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ACCURACY AND TIME EFFICIENCY OF FORESTSCANNER APP WHEN MEASURING PLOT-LEVEL DBH UNDER DIVERSE FOREST ECOSYSTEMS

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Abstract: *Accurate and efficient measurement of tree diameter at breast height (DBH) is essential for forest inventory and management. While traditional methods are time-consuming, new smartphone-based LiDAR applications like ForestScanner promise rapid, cost-effective solutions. However, their performance across diverse forest ecosystems requires thorough evaluation. This study aimed to assess the accuracy and time efficiency of the ForestScanner app for plot-level DBH measurements compared to manual caliper methods under varied growing conditions in Romania. One hundred circular plots (approx. 300 m² each) were established in forests near Brașov City, encompassing diverse forest tree species, ages, topographies, and understory conditions. DBH of 987 trees was measured manually with calipers and digitally using the ForestScanner app on a LiDAR-equipped iPhone. Time consumption for plot establishment, manual DBH, and app-based DBH measurements were recorded. Accuracy was assessed using bias, mean absolute error (MAE), and root mean squared error (RMSE), with heteroskedasticity checked via Breusch-Pagan and White tests. ForestScanner showed a negligible overall bias (-0.003 cm), but MAE reached 3.66 cm when all measurements were included. Occlusion by vegetation or nearby trees significantly impacted app's accuracy; for non-obstructed trees (n = 824), bias was +0.26 cm with an MAE of 2.07 cm. Manual DBH measurement averaged 14 seconds/tree, while ForestScanner averaged 16 seconds/tree. Plot establishment time and measurement time were influenced by tree density. ForestScanner offers a user-friendly, free tool for DBH measurement and tree mapping, but its accuracy may be affected by occlusion. On the other hand, the app comes equipped with several useful features, such as documenting*

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the plots by LiDAR point clouds, real time DBH measurement and data storage, while returning comparable time efficiencies. Future work should focus on more diverse forest types to refine its practical application in forestry.

Key words: *augmented reality, caliper, field conditions, LiDAR application, manual measurement, occlusion impact, smartphone-based LiDAR.*

1. Introduction

Forests provide a wide range of provisioning, supporting, regulatory, and cultural ecosystem services [14, 28]. For inventory, planning, utilization, and monitoring, tree biometrics such as diameter at breast height (*DBH*) are essential features [26]. Traditionally, *DBH* is measured and recorded in the field using a forest caliper and a pen-and-paper approach. However, collecting such data manually can be time-consuming, costly, and physically demanding [1, 9].

The latest trends in digitalization within forestry have introduced new techniques for measuring diameter at breast height (*DBH*). These range from simple apps designed for highly mobile, affordable, and multipurpose platforms like smartphones to more advanced and costly equipment, such as terrestrial mobile LiDAR scanners [7, 31, 35]. While these platforms are highly accurate, some of them, such as professional LiDAR scanners, have important limitations, including the level of expertise required for operation [15], issues of high cost and affordability [17], reliance on computationally intensive software and algorithms for feature extraction [16], and the lack of ability to provide instant readings in the field [24]. Moreover, with smartphones, many software apps developed for data collection are intended for general environmental purposes. Although they can accurately map three-dimensional environments, the resulting data still require further processing to localize trees and produce *DBH* estimates [20, 34].

Time effectiveness is an important concept in forestry, as it reflects the resources utilized and provides data necessary for assessing business competitiveness. Metrics such as efficiency and productivity are typically employed to describe, compare, model, and plan forest operations across various levels of decision-making [1, 9]. Collecting data for inventory purposes is a standard planning operation that requires individuals with the appropriate expertise, time, and financial resources. While this is crucial for data production, there are, in fact, few studies that quantify the time needed to establish plots and collect the requisite data [21].

Development and inclusion of LiDAR sensors in the latest generations of iPhone smartphones has revolutionized the measurement capabilities of these platforms [20]. With a typical scanning range of up to 5 m, for models up to the 14th generation, and 10 m after that [4, 6], these smartphones have provided the core functionalities for short-range scanning, which is useful in many industrial applications [40]. In forestry, for instance, they have triggered the development of new apps that are suitable for tree measurement such as Arboreal Forest [25], and ForestScanner [39]. In addition, Apple's Measure app comes for free as standard on iPhone devices [5, 12], and it is designed for general 3D measurements by integrating augmented reality (AR) technology. While very accurate and useful, it lacks important features for data storing and transfer. Arboreal Forest is a subscription-based AR-based app designed to set up field measurement projects, establish plots, collect the relevant data, store and transfer it to a dedicated web-based service. Previous studies have concluded that both Apple's Measure and Arboreal Forest apps are highly accurate considering the reference data collected manually [20, 25].

