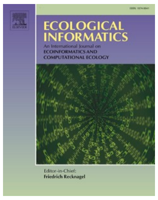
Ecological Informatics 91 (2025) 103417

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf



Accuracy and time efficiency of a new app developed to source and map single tree data: A comparison to state-of-art LiDAR data collectors in terms of basal area estimates

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ARTICLE INFO

Keywords:
Smart technology
Tree scanner
Effectiveness
Tree biometrics
Agreement
Polyfunctionality
LiDAR
Big data

ABSTRACT

The growing demand for effectiveness in forestry and the wood supply chain calls for the development of industry-specific digital tools. This study analyzed the accuracy of plot-level basal area estimates and the time efficiency of a new mobile application - Tree Scanner (hereafter referred to as Platform 1), using measurements sourced from a FDJ Trion P1 Scanner PLS (personal laser scanner, hereafter referred to as Platform 2) as a reference, by considering 50 plots of 300 m^2 each characterized by a wide diversity in tree biometrics, age, species, and density. The results indicate that the accuracy levels achieved by the mobile application are comparable to those derived from professional Light Detection and Ranging (LiDAR) scanners (BIAS = 1.950 m^2/ha, MAE = 2.292 m^2/ha, and RMSE = 3.085 m^2/ha). Furthermore, the average measurement time was significantly shorter with Platform 1 (11 s/tree) compared to Platform 2 (51 s/tree), not accounting for the additional processing time required to produce results with Platform 2. This research concludes that Platform 1 represents a promising tool for enhancing the efficiency of data sourcing for forest inventories, offering an alternative that can significantly improve the speed of acquiring crucial information for decision-making.

1. Introduction

Worldwide, forest ecosystems provide a diverse range of essential products and services that support environmental, economic, and societal welfare (Reid et al., 2005). Among essential services are soil and water protection, air purification, climate change mitigation, and carbon storage (The Economics of Ecosystems and Biodiversity (TEEB), 2010; Mullan, 2014). The products provided by forests range from raw materials for construction and energy, such as wood, to food and other products used in a highly diversified industry (Hurmekoski et al., 2018; Sahoo et al., 2019).

To ensure sustainable forest management that balances the environmental, economic, and societal roles of forests, careful planning is required to support decision-making at tactical, strategic, and operational levels (Andersson, 2005). Different levels of decision-making may require data collected at varying scales, with various features and levels of detail (Forzieri et al., 2009; White et al., 2016). National forest planning and monitoring may need plot-level data to characterize forests over large areas in terms of species composition, biometrics, and growth (Temesgen et al., 2007; Zeng et al., 2015). Forest management plans typically require more granular data that detail the structure and growth dynamics of forests, aiming to protect them, balance their structure according to specific goals, and plan harvesting schedules (Hasle et al., 2000). Those responsible for local management are more interested in operationalizing the provisions of forest management plans and may require more detailed tree-level data for transactional purposes (Astrup et al., 2014; Didion et al., 2024). Regardless of the level of decision-making, trees are typically characterized by measurements of their main biometrics, such as diameter at breast height (DBH) and tree height (Avery and Burkhart, 2015; Hegde et al., 2025). These measurements are commonly used in allometric equations to predict or estimate tree volume (Muukkonen, 2007; Zianis et al., 2005), which can then be extrapolated to the plot or compartment level for certain purposes (Abedi and Abedi, 2020; Roxburgh et al., 2015).

In several forest-based applications, DBH is an essential metric (Gollob et al., 2020; Van Aardt et al., 2008). Typically, it is used to

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https://doi.org/10.1016/j.ecoinf.2025.103417
Received 28 May 2025; Received in revised form 1 September 2025; Accepted 1 September 2025

estimate tree volume or basal area (Mulyana et al., 2018), which helps characterize various structural parameters of a forest stand (Bienert et al., 2012; Wang et al., 2021). When measured conventionally (i.e., by a caliper), DBH not only requires significant resources (Borz and Proto, 2022) but is also subject to measurement variability (Guenther et al., 2024; Gülci et al., 2023; Moran and Williams, 2002). For instance, recent studies have shown that manual plot-based measurements required to support forest inventory efforts can be tedious and time-consuming (Di Cosmo, 2023; Gao and Kan, 2022). Even if less documented in existing studies, manual measurement of DBH may also be influenced by operator's height and technique biases (Gao and Kan, 2022; Liu et al., 2018). In other words, two people of different heights measuring the DBH of the same tree may yield quite different results, primarily due to their height differences, and there are other studies documenting the influence of several other factors on measurement accuracy for other biometrics such as tree height (Stereńczak et al., 2019).

Recent developments in technology have provided forest management with increasingly effective methods for estimating DBH. LiDAR scanning using professional instruments currently stands as the leading method in the field because it accurately documents the shapes of trees in three-dimensional space (Akay et al., 2009; Mosin et al., 2019). However, processing LiDAR point cloud data requires advanced skills, a significant investment of time to collect and analyze the data, and sometimes expensive instruments and software (Balestra et al., 2024; Dassot et al., 2011; Jakubowski et al., 2013). Low-cost LiDAR collection platforms, such as smartphones, are a feasible alternative but are typically limited in scanning range (Borz et al., 2022a; Singh et al., 2024), which may be an important limitation when aiming to work with plot-level data collected through continuous scanning. In addition, they may require considerable effort to perform the scanning process, can be labor-intensive in terms of data processing, and may suffer from accuracy issues (Liang et al., 2022), particularly from drifts in point clouds due to movement. Additionally, in various types of forest ecosystems, the degree of occlusion can be a significant concern when planning for the acquisition, collection, and processing of LiDAR data (Borz et al., 2024; Xu et al., 2021).

Besides accuracy, the technology affordability, degree of mobility, less effort and improved safety, real- or near-real time data transfer, exchange, synchronization, and storage, are essential features in a modern forestry. While several smartphone apps that use LiDAR to measure forest and tree parameters (e.g., ForestScanner and 3DScanner) have shown promise in meeting these needs, their functionality and integration with comprehensive inventory workflows and traceability functionalities are frequently lacking. Most smartphones come equipped with the technologies required for such purposes, and some of them are coming further equipped with LiDAR sensors, which enable advanced 3D spatial scanning directly from the device. The accuracy of some of these existing apps in measuring the DBH has been fairly documented by several studies (Borz et al., 2024; Gollob et al., 2021; Gülci et al., 2023; Niţă and Borz, 2023; Ofner-Graff et al., 2025; Singh et al., 2024; Tatsumi et al., 2023; Ucar et al., 2022; Wang et al., 2021; Wang et al., 2022) indicating a specific market characterized by various solutions in terms of functionality. Realizing the potential to overcome existing limitations by integrating the functionality of log volume, tree DBH, and height measurements with capabilities such as data transferability, storage, mapping, and processing, while providing instant readings, helping to document the origin of trees and wood-based products, and supporting the traceability of such products, the EU-funded SINTETIC project (https://sinteticproject.eu/) has set the ambition to develop and test a smartphone-based app that covers non-exclusively such functionalities.

The aim of this study was to evaluate the accuracy of the developed app and estimate the time consumed while operating it, with the goal of producing plot-level basal area estimates based on DBH measurements. Given the recent improvements in the accuracy of LiDAR data, and the availability of professional data acquisition platforms on the market that display scanning progress in real time and are equipped with forestry-specific LiDAR software, reference data collected and processed by such a platform was used to: i) assess per-hectare accuracy of the app-sourced basal area estimates based on DBH measurements, and ii) compare the plot-level time consumption of app measurements to that of a personal laser scanner (PLS). In addition, iii) we attempted to compare the magnitude of DBH data sourced from the two platforms used and to develop a model to predict time consumption for tree-level measurements with the app.

