Advancing forest inventory: a comparative study of low-cost MLS lidar device with professional laser scanners

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Keywords: Forest Inventory, Lidar, Low-cost, Handheld, Point Cloud.

Abstract

In the context of forest inventory, there is a growing need for 3D data to produce detailed geometric information. While terrestrial laser scanning (TLS) is traditionally used for this purpose , several factors have prompted the exploration of alternative solutions, such as handheld mobile laser scanners (MLS). One key limitation of TLS is its static data acquisition, which makes it less suited for the complex and heterogeneous nature of forest environments. A primary challenge with TLS in forestry is the occlusion effect, where parts of trees (such as stems, branches, or leaves) may not be captured due to obstacles between the scanner and the target. Additionally, TLS is known for long acquisition times, which, while yielding high-quality data, may exceed the requirements for standard forest inventory tasks. The cost associated with TLS is also significant; although feasible for small forest patches, scaling these methods to larger areas would demand substantial resources. Similarly, while handheld MLS devices offer more flexibility in data acquisition and the possibility to cover a wider area in the same acquisition time, professional versions are still relatively costly, adding to the need for more affordable alternatives. This underlines the demand for a low-cost, efficient method for 3D data acquisition in forest inventories. In this study, forest structural variables obtained with a low-cost MLS (LC-MLS; Mandeye) were compared with two professional MLS devices (GeoSlam Horizon and GreenValley LiGrip H120) and a professional TLS (Trimble X7). With the open-source software 3DFin, we processed the point cloud data from all the devices, enabling the extraction of diameters at breast height (DBH) and total tree heights (TH). The LC-MLS device shows a positive bias in DBH measurements (1.62 cm), indicating it tends to overestimate compared to the TLS reference. Despite this, it demonstrates competitive quality relative to the two other MLS systems. In terms of TH, the LC-MLS has a negative bias of -2.16 m, suggesting it underestimates tree height. When compared to other professional MLS devices, the LC-MLS exhibits a higher RMSE% in TH measurements (12.97%), indicating less accuracy in tree height estimation.

1. Introduction

In precision forestry, the demand for precise and detailed spatial information is driving advancements in forest inventory techniques (White et al., 2016; Shang et al., 2020; Baskent et al., 2024). Accurate three-dimensional (3D) data enables forest managers to monitor and evaluate structural parameters that influence biodiversity and ecosystem resilience (Ma et al., 2024). Conventionally, the preferred technology for capturing high-resolution 3D data of tree variables, including total height (TH), diameter at breast height (DBH) and canopy-related parameters is terrestrial laser scanning (TLS) (Bauwens et al., 2016; Liang et al., 2016; Arrizza et al., 2024). However, while TLS offers high accuracy, its static data acquisition process requires multiple setups and significant time investment to collect data. The static nature of TLS makes it susceptible to occlusion effects, particularly problematic in forests with dense undergrowth or multi-layered canopy structures. Indeed, TLS performance can vary depending on the site characteristics, when occlusions limit its effective range and accuracy. This issue often necessitates multiple scan positions, further increasing setup time and limiting scalability for large plots (Calders et al., 2020). Efforts to enhance the usability of TLS in forest environments include integrating TLS data with aerial lidar to improve coverage and reduce occlusions (Balestra et al., 2024). Additionally, the high cost of TLS equipment further limits its practical feasibility, especially for extensive or remote forested areas (Liang et al., 2016). To address these limitations, mobile laser scanning (MLS)

https://doi.org/10.5194/isprs-archives-XLVIII-2-W8-2024-9-2024 | © Author(s) 2024. CC BY 4.0 License.

