Bulletin of the *Transilvania* University of Brasov
Series II: Forestry • Wood Industry • Agricultural Food Engineering • Vol. 19(68) No. 1 – 2026
https://doi.org/10.31926/but.fwiafe.2026.19.68.1.3

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

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Abstract: *Accurate information on forest structure is essential for sustainable forest management, carbon accounting, and ecosystem monitoring. Traditional field-based forest inventory methods are labour-intensive, time-consuming, and have low temporal resolution. Advances in technology (specifically, Light Detection and Ranging, or LiDAR) – specifically mobile and low-cost systems of LiDAR - present new opportunities to conduct forest measurements with greater efficiency and repeatability. This study employs a systematic literature review of the application of mobile and consumer-grade LiDAR technology for conducting inventory of forests, with focus on their accuracy and effectiveness in quantifying key dendrometric variables and their capacity as tools for multi-temporal monitoring. The literature search utilised the PRISMA 2020 framework and was conducted using the PECO framework, identifying studies published between 2015 and 2026. The results show that mobile LiDAR systems, including handheld and smartphone-based systems, can be used to obtain reliable estimates of relevant dendrometric attributes, particularly DBH, under appropriate conditions. Additionally, these technologies improve data collection efficiency in comparison to traditional forest inventory methods; however, they still have limitations regarding the estimation of total tree height due to canopy obstructing measurements and the inability of sensors to measure tree height. The performance of measurement is affected by environmental and operational factors such as seasonal conditions, the density of point clouds, the characteristics of species, and the strategies used to scan. Potentially, the analysis of point clouds over multiple time periods can be used to detect changes in structure; however, the reliability of the analysis is dependent upon data quality and accurate registration relative to one another. Overall, mobile laser scanning with LiDAR is a promising alternative to traditional inventory methods in forestry.*

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Key words: *mobile LiDAR, forest inventory, smartphone LiDAR, point clouds, SLAM, forest monitoring, dendrometry, multi-temporal analysis.*

1. Introduction

Accurate and up-to-date information on forest stand structure is essential for sustainable forest management, carbon accounting, and ecosystem monitoring across multiple spatial scales [47], to name just a few of its applications, whereas inventories are the main source of information regarding the structure of forests [34]. For many years, forest inventories have been carried out through measurements taken from sample plots using tools for measuring trees manually, such as diameter tape, callipers, and hypsometers [13, 44, 58].

Though such an approach has been widely used in various countries for applications such as national forest inventories (NFIs) and other research purposes, there are several limitations of using conventional methods [34]. For instance, they are considered labour-intensive, time-consuming, and prone to measurement errors, as well as subjective in estimating some of the critical parameters such as diameter at breast height (*DBH*) and tree height (*H*) [26, 44, 62]. Small inaccuracies in measuring tree parameters can result in large uncertainties in forest stand-level information on biomass and carbon pools [30]. Another major limitation of conventional methods is their restricted temporal resolution [35]. Field campaigns are commonly conducted in cycles of five to 10 years, which constrains the capacity to detect short-term structural changes caused by growth processes or disturbance events [25, 47]. However, forests are highly dynamic systems in which structural attributes may change rapidly due to phenological dynamics, extreme weather events, fires or snow damage [11, 25, 36]. Consequently, there is an increased need to find methods that are faster, reliable, repeatable, and accessible.

Recent developments in Light Detection and Ranging (LiDAR) technology have enhanced the techniques available for carrying out forest inventories, and Terrestrial Laser Scanning (TLS) has emerged as one of the most accurate ways of obtaining a detailed three-dimensional representation of forest structure [22, 39, 40, 65]. TLS instruments can produce dense point clouds that allow precise measurement of tree geometry and stand structure [4, 34]. Nevertheless, their operational efficiency in forest environments remains limited due to the need for multiple scan positions, target-based registration, and relatively time-consuming field procedures [4, 33, 34, 48].