2. Materials and methods

2.1. Description of the platforms used

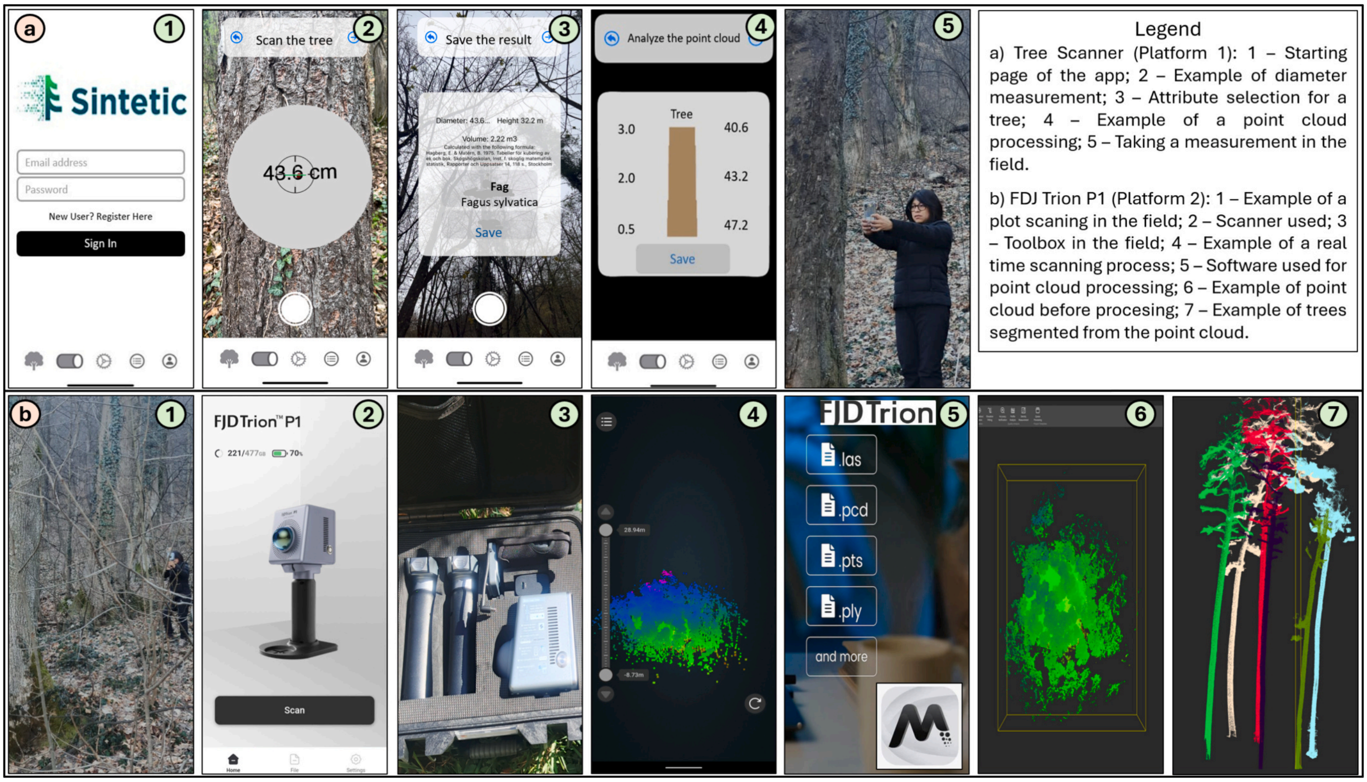
The Tree Scanner (Fig. 1a) is a mobile app developed within the framework of the SINTETIC project (https://sinteticproject.eu/, Sintetic Project, 2025) for accurate tree and log measurement and tracking. It utilizes LiDAR sensors, Global Navigation Satellite System (GNSS), and cameras to take measurements of standing trees and logs, enabling the collection of data such as tree location, DBH, height, log diameter, length, and volume.

The app generates high-resolution 3D point clouds using LiDAR technology included into compatible, pro versions of iPhones and iPads, making it applicable and suitable worldwide. It is designed to measure the log ends using a convex hull approach on the LiDAR point cloud for uniform cuts, and relies on camera image analysis and artificial intelligence (AI) - based algorithms, to detect relevant features. The RANSAC (Random Sample and Consensus) algorithm is used to estimate diameters and centers along the tree including the DBH and tree height. The app is optimized for both, LiDAR-enabled and non-LiDAR iOS devices. Technical criteria call for an iOS operating system and an internet connection for data synchronization with Arboreal and ForestHQ servers. Currently under testing via the Apple TestFlight, the app calls for downloading the TestFlight app then using an invitation link. The app has been published in multiple iterations; 0.95 is the most recent (Poveda and Ekenstedt, 2024). For inventory purposes, the app allows users to set plot parameters and provides a user-friendly interface for taking measurements. Hereafter, the measurements taken by the app are referred to as measurements taken by Platform 1.

The FJD Trion P1 (Fig. 1b) is a compact PLS, weighing 1 kg, making it ideal for data capture in various applications including forest environments (FJDynamics, 2025). It employs LiDAR technology to measure distances and generate 3D point clouds, by a process which can be visualized in real time. It provides a precision of approximately 2 cm, with a scanning range of 40 m. The scanner features a LiDAR field of view of $360^\circ \times 59^\circ$ and can capture data at a rate of up to 200,000 points per second utilizing the SLAM technology. The FJD Trion P1 creates universal point cloud data formats such as .LAS, .PCD, .PTS, and .PLY, which are compatible with FJDynamics' Trion Model software (FJDynamics, 2025). This software was used for processing, filtering, and refining the point clouds. Hereafter, the measurements taken by this scanner are referred to as measurements taken by Platform 2. To ensure complete capture, the scanner's real-time visualization capability was utilized. This allowed point cloud formation to be directly monitored in the field, ensuring adequate coverage and identifying the need for immediate readjustments to capture all tree structures. Furthermore, once the point clouds were processed in FJDynamics' Trion Model software, a thorough visual review was conducted. This detailed inspection from multiple angles allowed the presence of all trees within the scanned area to be identified and verified according to the criteria, ensuring data integrity.

2.2. Study location and data collection

The study area was selected with careful consideration of the essential factors that may affect the accuracy of collecting DBH data



Legend

a) Tree Scanner (Platform 1): 1 – Starting page of the app; 2 – Example of diameter measurement; 3 – Attribute selection for a tree; 4 – Example of a point cloud processing; 5 – Taking a measurement in the field.

b) FDJ Trion P1 (Platform 2): 1 – Example of a plot scaning in the field; 2 – Scanner used; 3 – Toolbox in the field; 4 – Example of a real time scanning process; 5 – Software used for point cloud processing; 6 – Example of point cloud before procesing; 7 – Example of trees segmented from the point cloud.

Fig. 1. Data collection platforms used in the study: a – Tree Scanner (Platform 1), b – FDJ Trion P1 (Platform 2).