has emerged as a viable alternative for forest inventory. MLS, particularly in handheld formats, offers a dynamic and flexible approach to data acquisition and to solve the occlusion effects (Balenović et al., 2021; Balestra et al., 2023). By allowing operators to move freely within forest plots, handheld MLS devices can capture data efficiently over large areas, allowing adaptation to varied topography and mitigating some occlusion challenges that hinder TLS (Fassnacht et al., 2024; Chiappini et al., 2022). However, most commercially available handheld MLS systems are still relatively costly and the rising demand for scalable, efficient, and low-cost forest inventory solutions has spurred research into affordable MLS technologies (Sandim et al., 2023; Tatsumi et al., 2023). Low-cost MLS (LC-MLS) devices can emerge as a potential alternative. If proven effective, LC-MLS could support a wider array of forestry applications (Będkowski, 2024; Wang et al., 2021). However, the performance and accuracy of LC-MLS in capturing critical tree variables, such as DBH and TH, remain largely untested under field conditions compared to commercial and professional alternatives.

Studies conducted by Wilkes et al. (2018) and by Liang et al. (2016) highlight the ability of TLS to produce highly accurate data for forest biomass and carbon stocks estimations. In particular, Wilkes et al. (2018) demonstrates TLS's capability for precise biomass and carbon stock calculations, even in densely vegetated environments. While Liang et al. (2016) discusses the use of TLS in forest inventories, emphasizing its capacity to provide high-resolution, 3D data. Studies have shown that TLS-derived data can significantly improve the precision of forest inventory metrics, including basal area and tree volume (Kankare et al., 2013) and recent studies continue to support TLS's role as a benchmark for accuracy. For example, Krok et al. (2020) provide a comprehensive overview of TLS in forest inventory, covering key topics such as TLS data acquisition techniques, data processing challenges, and its effectiveness in measuring forest biometric characteristics. Additionally, new methods are emerging to complement TLS's limitations. As an example, Hu et al. (2020) integrated TLS with UAV-LS to extend data coverage and fill in gaps caused by dense understory vegetation, demonstrating that a multi-platform approach can improve inventory efficiency and spatial completeness. Moreover, recent software developments, such as AI-driven post-processing techniques, help address some limitations of TLS by streamlining data cleaning and enabling faster, more scalable analysis, as shown by Proudman et al. (2022). On the other hand, MLS offers a more flexible alternative to TLS by mounting lidar systems on different platforms, enabling mobile data acquisition over broader areas. The research conducted by Bauwens et al. (2016) compares the effectiveness of static TLS and handheld MLS for forest inventory tasks, particularly in dense forest environments, highlighting the MLS's strengths despite the lower data resolution if compared to static TLS acquisitions. Another comparative study assessed both TLS and MLS systems, finding that while TLS provides highly detailed data on tree structure, MLS allows for faster data collection across larger areas (Bienert et al., 2018). The study presented by Stovall et al. (2023) examines the importance of measuring and modeling tree stems for forest inventory, comparing the effectiveness of TLS and MLS in determining tree diameters at different heights across 20 harvested species. While both systems exhibited minimal bias, TLS demonstrated lower error rates, as expected.

According to Gollob et al. (2021), while laser scanners have enhanced forest measurements, their application was constrained by high costs and operational complexities. In their research, the lidar sensor incorporated into the Apple iPad Pro was used to collect 3D data at a more accessible price point. Their paper aims to assess the accuracy of the Apple lidar data in comparison to professional devices, evaluating the potential for professional forest inventory practices. Other studies, such as the one conducted by McGlade et al. (2022) and the other by Brach et al. (2023), suggested the exploration of plot-scale acquisitions using the iPad lidar as a low-cost device, to enhance forest measurements. They are more focusing on tree positions and DBH trying to emphasize the feasibility and ease of use of this low-cost lidar, demonstrating that it can serve as a valuable tool for forest measurements in real-world conditions.
Moreover, other studies have focused on evaluating low-cost lidar sensors for forest inventory, addressing both their technical specifications and applicability for precise forest data collection. For example, Wang et al. (2023) conducted a comparative analysis of several low-cost handheld MLS systems to assess their accuracy compared to TLS systems. Their study demonstrated that while TLS models achieve high levels of accuracy levels, advancements in SLAM-based handheld systems, such as those from the GeoSLAM and BLK2GO lines, offer high data accuracy with significantly lower costs and ease of mobility. The performance of the GeoSLAM ZEB Horizon and Stonex X120GO are evaluated in Chudá et al. (2024) focusing on two main goals: assessing positioning accuracy and identifying influencing factors. Key variables considered include scanner type, distance from the trajectory, forest structure, tree species, and DBH. Low-cost handheld MLS systems are emerging as viable tools for forest inventory, offering a balance between affordability and functionality. While accuracy challenges remain, ongoing advancements in sensor technology and data processing algorithmsm are likely to improve the capabilities of those LC-MLS, making it a valuable addition to forest inventory applications.

