure 5). This software allows to create the 3D point cloud and georeferencing it in a geographic system though the "Adjust to Control" tools that identified the reference points. Subsequently, the georeferenced point clouds were exported in ".las" format using the following parameters : 100% of points, "point color"=time, "timestamp"= None and "Smooth"=accepted".

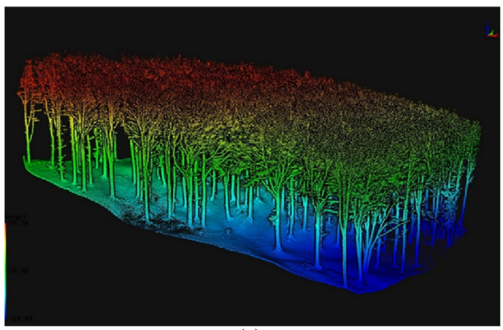
The point clouds were then processed with LiDAR360 desktop software (LiDAR360 Development Team, 2020) with semi-automatic data extrapolation algorithms, following the methodology presented in Sofia et al. (2022). A standalone software with a user-friendly interface was chosen to eliminate the need for programming skills (e.g., R or Python). This choice makes the tool more accessible and convenient for forest managers, who typically do not have experience in coding.

To obtain the tree level and plot level data the point clouds were processed in the LIDAR 360 software following these steps:

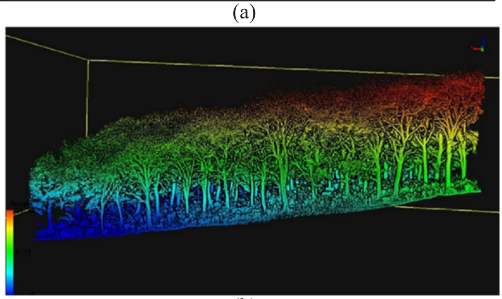
1) Each point cloud was cropped on the area of the field plots using the referenced points (i.e., 4 corners).

2) The point cloud was cleaned for the outliers using the specific function of the software "remove outliers" setting it to remove low and high-level outliers.

3) The point cloud was classified in ground



(a)



(b)

Figure 5 Camaldoli survey area Point Cloud from the graphical user interface of LIDAR360; (b) Ficuzza survey area Point Cloud from the graphical user interface of LIDAR360.

and non-ground point using the function "Filter Ground Points" and normalized using the function "Normalize by Ground Points" (LIDAR360 Development Team 2020, Chen et al. 2019).

4) The normalized point cloud was then used to segment each tree within the plot and extract automatically the tree level data (i.e. position, DBH and H). To segment each tree, the LIDAR360 software permits, through the implemented algorithm, to fit a circle on the tree stem and classify it into three levels: Low, Medium, and High. Based on the fitted circle, it is possible to proceed with the point cloud segmentation using the method proposed and developed by Tao et al. (2015), that allow to identified single trees, using a bottom-up approach that is preferred with HLMS data, since the stems can be easily identified below canopy. At the end of the single tree segmentation, the software allows to automatically extract the tree inventory parameters: the position, DBH and H of each tree of the plot and export the data into a spreadsheet-based CSV (LIDAR360 Development Team 2020, Tao et al. 2015).

5) The tree level data (DBH, H) automatically obtained, were used to estimate the forest variables at plot level such basal area (G m^2 ha-1), number of trees (N ha^{-1}) and V (m^3 ha^{-1}). V was estimated using Tabacchi et al. (2011) equations, following the same approach as traditional measures, to ensure comparability of the data.

Accuracy assessment of forest inventory data

The single-tree attributes (i.e. DBH and H) estimated with the three HLMS walking paths scans were compared with single-tree attribute obtained with traditional field measures at plot level. To calculate accuracy, the coefficient of determination (R^2), the root-mean-square error (RMSE), the percentage RMSE, and the bias were calculated according to the following formulas:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{TS}-X_{HLS})^2}{n}} \quad (1)$$

$$RMSE(\%) = \frac{RMSE}{\bar{X}} * 100 \quad (2)$$

$$bias = \frac{\sum_{i=1}^{n}(X_{TS}-X_{HLS})}{n} \quad (3)$$

where n represents the number of trees resulting from the traditional measures (TS), X_{TS} is the value of the tree attribute measured in the field (DBH, H) and X_{HMLS} is the estimated value of the attribute of each i-th tree derived by the processed of HLMS scans, while X is the mean value of the tree attribute computed in traditional measures. Furthermore, we compared the number of trees detected in the different scans with those recorded in the field, expressed as a percentage as follows:

$$N\% = \frac{N_s}{N_t} * 100 \quad (4)$$

where N_t is the number of trees measured in the field with traditional methods, and N_s is the number of trees detected in the scan.