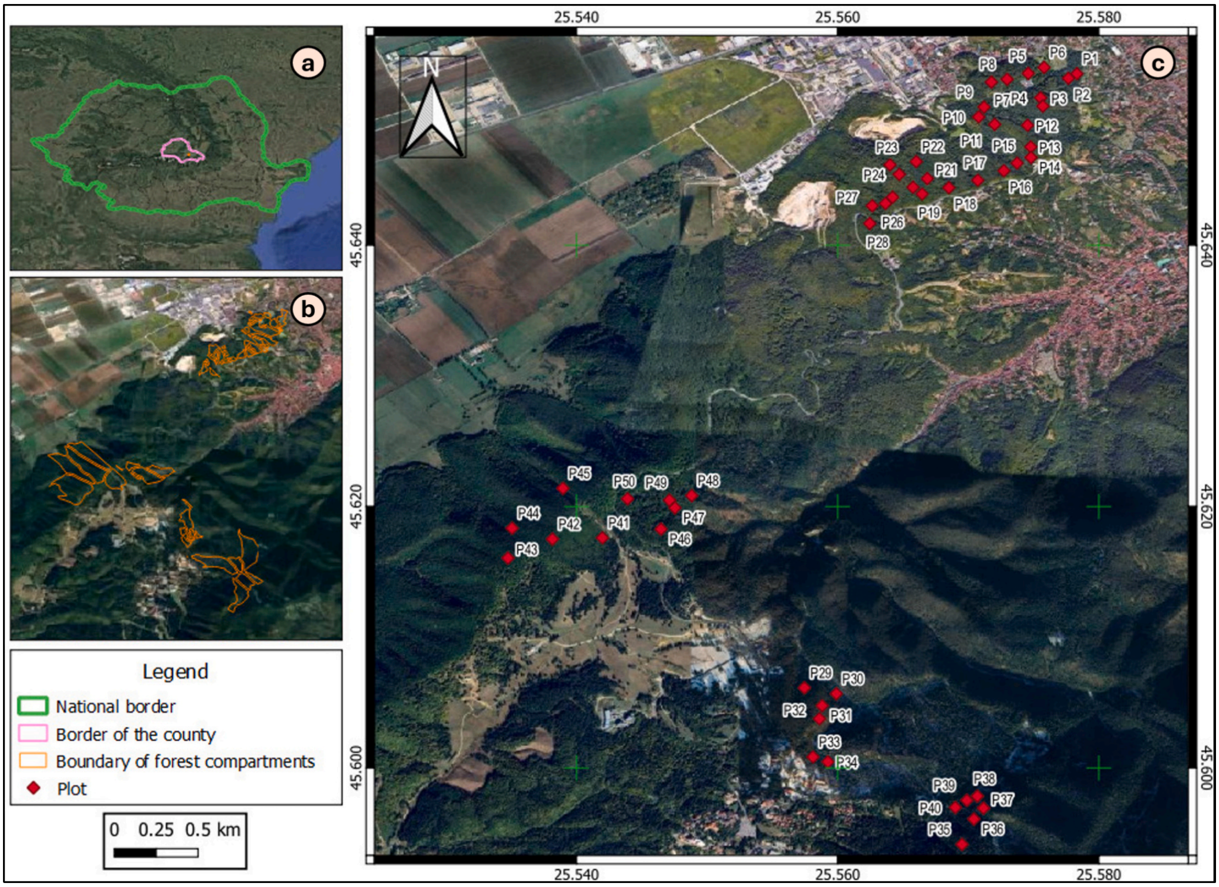


Fig. 2. Location of the data collection: a – the location of study area at the national level, b – the location of the selected forest compartments, and c – the locations of the plots.

using proximal sensing technologies (Fig. 2). Specific forest conditions, such as high tree density, dense undergrowth vegetation, complex canopy structure, terrain slope and roughness, and the age of the stand, can lead to occlusion and hinder the acquisition of clear data from the tree trunk (Balsi et al., 2018; Sandim et al., 2023; Wallace et al., 2014). Environmental factors, including lighting conditions and weather variations (sunny, cloudy, rainy), can also influence the quality of data collected by specific detection technologies (Borz et al., 2024; Sandim et al., 2023). Additionally, tree characteristics such as size, particularly smaller individuals, species, and irregularities in trunk form (e.g., ovality, curvature, and buttresses) can contribute to variability in measurements (Balenović et al., 2021; Gregoire et al., 2016; Vauhkonen et al., 2012). Fifty circular plots of 300 m^2 each were established in several forest compartments located near the city of Brașov (Romania). These compartments were characterized by a wide diversity of species, age, tree density, and slope, covering an altitudinal range of approximately 800 m.

Fig. 2 shows the study area and the location of the plots, while Table 1 provides the main descriptive statistics of the characteristics of the forest compartments selected for the study. Plots were delineated using a tape, spray, and a handheld GPS unit (GPSMAP 64sx, Garmin). A tree was designated as the center point of the plot, a number was assigned to it, and that tree was marked with a spray by creating a full circle around the trunk. The coordinates of the center point were obtained using the GPS unit. Subsequently, a circle with a radius of 9.80 m was virtually marked from the center point of the plot using the tape. The study considered trees with DBH above the 10 cm threshold to accommodate the capabilities of the used platforms and with at least 50 % of their DBH located inside the plot's radius. When using Platform 2, the scanning commenced from the central point and was carried out using four elliptic trajectories. Consequently, the plot was conceptually partitioned into four quadrants, with each quadrant scanned sequentially, by directing the beams inward, and executed with a steady and repetitive gradual descent from the top to the bottom. When scanning from the edge of the plot an approximate outward distance of 5 m was considered to accurately cover the border trees (Fig. 3).

Comparative DBH and time consumption data were collected in two steps. First, all the trees located within a plot (hereafter referred to as P1 to P50) were measured individually by Platform 1, and the DBH data for each tree (hereafter referred to as DA, taken to the nearest millimeter) was recorded in a notebook. Then, the plot was scanned by Platform 2, and the LiDAR data was stored in its internal memory. Scanning by Platform 2 was performed for each plot in a similar manner, following the pattern depicted in Fig. 3.

Data from Platform 2 served as the operational benchmark for subsequent comparisons due to its high accuracy, capability to document three-dimensional data of the trees, including DBH, which lacks in the use of manual measurements, and due to a similar technical principle used to source data. By Platform 2, obtaining the results for DBH and basal area required several processing steps. These steps include downloading or moving the data from the instrument to a PC and then cleaning the point cloud. FJDynamics' Trion Model software was used to carry on this cleaning. It mostly involved automatically getting rid of noise points or outliers that did not match real vegetation or terrain, aiming at making the point cloud quality better. Then, the same software was used to extract terrain and automatically divide trees into groups. This software uses algorithms to automatically fit circles or ellipses to the cross-section of trees at a height of 1.3 m. This way, it can get DBH from the LiDAR data without any help. Sometimes, it was necessary to carry on some manual segmentation or editing in the software to better identify complicated trees or fix small mistakes in the point cloud. All these steps were necessary to produce tree-level DBH estimates using Platform 2 and were performed on the computer architecture described in Section 2.3. However, time consumption comparisons were conducted only on data reflecting the time required to take the measurements in the field. All the data collected by the two platforms was obtained during the leaf-off season, between December 12th and 20th, 2024, covering a nine-day survey period. For consistency, none of the trees within a plot were marked, and there were no attempts to pair the tree-level DBH data sourced by the platforms used.

For simplicity and comparability, a connection to the web-based database was not established to transfer data following the measurement of each tree by Platform 1. Since we did not number the trees located in the plots, we lacked the certainty of tree-level data pairing, therefore we conducted the DBH measurement study at the plot, instead of tree level. Records of time consumption were maintained during the field phase of the study for each tree measured by Platform 1 (hereafter referred to as tDA, taken to the nearest second) and for each plot scanned by Platform 2 (hereafter referred to as TDS, taken to the nearest second). The time consumption for measuring each tree by Platform 1 included the time spent preparing the app, taking measurements, and saving the data in memory. By summing the tree-level times for measurements taken with Platform 1 from a given plot, the plot-level time (hereafter referred to as TDA) was derived for that plot. The time consumption for scanning each plot by Platform 2 was defined as the total time taken to set up the scanner, conduct the scan, and save the data collected.