This research evaluates the accuracy and performances of an LC-MLS device (*Mandeye*) against two commercial handheld MLS systems (*GeoSlam ZEB HORIZON* and *GreenValley LiGrip H120*) and a conventional TLS device (*Trimble X7*) for Scots pine (*Pinus sylvestris* L.) forest plots in the municipality of Allande, Spain. In this study we compare the devices' accuracy in estimate two forest structural variables: DBH and TH. For each device, data acquisition and processing methods were standardized to ensure comparable results, with the TLS data serving as the reference point cloud, knowing its tree metrics measurement capability. This study investigates the potential limitations of LC-MLS, examining whether this technology can reliably measure the main tree metrics without significant deviation from more established, high-cost professional systems. By providing a comparative analysis, this study contributes to enhancing the affordability of low-cost 3D data acquisition devices in sustainable forest management.

2. Materials and methods

2.1 Study area

The study area is located in the municipality of Allande, within the autonomous community of the Principality of Asturias, Spain. The study was conducted in three Scots pine (*Pinus sylvestris* L.) forest plots (Figure 1). Each plot measures 30 x 30 meters and is characterized by mature trees, medium understory density, and varying terrain features.

Figure 1. One of the three *Pinus sylvestris* forest plots scanned.

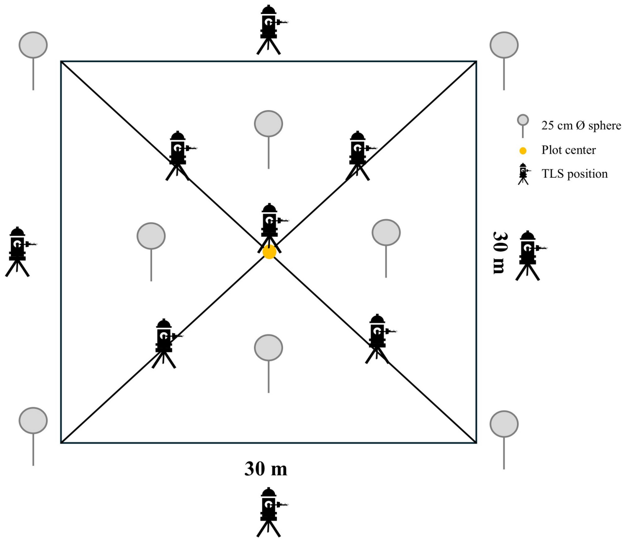

Figure 2. Positions of the eight reference spheres for the point cloud co-registration, along with the scanning locations of the TLS device.

2.2 Data acquisition

For data collection, all devices were used to scan the three plots. Nine TLS surveys setups were conducted for each plot, while the surveys with the different MLS devices followed similar trajectories, with a scanning duration of 10–12 minutes. To mitigate the occlusion effect in the TLS scans, the data were co-registered using the manufacturer-provided software. The TLS was positioned at multiple locations within each plot to ensure full coverage, ensuring a high point density and detailed representation of the forest's vertical structure. MLS point clouds were generated using the respective software solutions for each device, and all point clouds were aligned within a common coordinate system, using the TLS data as the reference. For the TLS, point cloud acquisition required the strategic placement of reference points consisting of polystyrene spheres of 25 cm diameter, positioned on the ground so that at least three spheres (with a minimum of two) were visible from the scanner's perspective for each position. Eight spheres were used for each acquisition, distributed across the study area. The arrangement of the spheres was designed to ensure precise co-registration between successive scans, regardless of the scanner's position in the plot. This allowed for obtaining a dataset that was aligned and accurately georeferenced. An example of the relative position of the spheres in the plot is shown in Figure 2. This approach enabled the alignment of MLS data with those collected via TLS, facilitating comparison between the different datasets.