To remove some of these limitations, mobile and handheld laser scanning technologies have been developed. Handheld Mobile Laser Scanning Technology uses SLAM to create 3D environments as the user walks in the forest [17, 66]. Mobile laser scanning technology has been proven to increase the speed of acquisition in different forest environments [10, 32, 54]. This technology has been shown to be more efficient in comparison to the use of conventional TLS while providing comparable or improved accuracy [17]. When comparing mobile laser scanner (MLS) technology to terrestrial laser scanner (TLS) technology, MLS is many times more efficient and retains the ability to detect the trees in the sampled plot locations [10, 17].

Another important technological advancement was the integration of LiDAR sensors into consumer mobile devices like the iPhone and iPad Pro, which allowed for the capture of three-dimensional point clouds using relatively low-cost hardware [17, 24]. These solid-state time-of-flight (*ToF*) sensors typically have an effective range of approximately five metres and therefore require close-range measurements [16]. Nevertheless, they enable rapid digital acquisition of point clouds while maintaining measurement protocols similar to traditional field inventories under suitable conditions [46]. Several mobile applications have been developed to support these measurements [6, 57]. For example, Arboreal Forest helps to measure tree characteristics through augmented reality [6, 24], while ForestScanner helps to quickly conduct tree inventories at the plot scale using mobile devices [13, 24].

Studies conducted between 2020 and 2026 also examined the efficiency of these low-cost LiDAR technologies and smartphone apps in forest measurements. The precision in measuring *DBH* has been reported to vary between 1-3 cm in terms of root mean squared error (*RMSE*), and some level of under- and overestimation has been noted [16, 49, 61]. In addition, notable improvements in field efficiency have been observed, including a decrease in the time required to collect the data (which has been reported to be more than 70% in specific circumstances) compared to conventional measurements in medium-sized plots [10, 13]. However, some limitations have been observed in the quality of LiDAR-measured data, such as occlusion, variation in point cloud density, differences between leaf-on and leaf-off campaigns, which might be affected by specific circumstances [13, 28, 63, 66].

Despite these advances, several knowledge gaps have remained. Most studies investigate specific cases or devices, and only a limited number of studies offer a comprehensive overview on low-cost LiDAR technologies applied in forest inventories, referring to consumer-grade devices such as smartphones and tablets, in contrast to professional tools [1, 6, 35, 57]. The performance of these technologies strongly depends on forest conditions and the protocols applied. Results reported in the literature vary in terms of *DBH* measurement accuracy, detection rates, and multi-temporal structure analysis, depending on forest type, seasonal conditions, and scanning protocol [20, 55]. Although there are studies addressing these topics, comprehensive comparative evaluations are limited: (1) the comparative accuracy and efficiency of consumer-grade LiDAR systems relative to professional sensors and traditional inventory methods [20, 24]; (2) the influence of seasonal conditions, such as leaf-on and leaf-off periods, on tree detection and measurement accuracy [28, 66]; and (3) the potential of multi-temporal point cloud comparison techniques, including algorithms such as C2C, DoD, and M3C2, for detecting structural changes and growth dynamics in forests [55]. Despite previous studies, the availability of an integrated analysis remains an area that requires further research.

Therefore, the objectives of this systematic review are to: *i)* synthesise the advances in using handheld mobile laser scanners and LiDAR applications with smartphones in forest inventories; *ii)* assess how accurately and efficiently these technologies perform as compared to traditional and professional-specific methods; *iii)* identify the main factors influencing point cloud quality and dendrometric measurement performance; and *iv)* describe the current limitations of technology related to the integration of low-cost LiDAR systems within national forest inventories while recommending future opportunities for integrating these systems.

2. Materials and Methods

2.1. Inclusion and Exclusion Criteria

The study adopted a systematic literature review method to summarise the existing knowledge on the technical and operational performance of mobile, low-cost LiDAR technologies (Figure 1). The systematic review process was conducted according to the PRISMA 2020 statement for transparent reporting of systematic reviews [45].

