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Accuracy, agreement and time efficiency of portable, LiDAR-based tools in tree inventories

Precizia și eficiența instrumentelor portabile bazate pe tehnologia LiDAR în inventarierea arborilor

SUMMARY

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INTRODUCTION

Forest inventory plays an essential role in sustainable forest management by providing information on tree characteristics—such as diameter, height, volume, and biomass—which are fundamental to describing forest structure and supporting management decisions (Temesgen et al., 2007; Avery & Burkhart, 2015; FAO, 2020). The accuracy of these measurements is critical, as errors can propagate into biomass estimates and reduce the reliability of forest assessments (Chave et al., 2014; Adhikari et al., 2024). Conventional field methods remain the most widely used approach for forest inventory; however, they are time-consuming, and their accuracy can vary depending on the operator, the instruments used, and the inventory design (Moran & Williams, 2002; Becker & Nichols, 2011; Larjavaara & Muller-Landau, 2013; Henttonen & Kangas, 2015; Stereńczak et al., 2019; Di Cosmo, 2023).

In recent years, LiDAR technologies have attracted increasing attention in the field of forest inventory due to their ability to capture three-dimensional information on vegetation structure (Lefsky et al., 2002; Dassot et al., 2011). Terrestrial laser scanning has demonstrated high accuracy in estimating dendrometric variables, such as diameter at breast height (DBH), tree height, and forest structure, under various conditions (Liang et al., 2016; Cabo et al., 2018; Liang et al., 2018a; Liu et al., 2018). More recently, portable and mobile LiDAR systems, including handheld scanners and smartphone applications, have emerged as practical alternatives that can simplify field procedures and reduce the time required for data acquisition (Liang et al., 2018b; Balenović et al., 2021; Tatsumi et al., 2022; Sandim et al., 2023).

Although previous studies suggest that these technologies can provide reliable estimates of forest characteristics while improving the efficiency of fieldwork (Forkuo et al., 2025), their performance may still vary depending on forest structure, device characteristics, and the processing methods used (Gülci et al., 2023; Guenther et al., 2024). Therefore, further evaluations and comparisons with conventional methods and professional systems are needed (Gollob et al., 2021; Howie & De Stefano, 2024). In addition to accuracy, assessing the agreement between methods is important to determine whether they can be used interchangeably in operational forest inventories (Bland & Altman, 1999; Borz et al., 2024; Morochó et al., 2025).

The aim of this study was to evaluate the potential of portable and mobile LiDAR technologies, including smartphone applications, for use in forest inventory. The thesis combines a review of the current state of the art with experimental studies focused on the accuracy, temporal efficiency, and characteristics of point clouds generated by different systems under various forest and seasonal conditions.

The specific objectives of the thesis were:

- * O1. To review low-cost and mobile LiDAR technologies for forest inventory, with an emphasis on their accuracy, efficiency, and potential for multi-temporal forest monitoring;
- * O2. To evaluate the accuracy of the TreeScanner application for estimating individual tree biometric parameters, based on data collected from different forest ecosystems;
- * O3. To evaluate the accuracy and time efficiency of the TreeScanner application for measuring and mapping individual trees, compared to the professional FJD Trion Model P1 scanner, based on data collected during the winter, with special emphasis on basal area estimation and field data acquisition time;
- * O4. To analyze the effect of seasonal variation on basal area estimation by comparing TreeScanner and FJD Trion Model P1 across the four seasons, separately evaluating the accuracy and acquisition time of each system in each season;
- * O5. To compare the point clouds generated by the FJD Trion Model P1 scanner in winter (reference) and spring (comparison) using the C2C and M3C2 algorithms, with the aim of identifying structural differences in the forest while ensuring temporal alignment between the datasets.

CHAPTER 1. LOW-COST AND MOBILE LIDAR TECHNOLOGIES FOR FOREST INVENTORY: A REVIEW ON ACCURACY, EFFICIENCY, AND MULTI-TEMPORAL MONITORING POTENTIAL

1.1. MATERIALS AND METHODS

The systematic literature review followed the PRISMA 2020 framework to synthesize existing knowledge on the technical and operational performance of low-cost mobile LiDAR technologies for forest inventory applications (Page et al., 2021). Eligibility criteria were defined using the PECO framework to ensure relevance and comparability across studies (Haddaway et al., 2018). The review included studies conducted in forest ecosystems using mobile or handheld LiDAR systems, such as personal laser scanning (PLS), backpack mobile laser scanning (BPLS), and smartphone-based LiDAR devices, while excluding airborne and satellite LiDAR studies unless TLS was used as a reference benchmark.

The literature search was performed between January and March 2026 using four major databases: Scopus, Web of Science, IEEE Xplore, and Google Scholar. Search terms combined keywords related to LiDAR technologies, forest inventory applications, and performance metrics. After duplicate removal, 680 studies remained for screening. Following title and abstract evaluation, 380 studies were excluded because they focused on airborne LiDAR, satellite remote sensing, or non-forest applications. Full-text assessment was conducted for 150 articles, and finally 56 studies met all inclusion criteria and were incorporated into the qualitative and quantitative synthesis (Page et al., 2021).



Figure 1.1. PRISMA flow diagram of the selection process

For each selected study, information was systematically extracted into a structured database, including LiDAR technology type, forest ecosystem, tree species composition, plot size, number of trees measured, DBH and height accuracy metrics, tree detection rates, acquisition efficiency, and environmental conditions. This dataset enabled comparisons among different LiDAR platforms and forest inventory contexts.

Methodological quality was assessed using an adapted version of the Mixed Methods Appraisal Tool (MMAT) (Holvoet et al., 2025). The evaluation considered methodological rigor, sample representativeness, and reliability of reference measurements. Studies were scored on a three-point scale, allowing assessment of the overall reliability of the evidence base included in the review.

The synthesis combined narrative and quantitative approaches. Results were grouped according to technological platform to facilitate comparisons of accuracy and operational efficiency. In addition, figures and comparative tables were developed to illustrate publication trends, which increased markedly after

2020, and to summarize forest inventory accuracy metrics and acceptable precision thresholds across different inventory applications.

1.2 RESULTS

1.2.1 Characteristics of the analyzed literature

This systematic review of scientific literature was established by conducting a comprehensive search across literature published between 2015 and 2026 which has been identified as a period with the highest degree of innovation within forest geomatics (Magnuson et al., 2024; Kokeza et al., 2026). The investigations followed the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) and were designed to assure the transparent and reproducible methodology used to identify the selection of studies included so that dominant trends of mobile and/or low-cost LiDAR sensor use could be identified, transparent and reproducible study selection process.

The geographical distribution of the reviewed studies shows a clear concentration in countries with highly developed forest technology sectors. In particular, Finland, China, South Korea, Germany, and the United States appear repeatedly as leading centers for innovation in personal laser scanning (PLS) systems and mobile-device-based applications. The distribution reflects the prominent role of these nations in developing and applying personal laser scanning (PLS) systems and mobile-device-based LiDAR applications. This pattern suggests that technology and existing programs for monitoring forests can be important factors for the utilization of these systems.

A noticeable temporal shift can also be identified. Earlier research between 2015 and 2019 mainly focused on testing and validating cumbersome PLS prototypes as well as the early development of SLAM algorithms (Tang et al., 2015; Bauwens et al., 2016; Liang et al., 2018). From 2020 onwards, however, the focus of the literature moved strongly toward the wider accessibility of these technologies, marking a clear shift in research trends. This transition was largely driven by the integration of LiDAR sensors into widely available consumer devices such as the iPad Pro and iPhone Pro models (Gollob et al., 2021; Výboštok et al., 2025; Kokeza et al., 2026). A marked increase in studies was observed in 2021, 2022, and 2023, particularly those involving Personal Laser Scanning (PLS), iOS-based LiDAR platforms and Close Range Photogrammetry (CRP). This demonstrates the rapid growth of mobile device applications that use low-cost LiDAR.

1.2.2 Evolution and mobile scanning technologies

In the forestry sector, LiDAR technology has evolved from high precision, stationary lasers that utilize a stationary/planar system and have limited operational flexibility, to mobile platforms that provide increased operational efficiency, with a certain trade-off in measurement accuracy (Balenić et al., 2020). PLS systems have been developed as a solution to limitations associated with terrestrial laser scanning (TLS): although TLS provides millimeter level accuracy it introduces large amounts of occlusion and requires a time-consuming setup process on rough terrain (Bauwens et al., 2016; Balenić et al., 2020; Li et al., 2025).

1.2.2.1 Timeline of technological transformation

Due to the reduced size of sensors and the enhanced capabilities of SLAM algorithms, which are necessary for operation under the dense canopy of a forest, where GNSS signal reception is not reliable, the forest digitization process has evolved over a period of time with technological advancements, which can be depicted by specific periods. In the pre-2013 period, Terrestrial Laser Scanning (TLS) was dominant, being characterized by millimeter accuracy and rather low operational efficiency due to the necessity to set up several systems (Maas et al., 2008; Brolly & Király, 2009). In 2013 ZEB1 (GeoSLAM) was introduced, which was the first portable personal laser scanning (PLS) system with a swinging head to scan in a dynamic way (Ryding et al., 2015; Bauwens et al., 2016). Then, in the 2015–2017 period, progress focused on the development of the ZEB-REVO and ZEB-REVO-RT systems, incorporating real-time visualization of scan data and improving the robustness of point clouds (Chen et al., 2019). In 2019 the ZEB Horizon, which extended the scanning range up to 100 m and made it possible to capture detailed information from the

upper canopy, was introduced (Gollob et al., 2020a). The period of 2020–2021 stands for a democratization milestone, since Apple Inc. equips their iPad Pro and iPhone 12 Pro with time-of-flight (ToF) LiDAR sensors to facilitate the collection of massive 3D data using consumer-level devices (Gollob et al., 2021; Luetzenburg et al., 2021). The following period, spanning approximately from 2022–2023, was characterized by the expansion and refinement of applications such as ForestScanner and Arboreal Forest, which integrate augmented reality to enable in-field estimation of forest variables (Tatsumi et al., 2022; Gülci et al., 2023; Borz et al., 2024; Howie & De Stefano, 2024). Finally, more recent developments, between 2024 and 2026, include the emergence of cost-efficient forest scanning solutions based on automotive LiDAR sensors (e.g., Livox MID-360) as well as open-source systems such as LCA-TLS. These approaches aim to achieve levels of accuracy comparable to professional systems while significantly reducing costs (Balestra et al., 2024a; Výboštok et al., 2025).

1.2.2.2 Technical comparison: professional PLS vs. smartphone LiDAR

The main distinction lies in the operational range and point density. The professional PLS systems (ZEB Horizon, Stonex, Mandeye) can collect point clouds of high density over ranges exceeding 100 m, depending on the device and environment (Li et al., 2022; Vandendaele et al., 2022). In contrast, smartphone-based LiDAR sensors (including latest iPhone and iPad models), only have a usable range of up to 10 m, and are often used to complement or serve as reference calibrators for other PLS systems (Vandendaele et al. 2022; Guenther et al. 2024). Despite these differences in operational range and point density, both professional PLS instruments and smartphones with LiDAR sensors can utilize advanced point cloud comparison techniques (such as M3C2) to identify structural changes to forests over time, providing higher accuracy than traditional methods (Lague et al., 2013; Winiwarter et al., 2021)

1.2.3 Dendrometric accuracy and temporal efficiency

1.2.3.1 Performance in the measurement of structural variables

The validation of mobile systems against conventional methods confirms that DBH is the most reliably measured variable, while TH exhibits systematic biases due to canopy occlusion. Professional MLS generally show higher accuracy with RMSE below 1.5 cm (Bauwens et al., 2016; Liang et al., 2018). When measuring tree DBH using traditional methods, the measurement is taken at one location with a caliper (White et al., 2015); however, with LiDAR technology, the diameter is extracted using algorithms that fit a circular or geometric shape around the trunk circumference, often averaging multiple points along it. The use of low-cost devices and mobile applications has resulted in accuracies of 1.5 cm to 4.0 cm. (Tatsumi et al., 2022; Výboštok et al., 2025). In DBH measurement, some applications such as ForestScanner and Arboreal Forest may show slight underestimation due to irregularities in the tree bark that affect LiDAR point sampling, and limited coverage around the full circumference of the trunk (Howie & De Stefano, 2024; Singh et al., 2024). When measuring height, ground-based systems, particularly professional and low-cost mobile laser scanning devices (rather than smartphone applications), tend to underestimate total tree height, with biases exceeding 2 meters for taller trees due to limitations in accurately capturing the true apex of the canopy (Balestra et al., 2024a; Mîzgaciu et al., 2025).