The TLS system used as a reference is the Trimble X7, a static terrestrial laser scanner with an acquisition range between 0.6 and 80 meters, a scanning frequency of up to 500,000 points per second, and an accuracy of about 2 mm at a 10 m distance. The retail price is around €45,000. We used three different MLSs: the GeoSlam ZEB HORIZON, the LiGrip H 120 and a low-cost MLS named Mandeye. The GeoSlam ZEB HORIZON is an handheld laser scanner capable of collecting up to 300,000 points per second, with a maximum range of 100 meters and an accuracy between 1 and 3 cm. Its retail price is around €35,000. The device uses a Simultaneous Localization and Mapping (SLAM) algorithm to create a model of the surrounding environment and locate the device itself within it. The acquired data were processed using GeoSLAM Connect software, which generated trajectory files and .las files representing the point clouds. In this software, we used the "forest" filter and the "clean" option to correctly process and export the dataset acquired. The LiGrip H 120, produced by GreenValley International, is a handheld laser scanner with a range of 120 meters and a capacity to acquire 320,000 points per second thanks to the XT32M laser. The retail price is around €25,000. The device supports various mapping modes, including the SLAM mode. The instrument includes a camera with a resolution of 6080×3040. The device weighs 1.74 kg and offers a relative accuracy of ±3 cm and an absolute accuracy of 5 cm. The Mandeye is a LC-MLS designed to capture 3D environmental data using SLAM technology. The retail price is around €7,000, making it an accessible option for many users. Equipped with a Livox Mid-360 lidar sensor and an inertial measurement unit (IMU), it tracks its position and orientation as the operator moves freely through the environment. The device offers a point rate of 200,000 points per second and an effective detection range of up to 70 meters for objects with high reflectivity, though in forest environments the practical range is around 30–35 meters. With a 360° horizontal field of view and a vertical field of view from -7° to 52°, the Mandeye provides comprehensive spatial coverage. Powered by a Raspberry Pi 4 and operating on open-source SLAM algorithms, it exports data in formats like .LAS, .ply, and .e57. Weighing approximately 1.5 kg and featuring a rechargeable lithium-ion battery with about 4–5 hours of continuous operation, it is both portable and efficient for rapid data acquisition.

2.3 Point cloud processing

The acquired point clouds were imported into CloudCompare software and georeferenced using the spherical markers placed in the field. The georeferencing phase ensured accurate alignment of data from the different scanning systems. Subsequently, the point clouds were processed using the 3DFin plugin in CloudCompare (Laino et al., 2024), to extract the main variables (DBH and TH). DBH was calculated by measuring the section circumference at 1.3 meters from the ground, while total height was determined as the maximum vertical distance from the base to the top of the canopy. For the post-processing of the Mandeye point cloud within CloudCompare, we applied the Statistical Outlier Removal (SOR) filter with default parameters (k=6 and nSigma=1). The SOR filter calculates the average distance of each point relative to its nearest neighbors and eliminates points that significantly deviate from the mean. We applied the SOR filter prior to metric extraction to reduce noise caused by the absence of integrated noise suppression algorithms in the device itself. We conducted a comparative analysis of different laser scanner devices to assess their accuracy. This evaluation employed both absolute and percentage Root Mean Square Error (RMSE) and bias statistics, as outlined in equations 1, 2, and 3. The parameters considered for statistical accuracy assessment were DBH and TH of 61 trees, measured and estimated using each device. These statistical measures provide an objective and quantitative evaluation of the variation among results from the different MLSs (GeoSlam, LiGrip and Mandeye) and the benchmark values obtained from TLS.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{1}$$

$$bias = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i) \tag{2}$$

$$RMSE\% = \frac{RMSE}{\bar{x}} \times 100 \tag{3}$$

The parameter x_i represents the tree parameters measured by the MLSs, $\hat{x}_i$ represents the ones measured with the TLS, n is the tree total number, and $\bar{x}$ represents the mean of the reference TLS values.