The accuracy was calculated for each field plots and for each one of the study area, in order to compare the results not only among different walking path schemes but also taking in consideration the varying characteristics of the field plots and study areas (i.e. slope, forest types, number of trees, and shrubs layers).

Comparison of time and costs of traditional and HLMS measures

To compare traditional and HLMS approaches, we conducted a comparative analysis specifically focusing on: (i) the forest inventory measurements phase (traditional) versus the forest scans phase (HLMS); and (ii) plot-level analysis of the data (traditional) versus the processing of HLMS point cloud forest inventory plot data.

For each of these phases, the time required to obtain results was recorded. Regarding costs, we referenced the personal cost per hour based on the Italian national tariff for forest workers, considering a rate of 20 €/h for a Junior Forest Engineer. In the field phases, both

HLMS and traditional methods necessitate the involvement of two Forest Engineers, whereas for data processing, we accounted for the work of one person. It is important to highlight that, in comparing costs between traditional methods and HLMS, we do not consider the cost of the HLMS equipment and training. The calculation involves two individuals for field data acquisition and one person for data processing in both HLMS and traditional methods.

Results

Based on the three identified walking paths (STAR, GRID, BORDER), we observed variations in the point cloud density, measured in terms of the number of points per square meter (pts/m²). The GRID path yielded the highest average point density (89,537 pts/m²), followed by the STAR (42,522 pts/m²), while the BORDER path had the lowest average point density (27,133 pts/m²).

Table 2 presents accuracy data for DBH, and

Table 2 Accuracy assessment of both HLMS and traditional methods concerning the number of detected trees (N%) and individual tree attributes such as Diameter at Breast Height (DBH) and Height (H).

ID PLOT	Path type	Point cloud point/m^3	N %	DBH (cm)				H (m)			
				RMSE (cm)	Bias (cm)	RMSE (%)	R^2	RMSE (m)	Bias (m)	RMSE (%)	R^2
Camaldoli tot	Star	177980	93	2.99	1.71	10	0.88	2.07	-0.82	9.6	0.59
	Grid	400936	94	2.58*	0.89*	9*	0.94*	2.08	-1.04	9.6	0.57
	Border	111472	98	2.97	0.93	10	0.87	1.83*	-0.62*	8.5*	0.62*
Ficuzza tot	Star	162200	94	3.16*	0.56*	11*	0.75*	2.25	-0.06	16	0.26
	Grid	315360	88	3.59	0.26	12	0.71	2.26*	-0.07*	16*	0.34*
	Border	105596	85	3.63	0.01	13	0.68	2.10	-0.28	15	0.29
Camaldoli C1	Star	43820	95	3.87	2.32	13	0.8	2.22	-1.30	11	0.11
	Grid	89480	99	3.35	1.81	12	0.72	1.90	-0.89	9	0.15
	Border	28800	97	2.70*	1.12*	9*	0.86*	1.65*	-0.6*	8*	0.21*
Camaldoli C2	Star	42404	96	2.48	1.69	8	0.91	1.84*	-0.88*	9*	0.69*
	Grid	85592	100	1.77*	0.71*	6*	0.93*	1.91	-0.86	9	0.63
	Border	25236	100	2.39	0.65	8	0.90	1.92	-0.39	9	0.57
Camaldoli C3	Star	43764	92	1.97*	1.02*	6*	0.93*	2.14*	-0.94*	10*	0.73*
	Grid	121304	88	2.28	1.13	7	0.92	2.27	-0.99	10	0.72
	Border	30664	100	2.95	0.92	10	0.90	2.20	-1.00	10	0.73
Camaldoli C4	Star	47992	88	2.96	1.69	10	0.88	1.69*	-0.56*	8*	0.67*
	Grid	104560	90	2.75*	-0.24*	9*	0.88*	2.31	-1.56	10	0.57
	Border	26772	93	4.10	0.82	14	0.75	1.75	-0.38	8	0.56
Ficuzza F1	Star	46540	96	2.40*	0.60*	8.5*	0.80*	1.90	-0.6	14	0.34
	Grid	74952	96	3.54	-0.10	12	0.64	1.89	-0.56	14	0.32
	Border	24516	85	3.89	-0.21	14	0.66	1.84*	-0.42*	14*	0.41*
Ficuzza F2	Star	36984	91	3.62	0.50	12	0.68	2.36*	0.35*	17*	0.13*
	Grid	80788	83	3.95	0.18	13	0.60	2.21	-0.50	16	0.08
	Border	28304	87	3.70*	0.51*	13*	0.69*	2.07	0.19	15	0.20
Ficuzza F3	Star	41204	87	2.88*	0.58*	10*	0.82*	2.25	-0.06	15	0.45
	Grid	80120	88	3.00	0.45	10	0.80	2.01*	-0.16*	14*	0.58*
	Border	27528	70	4.02	-0.26	14	0.65	2.62	-0.53	18	0.11
Ficuzza F4	Star	37472	100	3.61*	0.53*	13*	0.61*	2.49*	0.17*	19*	0.02*
	Grid	79500	84	3.80	0.05	14	0.59	2.24	-0.15	17	0.02
	Border	25248	96	3.11	0.11	11	0.73	1.89	-0.43	14	0.39