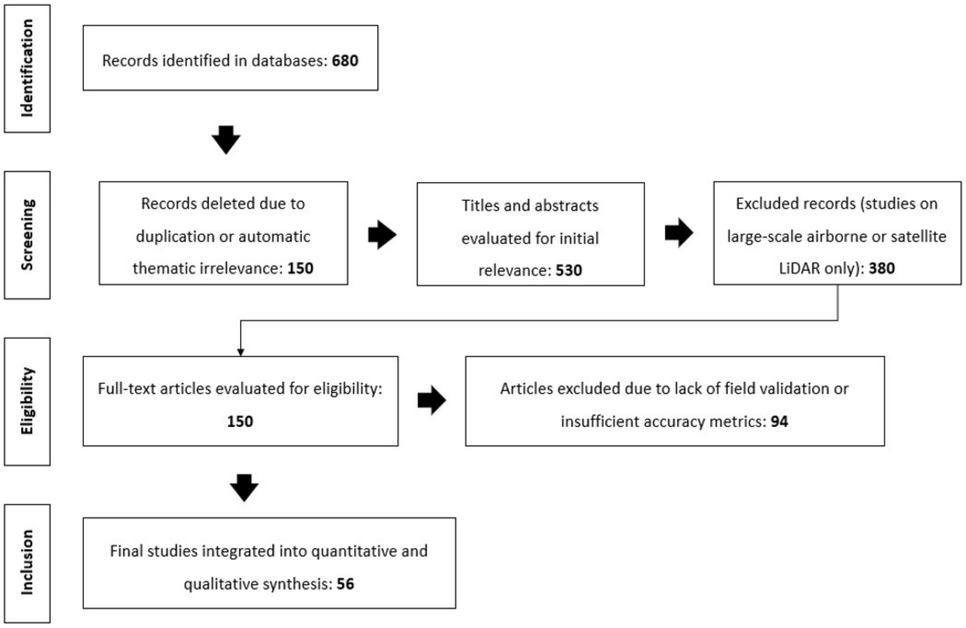

Fig. 1. *PRISMA flow diagram of the selection process.*

The methodology was designed to ensure reproducibility, transparency, structured and transparent evidence synthesis in accordance with established systematic review practices. To ensure the relevance of the analysed studies for the forest inventory applications, eligibility criteria were defined using the PECO framework (Population, Exposure, Comparator, Outcome, Table 1), which is widely used in environmental and ecological systematic reviews [21].

2.2. Search Strategy

The literature review was done in four major databases frequently used for forestry and remote sensing research: Scopus, Web of Science (WoS), IEEE Xplore, and Google Scholar. These databases were selected to maximise coverage of both peer-reviewed forestry research and technical publications related to LiDAR technologies.

The search strategy combined keywords related to LiDAR technologies, forest inventory applications, and performance evaluation metrics, with tree height being implicitly included within broader terms such as “forest mensuration” and “tree measurement”. Boolean operators were used to construct the final search string. The search query used to retrieve relevant documents was the following: (*"handheld LiDAR" OR "personal laser scanning" OR "mobile laser scanning" OR "smartphone LiDAR" OR "iPhone LiDAR" OR "mobile app" OR "ForestScanner" OR "Arboreal" OR “TreeScanner”) AND ("forest inventory" OR "tree measurement" OR "basal area" OR "DBH" OR "forest mensuration") AND ("accuracy" OR "precision" OR "efficiency" OR "time" OR "seasonal" OR "phenology" OR "multitemporal" OR "point cloud comparison" OR "C2C" OR "M3C2").*