1.2.3.2 Operational efficiency analysis

The transition from traditional manual measurements and static TLS to mobile LiDAR systems represents a substantial improvement in productivity, consistently reducing data acquisition times (Li et al. 2023; Li et al. 2025). The use of tablets and smartphones enables faster LiDAR data acquisition, reducing field time by approximately 2 to 4 times compared to traditional methods, depending on the study (Proudman et al., 2022; Morocho et al., 2025). The effort required for measurement using mobile apps can be reduced to as little as 25.7% of the person-hours needed for the manual method in specific cases (Tatsumi et al., 2022), while several studies report substantial reductions in labor requirements (Morocho et al., 2025; Kokeza et al., 2026). Recent studies using the Tree Scanner app have shown that using smartphones is several times faster than in some reported cases using high-cost professional PLS systems because of the

absence of complex post-processing in the lab (Morocho et al., 2025). This agility in operation allows for a higher sampling density to ensure the statistical representativeness of forest inventories at the stand level.

1.2.3.3 Seasonal effects on data quality and forest detection

Seasonal environmental variability is recognized as one of the most important factors in the operational implementation of LiDAR technologies, particularly in deciduous and mixed forest environments where foliage affects the physics of the laser return. Foliar occlusion during the leaf-on season acts as a physical barrier that limits the penetration of pulses toward deeper canopy layers and the understory.

While for leaf-off conditions, authors such as Ko et al. (2024) report tree detection rates of up to 100%, this figure drops dramatically during the growing season. Research done in dense stands (Ko et al., 2024) indicates that the rate of detection was seen to reduce to 80 to 85% under leaf-on conditions, which implies that 18% of tree trunks are not detected due to the occlusion effects. However, other authors like Wu et al. (2025a) argue that in leaf-off conditions, laser penetration is more effective to an extent that even suppressed trees are detected.

Seasonality also causes significant variations in the root mean square error (RMSE) of structural variables. According to Ko et al. (2024), during the leaf-on season, understory growth obstructs the base of the trunks at 1.3 m, introducing noise that reduces the availability of valid reference points and limits the reliability of automatic diameter fitting, despite advances in filtering algorithms.

DBH accuracy is higher in winter (R^2 up to 0.97), whereas in summer the RMSE increases due to interference from surrounding vegetation (Ko et al., 2024; Singh et al., 2024; Wu et al., 2025a). Tree height is the most sensitive variable. Wu et al. (2025a) observed that in summer, foliage prevents the beam from reaching the actual tree apex, resulting in errors that can be up to four times greater than in winter. In experiments by Ko et al. (2024), RMSEs for height of 1.27 m were obtained under leaf-off conditions, compared to 5.07 m under leaf-on conditions.

The density of usable points on the stem depends on how many pulses strike the trunk without being intercepted by the leaves. Research by Khan et al. (2025) indicates that to keep DBH errors below 1 cm, densities of between 600 and 700 points/m³ are required, which are difficult to achieve in summer under closed canopies. Terrain visibility is critical for generating accurate digital terrain models (DTMs). Ko et al. (2024) showed that most LiDAR pulses reach the ground from late fall through early spring in dense temperate deciduous forest, whereas far fewer reach the ground during summer, making it difficult to accurately identify tree bases, as also noted by Holvoet et al. (2025) in structurally complex forests.

1.2.3.4 Optimal scanning windows and hyper-temporal monitoring

According to the literature, the most suitable time for LiDAR data collection in temperate forests is during late fall to early winter (typically in November), when leaf cover is minimal (Ko et al., 2024; Wu et al., 2025a). Tree size also plays an important role: very small trees with DBH less than 5 cm are generally not captured reliably by terrestrial or mobile LiDAR systems (Ko et al., 2024). Additionally, snowfall can affect the determination of tree base elevation and total tree height if a snow-free reference DTM is not available. The application of hyper-temporal point clouds (frequent LiDAR acquisitions within a single growing season) enables monitoring of sub-annual changes in tree structure and branch dynamics. This differs from multi-temporal LiDAR surveys, which are acquired seasonally or annually (Bienert et al., 2024; Campos et al., 2024). Hyper-temporal monitoring may allow the detection of tree responses to environmental factors such as precipitation and temperature, allowing for more detailed forest monitoring.

1.2.4 Multitemporal point cloud analysis and forest dynamics

1.2.4.1 Algorithms for multi-temporal comparison

The use of mobile LiDAR can provide a transformative way for forest inventories (Bienert et al., 2024; Campos, 2024). The detection of changes depends on the accuracy of the algorithm applied and the

quality of point cloud registration and alignment between successive scans (Winiwarter, 2021; Shafaat et al., 2025). Scientific evidence identifies a clear hierarchy in the performance of direct 3D processing algorithms. Cloud-to-Cloud (C2C) is defined as the most straightforward method, as it calculates the Euclidean distance to the nearest neighbor (Lague et al., 2013). However, results show that it is highly sensitive to variations in point density and noise, which generates unsigned distances that prevent distinguishing between biomass gain or loss (Winiwarter et al., 2021; Mîzgaciu et al., 2025). This approach is mainly suited for identifying large and sudden changes (typically greater than 0.5 m), such as tree removal or terrain displacement (Winiwarter et al., 2021; Shafaat et al., 2025). The Multiscale Model-to-Model Cloud Comparison (M3C2) method has been widely accepted as a very reliable technique for monitoring forests (Lague et al., 2013; Shafaat et al., 2025) since it measures distances between two point clouds along their respective local surface normals, thus decreasing the potential effect of point density, and creating a statistically valid threshold for detecting change (Lague et al., 2013; Winiwarter et al., 2021). M3C2-EP (Multiscale Model-to-Model Cloud Comparison with Error Propagation) is one such advanced implementation that also accounts for how errors propagate through the modeling process to help reduce false positives in locations where the surfaces are highly complex or uneven (Winiwarter et al., 2021).

1.2.4.2 Detection of phenological changes vs. actual growth

Environmental noise and seasonal biological cycles can mask actual tree growth in LiDAR point clouds. Spring foliage growth affects the structure of the trees that LiDAR instruments measure, resulting in noticeable differences in how canopy points are distributed (Simonson et al., 2018). Studies using hyper-temporal datasets show that these technologies can detect shifts in leaf phenology to within centimeters, including temporal differences among trees of the same species, up to approximately 12 days (Bienert et al., 2024; Campos et al., 2024). Environmental conditions such as rainfall temporarily change the position of branches as they absorb water and change their elasticity, an effect that can be measured using M3C2-based comparisons (Bienert et al., 2024). Growth rates measured from mobile devices (derived from repeated LiDAR scans of the same trees over time) have also been shown to accurately capture growth trajectories while accounting for point density variability in controlled experiments (Qi et al., 2023). By using low-cost ground-based measurements (manual DBH and TH data), local allometry models can be calibrated, creating biomass estimates with error rates as low as 3%, whereas the traditional estimates have error rates of approximately 15-30% (Qi et al., 2023).

1.2.4.3 Limitations due to noise, registration, and drift

The reliability of multi-temporal analyses is affected by several technical constraints associated with mobile scanning systems. Aligning point clouds accurately is an important process that can be achieved with the use of the ICP (iterative closest point) algorithm. Small misalignments can impact how structural changes are interpreted (Forkuo & Borz, 2023; Shafaat et al., 2025).

A typical level of detection (LoD95) for datasets that have been registered correctly is between 2-4 cm (Shafaat et al., 2025). Differences smaller than this threshold are usually due to uncertainty in registration, noise from the sensor or external factors such as wind (Winiwarter et al., 2021; Shafaat et al., 2025). SLAM-based methods have a tendency for cumulative position errors, especially in cases of long or complicated trajectory conditions. This can lead to inaccurate representational geometric information for each collected plot (Liang et al 2022; Balestra et al 2024b). To try to resolve the issue of cumulative positioning errors, loop closure techniques can be used to ensure geometric consistency across the various collection paths or time periods (Liang et al 2022). Wind causes ghosting in the point cloud, where one element is seen at multiple positions. This makes it difficult to detect changes in the tree crowns (Simonson et al., 2018).

1.2.5 Factors affecting point cloud quality

This subsection reviews the technical, biological, and operational factors that influence the quality and reliability of the 3D LiDAR reconstructions, identifying the critical thresholds for effective performance of

low-cost systems. The interaction between the laser beam and the trunk surface is influenced by the morphological properties of the species (Mîzgaciu et al., 2025). Rough bark has been pointed out to be one of the major causes of systematic noise; in fact, tree species with deeper bark texture, like *Pinus sylvestris* or *Quercus petraea*, have a broader residual band in the point cloud, which often causes overestimation of the DBH in circle fitting algorithms (Bauwens et al., 2016; Holvoet et al., 2025; Výboštok et al., 2025). Conversely, species with smooth bark, such as *Abies alba* or *Fagus sylvatica*, present specific challenges for consumer-grade devices (Výboštok et al., 2025). For instance, in Time-of-Flight (ToF) sensors of smartphone cameras, regions with low surface texture reduce the stability of depth frames alignment, causing software to depend on internal interpolations that heighten metric biases (Výboštok et al., 2025). Furthermore, trunk eccentricity in deciduous trees also causes error in cases where circularity is assumed to be perfect, indicating that an elliptical shape is more flexible in comparison (Wu et al., 2025a; Bauwens et al., 2016).

The quality of SLAM mapping results is highly dependent on user behavior and the geometry of the paths taken (Chen et al., 2019; Sae-Ngow et al., 2025). The closed-loop paths are critical to the mitigation of the drift phenomenon, enabling the system to detect familiar locations and correct errors that have built up in the odometry (Gollob et al., 2020b; Vandendaele et al., 2022). The way people walk influences the angles at which objects are scanned and the uniformity of scene coverage (Chen et al., 2019; Gollob et al., 2021a). Ensuring multiple scanning angles around each tree, including circular or randomized paths, improves data completeness compared to following a single straight trajectory. There are also limitations that can be caused by motion artifacts such as misaligned surveys and ghosting from high survey speeds or repeating the same survey multiple times (Gollob et al., 2021b). Finally, operator skill will be critical to the overall success of the mission plan due mainly to professional user capabilities to provide effective scanning solutions in more dense or occluded landscapes (Chen et al., 2019; Sae-Ngow et al., 2025).

The accuracy of dendrometric variables depends on achieving minimum density thresholds. If point density falls below these thresholds, the RMSE rises sharply, compromising the accuracy of the measurements. Point densities of between 600 and 700 points/m³ are required to stabilize the error below 1 cm for DBH assessments (Khan et al., 2025; Výboštok et al., 2025). Densities below 200 points/m³ result in incomplete stem profiles that may invalidate the automatic fit (Khan et al., 2025). For tree height, the requirement is less restrictive, reaching a plateau in accuracy (RMSE < 1 m) starting at 300 points/m³, provided that the sensor successfully captures the actual tree top (Khan et al., 2025; Výboštok et al., 2025).

1.3 CONCLUSION

The digitization of forest inventory applications is going through a paradigm shift due to the change from static data collection systems to mobile systems and consumer devices. The shift can be regarded as a democratization of the accuracy of forest inventories, as it has made possible for consumer devices and mobile apps to attain technical reliability in their use. The most powerful competitive advantage of the technology is its efficiency in collecting data from entire plots on the go, thus reducing the time spent in the field. Furthermore, the integration of applications with instant processing capabilities facilitates on-site decision-making and eliminates the logistical barriers of extensive post-processing in the office. However, widespread implementation faces persistent technical and environmental constraints. The height of trees remains the main challenge for ground-based sensors due to canopy occlusion and the limited range of low-cost devices, leading to a systematic tendency to underestimate vertical structure. Furthermore, data quality depends critically on the forest's phenological state, with the leaf-off period (late autumn to early winter) being the optimal scenario for ensuring visibility of tree trunks and accurate terrain reconstruction. For multi-temporal monitoring and growth tracking, these tools offer great potential provided that robust comparison algorithms are used to distinguish actual biological changes from technical or instrumental noise. Ultimately, the future of precision forestry does not lie in a single sensor, but in the adoption of hybrid workflows that integrate stem-level detail obtained via mobile LiDAR with aerial canopy coverage provided by airborne systems or drones. Low-cost LiDAR technologies have evolved from experimental tools into essential components of a digital, scalable, and accessible forest monitoring infrastructure—one that is necessary for the sustainability of global forest resources.