Note: RMSE: Root Mean Square Error. The most accurate results obtained are denoted by asterisks (*).

H, for the two study areas and for each plot. Our tests revealed significant variability in results across different study areas and plots. Generally, it can be noted that HLMS tends to overestimate all forest variables (DBH and H) compared to traditional methods. In the Ficuzza plots, characterized by a more complex forest structure with holm oak and a significant presence of shrubs, the results - measured in terms of the number of detected trees (N%), RMSE, bias, RMSE%, and R^2 - are less accurate than those obtained in the less complex Camaldoli plots (C1, C2, C3). However, in Camaldoli, Plot C4, which has the highest number of trees and the steepest slope, produced results comparable to those obtained in the Ficuzza plots.

In terms of RMSE and RMSE% in the Camaldoli, the GRID path produced more accurate results for DBH, while BORDER was more accurate for H. In the Ficuzza study area, STAR yielded accurate results for DBH, while GRID for H (Table 2). However, for all the common trees detected in the point clouds obtained with different paths, the *Kruskal-Wallis* test revealed no significant differences for DBH and H (p-value > 0.05) within each study area and within each plot.

BORDER method allowed to detect all the trees (100%) in C2 and C3 plots, while GRID in C2, and STAR in F4. However, on average the STAR allows to detect the large number of trees (93%) comparing the other two paths (91%).

In the plots, C4 and F3, characterized by high complexity in terms of number of trees, structure and slope, a smaller number of trees were detected (N%≤93 for C4; N%≤88)

Table 3 Time required for HLMS and traditional data acquisition, data processing and total time.

		HLMS			Traditional			Time difference
ID Plot	**Path type**	**Field Scan** hh.mm:ss	**Data processing** hh.mm:ss	**Total** hh.mm:ss	**Field measures** hh.mm:ss	**Data processing** hh.mm:ss	**Total** hh.mm:ss	**Traditional - HLMS** hh.mm:ss
	Star	00:12:14	01:42:00	01:54:14				01:31:46
C1	Grid	00:27:51	02:25:51	02:53:42	03:06:00	00:20:00	3:26:00	00:32:18
	Border	00:08:22	01:13:00	01:21:22				02:04:38
	Star	00:12:09	01:42:00	01:54:09				01:10:04
C2	Grid	00:23:33	02:25:00	02:48:33	02:45:13	00:19:00	3:04:13	00:15:40
	Border	00:07:41	01:13:00	01:20:41				01:43:32
	Star	00:10:19	01:42:00	01:52:19				01:48:56
C3	Grid	00:40:21	02:25:00	03:05:21	03:20:15	00:21:00	3:41:15	00:35:54
	Border	00:08:55	01:13:00	01:21:55				02:19:20
	Star	00:15:32	01:42:00	01:57:32				01:36:40
C4	Grid	00:33:07	02:25:00	02:58:07	03:15:12	00:19:00	3:34:12	00:36:05
	Border	00:06:45	01:13:00	01:19:45				02:14:27
	Star	00:12:11	01:38:00	01:50:11				01:40:49
F1	Grid	00:19:01	01:58:00	02:17:01	03:13:00	00:18:00	3:31:00	01:13:59
	Border	00:06:45	01:03:00	01:09:45				02:21:15
	Star	00:07:26	01:38:00	01:45:26				01:47:49
F2	Grid	00:20:38	01:58:00	02:18:38	03:12:15	00:21:00	3:33:15	01:14:37
	Border	00:07:24	01:03:00	01:10:24				02:22:51
	Star	00:10:48	01:38:00	01:48:48				01:46:31
F3	Grid	00:20:43	01:58:00	02:18:43	03:19:19	00:16:00	3:35:19	01:16:36
	Border	00:07:19	01:03:00	01:10:19				02:25:00
	Star	00:10:05	01:38:00	01:48:05				02:01:55
F4	Grid	00:12:09	01:58:00	02:10:09	03:25:00	00:25:00	3:50:00	01:39:51
	Border	00:06:55	01:03:00	01:09:55				02:40:05