2.3. *Experimental design and data analysis*

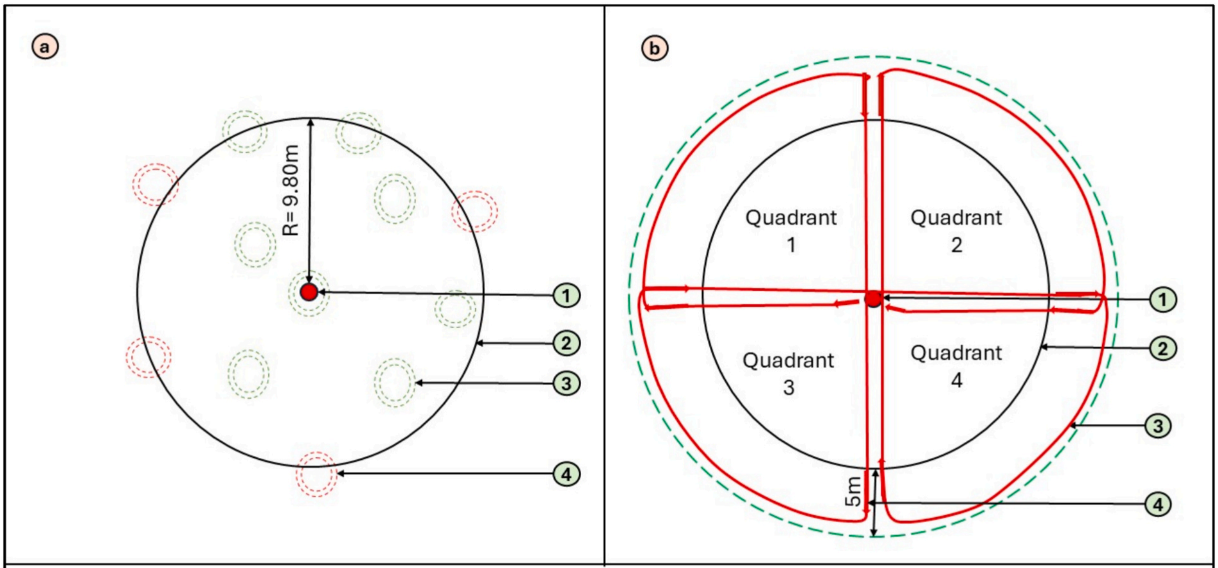
The experimental design was implemented to compare the datasets using a threefold approach. First, tree-level data was compared in terms of diameter estimates, and attempts were made to model the time consumption at the tree level for Platform 1 in relation to the measured diameters. For this part of the experiment, essential statistical steps were carried out, including testing for normality in the data (D'Agostino-Pearson test, $\alpha = 0.05$, $p > 0.05$, and QQ plots), developing the main descriptive statistics, and checking the assumptions of linear regression, employing a confidence threshold of 95 % ($\alpha = 0.05$) where relevant. Since it was not possible to pair the DBH measurements between the platforms used, their DBH estimates were ordered incrementally by magnitude and then plotted against that order.

To compare the agreement in basal area estimates at the plot and per-hectare levels, the DBH estimates from the two platforms were used to calculate the basal area of each tree in the dataset. Considering the size of the plots, the basal area estimates were calculated on a per-hectare basis, resulting in two new datasets: basal area sourced by Platform 1

Table 1
Descriptive statistics of the forest compartments selected for the study.

Parameter	Descriptive statistic					
	Minimum value	Maximum value	Range	Mean value	Standard deviation	Data distribution[1]
Mean age (years)	45	170	125	112	±4.0	Normal, $p = 0.594$
Canopy cover[2]	0.30	0.89	0.59	0.67	±0.02	Normal, $p = 0.223$
Stand density (trees/ha) [3]	166.67	800.00	633.33	410.00	±152.57	Normal, $p = 0.140$
Slope (degrees)	8	42	34	21.2	±0.99	Normal, $p = 0.129$
Elevation (m)	580	1350	770	793	±180.9	Normal, $p = 0.305$

Note[1]: – According to the D'Agostino-Pearson test ($\alpha = 0.05$, $p > 0.05$)[2]; – expressed as rational numbers from 0.1 to 1.0, indicating the projected canopy area to the total area of a given compartment, as sourced by the local forest management plan[3]; – based on figures sourced by this study.



Legend

a) Concept used for plot establishment: 1 – center of the plot; 2 – plot border; 3 – trees included in the plot; 4 – trees excluded from the plot.

b) Scanning pattern used: 1 – center of the plot; 2 – plot border; 3 – trajectory of scanning; 4 – outer scanning distance from the plot.

Fig. 3. Concept of plot establishment and scanning by Platform 2: a – geometry of a plot, b – scanning pattern implemented when using Platform 2.

(hereafter BAPHi, m^2/ha, rounded to the nearest square millimeter, where i represents the plot number, $i = 1$ to 50), and basal area sourced by Platform 2 (hereafter BASHi, m^2/ha, where i also represents the plot number, $i = 1$ to 50).

For each level of comparison regarding basal area, several statistical steps were implemented. The normality of the data was assessed using the same statistical test as that used for the DBH data. Afterward, the main descriptive statistics were generated, and the datasets were compared at the specified levels using statistical comparison tests deemed appropriate for the type of data distribution. Depending on the results of the normality test, two statistical comparison tests were considered: the independent two-tailed *t*-test, which is a parametric test for comparing the means of two groups, but its validity depends on the fulfillment of assumptions such as normality and homogeneity of variances, and the independent two-tailed Mann-Whitney test, which is a non-parametric test for comparing the distributions of two groups where normality cannot be assumed, serving this way as an alternative to the t-test in certain circumstances (Pereira and Leslie, 2010).

Agreement in basal area estimates was checked by three main metrics, by considering the sample size of the study ($N = 50$): bias (hereafter BIAS, Eq. 1), which is the mean of the signed differences between the paired measurements (Giavarina, 2015), mean absolute error (hereafter MAE, Eq. 2), which measures the average magnitude of errors (Holst and Thyregod, 1999; Willmott and Matsuura, 2005), and the root mean squared error (hereafter RMSE, Eq. 3), which measures the magnitude of errors in predictions, giving greater weight to large errors (Hodson, 2022; Willmott et al., 2009).

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}(BASH_i - BAPH_i) \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|BASH_i - BAPH_i| \tag{2}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(BASH_i - BAPH_i)^2}{n}} \tag{3}$$

To make comparisons, the data sourced from Platform 2 was used as the reference, while the data from Platform 1 was that under comparison. The data was subjected also to heteroskedasticity checking using the Breusch-Pagan (Breusch and Pagan, 1979) and White tests (White, 1980). These tests were necessary to determine whether there was proportional bias in the differences, its type, and to help characterize those differences. The Breusch-Pagan test identifies linear forms of heteroscedasticity through the execution of an auxiliary regression based on the squared residuals from the original model and the distribution adheres to a chi-squared model when the null hypothesis of homoscedasticity is considered (Breusch and Pagan, 1979). On the other hand, the White test can identify both linear and non-linear forms of heteroscedasticity. It employs a chi-squared distribution and demonstrates reduced dependence on the normality assumption of error terms. However, it may be cumbersome with numerous independent variables, which can lead to a loss of degrees of freedom and a decrease in statistical power (White, 1980).

The data was also compared using the regression through the origin to assess how much of the variation in data sourced by Platform 1 could be explained by the variation in data sourced by Platform 2. Additionally, to highlight the main difference metrics and their trends, a composite plot was created. This plot displayed the paired data, the regression model, the signed differences between the datasets, and the values of the selected difference metrics. Statistical analysis of plot-level time consumption estimates followed a similar design. First, the data was checked for normality, followed by attempts to model the time consumption as a function of relevant variables such as age, density, slope, and the number of trees per plot for both platforms. To achieve this, the assumptions of multivariate linear regression were first assessed. Subsequently, the datasets were subjected to statistical comparisons using an approach similar to that of basal area estimates. Finally, the time consumption data was reported per plot and tree, accompanied by comprehensive data processing figures for the time consumption of Platform 2.