CHAPTER 2. ACCURACY OF TREE SCANNER APP IN SOURCING TREE-LEVEL BIOMETRICS: A CASE STUDY BASED ON DATA FROM DIVERSE FOREST ECOSYSTEMS

2.1 MATERIALS AND METHODS

The study was conducted in 2025 across three forest sites in Romania representing different forest compositions and topographic conditions. The Buzău (BUZ) and Harghita (HAR) sites were located in the Romanian Carpathians and consisted mainly of mixed broadleaved-coniferous mountain forests, while the Botoşani (BOT) site represented a hilly broadleaved forest ecosystem. The stands included species such as European beech (*Fagus sylvatica* L.), Norway spruce (*Picea abies* (L.) H. Karst), silver fir (*Abies alba* Mill.), sessile oak (*Quercus petraea* (Matt.) Liebl), hornbeam (*Carpinus betulus* L.), field maple (*Acer campestre* L.), and wild cherry (*Prunus avium* L.).

Reference measurements of diameter at breast height (DBH) and tree height (TH) were collected using conventional forestry instruments. DBH was measured at 1.3 m above ground using a Haglöf Mantax Blue caliper with millimeter precision, while tree height was measured with a Haglöf ultrasonic hypsometer combined with a T3 transponder. Digital measurements were acquired using the TreeScanner (TS) beta mobile application developed within the SINTETIC project, running on an iPhone 13 Pro Max equipped with a Time-of-Flight (ToF) LiDAR sensor. The application integrates LiDAR point clouds, GNSS, imagery, and the RANSAC algorithm to estimate dendrometric variables. Measurements with both methods were performed during daylight under matched acquisition conditions whenever possible.

Field data collection followed a structured workflow involving three operational roles: a person responsible for measurements, a supporting team responsible for logistics and locating trees, and a person responsible for recording conventional measurements. Verbal communication was maintained throughout the process to ensure synchronization and data accuracy. For both DBH and TH, measurements were taken from comparable distances, directions, and fields of view, and any deviations from these conditions were documented in the field notes.

Before analysis, the dataset underwent a curation process to retain only paired measurements collected under consistent acquisition conditions. Out of 287 initially collected paired DBH and TH observations, 220 measurements were retained for statistical analysis. The statistical analysis followed a standard method-comparison framework. Descriptive statistics and accuracy metrics, including RMSE, MAE, and bias, were calculated (Heckman et al., 1998; Ross et al., 2013; Chai & Draxler, 2014; Hodson, 2022; Karunasingha, 2022). Data normality was assessed using the Shapiro-Wilk and D'Agostino-Pearson tests (Breton et al., 2008; D'Agostino et al., 1986; Shapiro & Wilk, 1965; Yap & Sim, 2011). Agreement between TreeScanner and reference measurements was evaluated using Bland-Altman analysis (Bland & Altman, 1999), while ordinary least squares regression models were used to assess relationships between datasets (Watson, 1967; Yuan et al., 2018; Van De Geer, 2008). Additional heteroscedasticity tests, including Breusch-Pagan and White tests, were performed to investigate the presence of proportional bias. Data management and visualization were conducted using Microsoft Excel, QGIS, and Microsoft PowerPoint. Statistical analyses were implemented in Python v. 3.12 using libraries such as numpy, pandas, seaborn, matplotlib, statsmodels, pathlib, and scipy, which enabled the development of a complete workflow for data import, analysis, visualization, and export of results.



Figure 2.1. Location of study sites and an overview of methodology used.

2.2 RESULTS

2.2.1 Description of data

Of the total 287 observations included in the initial dataset, 220 viable measurements were retained based on the criteria used for data curation. Of these, 90 (74%) were sourced from the BOT dataset, 10 (32%) from BUZ dataset, and 120 (89%) from HAR dataset, altogether accounting for about 77% of the original dataset. Table 2.1 summarizes the data on manual and digital DBH and TH measurements, indicating that the two methods produced similar mean and standard deviation values, as well as similar data distributions. Except for the height residuals, none of the data meet the normality assumption. For DBH, the distributions of both measurement methods were positively skewed, showing a high concentration of trees in the 15-35 cm range because of the dataset characteristics, which contained significantly more data from the HAR site. However, there was excellent agreement between the two methods regarding the distribution of data.

Table 2.1. Summary descriptive statistics of the data.

Variable	N	Minimum value	Maximum value	Mean $\pm$ Standard deviation	First quartile	Median	Third quartile
d_caliper (cm)	220	10.70	87.90	28.61 $\pm$ 14.285	20.35	24.95	31.53
d_treescanner (cm)	220	10.40	87.83	28.54 $\pm$ 14.533	20.39	24.65	31.40
h_vertex (m)	220	4.00	44.40	22.80 $\pm$ 6.182	19.00	22.60	25.73
h_treescanner (m)	220	3.77	42.87	22.54 $\pm$ 6.367	18.54	22.38	25.42

For tree height, the distributions were more symmetrical and approximated normal distributions, centered around a mean located in the 23–25 m range. The REF and TS density curves overlapped almost perfectly, indicating consistent measurement accuracy across variability in three height. The residuals, defined as the differences between predicted and actual values, should ideally be normally distributed, and centered around zero for regression modeling (Schmidt & Finan 2018, Montgomery et al. 2021). DBH residuals yielded a mean value very close to zero, indicating no major systematic over- or underestimations, with most errors falling within ± 1.5 cm and very few outliers exceeding ± 3 cm. In contrast, TH residuals were centered near zero, spread within ± 1.0 m, and displayed a clear bell-shaped curve, suggesting that errors in height measurement are random and not influenced by a systematic bias

of the TS. The height residual dataset was the only one confirmed to follow a normal distribution as per the implemented statistical tests.

2.2.2 Measurement agreement

The measurement agreement between TS (test) and REF (reference) data is illustrated in Figures 2.2–2.4. These figures include the results of Bland-Altman plots (Figure 2.2), scatter plots of diameter and height measurements fitted with ordinary least squares regression models (Figure 2.3) and trends in errors (Figure 2.4). The results shown in Figures 2.2–2.4 are consistent with those presented in Table 3 indicating a high degree of agreement. For the DBH measurement (Figure 2.2a), the bias was extremely low, at -0.07 cm (-0.3%), indicating rather the absence of systematic bias. Most observations fell within the 95% limits of agreement, roughly between ± 2 cm. Accordingly, the errors were consistently stable across the entire diameter range (from about 10 to nearly 90 cm), with only a few outliers at higher diameters. Considering the MAE (Mean Absolute Error) and RMSE (Root Mean Square Error) metrics, the average diameter measurement from TS differs from the manual reference by less than 1 cm (MAE = 0.75 cm). The RMSE metric, which is non-linear and serves as a measure of precision - giving more weight to larger error values - indicates a low variance in errors compared to the MAE. In agreement with the other DBH results, the RMSE was also less than 1 cm, highlighting a high level of agreement between TS and REF DBH data. Similar highly accurate results were found for tree height measured by TS. There was a slight systematic underestimation of -0.26 m (-1.1%) by TS, with narrower limits of agreement (approximately -1.7 to 1.2 m). The MAE was less than 1 m (0.65), and the RMSE was again below 1 m (0.79 m), indicating consistency in measurement with low variability in errors.

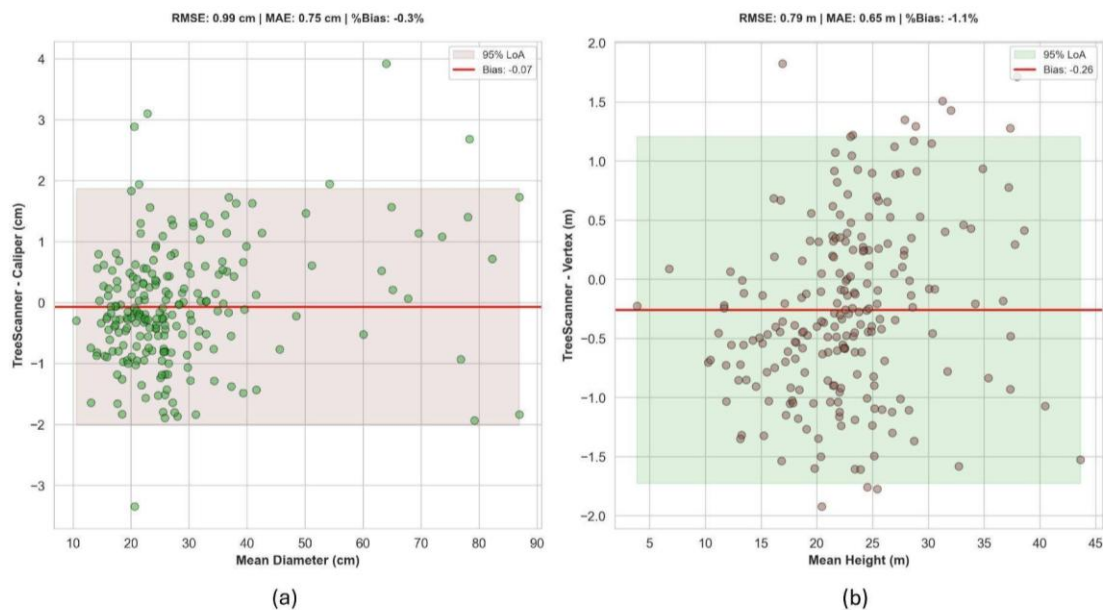


Figure 2.2. Bland-Altman plots of diameter and height agreement.

The scatter plots presented in Figure 2.3 demonstrate an exceptional correlation between the digital (TS) and manual methods (REF). For instance, the DBH measurements exhibited a relationship that was almost perfectly linear (intercept = 0.51 cm, slope = 1.02), capturing the variation in manual measurements to a high degree (99.6%, $R^2 = 0.996$). Although slightly lower than the diameter measurements, the TS measurement method demonstrated high accuracy for height (intercept = 0.79 m, slope = 1.02), also capturing the variation in manual measurements effectively (98.7%, $R^2 = 0.987$). The data points from the sites considered (BOT, BUZ, HAR) clustered tightly along the equality line (1:1 line), suggesting consistent performance across various forest environments, species, and tree sizes.

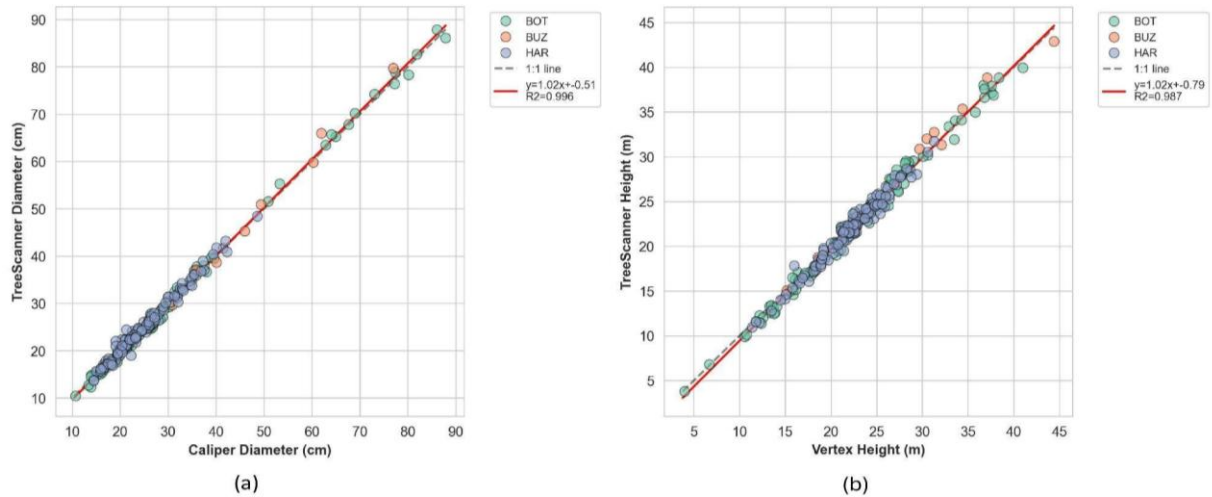


Figure 2.3. Scatter plots of diameter and height fitted with ordinary least square regression models.