The ForestScanner app [39] is a free application that features key functionalities such as tree detection, in-situ visualization of the results, data storage and sharing, and accurate tree location. The app has been developed for forest inventories and estimates the stem diameters and spatial coordinates of trees based on real-time instance segmentation and circle fitting. Tatsumi et al. [39] claim that ForestScanner enables cost-effective, labor-efficient, and time-efficient forest inventory applications, and that it is highly accessible for unskilled users. Additionally, the detection rate for trees with diameters greater than 5 cm was found to be 100%, with an approximate measurement time of 9 seconds per tree during a survey of 672 trees in a one-hectare plot.

Despite the proliferation of smartphone-based LiDAR applications for forest inventory, a critical gap exists in understanding their practical performance across diverse real-world conditions, particularly concerning measurement accuracy and time efficiency when challenged by factors like dense understory, stem occlusion, and varied forest structures. While initial studies on apps like ForestScanner show promise under controlled or specific settings, comprehensive evaluations are lacking that benchmark its capabilities against traditional methods and other digital tools across a spectrum of forest ecosystems. This limits the ability of forest managers and researchers to confidently adopt these new technologies, as the true operational trade-offs between accuracy, speed, cost, and ease-of-use in complex field environments remain largely unquantified, hindering the optimization of field data collection protocols and the broader digitalization of forestry practices.

The goal of this study was to evaluate the accuracy and time efficiency of the ForestScanner app in measuring the diameter at breast height (*DBH*) under diverse forest types and site conditions. The following objectives were set for the study: *i)* to estimate the accuracy of the *DBH* measurements obtained by ForestScanner, using manually measured *DBH* as reference data, *ii)* to compare the time consumption of ForestScanner measurements against those obtained manually, and *iii)* to determine whether there is a dependency of time consumption on the local characteristics of the plots, such as the number of measured trees.

2. Materials and Methods

2.1. Plot Description

For this study, 100 plots were established in the forests near Brasov City, Romania (Figure 1). The plots were circular and had an area of approximately 300 m² (radius of 9.8 m). Important criteria for location selection and plot establishment included diversity in: *i)* forest tree species, *ii)* age, and size, *iii)* topography, *iv)* stand density, and *v)* the presence of an understory layer. The selection of field locations was guided by specifications of the local forest management plan [18]. For instance, the plots included most of the forest tree species that occur in the area at elevations ranging from approximately 600 to 1050 m above sea level, such as European beech (*Fagus sylvatica* L.), sessile oak (*Quercus petraea* (Matt.) Liebl.), Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) H. Karst.), hornbeam (*Carpinus betulus* L.), silver fir (*Abies alba* Mill.), sycamore (*Acer pseudoplatanus* L.), wild cherry (*Prunus avium* (L.) L.), rowan (*Sorbus aucuparia* L.), grey alder (*Alnus incana* (L.) Moench), and small-leaved linden (*Tilia cordata* Mill.).

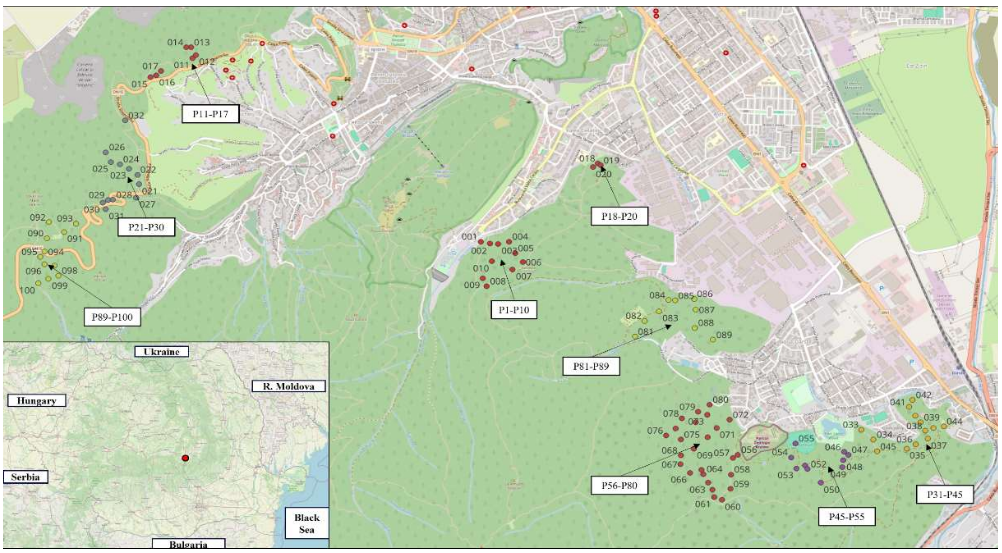

Fig. 1. *Study location at the national level (left bottom panel) and the spatial distribution of plot clusters in the study area. Note: the map was developed in QGis based on plots' center location collected in the field and open-source OSM standard maps*