compared to the others plots where at least one walking path produce more accurate results (N%≥99 for C1, C2, C3; N%≥91 for F1, F2, F4) (Table 2). When comparing the time and cost for data acquisition between traditional (field measures) and HLMS (field scan) per plot, our observations consistently show that the field scan method is both faster and more cost-effective than traditional measures, as reported in Tables 3 and 4. Conversely, the opposite trend is observed in data processing (Table 3 and 4).

On average, the BORDER path demonstrates the quickest and most cost-effective scan acquisition time, averaging 9 minutes at a cost of 5.01 €, per plot. Following this, STAR requires 12 minutes and costs 7.56 €, while GRID takes 22 minutes and costs 16.45 €. Similarly, in HLMS data processing, the trend persists: BORDER demands 1 hour and 17 minutes at a cost of 22.67 €, STAR takes 1 hour and 38 minutes costing 33.33 €, and GRID requires 2 hours and 1 minute, costing 43.87 €.

Specifically, BORDER saves an average of 2 hours and 7 minutes, resulting in a cost saving of approximately 100.34 € compared to traditional measures. Similarly, STAR saves 1 hour and 41 minutes, equating to a cost saving of 87.13 €, while GRID saves 1 hour and 8 minutes whit a cost saving of 67.70 €. Considering all paths, on average, employing HLMS in Ficuzza results in time savings of approximately 1 hour and 47 minutes and a cost saving of 92.74 €. In Camaldoli it results savings of about 1 hour and 22 minutes, with a cost reduction of 77.38 €.

Table 4 Costs associated with HLMS and traditional methods for data acquisition, data processing per plot, and the total cost.

Plot	Path type	HLMS (€)			Traditional (€)			Cost diff. (€)
		Scan acq.	Data proc.	Total	Field acq.	Data proc.	Total	HLMS-Traditional
C1	Star	8.16	34.00	42.16	124.00	6.67	130.67	-81.84
	Grid	18.57	48.62	67.18				-56.82
	Border	5.58	24.33	29.91				-94.09
C2	Star	8.10	34.00	42.10	110.14	6.33	116.48	-68.04
	Grid	15.70	48.33	64.03				-46.11
	Border	5.12	24.33	29.46				-80.69
C3	Star	6.88	34.00	40.88	133.50	7.00	140.50	-92.62
	Grid	26.90	48.33	75.23				-58.27
	Border	5.94	24.33	30.28				-103.22
C4	Star	10.36	34.00	44.36	130.13	6.33	136.47	-85.78
	Grid	22.08	48.33	70.41				-59.72
	Border	4.50	24.33	28.83				-101.30
F1	Star	8.12	32.67	40.79	128.67	6.00	134.67	-87.88
	Grid	12.68	39.33	52.01				-76.66
	Border	4.50	21.00	25.50				-103.17
F2	Star	4.96	32.67	37.62	128.17	7.00	135.17	-90.54
	Grid	13.76	39.33	53.09				-75.08
	Border	4.93	21.00	25.93				-102.23
F3	Star	7.20	32.67	39.87	132.88	5.33	138.21	-93.01
	Grid	13.81	39.33	53.14				-79.73
	Border	4.88	21.00	25.88				-107.00
F4	Star	6.72	32.67	39.39	136.67	8.33	145.00	-97.28
	Grid	8.10	39.33	47.43				-89.23
	Border	4.61	21.00	25.61				-111.06

Note:acq.: aquisition; proc.: processing; dif.: difference

Table 5 Findings from previous studies using ZEB HLMS across different forest types for DBH and H, in terms of RMSE, Bias.