3. Results

Visual inspection on the generated point clouds shows that all solutions provided good results overall. In Figure 3, a specific part of the dataset shows the trunk section as scanned by the three MLS solutions, with the TLS dataset as reference. It is generally observed that density-wise, the TLS remains the highest while the MSL-based solutions tend to provide lower density. In this regard, the use of TLS as a reference data is warranted. More specifically, the LiGrip h120 exhibited the lowest density among the three tested sensors. Additionally, no significant noise was observed across the tested methods.

To examine the presence of noise more closely, Figure 4 is given. In this figure, the trunk is inspected in more detail, as it may influence further analysis, especially when performing DBH measurements. Indeed, the issue of point cloud density is evident, with a stark difference between TLS and MLS results. GeoSlam and Mandeye visually exhibit more noise than the LiGrip counterpart. However, the point cloud density of the LiGrip data is also lower than that of the other two, which may contribute to the overall quality of the parameters extraction.

To present a more tangible conclusion, a quantitative analysis was thereafter applied to the generated datasets. In Table 1, both the bias and RMSE values are provided for each of the three sensors, specifically for measurements of DBH and tree height, with comparisons made against the TLS reference data. In absolute terms, Mandeye performed comparably well to both GeoSlam and LiGrip in DBH measurements. In general, Mandeye generated similar results to LiGrip, while GeoSlam was slightly more accurate. However, the difference between GeoSlam and the other two methods in DBH measurement may be considered statistically insignificant, especially considering the expected theoretical precision is in the centimeter range. However, for tree height measurement, Mandeye noticeably generated worse RMSE values. On the other hand, LiGrip achieved the best results, with a bias percentage of 0.23% and RMSE percentage 1.13%. These results must however be taken with nuance as the point cloud density and thus noise level on the LiGrip result is considerably lower than both GeoSlam and Mandeye. Overall, all three MLS sensors produced results with less than 10% bias and RMSE when compared to TLS, with the notable exception of Mandeye's results for the tree height computation.

	Bias		RMSE	
	DBH (cm)	TH (m)	DBH (cm)	TH (m)
GeoSlam	-0.84	-1.06	1.47	1.46
LiGrip	-1.85	0.04	2.18	0.21
Mandeye	1.62	-2.16	2.20	2.47
	Bias%		RMSE%	
GeoSlam	-2.35	-5.59	4.10	7.67
LiGrip	-5.15	0.23	6.06	1.13
Mandeye	4.51	-11.38	6.11	12.97

Table 1. Comparison of Bias, RMSE, Bias% and RMSE% for different MLS used with respect to the TLS.

In considering the correlation between the MLS datasets and the reference TLS, Figure 5 shows that no important and discernible systematic error is present. All three MLS sensor observations exhibit a strong correlation with the TLS reference dataset. Figure 6 further shows this fact, with all datasets showing minimal deviation from the normal distribution, with a minor exception on the Mandeye. GeoSlam was also shown to be the least affected by systematic error.

In regards to tree height measurement however, Figure 7 shows that only LiGrip follows a strong correlation with the reference. Both GeoSlam and Mandeye show weak correlation, with Mandeye being the worse of the two. This is also evident in Figure 8; LiGrip closely follows a normal distribution while both GeoSlam and Mandeye demonstrated significant deviation, as evidenced by their RMSE values.