While considering all these criteria, accessibility to the selected forest plots was an important factor. The forest compartments in which the plots were established were chosen based on ease of access from roads. This selection aimed to optimize the number of plots relative to the invested resources. Upon reaching a forest compartment, a given plot was set up at a randomly selected location. Plot establishment and data collection were carried out over eight days, specifically from May 5th to May 8th and from May 12th to May 15th, 2025. Two individuals established the plots and collected the data following a brief session to familiarize themselves with the instruments and methods used in the field.

2.2. Plot Establishment and Data Collection

Plot establishment consisted of tasks required to set up a plot, localize it geographically, identify the trees within it, and perform other measurements and documentation activities (Table 1). Upon reaching a tree deemed suitable as the plot center, the plot number was painted on that tree, and a painted mark was placed to indicate the level for *DBH* measurement at exactly 1.30 m above the ground (Figure 2). A rope was then used to determine the trees falling within a radius of 9.8 m, and those trees were numbered in four directions by painting (Table 1, Figure 2). Once these tasks were completed, four pictures were taken from the cardinal points, approximately 5 m from the center of the plot. The resulting images were labeled according to the plot number and the cardinal direction, serving to document the features of the plots under study.

Description of plot establishment and DBH measurement tasks Table 1

Task	Abbreviation	Description
Plot establishment	*E*	Setting up the plot. Includes the time spent from arriving at the location for a given plot, marking the plot center on a tree, taking the coordinates of the center, documenting the plot by images taken on the fourth cardinal points from nearby the plot's center, establishing which trees belong to the plot using the rope, measuring and marking the point on each tree at which *DBH* will be measured, and numbering by painting each tree from the plot. Marking the *DBH* reference point and tree numbering was done tree-by-tree for each tree in the plot. Numbers were placed on the fourth cardinal points for each tree.
Manual measurement of *DBH*	*M*	Measuring the *DBH* at the reference level using a caliper. Measurements were taken to the nearest millimeter. Includes the time spent by a person to move by free choice at each tree, taking the measurement and communicating/noting down the result.
App-based measurement of *DBH*	*A*	Measuring the *DBH* at the reference level using the ForestScanner app. Measurements were taken to the nearest millimeter. Includes the time spent by a person to set up the app and save the measurements, and to move by its choice at each tree to take the measurement.

Manual *DBH* measurement (Table 1, Figure 2) was conducted according to national guidelines [2, 3], which describe the height at which *DBH* should be measured, the procedures for measuring trees located on sloped ground, and the effective techniques for using the caliper. Following this, measurements using the ForestScanner app were taken for each tree (Table 1, Figure 2). Both manual and digital measurements were taken by referring to the same mark painted on each tree; therefore, they included measurements taken from the same side and at the same height.

The ForestScanner app uses the LiDAR sensor and capabilities of compatible iPhone or iPad devices to measure and map trees, as detailed by Tatsumi et al. [39]. The measurement process with the app (Figure 2) typically involves the operator aiming the device's camera towards the target tree stem at breast height. The app employs real-time instance segmentation, a deep learning technique, to automatically detect tree trunks within the LiDAR point cloud data captured by the device [39]. Once a tree is detected, ForestScanner performs a circle-fitting algorithm on the cross-sectional point cloud of the stem at the targeted height to estimate its diameter (*DBH*) [39]. The app provides an in-situ visualization of the detected trees and their measured *DBH* directly on the device's screen, allowing the operator to verify the detection and measurement. Furthermore, the application records the spatial coordinates (geolocation) of each measured tree, facilitating the creation of stem maps [39]. Data, including *DBH*, tree location, and associated plot information, can be saved within the app and subsequently exported for further analysis. The operator typically moves from tree to tree within the plot, repeating this process of aiming, allowing the app to detect and measure, and then saving the data for each tree identified within the plot boundaries.

Fig. 2. *The main steps used in plot establishment and DBH measurement (example of plot 23). From left to right, placing a painted mark at 1.3 m above the ground, measuring manually the diameter of a tree, setting the app for measurement, documenting the plot in the app, and taking the measurement with the app*

For each plot, a time study was conducted based on the tasks described in Table 1. One person took the measurements while another recorded the results. A digital watch was used for continuous timing [1, 9]. The field researchers were instructed to work as usual, but without breaks during each of the carried-out task. For all activities, the collected data was recorded in a field book, including the plot number, tree ID, species, *DBH* measured by the caliper (hereafter referred to as *DM*, in mm), *DBH* measured by ForestScanner (hereafter referred to as *DA*, in mm), degree of occlusion, as well as the starting and ending times reported in the hh:mm:ss format for the activities described in Table 1.