Studies	Species	Test plot	N/ha	Number of reference tree	Reference (ground-truth) data	RMSE of DBH (cm)	Bias of DBH (cm)	DBH threshold (cm)	RMSE of H (m)	Bias of H (m)	H threshold (m)
Jurjević *et al.* 2021	deciduous forest (*Quercus robur*)	6 plots (r=15 m)	305	130	Conventional field data	-	-	-	1.11	0.45	9-33
Tockner *et al.* 2021	mixed forest	1 plot area of 4.000 m²	870	235	Conventional field data	3.94	-0.67	-	2.25	-0.92	-
Gollob *et al.* 2021	broadleaved, coniferous, and mixed forest	21 plot (r=7m)	424	20	Conventional field data	1.90	-0.04	>5	-	-	-
Ahola *et al.* 2021	Scot spine forest	7 Scots pine trees	500	7	Conventional field data	0.94	−0.47	>25	-	-	-
Sofia *et al.* 2022	Turkey oak forest, Douglas fir forest, black pine forest, beech forest	20 plots (r=20 m)	500	200	Conventional field data	3.520	2.401	>5	4.026	0.192	5-34
Chiappini *et al.* 2022	coniferous forest (black pine)	One plot of 0.5 ha	800	50	Conventional field data	-	-	-	10.8	-8.6	-
Vatandaşlar *et al.* 2023	mixed forest (Oriental spruce, Scot spine Caucasian fir)	39 plots	350	39	Conventional field data	1.3cm	4.5	-	-	-	-
Winberg *et al.* 2023	mixed forest (Scots pine, silver birch, Eurasian aspen	54 plots	550	230	Conventional field data	1.765	−3.650	-	-	-	-
Tupinambá Simões *et al.* 2023	mixed forest (*Pinus pinaster, Quercus pyrenaica*, and *Alnus glutinosa*)	16 plots of 625 m²	433	418	Conventional field data and Airborne LIDAR data	5.42	0.09	-	3.50	0.23	-

Discussion

This study aims to evaluate the technical feasibility of HLMS in comparison to traditional field measures within sustainable forest management plans. It specifically assesses three commonly referenced walking paths (STAR, GRID, BORDER) to analyse differences in accuracy, time, and cost between HLMS scan acquisitions and traditional methods. To enhance usability, the research was conducted in two distinct broadleaf forests, known for their higher complexities in TLS/HLMS analysis (Giannetti et al. 2018): a mountainous beech-dominated deciduous forest in Camaldoli and a Natural Mediterranean holm oak forest in Ficuzza.

Our findings showed accurate results of HLMS in tree number detection, achieving detection rates between 83% and 100% in both forests (Table 2). This study observed significantly higher accuracy compared to the recent study of Kükenbrink et al. (2022) in Switzerland, where the ZEB REVO was employed on a GRID path in a mixed temperate forest. Their reported detection rates ranged from 26% in plots with dense shrub layers, resembling Ficuzza plots where we achieved a rate ≥ 83%, and of 78% in plots with less understory vegetation, like our Camaldoli plots where we observed a rate ≥ 88%.

In terms of average values for DBH and H, all the three paths in all the eight plots do not reveal significant differences ($p<0.001$). Moreover, for all the three paths in both study areas the results obtained for DBH and H in this study in terms of RMSE, and Bias are in line with previous studies as can be observed from Table 5, where the results employing ZEB-HORIZON HLMS in different forest types are reported. In terms of R2, the results showed in this study are congruent with those done by Jurjević et al. (2020), Vatandaslar & Zeybek (2021), Sofia et al. (2022), Giannetti et al. (2018), Del Perugia et al. (2019).

When considering the time and cost for data acquisition and processing, on average, the use of stand-alone software such as LIDAR 360 it was useful, because allow to reduce the timing needed for data processing using ad hoc developed codes using programming languages (Giannetti et al. 2018). Usually developing code using programming languages is not part of the skill of old forest managers and forest engineers especially in Italy and in Mediterranean countries in general (Corona et al. 2022), and as highlighted by Cadez et al. (2023) and Giannetti et al. (2023), stakeholders prefer the use of user-friendly tools.