All statistical analyses were conducted in Microsoft Excel, utilizing the Real Statistics add-in (*Real Statistics Using Excel*, 2025), a free tool that is effective for performing advanced statistical tests. These tests included checks for normality and heteroskedasticity, verification of linear regression assumptions, and statistical comparisons between datasets that may or may not follow a normal distribution. As a rule, a confidence threshold of 95 % ($\alpha = 0.05$) was consistently applied to evaluate the results of these statistical tests. The LiDAR data was processed on a system featuring a 13th generation Intel Core i9-13900F CPU with a frequency of 2.00 GHz and an x64 architecture, equipped with 64 GB of RAM, a NVIDIA GeForce RTX 4070 GPU, and running a Windows 11 Pro operating system. The LiDAR data was stored on an external disk with a capacity of 14 TB.

3. Results

3.1. Tree level measurements

The main statistics of tree-level measurements ($n = 618$) are illustrated in Fig. 4, whereas supplementary statistics of the considered variables are included in Fig. A1. The assumption of normality for the DA (diameter data sourced by Platform 1, Fig. 4a), tDA (tree-level time consumption data of Platform 1, Fig. 4b), and DS (diameter data sourced by Platform 2, Fig. 4a) was not met following D'Agostino-Pearson test ($\alpha = 0.05$, $p > 0.05$), which is also reflected in the QQ plots of DA (Fig. A1a), tDA (Fig. A1b), and DS (Fig. A1c). However, the data distributions of DA and DS were similar (boxplots shown in Fig. 4a), with a range for DA of 9.0 to 88.9 cm (mean ± SD: 34.3 ± 15.83 cm) and a range for DS of 10.0 to 87.8 cm (mean ± SD: 35.1 ± 15.88 cm).

Additionally, the two data distributions ordered incrementally by the magnitude of measured DBH showed a high degree of agreement between the two types of measurements (Fig. 4d).

3.2. Agreement and differences in basal area estimates

At the per-hectare level, there was a strong agreement and similarity in the basal area estimates, as shown in Table 2, Table 3, and Fig. 5. The interquartile ranges of the hectare level estimates for basal area using the two platforms were similar and, as shown in Table 2, the distributions of these variables were found to be similar and normal ($\alpha = 0.05$, $p > 0.05$), with no significant statistical differences ($\alpha = 0.05$, $p > 0.05$) found between their means (46.082 ± 13.909 vs. 48.033 ± 14.660). Additionally, there was a high degree of agreement in the estimates, as shown in Table 3 and Fig. 5, and Fig. A2, respectively.

With a BIAS value of 1.950 m^2/ha (Table 3), indicating a small trend (slope) in increment based on the magnitude of basal area (Fig. A2), the results regarding the accuracy of estimates are promising. Additionally, no statistical evidence of linear or other forms of heteroskedasticity was found (Table 3), which suggests stability in variance concerning both the data used to estimate basal area and the basal area estimates themselves. Therefore, this study identified, on average, minor differences in estimates (approximately 2 m^2/ha), with a tendency for Platform 1 to underestimate based on the data provided by Platform 2. The RMSE metric, known for penalizing large differences, also revealed small differences, accounting for approximately 3 m^2 per hectare.

Fig. 5 provides details on data comparison and agreement by considering the basal area estimates modeled by the regression through origin. The linear trend shows a high coefficient of determination when explaining BAPH as a linear function of BASH. In fact, almost all the variance in BAPH was explained by BASH. The differences in basal area

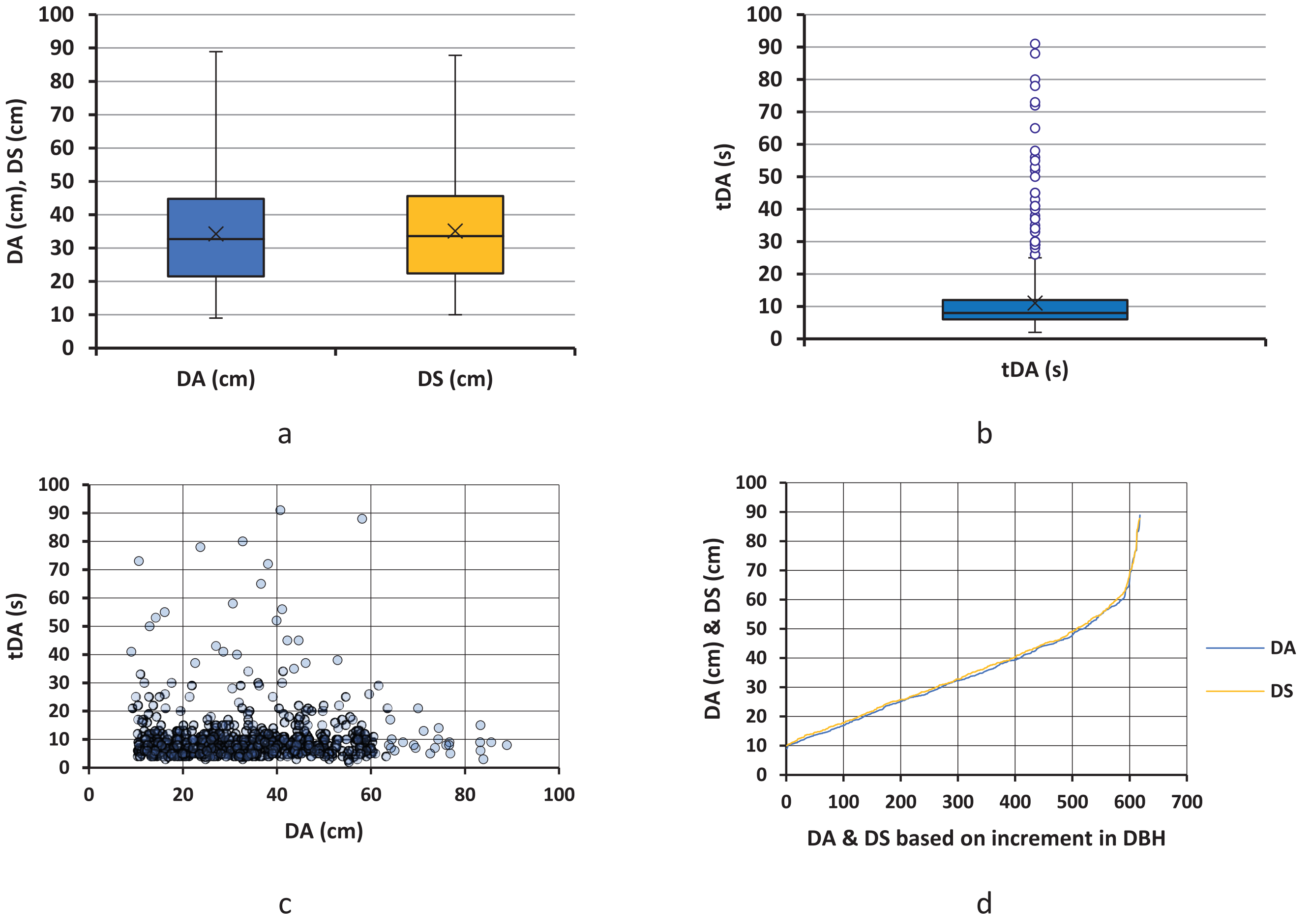


Fig. 4. Basic descriptive statistics of tree level measurements: a – descriptive statistics of DA and DS, b – descriptive statistics of tDA, c – dependence of tDA as a function of DA, d – difference between DA and DS based on data ordered incrementally. Legend: DA – DBH data sourced by Platform 1, tDA – tree-level time consumption data for Platform 1, DS – DBH data sourced by Platform 2. Note: in Fig. 4a, there was no statistically significant difference between DA and DS according to the Mann-Whitney test ($\alpha = 0.05$, $p = 0.351$).

Table 2

Descriptive statistics of the plot and per-hectare level basal area.