The trends in errors are illustrated in Figure 2.4 which explores whether the errors are random or influenced by the magnitudes of DBH and TH. For DBH, there was almost no dependence between the error and DBH magnitude ($R^2 = 0.05$); however, the statistical tests used indicated the presence of heteroskedasticity. Overall, the data from Figure 2.4a suggest a presence of heteroskedasticity with a low effect, ranging from a non-significant underestimation in lower diameter ranges to a very slight overestimation in larger diameter ranges. The data points remained relatively uniformly distributed in the scatter plot, with a flat residual profile. For TH, a very slight upward trend ($R^2 = 0.04$) suggests a minor shift from underestimation to overestimation in taller trees, although the variance remains stable, as shown in Figure 2.4b. The statistical tests also indicated the presence of heteroskedasticity.

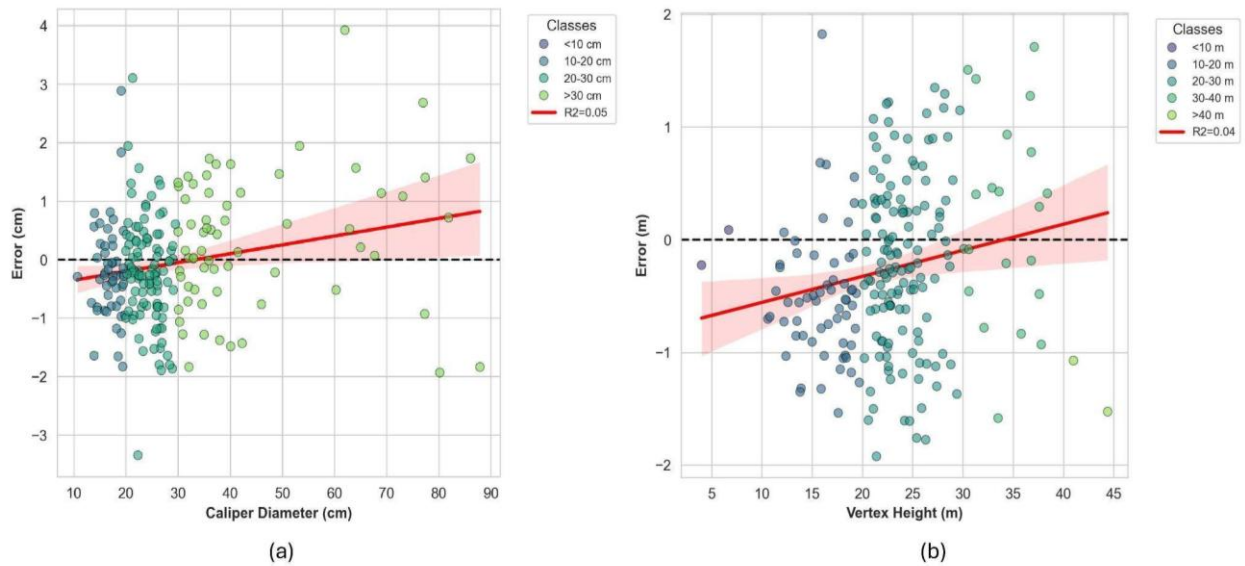


Figure 2.4. Trends in errors of measurement for DBH and TH.

2.3 CONCLUSION

The aim of the study was to evaluate the accuracy of the TS mobile app in estimating tree diameter at breast height (DBH) and total tree height (TH) in diverse forest ecosystems. The results show high levels of concurrence between the estimates obtained with the TS app and the REF estimates for three forest ecosystems considered in the study. The accuracy of the DBH measurement results obtained with the TS indicated high sub-centimeter fidelity, with no significant bias and errors. Similarly, the results obtained for TH measurement indicated high sub-meter accuracy with reference data, with results being slightly underestimated. Regression analysis confirmed that there was a very strong linear relationship between digital and manual measurements, thus validating the application's capacity to represent variability observed in conventional measurements. Agreement analysis and error trends evaluation indicated that differences in measurements were stable for all tree size classes with minor heteroskedasticity. These results suggest that Tree Scanner can produce reliable and accurate measurements across a variety of forest structures, species compositions, and terrain conditions. The portability of smartphones and the ability to directly record digital measurements emphasize the potential of this technology to support more efficient workflows in forest inventory and remove manual data transcription. Despite the encouraging findings from this study, it is important to note that it only covered a few locations and specific forest conditions. Therefore, it is suggested that additional research be carried out to assess the effectiveness of smartphone-based LiDAR technologies over a wider range of forest structures, including denser forest understories. It is also suggested that future developments of this technology focus on the integration of other forest parameters, such as species detection.

CHAPTER 3. 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

3.1 MATERIALS AND METHODS

The study compared two mobile LiDAR-based forest inventory platforms: the Tree Scanner mobile application (Platform 1) and the FJD Trion P1 personal laser scanner (Platform 2). Tree Scanner, developed within the SINTETIC project, uses LiDAR sensors, GNSS, camera imagery, AI-based algorithms, and the RANSAC algorithm to estimate dendrometric variables such as DBH and tree height from high-resolution 3D point clouds (Poveda & Ekenstedt, 2024). The application was operated on an iPhone 13 Pro Max equipped with a Time-of-Flight (ToF) LiDAR sensor. The FJD Trion P1 is a compact personal laser scanner capable of generating dense 3D point clouds using SLAM technology, with a scanning range of up to 40 m and a precision of approximately 2 cm (FJDynamic, 2025). Point clouds collected with Platform 2 were processed using the Trion Model software to identify trees and automatically estimate DBH through geometric fitting at 1.3 m above ground level. The study was conducted in forest compartments near Braşov, Romania, selected to represent a broad range of forest conditions that may influence LiDAR measurements, including variations in stand density, canopy cover, terrain slope, understory vegetation, and tree age (Wallace et al., 2014; Balsi et al., 2018; Sandim et al., 2023). Fifty circular plots of 300 m² were established across the study area. Trees with DBH greater than 10 cm and with at least 50% of their stem located inside the plot boundary were included in the analysis. Plot centers were georeferenced using a handheld GPS device (GPSMAP 64sx, Garmin).

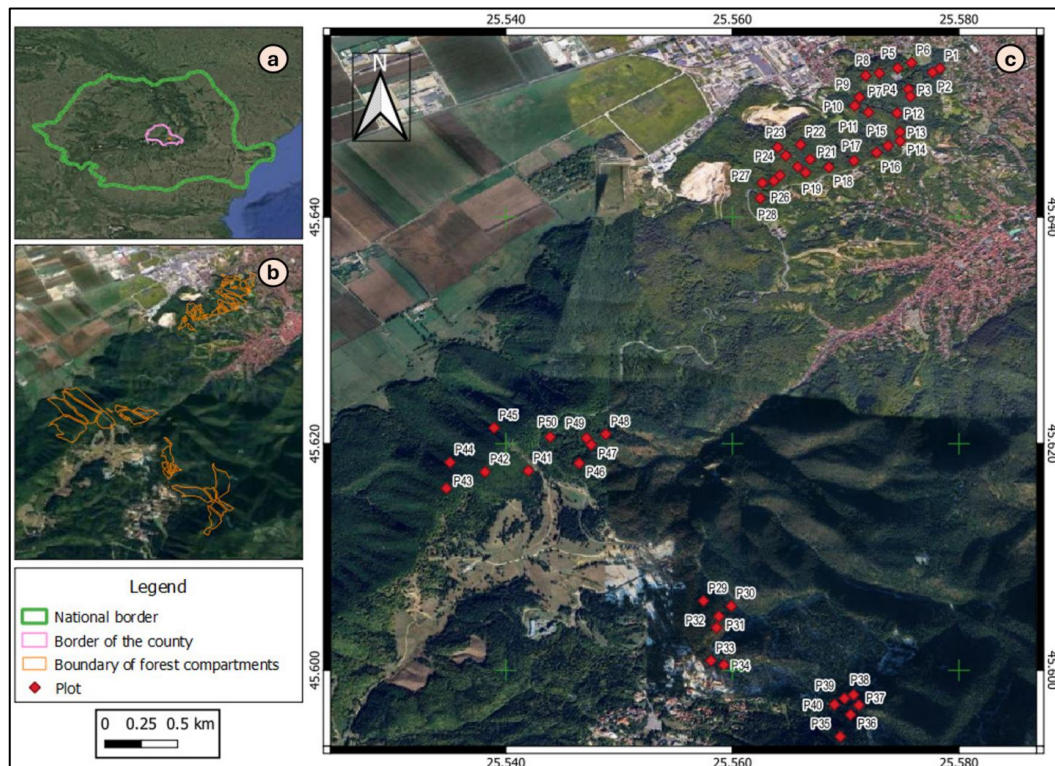


Figure 3.1. Study area showing: a – the location of study area at the national level, b – the location of the selected forest compartments, and c – the locations of the plots.

Data collection was conducted during the leaf-off season between December 12 and 20, 2024. In each plot, all trees were first measured individually using Platform 1, and DBH values were recorded manually. Subsequently, the same plots were scanned using Platform 2 following a standardized scanning pattern consisting of four elliptic trajectories around the plot. Real-time visualization of the point cloud was used in the field to ensure adequate coverage of all tree structures.

The comparison between platforms focused on DBH estimates, basal area (BA) estimates, and operational time consumption. Because trees were not individually marked and direct pairing of tree-level

measurements between platforms was not possible, DBH datasets were ordered incrementally by magnitude for comparison. Plot-level basal area per hectare was calculated separately for each platform using the corresponding DBH estimates. Platform 2 data were considered the operational reference due to the high precision and detailed three-dimensional information provided by the scanner.

The statistical analysis included descriptive statistics, normality assessment using the D'Agostino-Pearson test, and regression analysis to evaluate relationships between datasets. Agreement between basal area estimates was assessed using bias, mean absolute error (MAE), and root mean squared error (RMSE) (Holst & Thyregod, 1999; Willmott & Matsuura, 2005; Willmott et al., 2009; Hodson, 2022). Depending on data distribution, either independent two-tailed t-tests or Mann-Whitney tests were applied to compare datasets (Pereira & Leslie, 2010). Heteroskedasticity was assessed using the Breusch-Pagan and White tests to evaluate potential proportional bias in the residuals (Breusch & Pagan, 1979; White, 1980). Regression through the origin was also used to evaluate the proportion of variation explained between platforms.

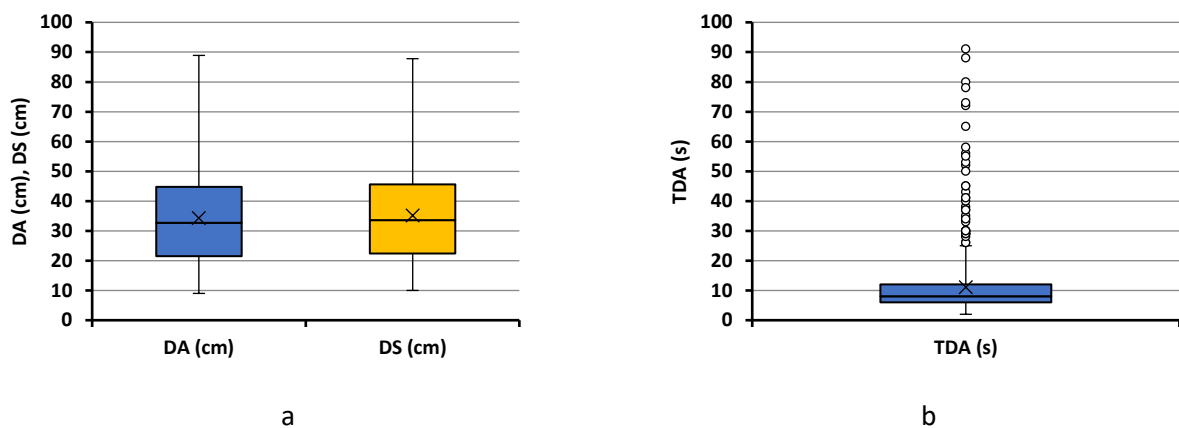
Operational efficiency was evaluated by recording acquisition times for both systems. For Platform 1, the time per tree included application setup, measurement, and data storage, while for Platform 2 the total scanning time included scanner setup, plot scanning, and data saving. Time consumption was further analyzed in relation to stand characteristics such as age, density, slope, and number of trees per plot.