For all the analysed plots, the point cloud density was consistently higher when using the GRID acquisition path (Table 2). Notably, we incorporated a perpendicular line, extending the walking path length compared to the approach used by Del Perugia et al. (2019). As a result, the GRID path was the longest route followed by the operators in the field, followed by the STAR and BORDER paths. This finding aligns with recent studies by Tiede et al. (2024) in Australia and Chirici et al. (2023) in Italy, which demonstrated that longer acquisition paths increase point cloud density. In general, our study found that more complex paths (i.e., STAR and GRID) resulted in denser point clouds and, on average, more accurate results for DBH and tree height (H). These paths help reduce occlusion in capturing 3D forest structures by allowing objects to be viewed from multiple angles (Del Perugia et al. 2019, Chirici et al. 2023, Tiede et al. 2024). However, it is important to note that no statistically significant differences were observed between the acquisition paths in the extraction of forest variables. This aligns with the findings of Tiede et al. (2024), who concluded that despite differences in point cloud data between acquisition paths, these did not significantly affect the final outputs (Table 2). However, in less complex forest structures such as C1 plot in Camaldoli, where less occlusion is produced by the vertical and horizontal structures, accurate results can be observed also with BORDER. Might be the accurate results can be also obtained thanks to the large laser range of ZEB HORIZON (100 m), that allowed to overcome the limitation of the HLMS instrument with smaller laser range (Ryding et al. 2015, Giannetti et al. 2018, Del Perugia et al. 2019, Chirici et al. 2023).

In general, the STAR path scheme has proven highly effective in forest planning, demonstrating acceptable error for DBH and H (Table 2) that are considered accurate in forest management activities, and in line with the errors that can be assimilated also with traditional field measures.

In Ficuzza forest, characterized by highly complex structure, accuracy varied significantly, comparing to Camaldoli, especially for H. The occlusion in observing the top-canopy in complex vertical forest can be a challenge for both traditional and HLMS measures (Jurjević et al. 2020). Specifically, determining the top-hight from the ground using the traditional hypsometers can be difficult, and subjective errors associate with the technical field experience of the operator can determinate inaccuracies in determining

H (Jurjević et al. 2020, Larjavaara & Muller-Landau 2013). Also, in HLMS measures, the complexity of the forest structure can hinder the quality of the 3D reconstruction (Giannetti et al. 2018). Furthermore, the standard algorithms employed for post-processing HLMS data, usually developed for more uniform forests like even-aged stands of coniferous stands, can result in larger errors when applied to more complex forest environments.

Maybe in deciduous forests, the occlusion in observing the top-canopy with HLMS can be reduce using leaf-off point-cloud, as for example in Camaldoli beech forest, while it is not applicable in evergreen broadleaves forests such as the Holm oak Ficuzza forest. In Ficuzza, the error for H might be reduced through the fusion of two distinct point clouds i.e. HLMS and Airborne/UAV Laser Scanning as done for example by Giannetti et al. (2018), Panagiotidis et al. (2022), and Fekry et al. (2022). That enables a more comprehensive capture of the forest's 3D structure, thereby minimizing occlusions that hinder the accurate determination of the top canopy when solely relying on HLMS data.

However, to the best of our knowledge, the fusion of data between two distinct LiDAR point clouds remains applicable at the research level and is still challenging to implement in the daily work of forest managers and engineers, because required high level of knowledge in computer vision and data fusion (Cucchiaro et al. 2020, Guo et al. 2023).

Moreover, stand-alone software could also serve as a strategy to promote the adoption of innovation in the sustainable forest management sector, that is a requirement of EU and Italian Forest Strategy (European Commission 2021, MIPAF 2021), because they are perceived as less complicated (Cadez et al. 2023, Corona et al. 2023, Giannetti et al. 2023, Pavlíková et al. 2023, Weiss et al. 2021).

The STAR path emerges as the most valuable. Despite being comparatively slightly higher time-consuming and costly than the BORDER path, it allows, as we already reported, for increased accuracy in tree measurements (Table 2).