Inclusion and exclusion criteria used in the systematic review Table 1

Criterion	Inclusion	Exclusion
Population	Forest ecosystems including natural forests, managed stands, plantations, and urban forests.	Agricultural crops, greenhouses or non-forest vegetation.
Exposure	Use of mobile or handheld LiDAR systems, including personal laser scanning (PLS), backpack mobile laser scanning (BPLS), and LiDAR-enabled smartphones or tablets.	Studies using airborne LiDAR (ALS) and satellite LiDAR were excluded. Static terrestrial laser scanning (TLS) studies were excluded unless they were used as a reference benchmark for accuracy assessment.
Comparator	Comparison with reference measurements, such as traditional field inventory methods (diameter tape, hypsometer, calliper) or professional TLS systems.	Studies lacking ground-trut measurements or validation data
Results (Outcomes)	Quantitative metrics such as DBH RMSE, height RMSE, bias, tree detection rate, acquisition time efficiency, seasonal effects, or point cloud comparison methods (C2C, M3C2, DoD).	Studies focusing exclusively on visualisation, software workflows or algorithm development without accuracy metrics.
Type of study	Peer-reviewed journal articles and relevant international conference proceedings.	Editorials, book chapters, opinion papers or previous literature reviews.
Time window	Publications between 2015 and 2026.	Studies published before 2015 (except foundational references used for contextual background).

The literature searching process was conducted between January and March 2026, covering studies published between 2015 and 2026, a period corresponding to the emergence and rapid development of mobile and low-cost LiDAR technologies that define the scope of this review. References were compiled manually and organised in alphabetical order, and duplicate entries were removed. The literature searching process was limited to title, abstract, and keywords, as far as possible, in order to enhance their relevance.

2.3. Selection Process

The selection of studies was based on the four-stage approach of the PRISMA framework, which includes study identification, screening, eligibility, and inclusion [45]. The following four phases of study selection were adopted in this review:

1. identification – the initial number of studies identified in the databases was 720. However, after excluding 40 duplicate studies, a total of 680 studies were identified for the next step;
2. screening – the titles and abstracts were checked to determine suitability in terms of relevance to forest inventory and mobile LiDAR technology. In this phase, 380 references were removed, since they exclusively discussed airborne LiDAR, satellite remote sensing, and non-forest related issues;
3. eligibility – the full texts of 150 potentially relevant articles were evaluated against the predefined inclusion and exclusion criteria. Excluded studies were those without field validation, quantitative accuracy metrics or those that dealt only with methodological development without any practical application to the forest environment;
4. inclusion – after eligibility checking, 56 studies met all the criteria to be included in the final qualitative synthesis with quantitative support. The final set of 56 studies consists exclusively of primary research articles, while previous systematic reviews were used only for contextual purposes and were not included in the final dataset.

2.4. Data Extraction and Quality Assessment

For each selected study, relevant information was systematically extracted and organised in a structured data matrix. The extracted variables were selected to enable comparisons between different LiDAR technologies and forest inventory contexts. The following variables were extracted and systematically added to the database:

1. study reference – author and year;
2. LiDAR technology category;
3. device or sensor type;
4. forest ecosystem type;
5. tree species composition;
6. plot size;
7. number of trees measured;
8. DBH accuracy metrics – RMSE and bias;
9. tree height accuracy;
10. tree detection rate;
11. data acquisition time or efficiency;
12. environmental or seasonal conditions (leaf-on / leaf-off).

This structured dataset enabled both qualitative comparisons and quantitative synthesis across studies.

2.5. Quality Assessment

The methodological quality of each study was assessed using an adapted version of the Mixed Methods Appraisal Tool (MMAT) [23]. This approach is commonly used in systematic reviews involving heterogeneous methodological designs. Three main criteria were evaluated:

1. methodological rigour – clarity of experimental design and measurement protocol;
2. sample representativeness – adequacy of the number of plots or trees measured;
3. ground-truth reliability – use of reference measurements for validation such as traditional field inventory methods or high-precision TLS data.

Each criterion was scored using a three-point scale, from 0 to 2, where 0 stands for low methodological quality, 1 stand for moderate methodological quality, and 2 stands for high methodological quality. The resulting scores were calculated as the mean value across all criteria for each study and were used to assess the overall reliability of the evidence base included in the review.