Parameter	Descriptive statistic						
	Minimum value	Maximum value	Range	Mean value	Standard deviation	Data distribution[1]	Data comparison[2]
Basal area per hectare sourced by Platform 1, BAPH (m^2/ha)	15.951	72.526	56.575	46.082	±13.909	Normal, $p = 0.129$	No diff. $p = 0.497$
Basal area per hectare sourced by Platform 2, BASH (m^2/ha)	16.262	77.886	61.625	48.033	±14.660	Normal, $p = 0.305$	

Note[1]: – According to the D'Agostino-Pearson test ($\alpha = 0.05$, $p > 0.05$),[2] – according to the independent two-tailed *t*-test ($\alpha = 0.05$, $p > 0.05$).

Table 3

Differences in basal area estimates.

Parameter	Difference metric, data distribution & presence of heteroskedasticity				
	BIAS	MAE	RMSE	Data distribution[1]	Heteroscedasticity[2]
Basal area per hectare sourced by Platform 1, BAPH (m^2/ha)	1.950	2.292	3.085	Normal, $p = 0.129$	No heteroskedasticity $p_{BP} = 0.320$, $p_W = 0.608$
Basal area per hectare sourced by Platform 2, BASH (m^2/ha)				Normal, $p = 0.305$	

Note[1]: – According to the D'Agostino-Pearson test ($\alpha = 0.05$, $p > 0.05$),[2] – according to the Breusch-Pagan and White tests ($\alpha = 0.05$, $p > 0.05$), where p_{BP} and p_W are the two-tailed *p* values of the Breusch-Pagan and White tests, respectively.

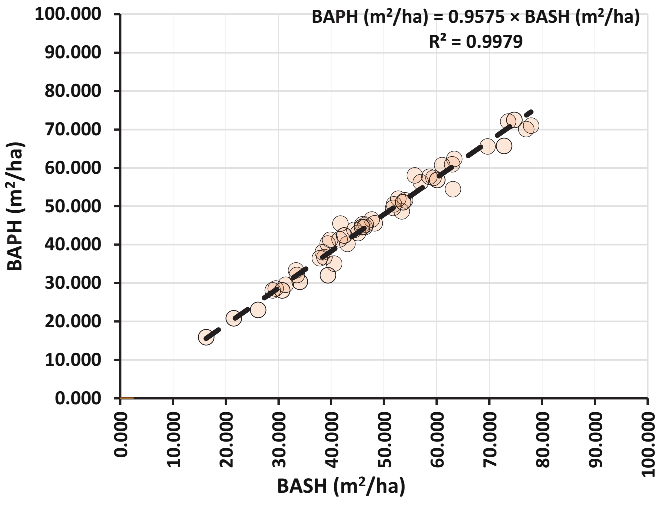


Fig. 5. Agreement in basal area estimates: Legend: BAPH – basal are estimate by Platform 1 (compared variable), BASH – basal area estimate by Platform 2 (reference variable). Note: regression through origin resulted in a value of R^2 close to 1, reinforcing the agreement in data.

estimates were consistently lower than 3.1 m^2/ha, irrespective of the difference metric considered. However, depending on the situation, one may expect signed differences to fall within the range of −4 (overestimation) to 9 m^2/ha (underestimation), as shown in Fig. A2.

3.3. Time consumption

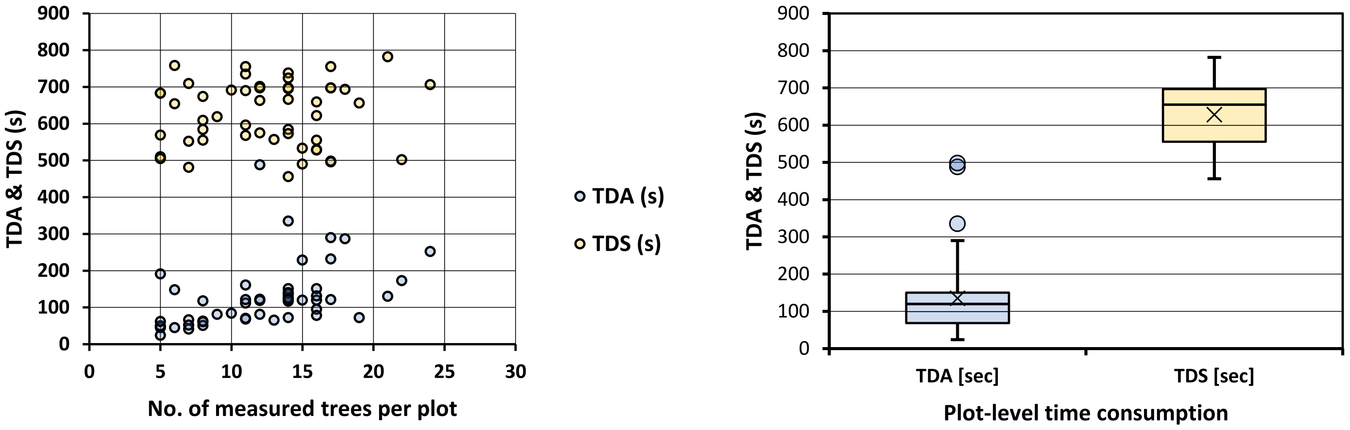
Tree-level time consumption by Platform 1 (tDA) generally exhibited a wide range of values (Fig. 4a), primarily due to the presence of values considered statistically as outliers; however, no evident dependence on DA was found (Fig. 4b), and the average tree level time consumption for measurement with Platform 1 was of 11 s.

Linear trends between plot-level time consumption (TDA or TDS) and independent variables, such as the number of measured trees, age, density, and slope characterizing the considered forest compartments, were weak, as shown, for instance in the data illustrated in Fig. 6a. Consequently, our attempt to develop models to predict the effective time consumption for the platforms used was unsuccessful, since the linearity assumption was not met. However, with Platform 1, the plot-level time required to measure the DBH of trees was significantly lower, as demonstrated by Fig. 6b and Table 4, averaging about five times less compared to that of Platform 2. On a per-tree basis, this resulted in approximately 11 s spent to measure a tree with Platform 1, compared to about 51 s for Platform 2.

However, one must consider the important differences when evaluating an end-to-end approach to the problem. We did not synchronize the data from Platform 1 because that platform was a prototype, and thus an end-to-end figure could not be obtained. In contrast, we conducted an end-to-end experiment for Platform 2, allowing us to produce figures that characterize tree-level time consumption. Specifically, with Platform 1, the time consumption per plot and per tree was found to be approximately 2 min. and 17 s. and 11 s, respectively. For Platform 2, scanning alone took about 10 min. and 26 s. and 51 s. per plot and per tree, respectively. When accounting for all the effort to obtain the DBH data as of Platform 2, the time consumption per plot and per tree increased to 118 min. and 8 s. and 9 min. and 32 s., respectively.

4. Discussion

The findings of this study were promising, as they revealed a high degree of agreement in basal area estimates at both the plot and per-hectare levels between the two platforms, further supported by the absence of statistically significant differences between the datasets. This level of agreement is in line with other research that has shown that modern LiDAR-based methods are just as good as older ones at estimating basal area (e.g., Gollob et al. (2020) found that DBH estimation error with PLS was often less than 2.32 cm, while Liang et al. (2016) showed that TLS was very accurate at estimating basal area in forest plots). Platform 1, however, has been found to slightly underestimate the basal area when compared to the data sourced by Platform 2. Small biases like these are not uncommon in forestry measurements, even between different established methods. They are usually within acceptable error margins for practical uses (e.g., Liu et al. (2018) and Gülci et al. (2023) looked at the variability in DBH and volume measurements between different equipment and operators, and found small biases in DBH measurements with smartphones compared to manual methods. Nevertheless, the measurements taken by Platform 1 to estimate the basal area were several times faster in terms of the time resources allocated in the field, which is consistent with studies that show how mobile apps can make data collection more efficient, such as that of Wang et al. (2021), who found a significant decrease in field time using smartphone-based solutions for forest inventories, or Borz et al. (2024),



a

b

Fig. 6. Statistics of plot-level time consumption: a – scatterplot of TDA and TDS measurements as a function of number of trees per plot, b – boxplots of TDA and TDS data. Legend: TDA – time consumption of Platform 1 at plot level, TDS – time consumption of Platform 2 at plot level.