These observations indicate that the tested MLS sensors, including the Mandeye, are comparable to each other up to a certain level, resulting in DBH readings from all sensors being precise within a 10 % deviation from the TLS measurements. However, for tree height, both Mandeye and GeoSlam struggled to provide accurate results. While LiGrip performed better, its point density must also be taken into account.

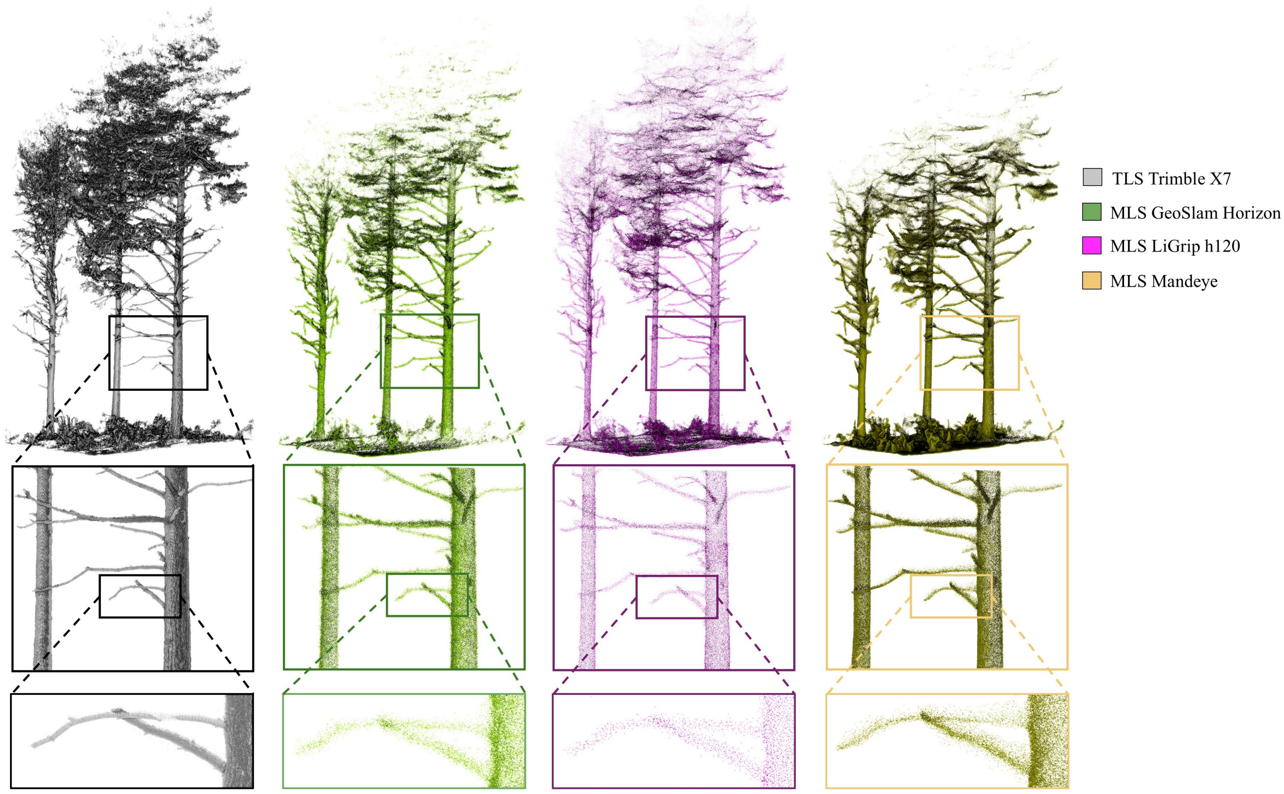

Figure 3. Clipping of the point clouds obtained with the four different laser scanner devices, with two close-up and detailed views of a trunk section.