2.6. Synthesis of Results

The synthesis of results was conducted in a narrative and quantitative manner. The findings were grouped by technological platform to allow direct comparisons of efficiency and accuracy. Figures were developed to show the temporal evolution of the publications (with a notable increase starting in 2020) and the comparative tables of forest inventory metrics to identify acceptable precision thresholds according to the type of inventory.

3. Results

3.1. Characteristics of the Analysed 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 [29, 40]. The investigations followed the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) and were designed to ensure 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, as well as the 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 centres for innovation in personal laser scanning (PLS) systems and mobile-device-based applications (Figure 2). 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 utilisation of these systems.

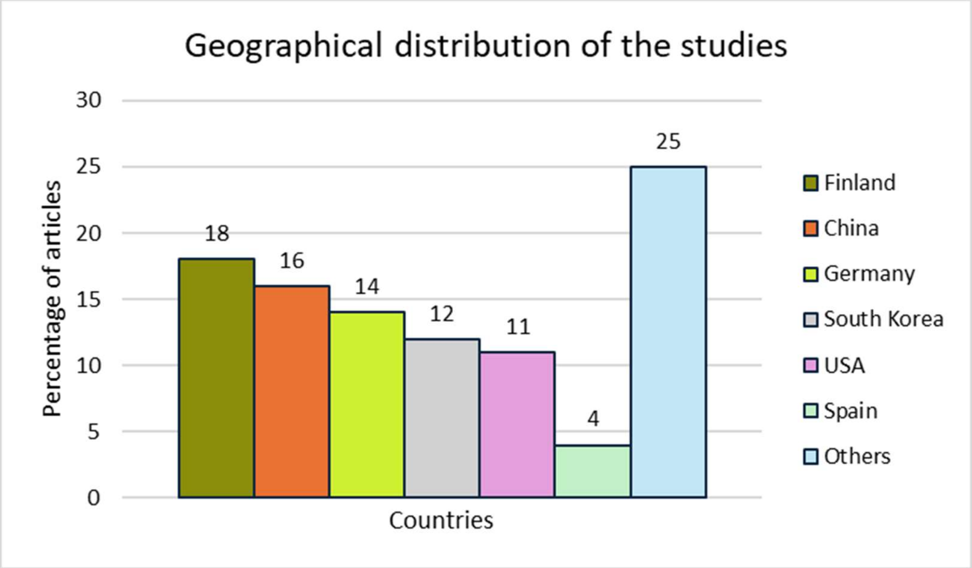

Fig. 2. *Distribution of studies on PLS and mobile LiDAR technologies by country (2015-2026), showing a strong concentration in technologically advanced countries. Note: The rest of the data aggregates countries with 1–2 studies each*