Table 4
Descriptive statistics of plot- and tree-level time consumption.

Parameter	Descriptive statistic						
	Minimum value	Maximum value	Range	Mean value	Standard deviation	Data distribution[1]	Data comparison[2]
TDA (s/plot)	24	498	474	135.3	±100.83	Non-normal $p < 0.001$	Significant differences $p < 0.001$
TDS (s/plot)	456	782	326	628.1	±87.32	Non-normal $p < 0.001$	
tDA (s/tree)	–	–	–	11	–	–	–
tDS (s/tree)	–	–	–	51	–	–	

Note[1]: – According to the D'Agostino-Pearson test ($\alpha = 0.05$, $p > 0.05$),[2] – according to the independent Mann-Whitney non-parametric test ($\alpha = 0.05$, $p > 0.05$).

who compared the time efficiency of manual and digital methods for collecting biometric data.

The high agreement in basal area estimates between the mobile application and the PLS is, therefore, a promising finding of this study. The BIAS (1.950 m^2/ha), MAE (2.292 m^2/ha), and RMSE (3.085 m^2/ha) values for basal area indicate small differences between the two platforms. While some of these findings suggest the presence of a small systematic bias, the advanced statistical tests showed that there was no evidence of proportional bias, indicating, therefore, the stability of Platform 1 across a wide range of DBH, from about 10 to 90 cm.

One can argue that a different kind of scanning pattern adopted when using Platform 2 could provide the conditions for faster measurements. In fact, several scanning patterns were documented by the literature to lead to accurate results (Del Perugia et al., 2019; Gollob et al., 2020; Guenther et al., 2024). However, from our experience with Platform 2, a pattern such as that described in this paper is essential to produce usable data. Reducing it, say, to only two closed loops, will likely halve the scanning time, but it will still be less time-effective compared to Platform 1, while questionably covering the trees located in a plot where there is a high degree of occlusion or a very developed understory. Platform 1, on the other hand may be more sensitive to the number of trees included in a plot and ground conditions, and, as such, to the size of the plot, a fact that should be verified in the future, particularly when one targets to measure both DBH, and tree height. However, the shape and size of the plots used in our study resemble many of the international practices in forest inventories (e.g., Sandim et al., 2023 – 400m^2; Šmelko and Merganič, 2008 - 500m^2; Henttonen and Kangas, 2015 - 50m^2), therefore, the choice of plot geometry in our study validates the results on basal area estimates and to a high extent the time resources required. Platform 2, on the other hand, can provide the data required to estimate the tree height by exploiting the information contained in the collected point clouds, as proved by other studies (Sibona et al., 2016), which for Platform 1 would mean that additional measurements and time are required. However, when using a PLS, one needs also to consider the higher computing resources required to process large point clouds as specific to plots of higher sizes, since computer architectures such as that used in this study are not widely used in the forestry practice.

In the individual measurement phase, Platform 1 took about 11 s per tree, which was significantly less than the 51 s per tree required for scanning by Platform 2. This supports the idea that mobile apps can facilitate faster data collection in the field during the measurement phase. While acknowledging that connecting and synchronizing the data sourced by Platform 1 to a web-based service could increase the time spent per plot, it is important to also consider that overall time efficiency will still be better when considering the complete process of obtaining data from point clouds generated by Platform 2 (9 min. and 32 s. per plot). Additionally, Platform 1 offers the advantage of instant readings, which is beneficial in situations requiring quick feedback in the field.

Examining the relevance of these findings further, several authors have conducted research on the accuracy of LiDAR technology and smartphone applications for measuring tree biometrics. Borz et al. (2022b) found that the Measure App (which works with LiDAR on iPhones) could be a very useful tool for estimating DBH, which is a proxy of basal area, within a range of a few centimeters compared to manual measurements. Additionally, Gülci et al. (2023) tested the accuracy of the ForestScanner app for measuring DBH using LiDAR sensors on iPhones, achieving promising results. These studies, along with the findings of the current study, indicate that improvements in LiDAR sensors and software for mobile devices are increasing the accuracy of forest data collection tools, bringing them closer to the precision of PLS equipment for measurements such as diameter and, by extension, basal area. In terms of time efficiency, Sandim et al. (2023) found that digital tools outperform manual methods. However, due to LiDAR post-processing, careful consideration of overall workflow times is necessary. While applications may provide almost instantaneous results in the field, LiDAR data often requires significant processing for tasks such as tree segmentation, parameter extraction, and basal area estimation when using PLS. Thus, efficiency must be evaluated within the context of the overall effort required to obtain the desired results.

Considering things like the technology used, this study directly compares the results provided by a high-end LiDAR sensor with those provided by sensors built into smartphones, which usually have a shorter range and less accuracy (Guenther et al., 2024; Luetzenburg et al., 2021). But our results show that when it comes to estimating basal area based close range sensing measurements, the differences in sensing technologies are not relevant anymore besides their costs. Xu et al. (2021) mentioned that the capability of these technologies to precisely detect trees may depend on study site circumstances (forest density, occlusion, etc.). High understory density, for instance, might make it challenging for a trajectory-based PLS collector to identify trees from a far ground location and may also compromise the user's clear view of the tree at the breast height level (Singh et al., 2024). In comparison, tree level measurements may remove many of these limitations, as proved by our study which covered a wide diversity of species, age, and tree density in the plots, consistently showing the app's capability to generate fast and accurate DBH data.

In this study, data collection took place during the winter season and presented some limitations both at the time of collecting and processing the data. For instance, working with Platform 1 presented some limitations at the time of data collection, such as an accelerated battery discharge when the temperature was decreasing, and some app crashing. However, improvements are expected in the app's development, and the observed failures were not critical since the data was collected accurately for all the trees (Fig. 4c). However, Platform 2 also presented some limitations. It required maintaining a specific distance to the target for accurate detection, and a consistent scanning pace. It was often hard to keep up this steady pace, especially when the ground was uneven, snowy, had many trees, or was very steep. In addition, at the processing time, manual tree segmentation was required frequently to produce clean objects in the point cloud.

Based on our findings, several improvements can be added in the future to better understand and improve the estimates. It is important to continue with this type of experiments, by increasing the sample size and focusing on the validation and extension of existing methodologies in different forest contexts, deepening the analysis by incorporating additional variables and developing improved models. In this study, 50 plots with a radius of 9.80 m were used to source the data. However, with larger plots, the agreement rate between methods could change, particularly for plots containing trees at the extremes in DBH. Time estimates will also change on per-plot basis. Including in the experiments very small or very large trees, would improve our understanding on the capabilities of the used platforms in accurately estimating the DBH. Then, our study was conducted in the leaf off, cold season. While this period introduced challenging operating conditions for human observers due to the cold weather, it presented a mixed scenario for the used technologies. In particular, the lack of leaves in most plots, and ground vegetation condition during leaf-off conditions probably made Platform 2's scans better by making things easier to see and blocking less, which made it easier to see tree stems and branches. But events like snow or uneven, steep ground during this time of year could still make operations harder or affect scan consistency. Changing conditions of operational environment, such as warmer periods, may be reflected mainly in the time consumption estimates, which could improve particularly in the case of Platform 1 due to more comfortable operation.

Future research should focus on testing the application in various forest types and operational environments, characterized by a broader diversity of tree species and sizes, as well as varying environmental parameters. This includes figuring out how plot size affects the performance. Smaller plots could increase time performance by cutting down on the scan area, but they could also make things less accurate by increasing the edge effect and the need for very precise delineation under urban environments. Larger plots, on the other hand, usually provide data for a better characterization of the stand, even though they take longer to collect data.