2.3. Data Processing

All the plot-level data (measurements, comments, starting and ending times, images, and data collected using the ForestScanner app) were moved to a data repository that included documentation for the measurements taken at the plot level. A central data repository was created for this purpose via Google Drive, and the plot-level data was then stored based on intended use. Time measurements were computed in seconds as the difference between the ending and starting times of the measurements, and *DBH* data was converted to centimeters. Conventionally, the plot level time consumption for establishment, manual and digital measurement of *DBH* were named *TE*, *TM* and *TA*, respectively.

Each plot was then documented in terms of the number of trees, average *DBH* (taken manually), species composition, and tree density. The final data repository was that resulting from after two sessions of data curation, which included checking for correctness in data and comparison with the data included in the field book.

2.4. Data Analysis

Data analysis involved several workflows. The plots were described in terms of the number of trees (hereafter called *NT*), tree density (hereafter called *TD*, trees/hectare), and average *DBH* (cm), using indicators such as minimum, maximum, mean, median, and standard deviation values. The accuracy of the measurements was documented by calculating the bias [19], mean absolute error [43], and root mean squared error [43]. Evidence of proportional bias was assessed using the Breusch-Pagan and White [42] tests. These tests were particularly useful for identifying heteroskedasticity in the data and its type, which can occur due to proportional change in differences between methods' estimates as the magnitude of the observed variables changes. The same metrics were also used as proxies for agreement [10, 11, 19], along with scatterplots to illustrate the dependence in the data.

However, field observations revealed several instances where measurements taken with the ForestScanner app differed significantly from manual measurements. These discrepancies were attributed to the degree of occlusion caused by nearby trees and the presence of understory vegetation. Therefore, these instances were documented in the field to indicate the presence of occlusion, and the corresponding codes were used to sort the data and to conduct accuracy assessments, comparing data with and without those instances of occlusion.

The time consumption analysis aimed to statistically describe the data, assess whether there were significant differences between the two methods in terms of time consumption, and detect any dependency relationships between local parameters – such as the number of trees per plot or tree density per plot – and the magnitude of time consumption. The commonly used statistical procedures were employed for the time efficiency analysis, as detailed in [1]. These included checking for normality in the time data distribution by robust tests accompanied by histograms with a normal curve overlaid, developing the main descriptive statistics as numbers accompanied by boxplots, comparing time consumption at the plot level using tests deemed appropriate for the data, and modeling the time consumption dependency on local operational factors using simple linear regression analysis.

Where relevant, a confidence level of 95% was considered. Part of data analysis was carried out using the standard functionalities of Microsoft Excel, whereas for simplicity, Real Statistics add in [44] was used for Breusch-Pagan, White and statistical comparison tests, as well as for developing some of the graphics included in the study.

3. Results and Discussion
3.1. Description of Plots

Plot level species composition varied widely, starting with pure and ending with mixed stands, in various proportions between the broadleaved and coniferous trees within each plot. Plots were statistically characterized by the number of trees, tree density and average *DBH*, as shown in Table 2. There were between 4 and 22 trees per plot, averaging about 10 trees per plot, accounting for minimum, maximum and average tree densities of about 133, 733 and 329 trees per hectare. Based on averaged plot-level manual measurements, the *DBH* was characterized by a minimum, maximum and average of 15.5, 67.8, and 35.1 cm.

Descriptive statistics of experimental plots taken into study Table 2

Attribute	Number of plots	Minimum value	Maximum value	Mean value	Median value	Standard deviation
Number of trees (*NT*)	100	4	22	9.87	9.00	4.15
Tree density (*TD,* [trees/ha])	100	133	733	329	300	138.18
DBH [cm]	100	15.5	67.8	35.1	34.2	9.94

By considering all the trees measured in the plots (*N* = 987), there was a dominance of beech trees (57.85%), followed by hornbeam (13.88%), Norway spruce (10.33%), sessile oak (6.38%), and other species (11.56%). Moreover, by considering plot composition, half of the plots included only broadleaved species, one plot included only coniferous species, and the rest (49%) included both, broadleaved, and coniferous species.