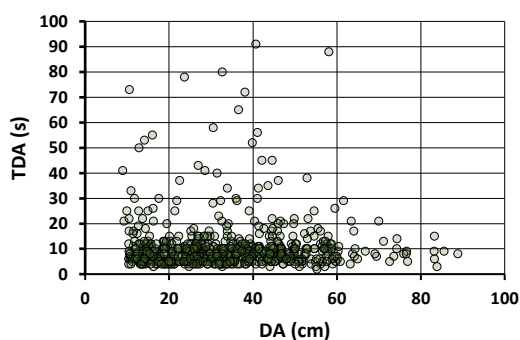
All statistical analyses were conducted in Microsoft Excel using the Real Statistics add-in (Real Statistics Using Excel, 2025). LiDAR data processing was performed on a high-performance workstation equipped with an Intel Core i9 processor, 64 GB RAM, NVIDIA GeForce RTX 4070 GPU, and Windows 11 Pro operating system.

3.2 RESULTS

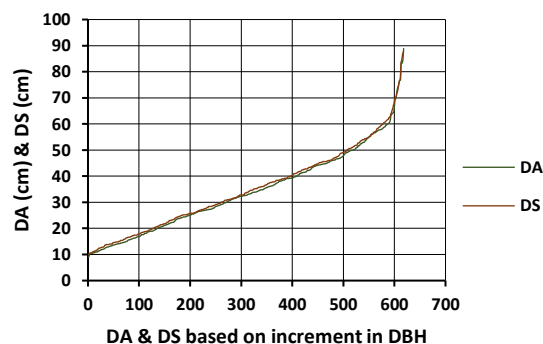
3.2.1 Tree level measurements

The main statistics of tree-level measurements ($N = 618$) are illustrated in Figure 3.2. The assumption of normality for the DA (diameter data sourced by Platform 1, Fig. 4a), TDA (tree-level time consumption data of Platform 1, and DS (diameter data sourced by Platform 2) was not met following D'Agostino-Pearson test ($\alpha = 0.05$, $p > 0.05$), which is also reflected in the QQ plots of DA, TDA, and DS. 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 $\pm$ SD: 34.3 ± 15.83 cm) and a range for DS of 10.0 to 87.8 cm (mean $\pm$ 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 (Figura 3.2d).





c



d

Figure 3.2. 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.

3.2.2 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 3.1, 3.2 and Figure 3.3. The interquartile ranges of the hectare level estimates for basal area using the two platforms were similar (20.130 vs. 19.334 m²). As shown in Table 3.1, 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 3.2 and Figure 3.3.

Table 3.1. 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, BAAH (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 3.2. Differences in basal area estimates

Parameter	Difference metric, data distribution & presence of heteroskedasticity				
	BIAS	MAE	RMSE	Data distribution1	Heteroscedasticity2
Basal area per hectare sourced by Platform 1, BAAH (m ² /ha)	1.950	2.292	3.085	Normal, $p = 0.129$	No heteroskedasticity $pBP = 0.320$, $pW =$
Basal area per hectare sourced by Platform 2, BASH (m ² /ha)				Normal, $p = 0.305$	0.608

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 pBP and pW are the two-tailed p values of the Breusch-Pagan and White tests, respectively.

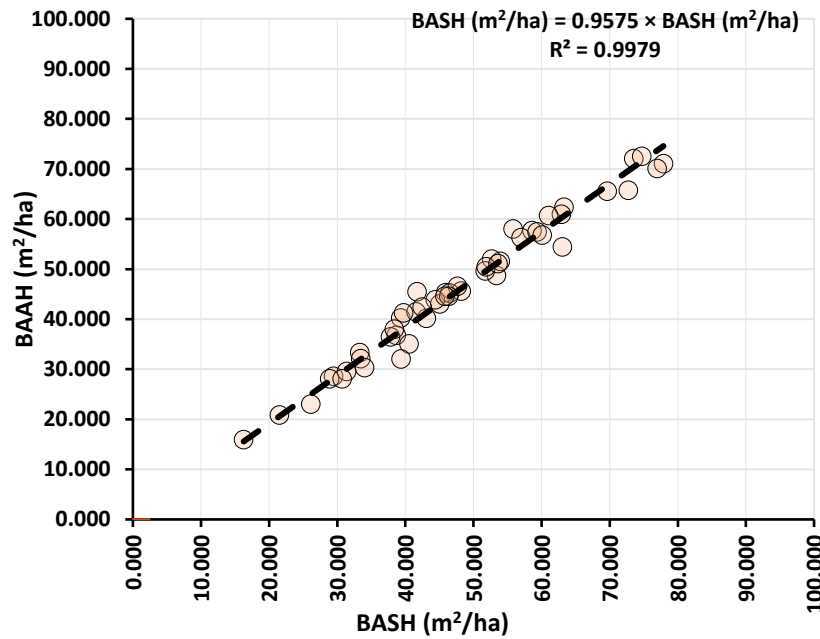


Figure 3.3. Agreement in basal area estimates.

With a BIAS value of 1.950 m²/ha (Tabelul 3.2), indicating a small trend (slope) in increment based on the magnitude of basal area, the results regarding the accuracy of estimates are promising. Additionally, no statistical evidence of linear or other forms of heteroskedasticity was found (Table 3.2), 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 m²/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 m² per hectare. Figure 3.3 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 BAAH as a linear function of BASH. In fact, almost all the variance in BAAH was explained by BASH. The differences in basal area estimates were consistently lower than 3.1 m²/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 m²/ha (underestimation).

3.2.3 Time consumption

Tree-level time consumption by Platform 1 (TDA) generally exhibited a wide range of values (Figure 3.2a); primarily due to the presence of values considered statistically as outliers; however, no evident dependence on DA was found (Figure 3.2b), and the average tree level time consumption for measurement with Platform 1 was of 11 seconds.

Using Platform 2, obtaining the results for DBH and basal area requires several further 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 meters. 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 TDA and TDS data, which reflect the time required to take the measurements in the field.

Linear trends between 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 Figure 3.4a. 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 Figure 3.4b and Table 3, averaging about five times less compared to that of Platform 2. On a per-tree basis, this resulted in approximately 11 seconds spent to measure a tree with Platform 1, compared to about 51 seconds for Platform 2.

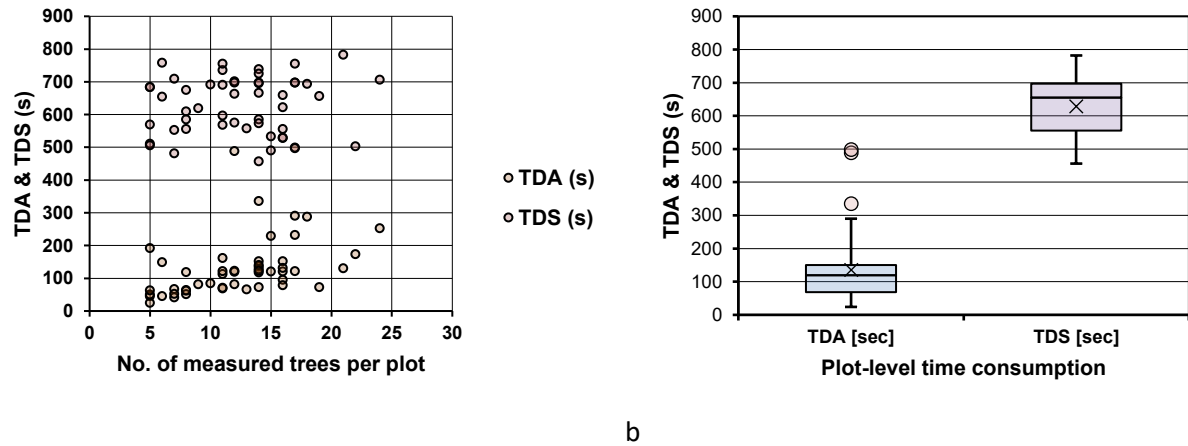


Figure 3.4. Statistics of plot-level time consumption: a – scatterplot of TDA and TDS measurements as a function of number of trees per plot, b – boxplots of TDA and TDS data.

Table 3.3. 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
TDS (s/plot)	456	782	326	628.1	±87.32	Non-normal p < 0.001	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 ($\alpha = 0.05$, $p > 0.05$)

However, one must consider the important differences when evaluating an end-to-end approach to the problem. Was 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 0.038 hours = 2 min. and 17 sec. and 0.003 hours = 11 seconds, respectively. For Platform 2, scanning alone took about 0.174 hours = 10 min. and 26 sec. and 0.014 hours = 51 sec. hours 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 1.969 hours = 118 min. and 8 sec. and 0.159 hours = 9 min. and 32 sec., respectively.

3.3 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.

CHAPTER 4. SEASONAL PERFORMANCE IN BASAL AREA ESTIMATION: A COMPARATIVE STUDY OF A SMARTPHONE LIDAR APPLICATION AND A PROFESSIONAL PERSONAL LASER SCANNING

4.1 MATERIALS AND METHODS

The study was conducted in temperate mountain forests near Braşov, Romania, using fifty circular plots of 300 m² distributed across an altitudinal gradient of 580–1350 m a.s.l. The plots were selected to represent a broad range of forest structures, compositions, and successional stages, including stands dominated by European beech (*Fagus sylvatica*), Norway spruce (*Picea abies*), Silver fir (*Abies alba*), Sessile oak (*Quercus petraea*), Scots pine (*Pinus sylvestris*), and European hornbeam (*Carpinus betulus*). The study area included variable terrain conditions, with slopes ranging from 8° to 42°, diverse understory vegetation, and tree densities between 5 and 24 trees per plot, creating conditions with frequent stem occlusion. Only trees with DBH > 10 cm and with more than 50% of the stem cross-sectional area located inside the plot radius were included, following recommendations for reliable LiDAR-based stem detection (Liang et al., 2018a; Gollob et al., 2020; Tatsumi et al., 2022; Forkuo et al., 2025). The study compared two proximal sensing platforms: the TreeScanner smartphone application and the professional FJD Trion P1 personal laser scanner. TreeScanner, developed within the SINTETIC project, operates on LiDAR-enabled iOS devices and integrates VCSEL LiDAR technology, GNSS positioning, and AI-RANSAC algorithms for stem detection and DBH estimation (Luetzenburg et al., 2021; SINTETIC, 2023). The FJD Trion P1 was used as the professional benchmark due to its high point density, SLAM-based scanning capability, and nominal relative accuracy of approximately 2 cm (FJDynamics, 2026).

A longitudinal repeated-measures design was implemented across four phenological seasons: winter (WI, leaf-off), spring (SP, early leaf-on), summer (SU, dense foliage and understory), and autumn (AU, partial leaf-off). Seasonal surveys were conducted between December 2024 and October 2025. This design allowed the evaluation of how seasonal vegetation conditions influenced point cloud quality, stem detection, basal area estimation, and operational efficiency.

For each plot, TreeScanner measurements were collected individually for all qualifying trees, while the FJD Trion P1 scans were performed using four elliptical trajectories extending beyond the plot radius to ensure complete coverage. Time consumption was recorded separately for both platforms. For TreeScanner, acquisition time included app initialization, stem scanning, DBH computation, and file saving, but excluded inter-tree movement. For the FJD Trion P1, total scanning time included scanner setup, movement along the scanning trajectories, SLAM closure, and data saving.

Point cloud data from the FJD Trion P1 were processed using the official Trion Model software, which performed refinement, segmentation, and automatic DBH estimation by fitting geometric shapes to stem cross-sections at breast height. Tree-level measurements were aggregated to estimate plot-level basal area (BA). Statistical analyses were conducted in Python 3.12 using custom scripts for seasonal aggregation, error estimation, and hypothesis testing, while Microsoft Excel was used for data organization and verification.

The statistical analysis evaluated inter-platform agreement and operational efficiency across seasons. Normality of basal area and time datasets was assessed using the Shapiro-Wilk and Kolmogorov-Smirnov tests. Descriptive statistics were computed for each season, and agreement between platforms was analyzed using Bland–Altman analysis and linear regression. Error metrics included Bias, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) (Willmott & Matsuura, 2005; Chai & Draxler, 2014). Depending on data distribution, paired t-tests or Wilcoxon signed-rank tests were used to compare basal area estimates and acquisition times between platforms (Wilcoxon, 1945; Pereira & Leslie, 2010; Mishra et al., 2019). Scatter plots and regression analyses were further used to evaluate seasonal agreement between TreeScanner and the FJD Trion P1, with slopes close to 1 and higher R² values interpreted as stronger agreement (Giavarina, 2015).