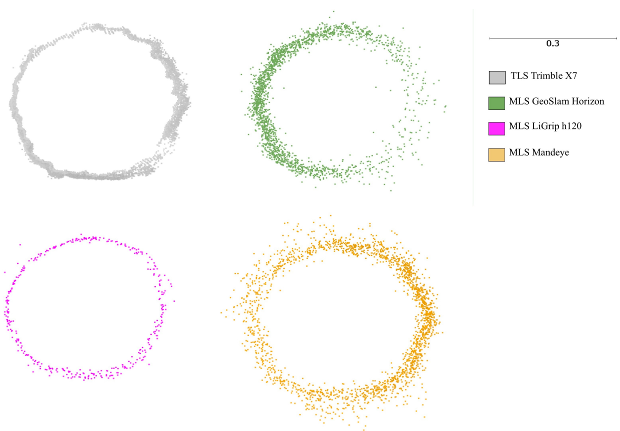

Figure 4. Horizontal cross-sections of four trunks scanned with different laser scanner devices. The point cloud noise level from the various devices can be observed, which affects the DBH measurements.

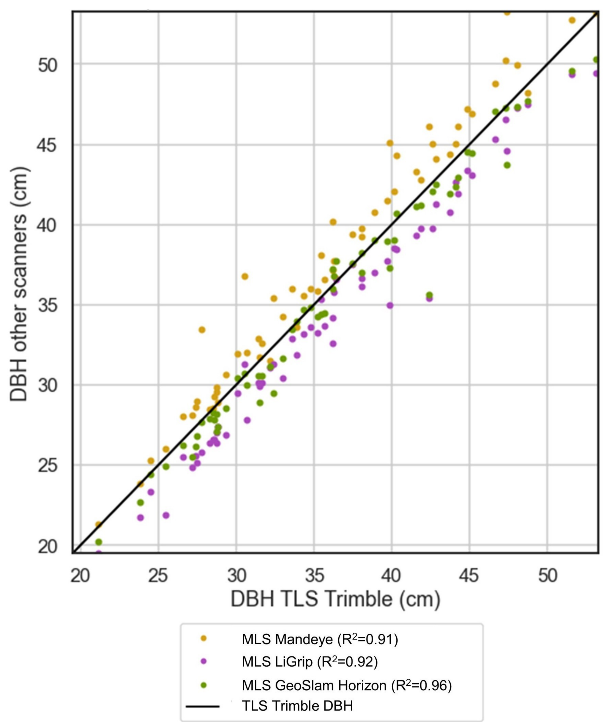

Figure 5. Correlation of DBH between MLS scanners and TLS reference data.

4. Conclusions and future works

The use of 3D data acquisition technologies, such as laser scanning systems, represents a significant advancement in precision forestry and forest inventory methods. This study presents an evaluation of an LC-MLS technology in comparison to one professional TLS and two commercial handheld MLS devices. The growing interest in affordable yet effective alternatives arises from the increasing demand for efficient forest inventory practices. Our findings demonstrate that the LC-MLS device, in addition to its cost efficiency and ease of use, offers competitive accuracy in measuring essential tree metrics. In our case, the accuracies reached with our LC-MLS device Mandeye were generally comparable to professional alternatives like GeoSlam and LiGrip for DBH measurements, showcasing minimal deviation from TLS used as reference data. Nevertheless, chal-

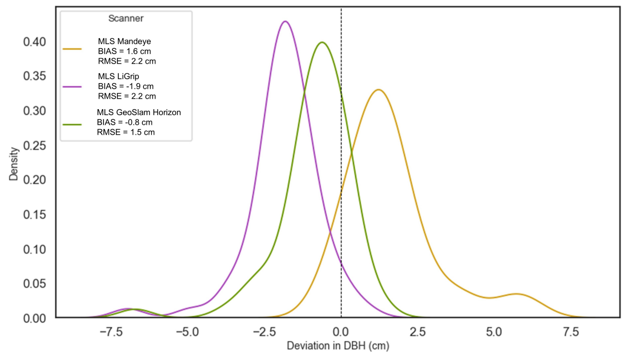

Figure 6. DBH deviations between MLS scanners and TLS reference data.