3.2. Accuracy and Agreement

The main results concerning accuracy and data agreement are reported in Table 3, along with the results of the Breusch-Pagan and White tests. The dataset, which included both regular and obstructed measurements, comprised 987 trees, resulting in a very small bias (-0.003 cm), indicating a negligible overestimation by the ForestScanner app. However, the magnitude of the differences was as high as 3.66 cm (MAE = 3.656). For this dataset, the results of the heteroskedasticity tests indicated that the data were homoscedastic.

The inclusion of obstructed measurements in the analyzed dataset clearly influenced the accuracy metrics. Figure 3 illustrates the trends and distributions in the difference data before and after the removal of measurements affected by obstruction. The dataset consisting of unobstructed measurements comprised 824 trees (Table 3). In this case, the digital measurements underestimated the actual values by an average of 0.26 cm (bias = 0.261), while the magnitude of the mean absolute error (MAE) was lower, approximately 2 cm. However, heteroskedasticity was detected in this dataset (Table 3).

Agreement in data and accuracy of digital measurements Table 3

Dataset	Number of observations	BIAS	MAE	RMSE	Breusch-Pagan	White
All data	987	-0.003	3.656	6.344	0.771	0.327
Non-obstructed trees	824	0.261	2.066	2.688	<0.001	<0.001

The inclusion of obstructed measurements in the analyzed dataset clearly influenced the accuracy metrics. Figure 3 illustrates the trends and distributions in the difference data before and after the removal of measurements affected by obstruction. The dataset consisting of unobstructed measurements comprised 824 trees (Table 3). In this case, the digital measurements underestimated the actual values by an average of 0.26 cm (bias = 0.261), while the magnitude of the mean absolute error (MAE) was lower, approximately 2 cm. However, heteroskedasticity was detected in this dataset (Table 3).

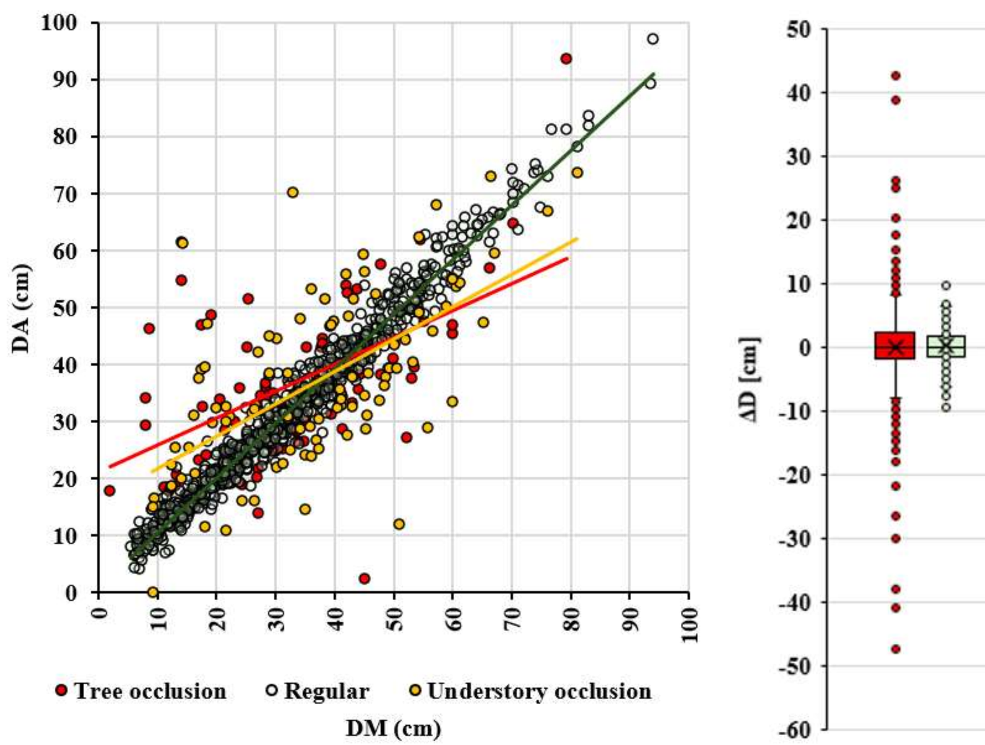

Fig. 3. *Agreement in data and distribution of differences. From left to right are the trends in data measured without obstruction (green), and with tree (red) and understory (orange) obstruction, and the distribution in differences before (red) and after (green) removing from analysis the measurements coded as obstructed*

3.3. Time Efficiency

On average, plot establishment took 175 seconds (about 3 minutes), with a range from 1 minute to approximately 10 minutes. Manual *DBH* measurements averaged 136 seconds (about 2.3 minutes), while digital measurements averaged 163 seconds (about 2.7 minutes). The data characterizing *TM* and *TA* failed the normality assumption according to the Shapiro-Wilk tests. Figure 4 shows the data distribution of the two variables in the form of histograms plotted against a normal distribution curve, pointing out the deviance from normality in data, as well as similar distributions of the variables under analysis. Accordingly, there were statistically significant differences between the two according to Mann-Whitney non-parametric test ($\alpha = 0.05$, $p_{two\text{-}tailed} = 0.03$).