It will also be very important to investigate the effects of seasonal characteristics on the performance measured as time efficiency and measurement accuracy, which we plan to study in the future. This study was carried out when the leaves were off, which is usually better for LiDAR scanning because it makes trees easier to see and cuts down the effects of occlusion. However, the thick leaves and dense ground vegetation that are present during the leaf-on season are likely to affect measurement accuracy and scanning time. This may mean that more passes, repeated measurements, or more advanced processing methods could be needed to reduce the effects of occlusion for both platforms.

Finally, it is important to think about whether the app will work in dense or unevenly spaced stands, which are common in many forests and urban environments. In these situations, the application might have trouble accurately separating individual trees, especially if they have more than one stem; however, scanning by PLS could be affected by urban (moving) elements that produce noise in the point cloud during scanning. Future tests should look at how the app deals with the above-mentioned environments to ensure its wide-scale application. However, we need to acknowledge here that the app was intended purely for forest environments.

5. Conclusion

Based on the study, the developed application demonstrated remarkable performance in terms of accuracy and time efficiency for measurements at both the tree and plot levels. Moreover, its mobility offers a practical alternative for tree-level data collection at significantly lower costs. However, improvements are still necessary, and further research is required to fully understand and characterize the app's capabilities. Despite some technical challenges, the results clearly indicated a high degree of effectiveness for the developed app. Future research should focus on testing the application in various forest types and operational environments, characterized by a broader diversity of tree species and sizes, as well as varying environmental parameters.

CRediT authorship contribution statement

Jenny Magali Morocho Toaza: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Investigation, Formal analysis, Data curation. **Gianni Picchi:** Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Carla Nati:** Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Stelian Alexandru Borz:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Funding sources

This study is part of project SINTETIC funded by the Horizon Europe research and innovation program of the European Union, under grant agreement No 101082051. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or European Commission. Neither the European Union nor the granting authority can be held responsible for them. Part of this work was supported by two grants of the Romanian Ministry of

Education and Research, CNCS – UEFISCDI, project number PN-IV-P8–8.1-PRE-HE-ORG-2023-0141, and project number PN-IV-P8–8.1-PRE-HE-ORG-2024-0186, within PNCDI IV, which helped with the acquisition of the Platform 2 and the computers used for data processing and analysis.

Declaration of competing interest

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

Acknowledgements

The authors gratefully acknowledge the support of RPLP Kronstadt, the managing entity of the forests in which the data were collected through the two platforms. The authors also acknowledge the support of the Department of Forest Engineering, Forest Management Planning, and Terrestrial Measurements for providing some of the instruments required to conduct this study. Special thanks go to Owuor Evans Ochieng, Reyes Alexandra, Elias Mirella, and Chacón Angel for their assistance with field data collection.

Appendix A. Appendix

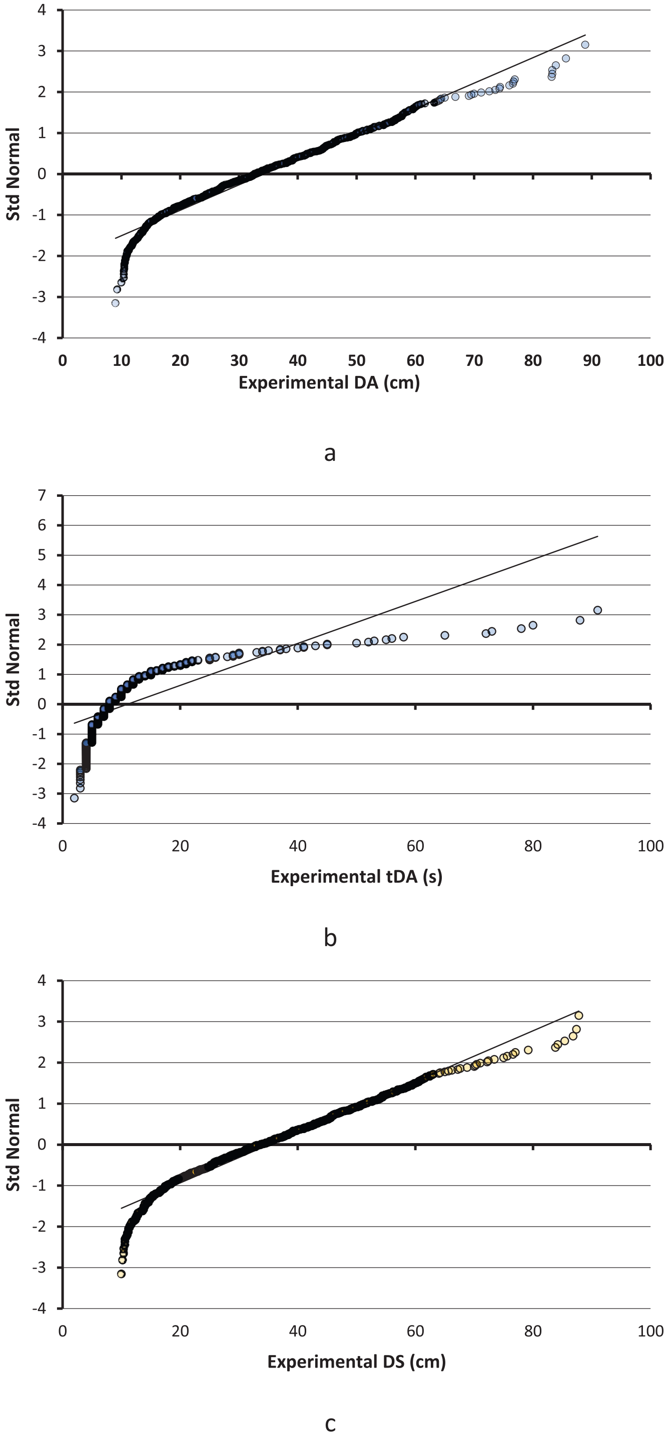


Fig. A1. Complementary statistics of tree level measurements: a – QQ plot of DA, b – QQ plot of tDA, and c – QQ plot of DS. Legend: DA – DBH data sourced by Platform 1, tDA – tree-level time consumption data for Platform 1, DS – DBH data sourced by Platform 2.

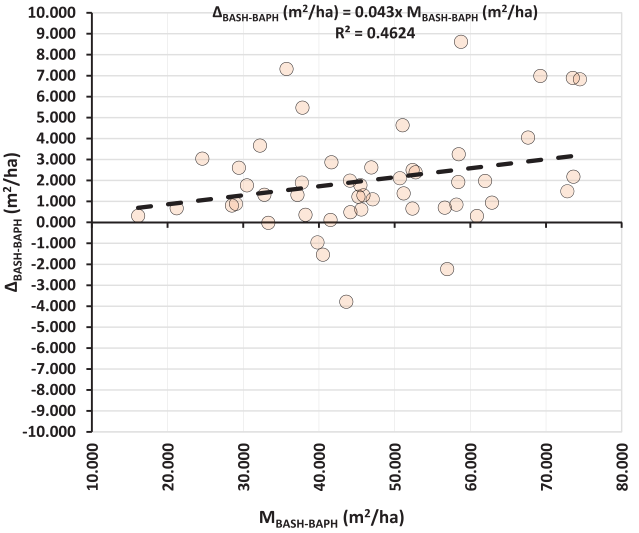


Fig. A2. Residuals plot of the compared variables: Legend: $\Delta_{BASH-BAPH}$ – signed difference between basal are estimate by Platform 2 (reference variable, BASH) and basal area estimate by Platform 1 (compared variable, BAPH), M $_{BASH-BAPH}$ – mean value between basal are estimate by Platform 2 (reference variable, BASH) and basal area estimate by Platform 1 (compared variable, BAPH).

Data availability

The data used for this study are available and archived in Zenodo (https://doi.org/10.5281/zenodo.16522159) to ensure the reproducibility of the study.

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