4.2 RESULTS

4.2.1 Seasonal plot-level BA estimates and acquisition time

The full annual inventory cycle was successfully completed across all the plots. A total of 618 trees were recorded in Winter (WI) and Spring (SP), decreasing to 617 in Summer (SU) and Autumn (AU) due to the fall of one tree in Plot 16. Table 4.1 summarizes stand-level biometric metrics and operational times per season.

Table 4.1. Plot-level BA and acquisition time by season ($n=50$).

Season	NT (Tree/plot)	BAA (m ²)	BAS (m ²)	TA (s/plot)	TS (s/plot)
WI	12.36 ± 4.68	1.38 ± 0.41	1.44 ± 0.43	136.18 ± 99.46	628.12 ± 86.44
SP	12.36 ± 4.68	1.54 ± 0.43	1.73 ± 0.49	109.16 ± 50.48	653.96 ± 146.1
SU	12.34 ^a ± 4.67	1.63 ± 0.44	1.79 ± 0.51	135.08 ± 60.48	604.44 ± 87.87
AU	12.34 ^a ± 4.67	1.75 ± 0.55	1.68 ± 0.49	110.98 ± 39.86	498.66 ± 86.09

Note: Values are mean ± standard deviation. BAA, basal area estimated using TreeScanner; BAS, basal area estimated using FJD Trion P1; TA, acquisition time per plot (TreeScanner); TS, scanning time per plot (FJD Trion P1). ^aReduction due to a fallen tree in Plot 16.

TreeScanner estimations showed good agreement compared to those obtained using the FJD Trion P1 in WI and AU, with an average difference of up to 0.06 m². The highest differences were observed in SP, reaching 0.19 m². Both the FJD Trion P1 and TreeScanner showed similar patterns in the trend toward an increase in average BA throughout the phenological cycle, which coincides with seasonal growth patterns in temperate mixed forests. In terms of operational efficiency, the season-level average scanning time per plot using the FJD Trion P1 (TS) varied from 498.66 ± 86.09 s in AU to 653.96 ± 146.1 s in SP. These values reflect the time spent to setup the equipment and save the data, as well as the time required to follow predetermined scanning routes. For the TreeScanner, total acquisition time per plot (TA) ranged from 109.16 ± 50.48 s in SP to 136.18 ± 99.46 s in WI. TA was measured for individual trees and does not include the time spent walking between them. Normality tests showed that forest-level BA variables were normally distributed in all seasons (Shapiro-Wilk, $p > 0.05$), supporting the use of paired t-tests. In contrast, TA and TS data were not normally distributed ($p < 0.05$), supporting the use of Wilcoxon signed-rank tests.

4.2.2 4.3.2. Inter-platform agreement and error metrics

The seasonal agreement between TreeScanner (BAA) and FJD Trion P1 (BAS) estimates varied for different phenological stages, as indicated in Table 4.2 and visualized in Figure 4.1.

Table 4.2. Seasonal error metrics for plot-level BA (m²).

Season	Bias (m ²)	MAE (m ²)	RMSE (m ²)	Coefficient of determination (R ²)
Winter (WI)	-0.059	0.069	0.093	0.097
Spring (SP)	-0.184	0.299	0.391	0.031
Summer (SU)	-0.158	0.256	0.317	0.075
Autumn (AU)	0.073	0.232	0.306	0.056

Note: Bias, MAE, RMSE, and R² (residuals vs. mean) are reported per season. Low R² values suggest limited evidence of proportional bias.

WI showed the highest agreement in BA, with the lowest RMSE (0.093 m²) and near-zero bias (-0.059 m²). On the other hand, the lowest level of agreement was observed for SP, where the RMSE increased to 0.391 m². In addition, the systematic underestimation bias increased to -0.184 m². SU and AU showed intermediate performance in terms of agreement. However, the latter (AU) showed a partial recovery with an RMSE of 0.306 m² and a bias of 0.073 m², indicating that, on average, the differences were small but there were some high differences in these datasets. The narrowest 95% limits of agreement (LoA)

were observed in WI, where values ranged from -0.199 to 0.082 m². The widest 95% LoA occurred in SP, where values ranged from -0.861 to 0.492 m². This suggests greater variation in the measurements taken during leaf-on season. However, most measurements remained within the 95% LoA at all the seasons. Residual coefficients of determination remained low ($R^2 < 0.100$), confirming the absence of significant proportional bias. These results provide a quantitative basis for assessing inter-platform agreement across seasons.

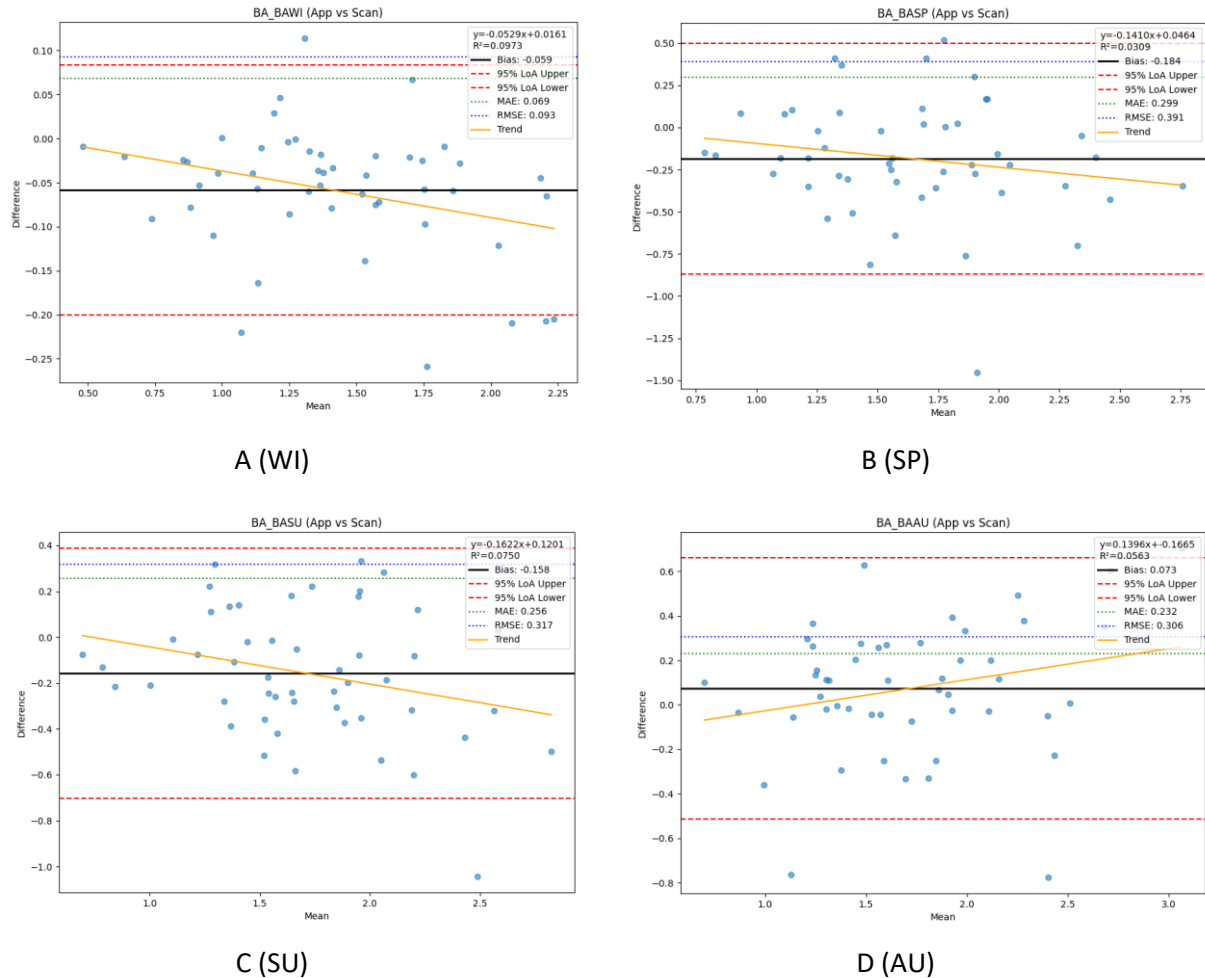


Figure 4.1. Bland–Altman plots for plot-level BA agreement across phenological seasons (WI, SP, SU, AU).

Note: Each data point represents the aggregated BA of an individual circular plot ($n = 50$). The solid black line shows the mean bias; dashed red lines mark the 95% LoA. The orange line represents the linear trend of residuals, which remained low across the full range of measurements ($R^2 < 0.100$).

4.2.3 4.3.3. Statistical parity between platforms

Paired statistical comparisons between TreeScanner (BAA) and FJD Trion P1 (BAS) estimates revealed significant differences in Winter (WI), Spring (SP), and Summer (SU) ($p < 0.001$), with statistical parity achieved only in Autumn (AU) ($p = 0.093$) (Table 4.3). Regarding intra-platform dynamics, seasonal differences in stand-level BA were significant for both systems ($p < 0.05$). The TreeScanner data showed a gradual increase of BAA from 1.38 m² (WI) to 1.75 m² (AU). In contrast, the estimates of FJD Trion P1 showed greater seasonal variability.

Table 4.3. Technical parity and operational consistency ($n=50$).

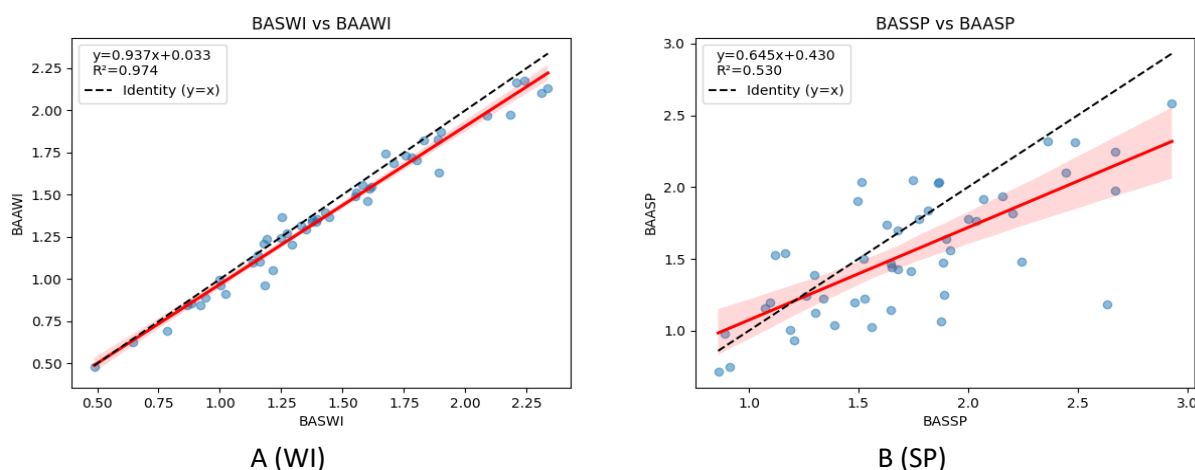
Variable	Comparison pair	Statistical test	p-value	Test outcome
Basal Area	BAA_WI vs BAS_WI	Paired t-test	< 0.001	Significant difference
	BAA_SP vs BAS_SP	Paired t-test	< 0.001	Significant difference
	BAA_SU vs BAS_SU	Paired t-test	< 0.001	Significant difference
	BAA_AU vs BAS_AU	Paired t-test	= 0.093	Non-significant difference
Acquisition Time	TA_WI vs TS_WI	Wilcoxon	< 0.001	Significant difference
	TA_SP vs TS_SP	Wilcoxon	< 0.001	Significant difference
	TA_SU vs TS_SU	Wilcoxon	< 0.001	Significant difference
	TA_AU vs TS_AU	Wilcoxon	< 0.001	Significant difference

Note: NS refers to Non-Significant differences ($p \geq 0.050$), indicating statistical parity.

The acquisition time was analyzed separately for each platform. The results showed that the TA per plot using TreeScanner remained relatively constant across the seasons, with no significant differences recorded when compared to the WI reference value (SP: $p = 0.197$, SU: $p = 0.180$, AU: $p = 0.194$). The mean TA value was approximately 16 seconds per tree. The results showed that there were significant differences in the TS values per plot when using FJD Trion P1 across the seasons ($p < 0.05$). The highest mean value was recorded in SP (653.96 s) and the lowest in AU (498.66 s). TA values remained lower than TS across all seasons.