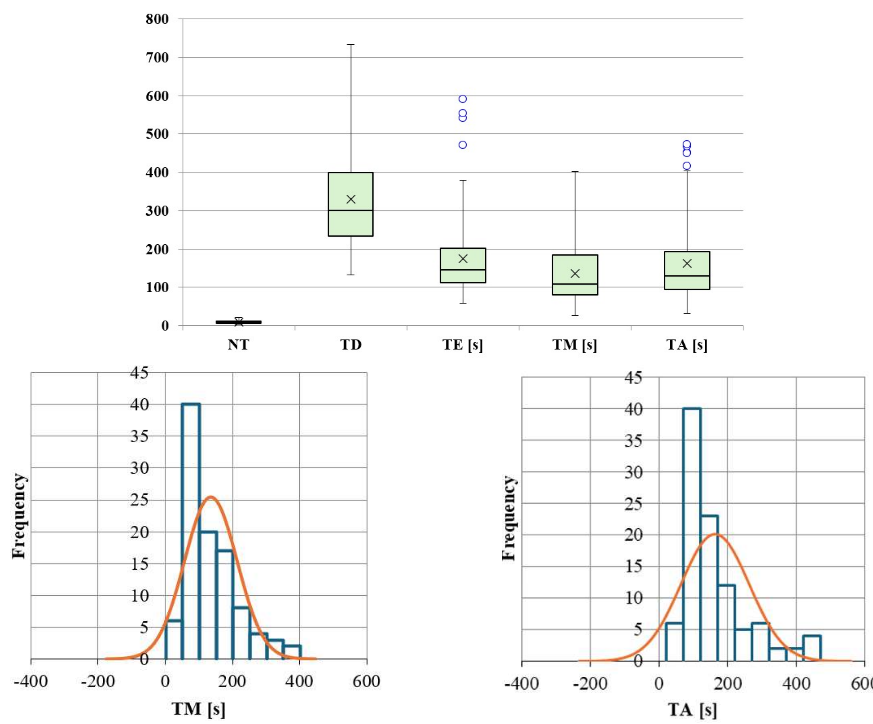

Fig. 4. *Descriptive statistics of local operational conditions and time consumption. At the top the main descriptive statistics are shown in the form of boxplots. At the bottom, the distribution of data against a normal overlaid curve is shown. Legend: NT – number of trees per plot, TD – tree density [trees/hectare], TE – time consumption for plot establishment, TM – time consumption for manual DBH measurement, TA – time consumption for app measurement*

Plot establishment time (*TE*, Figure 5) depended ($\alpha = 0.05$, $p < 0.001$) on plot-level tree density, and generally the model describing this dependence was statistically significant ($\alpha = 0.05$, $p < 0.001$). However, the tree density alone explained the variation in plot establishment time only to a limited extent ($R^2 = 0.29$).

Models developed using simple linear regression to characterize the time consumption of manual (*TM*, s) and digital (*TA*, s) measurements as a function of the number of measured trees per plot were statistically significant ($\alpha = 0.05$, $p < 0.001$). Figure 6 illustrates the trends in time consumption for the two methods based on the number of measured trees. According to the coefficients of determination, the manual measurement time was explained by the number of measured trees to an extent of 56.2%, while the digital measurement time was explained to an extent of 40.4%.

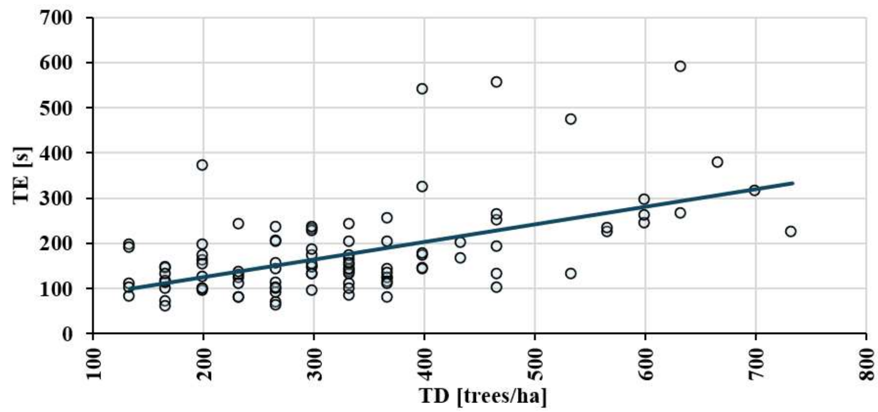

Fig. 5. *Dependence between plot establishment time (TE, s) and tree density. Legend: TE – plot level establishment time, TD – tree density [trees/ha]*