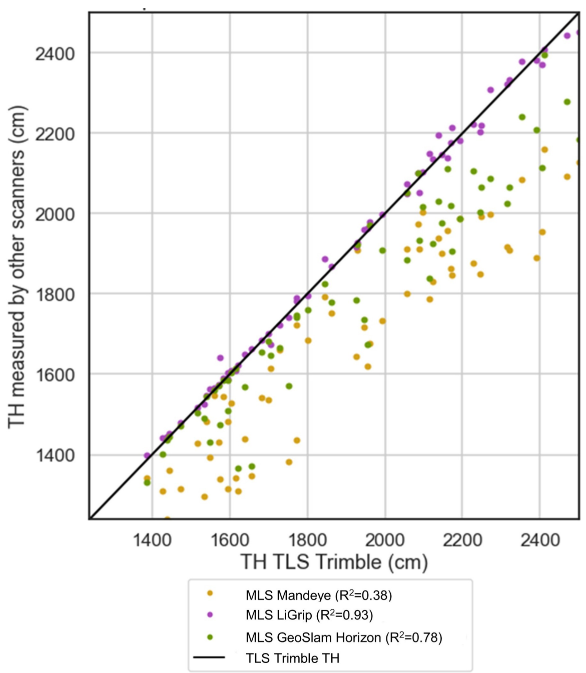

Figure 7. Correlation of TH between MLS scanners and TLS reference data.

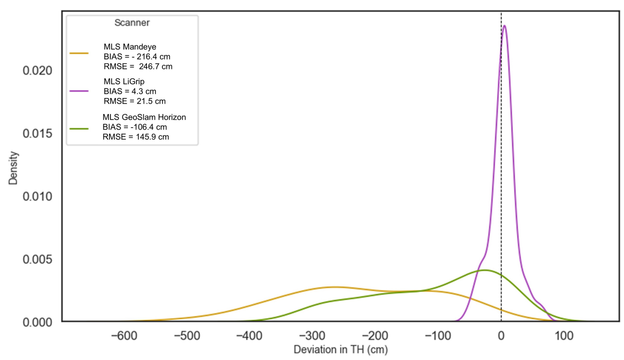

Figure 8. TH deviations between MLS scanners and TLS reference data.

lenges persist in TH estimation, where the Mandeye exhibited higher RMSE values compared to the other professional devices. While TLS remains the benchmark for high-density, accurate 3D data, it poses significant limitations, such as lengthy setup times and susceptibility to occlusion in complex forest environments. In contrast, MLS systems present a more agile and flexible alternative, allowing for efficient data capture over larger areas. However, the trade-offs between point cloud density, noise levels and data processing complexity must be considered. Nonetheless, the balance between affordability and device accuracy is crucial for widespread adoption of LC-MLS technologies. While the LC-MLS device shows promising results in forest inventory tasks, further advancements in sensor technology and SLAM algorithms are needed to close the gap with high-end systems, particularly for tasks requiring high vertical accuracy. Future research should continue to explore the integration of low-cost platforms with emerging data processing techniques, such as artificial intelligence and data fusion, to enhance their applicability in the forestry sector. Additionally, comparative studies across different forest types and varying environmental conditions would help to further validate the LC-MLS systems. Democratizing access to rapid, low-cost technological tools for forest measurement could significantly impact sustainable forest management practices and contribute to expanding the use of these devices across different countries and their different forest types.

Acknowledgments

This work was supported by the project titled ”Open, Reusable, and Multimodal Large Language Model Technology for Point Cloud Understanding” (acronym ”3D.LLM”), funded under the cascade call of Spoke 7 Politecnico di Torino, as part of the FAIR research program financed through the PNRR Mission 4 – Component 2 – Investment 1.3 Extended Partnerships. The authors would like to thank the project for funding the publication and participation in the workshop.

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