4.2.4 Seasonal correlation of treescanner and FJD Trion P1 basal area estimates

The linear regression of the TreeScanner (BAA) versus the FJD Trion P1 (BAS) estimates showed that the relationship varied across phenological stages (Figure 4.3). In Winter (WI), the coefficient of determination was the highest ($R^2 = 0.974$). The regression slope was 0.937, and the intercept was low (0.033). Spring (SP) showed the lowest fit, with $R^2 = 0.530$ and a regression slope of 0.645. Summer (SU) and Autumn (AU) had intermediate R^2 values (0.719). The regression slope in AU was closest to 1 (0.965), indicating the closest correspondence to the identity line.



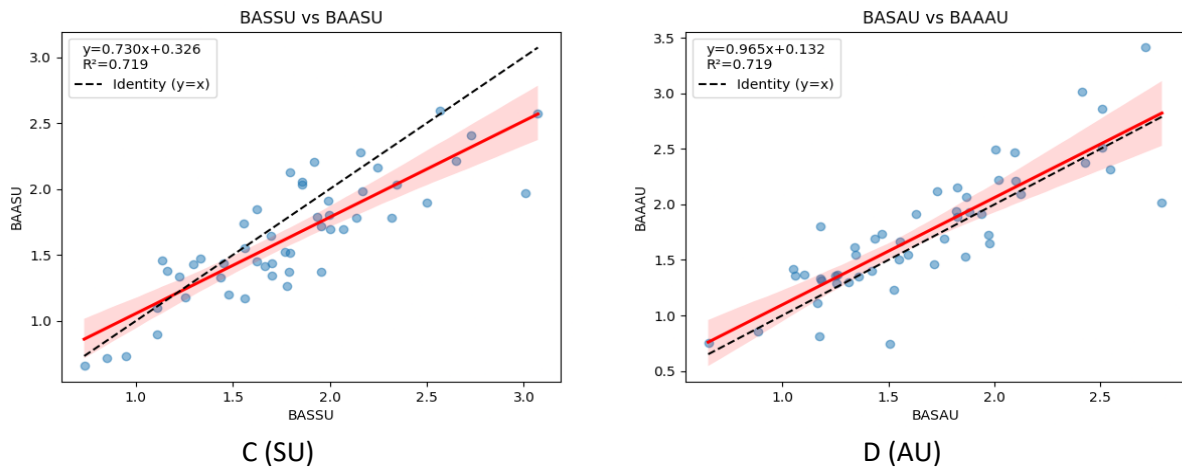


Figure 4.2. Scatter plots and linear regression of BAA vs BAS across phenological seasons.

Note: Dashed line: theoretical identity ($y = x$); solid red line: fitted regression; shaded area: 95% confidence interval.

The shaded pink areas in Figure 4.2 indicate the 95% confidence intervals for the regression lines. The interval was narrowest in WI, reflecting the high R^2 , and widest in SP. SU and AU showed intermediate widths. In AU, the confidence band was located close to the identity line ($y = x$), in agreement with the regression slope.

4.3 CONCLUSION

This study shows that phenological conditions influence the level of agreement between smartphone LiDAR systems and professional PLS in forest inventories, as evidenced by seasonal variations throughout the phenological cycle. The interpretation that the presence of foliage appears to be an important driver of seasonal variability is supported by the highest agreement between the professional PLS and the smartphone application during leaf-off and senescence conditions. While AU demonstrated the highest statistical agreement between platforms, WI offered the most consistent measurement conditions. In field conditions, the smartphone application showed a relatively stable and consistently faster acquisition rate compared to the professional SLAM-based application. However, this comparison should be interpreted with caution due to differences in acquisition protocols used in this study. Within the studied conditions, efficiency appeared to be only weakly influenced by terrain slope. These results suggest that smartphone-based acquisition may offer efficiency advantages under the tested conditions for rapid stand-level assessments in structurally complex and topographically challenging environments. The absence of significant proportional bias implies that the detected errors are primarily independent of tree diameter, which indicates that measurement errors were largely independent of the measurement technique in the context of good visibility conditions. The lower agreement observed during SP points to the importance of aligning the inventory campaigns with the phenological windows with less vegetation interference. In summary, smartphone-based LiDAR technology shows considerable potential for efficient estimation of rapid stand-level BA using this method under favorable conditions. Additional research incorporating more validation data and tests on various types of forest stands could help enhance the robustness of this method.

CHAPTER 5. COMPARING POINTCLOUDS USING C2C AND M3C2 ALGORITHMS IN DIVERSE FOREST ECOSYSTEMS

5.1 MATERIALS AND METHODS

The study was conducted in forest ecosystems located between Braşov and Poiana Braşov, Romania. Fifty circular plots with a radius of 9.80 m were established to capture variability in species composition, canopy structure, and terrain conditions. Plot centers were georeferenced using a Garmin GPSMAP 64sx receiver, and plots were delimited using a tape measure. The selected forests included species such as European beech (*Fagus sylvatica*), Norway spruce (*Picea abies*), silver fir (*Abies alba*), sessile oak (*Quercus petraea*), Scots pine (*Pinus sylvestris*), and European hornbeam (*Carpinus betulus*), covering a range of stand structures characterized by differences in age, slope, elevation, canopy cover, and stand density.

Data acquisition was performed using the FJD Trion P1 mobile laser scanner, a SLAM-based system with a $360^\circ \times 59^\circ$ field of view, a scanning rate of up to 200,000 points per second, and an estimated accuracy of approximately 2 cm (FJDynamics, 2026). Each plot was scanned following a standardized elliptical trajectory, conceptually divided into four quadrants, with the operator moving around the plot while keeping the scanner oriented toward the center. Scans extended approximately 5 m beyond plot boundaries to ensure full spatial coverage. Data were collected during two field campaigns representing winter (December 2024) and spring (May 2025) conditions.

Point cloud processing was carried out in CloudCompare. Winter point clouds were used as the reference dataset and were aligned with spring datasets using Iterative Closest Point (ICP) fine registration. Both datasets were then cropped using a 10 m cylindrical boundary to ensure identical spatial extent, followed by noise removal using the Statistical Outlier Removal (SOR) filter. This produced cleaned and spatially consistent point clouds for comparison. Two complementary methods were used to quantify seasonal differences: Cloud-to-Cloud (C2C) distance analysis, which computes nearest-neighbor point differences, and Multiscale Model-to-Model Cloud Comparison (M3C2), which estimates distances along local surface normals and accounts for point cloud structure and density (Lague et al., 2013).

C2C provided metrics such as mean distance, standard deviation, RMSE, coverage, and distribution of distances, based on k-d tree nearest-neighbor searches. M3C2 provided analogous metrics while incorporating surface orientation and local scale parameters, improving robustness to noise and variable point density. Together, both methods enabled a quantitative assessment of seasonal changes in forest structure from mobile LiDAR data, combining point-based and surface-based comparison approaches.

Statistical analysis was performed in Microsoft Excel using the Real Statistics add-in. Descriptive statistics (mean, median, standard deviation, range) were calculated for all main metrics, and data normality was tested using the Shapiro–Wilk test.

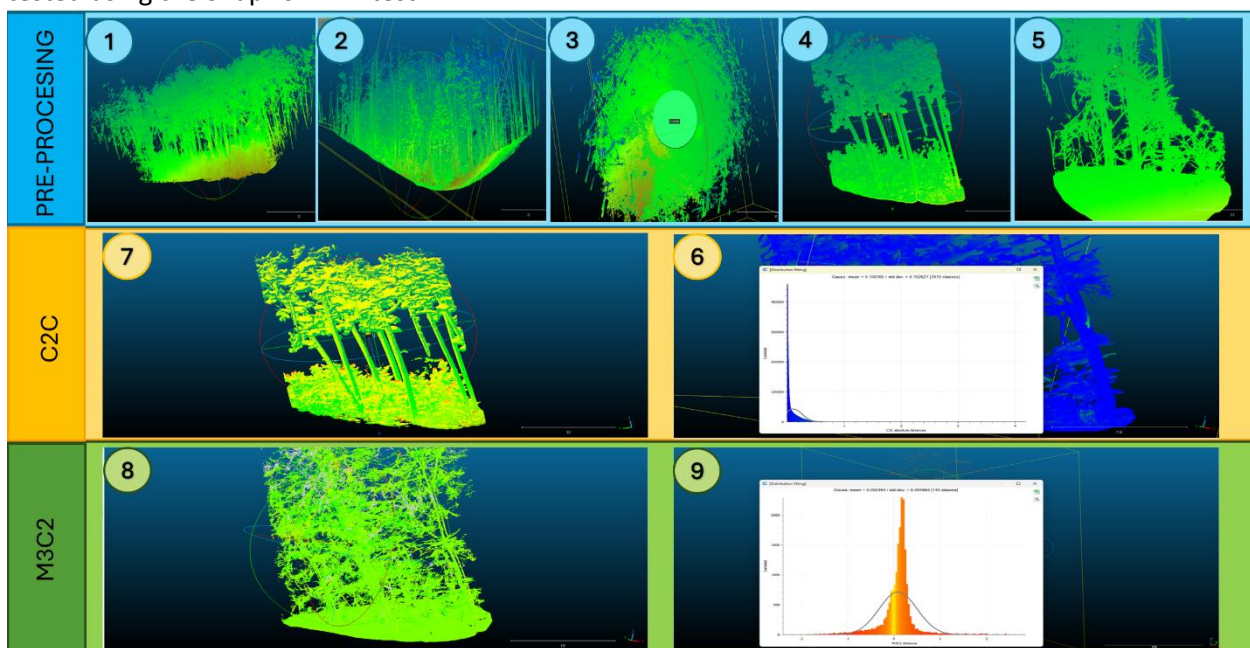


Figure 5.1. Description of the point cloud comparison workflow.

5.2 RESULTS

5.2.1 Cloud to cloud comparison (C2C)

The results of the Cloud-to-Cloud (C2C) comparison are summarized in Table 2. The mean distance between the winter and spring point clouds was 0.091 m, with the standard deviation of the distances at 0.027 m. This shows that the points were closely aligned. The standard deviation of the distances, which is an indicator of the variability in the distances between the points, was on average 0.115 m, with the higher standard deviation at 0.038 m. This shows that there were some local variations in the geometry of the point cloud. The coverage was also 100%, indicating that the entire study area was well represented. The RMSE for the alignment of the point clouds was 0.147 m on average. This is an indicator of the magnitude of the deviation between the two point clouds. The results provide an overview of the changes between the winter, and the spring point clouds, indicating that the changes were low.

Table 5.1. Summary statistics of the C2C point cloud comparison.

Parameter	Mean $\pm$ Standard Deviation	Minimum value	Maximum value	Range
Distance (m) ¹	0.091 $\pm$ 0.027	0.036	0.201	0.165
Standard deviation of distance (m) ¹	0.115 $\pm$ 0.038	0.051	0.290	0.239
Coverage (%) ¹	100.0 $\pm$ 0.0	100.0	100.0	0.000
RMSE of point cloud alignment (m) ¹	0.147 $\pm$ 0.045	0.063	0.353	0.290

Note: ¹ – variable for which normality assumption was violated.

All core points (CP) and valid points (VP) were used in the C2C comparison, with identical values for both parameters across all plots, ranging from approximately 11.6 to 23.2 million points. Median values for distance, standard deviation, coverage, and RMSE were slightly lower than the mean values (see Table 5.2).

5.2.2 Model to model cloud comparison (M3C2)

The results of the Multiscale Model-to-Model Cloud Comparison (M3C2) are summarized in Table 5.3. The mean distance between the winter and spring point clouds was -0.004 m, with a standard deviation of 0.035 m, showing that on average, no systematic displacement was recorded between the two datasets. The standard deviation of distance, on the other hand, showed a higher variability, with a mean value of 0.295 m and a standard deviation of 0.070 m. This value represents local variations in surface geometry. Coverage was high across all plots, with an average of 98.41%, showing that most of the plots' area was included in the comparison. The RMSE had a mean value of 0.297 m, showing a general level of difference between the two point clouds. Overall, the results show small average changes but some variability at the local scale.

Table 5.3. Summary statistics of the M3C2 point cloud comparison.