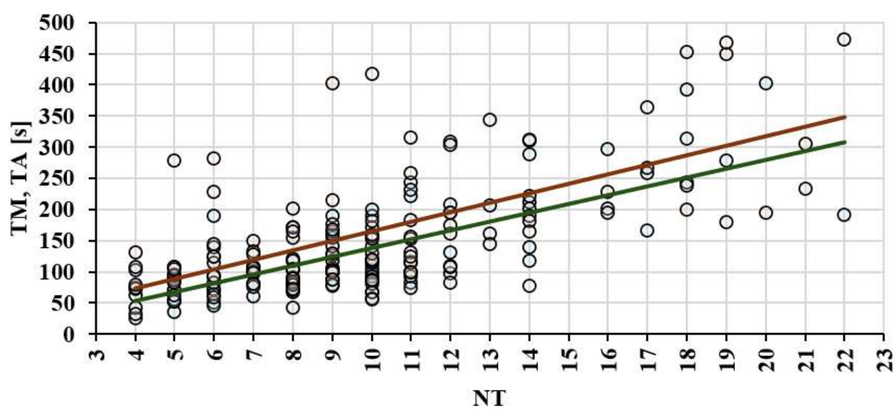

Fig. 6. *Dependence between manual measurement (TM, s) and digital measurement (TA, s) time on number of measured trees (NT). Note: line in green indicates the trend in manual measurement time as a function of number of measured trees, whereas the line in brown indicates the trend in digital measurement time as a function of number of measured trees*

To summarize, plot establishment took an average of about 18 seconds per tree, while manual measurement took approximately 14 seconds per tree. Digital measurement, on the other hand, took about 16 seconds per tree. All these times were influenced by variations in local operational conditions, such as the number of trees and tree density per plot. Additionally, the time consumption results were found to be statistically different, although the magnitude of the per-tree differences was low.

4. Discussion

This study aimed to evaluate the accuracy and time efficiency of the ForestScanner app for *DBH* measurements under diverse site conditions, comparing its performance against manual methods and considering local plot characteristics. The objectives were largely fulfilled by quantifying *DBH* accuracy using bias, MAE, and RMSE [19, 43], comparing time consumption for both ForestScanner and manual measurements, and examining the influence of tree number on measurement time. The results indicated that while ForestScanner can provide accurate *DBH* estimates, its accuracy is influenced by obstructions, and its time efficiency in this study did not surpass manual caliper measurements under the varied field conditions encountered.

The accuracy of ForestScanner, particularly the influence of occlusion, aligns with challenges noted for other mobile LiDAR and photogrammetry-based applications in forestry [20, 34]. While Tatsumi et al. [39] reported high accuracy for ForestScanner, their study involved a specific context, and our findings highlight that dense understory or closely packed trees can lead to discrepancies, a common issue in remote sensing and close-range sensing in complex forest environments [31, 33]. Other studies on smartphone-based measurement apps, such as those evaluating Apple's Measure app or Arboreal Forest, have also reported high accuracy [12, 25], but often under less occluded conditions or with different underlying technologies which may handle point cloud processing differently.

Occlusion significantly impacted ForestScanner's accuracy in this study. The app's reliance on circle-fitting algorithms for *DBH* estimation [39] can be influenced when parts of the stem are obscured, leading to incomplete point clouds and consequently, less accurate diameter estimations [13, 36]. Manual measurements, while also subject to operator-induced variability [8, 23], can often better adapt to irregular stem shapes or minor obstructions by allowing the operator to physically position the caliper optimally. This operator subjectivity in manual measurement is a known factor [26], but in cases of partial visibility, human judgment might still outperform automated algorithms that require a sufficiently complete representation of the stem's cross-section.

Regarding general functionality, ForestScanner's instant visualization of results, data storage and tree locations [39] are significant advantages over methods requiring offline point cloud processing, a common feature in more traditional terrestrial laser scanning (*TLS*) or some mobile mapping systems [30, 31]. This immediacy is highly valuable for in-field verification. The free availability of ForestScanner [39] makes it an attractive option for large-scale or low-budget inventories, contrasting with the often-high costs associated with professional LiDAR scanners and their software [17, 22]. The data stored by the app, including tree locations and *DBH*, is crucial for inventory purposes [39], and its exportability supports integration into broader forest management information systems.