On average, using HLMS it is possible to save on average 1 hour 37 minutes and 85 € per plot. If we considered that in a forest management plan on average at least 80 plots need to be measured in the field in an area of 1000 ha, with the HMLS it is possible to save on average approximately 10 hours of work, that means 2/3 working days and 6804 €. Considering the cost of the instruments, approximately € 45,000 medium price of market, the cost can be amortized by a company after approximately 530 plots that means after at least 7 forest management plans. However, it is essential to recognize that the costs associated with these instruments extend beyond the initial acquisition price. Ongoing maintenance expenses, related to factors such as battery obsolescence and regular servicing, should also be taken into account. Based on our experience, these costs can be estimated at €1,000 every three years. Generally, it can be confidently stated that the lifespan of a HMLS typically ranges from 5 to 10 years, even as technology evolves rapidly. This evolution can present disadvantages, as the obsolescence of instruments may occur more quickly. However, it also offers advantages, as there are now more affordable versions of HMLS on the market compared to the one we tested, which may help reduce the amortization period of the instrument in the future.

Moreover, another important factor to consider is the training of personnel for forest data acquisition and processing, which can be viewed as a cost for educating individuals who are not currently familiar with this type of technology. It is important to note that many forestry degree programs across Europe now include the use of these technologies in their curricula, leading to an increasing number of trained individuals in the future. However, for personnel who have not received university training in the use of this technology, it can be stated that utilizing standalone software can reduce training costs and improve their ability to use HMLS for forest management plans. In our experience, training courses of this kind generally range from €1,000 to €1,500 per operator in Italy.

The results, confirmed that the HLMS can be applied to develop sustainable forest management plans, also in Italian context confirming the findings of Sofia et al. (2021), were the HLMS was used to update the 2023-2035 forest management plan for the complex "Alpe di Catenaia" forest.

Our study specifically focused on extracting traditional forest variables like DBH and H. Nonetheless, it's crucial to note that when acquiring a 3D point cloud, it can also be utilized to detect additional forest variables, facilitating the extraction of further sustainable forest indicators, that can help forest managers with the development of multi-objective forest management plans that deal not just with productive aspect of forests (Prins et al. 2023). Therefore, as new digital tools are developed to extract these additional forest variables, older point cloud data can also be processed accordingly. Additionally, Italian sustainable forest management plans typically maintain permanent sample plots. HLMS scan conducted at intervals, typically every 10 years in Italy, aligning with plan durations, have the potential to generate growth models and comparative structural models (Campos et al. 2021). These models are valuable for comprehending the evolutionary dynamics of forest stands or monitoring the effects of proposed interventions in the management plans (Campos et al. 2021).

Conclusions

The study aimed to compare HLMS with traditional field measures within sustainable forest management plans, assessing three walking paths (STAR, GRID, BORDER) demonstrated high accuracy in tree detection, and DBH and H. The STAR paths yielded denser point clouds and generally more accurate results in DBH and H measurements compared to GRID and BORDER. The complexity of forests like Ficuzza posed challenges for HLMS measures due to occlusions in observing the top canopy, impacting accuracy especially in H determination.

Future studies should consider the extraction and comparison of more complex forest variables that allow to extract other forest indicators maybe linked with biodiversity, even in more complex forest structures like Italian coppice forests which are even more complex than the natural holm-oak stands in Ficuzza.

Furthermore, future studies should consider not only the acquisition walking path but also, for example, the impact of different walking speeds and the positioning of scans (i.e., placing the mobile laser scanner at a higher elevation, such as on a backpack), which were kept constant in the present work. This could be useful for avoiding some occlusions caused by the presence of shrubs.

However, it is important to point out that the use of a user-friendly tools and software were highlighted as preferred for stakeholders, so future studies need to be focus on continual technological advancements and user-friendly tools to extract even more complex forest variables using TLS/HLMS scans designed for sustainable forest management plans.

The HMLS has demonstrated significant time and cost savings, potentially reducing both fieldwork and office work hours, along with associated expenses. This efficiency is advantageous not only for developing forest management plans but also for monitoring plots in areas where resources are still limited, such as those located within protected areas.

In this sense, in the future, at least two-time HLMS scans need to be tested, to produce double forest inventories, that can be used for modelling growth and dynamics of the stands, that are requirement of new multi-objective forest management plans that deal not just with productive aspect of the forests (Prins et al. 2023).

Author Contributions

Conceptualization: SS, FM, DSLMV, MM; methodology: SS, DSLMV, MM, FG; data acquisition: SS, SB; data curation: SS, FG; formal analysis: SS, FG; writing - original draft preparation: SS, FG; writing - review and editing: SS, FG, SC, FM, GC, DT, DSLMV; supervision: DSLMV, FM, FG; funding acquisition: MM, FM, DSLMV.

Compliance with ethical standards

Conflict of interest

The authors declare that they have no conflict of interest.

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