Parameter	Mean $\pm$ Standard Deviation	Minimum value	Maximum value	Range
Distance (m) ¹	-0.004 $\pm$ 0.035	0.151	0.435	0.284
Standard deviation of distance (m)	0.295 $\pm$ 0.070	0.151	0.435	0.283
Coverage (%) ¹	98.41 $\pm$ 1.448	92.56	99.90	7.34
RMSE of point cloud alignment (m)	0.297 $\pm$ 0.071	0.063	0.353	0.290

Note: ¹ – variable for which normality assumption was violated.

The core points (CP) and valid points (VP) used in the M3C2 comparison ranged from approximately 9.57 to 22.57 million points (CP) and from about 9.56 to 21.95 million points (VP) in the datasets. Median values for distance and coverage were -0.0036 m and 98.83%, respectively (see Table 5.3).

5.3 CONCLUSIONS

The two methods, C2C and M3C2, are consistent in comparing point clouds obtained in different seasons, enabling the assessment of structural changes in forests. C2C offers a general and uniform representation of the point cloud, while M3C2 represents local variations in greater detail. It can be inferred that the choice of method depends on the objective of the analysis. Point density, occlusion, and noise affect the accuracy of the comparison metrics. It is evident that the M3C2 is more robust to these factors. Some limitations of the study include the fact that it is applicable only to a limited set of forest ecosystems and two seasons. It is recommended to extend the scope to other ecosystems and seasons. The results provide a methodological basis for the selection of comparison techniques in multi-temporal forest inventories, contributing to improving the reliability in the structural monitoring of forests.

CHAPTER 6. CONCLUSIONS. ORIGINAL CONTRIBUTIONS. DISSEMINATION OF RESULTS

6.1. CONCLUSIONS

This thesis aimed to explore the potential of portable and mobile LiDAR technologies, including smartphone-based applications, for forest inventory. The work was based on a review of the state of the art and a series of experimental studies that evaluated the accuracy and efficiency of these technologies under various forest conditions. Their ability to complement or even replace traditional field methods was also analyzed. The key conclusions are presented below, organized according to the specific objectives of the thesis:

1. Review of mobile and low-cost LiDAR technologies for forest inventories (O1): These tools are rapidly developing and combine precision and efficiency. Emerging technologies, such as smartphone-based applications, can change the way data is collected in the field. They enable faster and more accessible forest monitoring, particularly in contexts with limited resources.

2. Accuracy of the TreeScanner application in estimating tree-level biometric parameters (O2): The TreeScanner application proved accurate for estimating diameter at breast height (DBH) and tree height across different forest ecosystems, with low bias. This validates its use for conducting tree-level inventories where speed and simplicity are important.

3. Comparison of mobile application and professional LiDAR systems in terms of temporal efficiency and basal area estimation (O3): The mobile application significantly reduced field data collection time compared to conventional methods and, in many cases, even outperformed professional LiDAR systems, particularly for basal area estimation. This time advantage is critical in complex terrains or when rapid inventories are needed.

4. Effect of seasonal variation on basal area estimation (O4): Seasonal conditions affected the accuracy of basal area estimates. The best results were obtained during leaf-off periods (winter), when trunk visibility was optimal. During leaf-on periods (spring), measurements were influenced by canopy cover and vegetation density, although the application still provided reliable estimates.

5. Comparison of point clouds using C2C and M3C2 methods (O5): Both methods were useful for detecting structural differences between mobile and professional LiDAR point clouds. M3C2 provided more stable results under complex conditions, while C2C was better suited for obtaining general structural overviews. These methods have complementary applications depending on the level of detail required. In summary, this thesis shows that portable and mobile LiDAR technologies, including smartphone-based LiDAR, represent a promising and viable tool for improving forest inventories. These technologies offer a good balance between accuracy, efficiency, and cost. However, it is important to consider their limitations, such as the dependence on field conditions and seasonal variability. Future work could focus on improving accuracy in environments with dense vegetation and integrating these systems with other technological platforms, such as drones and satellites, to overcome current limitations and expand their applicability in different forest contexts.

6.2. ORIGINAL CONTRIBUTIONS

The original contributions of this work focus on how mobile LiDAR technologies can complement or even replace traditional field measurement methods, improving both data accuracy and operational efficiency in forest management. Throughout the five chapters that make up this thesis, topics range from comparative evaluations of mobile LiDAR systems versus professional sensors to the analysis of the impact of phenological conditions on measurements, including the validation of mobile applications for estimating dendrometric parameters. The contributions of each chapter are detailed below, followed by a discussion on the limitations of the work and the future lines of research necessary to advance in this field.

Chapter 1 – Review and Evaluation of Low-Cost Mobile LiDAR Technologies for Forest Inventories:

The main contribution of this chapter lies in synthesizing recent advances in the use of mobile LiDAR in forest inventories, with a special focus on comparing low-cost technologies with professional sensors. Although these topics have been previously covered by other authors, their integration and comparative analysis had not yet been performed. The research demonstrates that the use of mobile equipment with

LiDAR integrated in it (e.g., smartphones) provides the same level of technical reliability as traditional methods, but with the advantage of significantly reducing field measurement time. Additionally, the study analyzes the effects of phenology on measurement precision and concludes that the period without leaves is the best time for measurements. The contribution also emphasizes the importance of mobile applications with instant processing capabilities, which facilitates on-site decision-making and eliminates logistical barriers to post-processing data. Finally, the need to adopt hybrid workflows that integrate mobile LiDAR with other aerial systems for more comprehensive forest coverage is proposed, suggesting that these technologies are at a stage of maturity that can transform forest inventories into a more accessible and scalable digital infrastructure.

Chapter 2 – Evaluation of the Accuracy of the TreeScanner Application in Various Forest Ecosystems:

This study is an original contribution by providing empirical evidence that the TreeScanner application can offer accurate measurements of DBH and tree height in various forest ecosystems, with high concordance with conventional methods. The results show that the application can accurately measure DBH at sub-centimeter level and tree height at sub-meter level, which is an important advancement, as LiDAR mobile applications have not been considered sufficiently accurate to perform such detailed measurements in the past. This study provides empirical validation for the possibility of utilizing mobile devices to accurately capture the variability inherent in conventional measurements and provides a more accessible and economical option for field data collection. Additionally, it highlights the importance of conducting further research of the application of this technology in different kinds of forests, particularly in the denser ones.

Chapter 3 – Evaluation of the Accuracy and Temporal Efficiency of the Mobile Application for Basal Area Estimations:

The contribution of this chapter is significant in demonstrating that LiDAR mobile applications, such as the one tested in this study, can provide accurate basal area estimates at the plot level with notably improved time efficiency. Compared to professional systems, the mobile application showed a considerable reduction in measurement time per tree, which implies an increase in operational efficiency and a reduction in costs for forest inventories. Although the application showed outstanding performance, areas for improvement were also identified, especially in the integration of additional parameters and in the expansion of its validation across a greater variety of forest ecosystems. This contribution not only demonstrates how mobile applications can complement traditional methods but also highlights the potential of these technologies to offer more economical and accessible alternatives in forest monitoring.

Chapter 4 – Effect of Seasonal Variation on Basal Area Estimates Using Mobile LiDAR:

This chapter makes a novel contribution by proving that the influence of phenological factors, particularly the presence or absence of foliage in trees, plays an important role in determining the effectiveness and precision of the measurement process using mobile LiDAR technologies. The results show that mobile LiDAR is more efficient and accurate during the leaf-off period. This chapter highlights the importance of considering phenology when planning forest inventories. The research also suggests the possibility that mobile LiDAR may have practical applications in difficult environments, such as mountain forests, in contrast to traditional measurements that are less efficient in this setting. Additionally, the best periods for conducting inventories were identified, which can optimize work times and the quality of the data collected under different conditions.

Chapter 5 – Comparison of C2C and M3C2 Methods for Point Clouds in Multitemporal Forest Monitoring:

This chapter presents a key methodological contribution by providing a detailed comparison between the C2C and M3C2 methods in the context of multitemporal forest monitoring. The research shows that while the C2C method offers a more uniform overview of the point cloud, M3C2 allows for a more detailed representation of local variations in forest structure. This is highly important from a practical point of view since it can be necessary for forest managers to select one of these methods based on the goals of forest monitoring. Additionally, the effects of point density, occlusion, and noise on the accuracy of the results are analyzed, which enhances the reliability of multi-temporal monitoring under various forest conditions. This contribution not only enhances the understanding of point cloud comparison techniques but also provides a methodological basis for improving the reliability of forest inventories over time.

Limitations and future research directions

Despite the contributions of this thesis, there are certain limitations that need to be highlighted. The studies were conducted in a limited number of ecosystems and specific conditions, which restricts the ability to generalize the results to other areas. Moreover, measurements in complex terrains or dense forests still present challenges that require further research. Future lines of research include increasing the scope of field testing with mobile LiDAR in various forests and under different phenology conditions, as well as incorporating new technology like artificial intelligence in the process.

6.3. DISSEMINATION OF RESULTS

6.3.1. Scientific publications based on this PhD thesis

A. Papers published in BDI journals

1. **Morocho Toaza, J. M.** (2026). Low-cost and mobile LiDAR technologies for forest inventory: A review on accuracy, efficiency, and multi-temporal monitoring potential. Accepted to be published in Bulletin of the Transilvania University of Brasov. Series II: Forestry• Wood Industry• Agricultural Food Engineering. (Accepted). Journal indexed in databases Scopus.
2. **Morocho Toaza, J. M.** (2026). Comparing point clouds using C2C and M3C2 algorithms in diverse forest ecosystems. Submitted to *Revista Pădurilor* (in review). Journal indexed in CABI and RePEc.

B. Papers published in journals indexed by Clarivate Analytics (former ISI Web of Science)

1. **Morocho Toaza, J. M.**, Picchi, G., Nati, C., Borz, S. A. (2025). Accuracy and time efficiency of a new app developed to source and map single-tree data: a comparison to state-of-the-art lidar data collectors in terms of basal area estimates. *Ecological Informatics* 91. 103417. DOI: <https://doi.org/10.1016/j.ecoinf.2025.103417>. *Ecological Informatics* is a peer-reviewed, Q1 journal indexed by Web of Science. Link Web of Science <https://www.webofscience.com/wos/woscc/full-record/WOS:001567319900001>.
2. **Morocho Toaza, J. M.**, Elias, M., Alfaro, V. D. S., Naiman, D. E., Musca, C. D., Picchi, G., Nati, C., Forkuo, G. O., Borz, S. A. (2026). Accuracy of tree scanner app in sourcing tree-level biometrics: A case study based on data from diverse forest ecosystems. Submitted to *Annals of Forest Research* (in review). *Annals of Forest Research* is a peer-reviewed, Q1 journal indexed by Web of Science.
3. **Morocho Toaza, J. M.**, Borz, S. A. (2026). Seasonal performance in basal area estimation: A comparative study of a smartphone lidar application and a professional personal laser scanning. *Frontiers in Forests and Global Change* 9. 1844787. DOI: <https://doi.org/10.3389/ffgc.2026.1844787>. *Frontiers in Forests and Global Change* is a peer-reviewed, Q1 journal indexed by Web of Science.

6.3.2. Papers presented at scientific conferences based on this PhD thesis

A. Papers presented at national scientific conferences

1. **Morocho Toaza, J. M.**, Borz, S.A., 2024. Applications of LIDAR, UAV Remote Sensing and Digital Twinning Technologies in Forest Engineering. Graduates in Front of Companies (AFCO) 2024. National conference contribution. Available online at: https://afco.unitbv.ro/2024/images/Documente/AFCO_2024_Lucrari_inscrise_.pdf
2. **Morocho Toaza, J. M.**, Borz, S.A., 2024. Applications of LIDAR, UAV Remote Sensing and Digital Twinning Technologies in Forest Engineering. DoCo2024. National academic conference presentation. Available online at: <https://www.unitbv.ro/en/research/doctoral-studies/2024-doctoral-conference.html>. Conference program details are available online at: https://www.unitbv.ro/Detailed_Programme.pdf

B. Papers presented at international scientific conferences

1. **Morocho Toaza, J. M.**, Borz, S.A., Elias, M., Forkuo, G.O., Picchi, G., Nati, C. (2025). DIGIFOR – A project setup to collect and document multi-temporal plot-level LiDAR data. Book of Abstracts: Proceedings of the 57th International Symposium of Forest Mechanization (FORMEC), Finland. International symposium contribution. Available online at: <https://erepo.uef.fi/server/api/core/bitstreams/2dd5580c-e499-4590-a04f-aebea21969d4/content>