In terms of tree feature coverage, ForestScanner primarily focuses on *DBH* and tree location [39]. It does not inherently measure tree height, a capability found in some other LiDAR platforms or specialized dendrometers [27, 29, 38]. While advanced LiDAR systems can provide detailed 3D point clouds for comprehensive structural analysis [31, 37], smartphone LiDAR, including ForestScanner, offers a more streamlined approach for specific parameters like *DBH*, trading some comprehensiveness for ease of use and speed in specific tasks.

The expectation that ForestScanner would offer higher time efficiency than manual methods was not strongly supported by our findings under these diverse conditions. Still, it provided comparable results in terms of time consumption, in addition to other key features for forest inventories. Our average of approximately 16 seconds per tree with ForestScanner was higher than the 9 seconds per tree reported by Tatsumi et al. [39] in their 1-hectare plot study. Several factors are likely to contribute to this difference. Firstly, Tatsumi et al. [39] used a diameter tape for their manual reference measurements, which is generally more time-consuming, especially for larger trees, than the caliper measurements used in our study [26]. This methodological difference alone could explain why our manual measurements (approx. 14 seconds/tree) were slightly faster than our ForestScanner measurements, and appeared more competitive than if compared against diameter tape. Our platform running ForestScanner had similar scanning range characteristics as that used by Tatsumi et al. [39], which was of 5 m, whereas newer versions allow for a practical scanning range potentially closer to 10 m capabilities [4, 6]. While a larger radius might seem advantageous, the 5 m radius in both studies might have necessitated operators to position themselves closer to each tree, potentially increasing walking time per tree but perhaps also allowing for more optimized scan angles to avoid minor occlusions within a smaller, more controlled scanning zone. However, approaching the trees in our study was not set to follow the exact same path as that of taking manually the diameters, whereas there was a diversity in slope and understory conditions. The experimental plot arrangement and scanning path might also have differed in the study of Tatsumi et al. [39], potentially allowing for more optimized, direct lines of sight. In contrast, our protocol required measurements from the same side for both manual and digital methods to ensure comparability, which may not have always represented the absolute shortest or most efficient scanning path for the app if obstruction was present. These combined factors could explain some of the longer per-tree times observed in this study. Models predicting time consumption in tree measurement are relatively few, but our regression models demonstrated a clear dependency of measurement time on the number of trees, a common factor in inventory work [32].

Several strong points of this study enhance the robustness of its findings. The investigation across diverse forest ecosystems (species, age, size, density, slope, topography) with a large sample size (close to 1000 trees across 100 plots) provides a comprehensive evaluation. The robust experimental design, with controlled conditions for comparing diameters (same mark, same side), and the use of multiple robust metrics (bias, MAE, RMSE, Breusch-Pagan, White tests) for accuracy assessment [10, 11, 19, 42, 43] offered the conditions for a detailed comparison.

However, certain limitations should be acknowledged. The comparison of time consumption using non-parametric tests, while appropriate given the data distribution, might be less robust than parametric tests if normality assumptions were met, as they compare medians which can sometimes obscure the full picture of variability. Not all assumptions for the regression analyses were exhaustively tested, which could influence the interpretation of the derived models. Furthermore, the field data collectors were at their first extensive experience with the ForestScanner app. It is plausible that their operational efficiency with the app could improve over time with increased familiarity, potentially reducing the time taken for digital measurements and altering the time-efficiency comparison. Finally, there was no explicit control for the inter-operator variability or learning curve between the two students who collected the data, which is a common challenge in field studies [1, 8, 41].

5. Conclusions

This study provides a comprehensive evaluation of the ForestScanner app's accuracy and time efficiency for measuring plot-level *DBH* across diverse forest ecosystems in Romania. While ForestScanner offers a user-friendly, free, and modern approach to forest inventory with useful features like instant data visualization and geolocation, its *DBH* measurement accuracy was found to be sensitive to stem occlusion by nearby vegetation or trees, leading to larger errors compared to unobstructed measurements. Under the varied and sometimes challenging field conditions encountered, which included diverse topography and understory presence, the time taken to measure *DBH* using ForestScanner did not demonstrate a significant advantage over traditional manual caliper measurements; in fact, manual measurements were slightly faster on average per tree. The number of trees per plot and tree density significantly influenced the time for plot establishment and measurement. Although ForestScanner provides a valuable digital tool, particularly for rapid tree mapping and data recording, practitioners should be aware of potential accuracy limitations in occluded environments. Further research should explore accuracy and time effectiveness across an even broader range of forest types and conditions to fully delineate its optimal use cases in modern forestry.

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