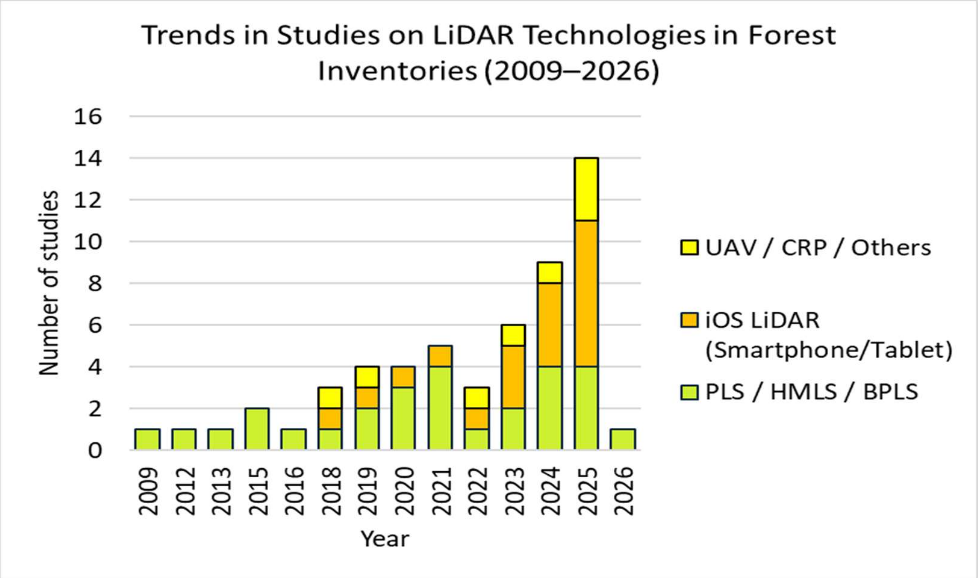

Fig. 3. *Temporal distribution of reviewed studies by platform used (n = 56), illustrating the post-2020 increase in mobile LiDAR studies. Note: Studies may appear in more than one category if multiple technologies were used. Data was extracted from the selected 56 studies following the PRISMA methodology*

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 [4, 34, 56]. From 2020 onward, 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, as shown in Table 2 [15, 29, 61]. This temporal evolution of studies according to the platform used is summarised in Figure 3. 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.

3.2. Evolution and Mobile Scanning Technologies

In the forestry sector, LiDAR technology has evolved from high precision, stationary lasers that utilise 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 [1]. PLS systems have been developed as a solution to limitations associated with terrestrial laser scanning (TLS): although TLS provides millimetre level accuracy, it introduces large amounts of occlusion and requires a time-consuming setup process on rough terrain [1, 4, 33].

3.3. Timeline of Technological Transformation

Due to the reduced size of the 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 digitisation 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 characterised by millimetre accuracy and rather low operational efficiency due to the necessity to set up several systems [8, 33, 38]. 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 [4, 48]. Then, in the 2015-2017 period, progress focused on the development of the ZEB-REVO and ZEB-REVO-RT systems, incorporating real-time visualisation of scan data and improving the robustness of point clouds [10]. In 2019 the ZEB Horizon was introduced, which extended the scanning range up to 100 m and made it possible to capture detailed information from the upper canopy [17]. The period 2020–2021 stands for a democratisation milestone, since Apple Inc. equipped 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 [16, 37]. The following period, spanning approximately from 2022-2023, was characterised 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 [6, 20, 24, 57].

Summary of the characteristics of the studies included (n = 56) Table 2

Dimension of analysis	Category	Frequency	Technical details / Notes
Time distribution	2015-2019	10 studies (18%)	Period of validation of heavy PLS prototypes and early-stage SLAM algorithms
	2020-2026	46 studies (82%)	Period of wide adoption - rapid adoption of LiDAR on iOS devices following its integration in 2019 iPhone models
Technology platform	Personal laser scanning (HMLS / PLS / BPLS)	25 studies (45%)	Professional systems (ZEB Horizon, Stonex) and prototypes (Mandeye, Mid-360)
	LiDAR on smartphones / tablets (iOS LiDAR)	21 studies (37%)	d-ToF sensors on iPhone/iPad; use of apps such as ForestScanner and Arboreal
	Close-range photogrammetry (CRP) and Computer Vision	10 studies (18%)	Terrestrial photogrammetry and Structure from Motion-based workflows
Countries with the highest number of studies on PLS and mobile LiDAR technologies	Leading countries	42 (75%)	Concentration in Finland, China, Germany, South Korea, the U.S., and Spain
	Rest of the world	14 (25%)	Studies in Slovakia, Canada, Romania, Thailand, Switzerland, Italy, Japan, and others
Ecosystems evaluated	Mixed / natural forests	25 (45%)	Focus on structural complexity and canopy occlusion effects
	Plantations (conifers / broadleaves)	22 (39%)	High-precision studies on the Picea, Pinus, Larix, and Eucalyptus genera
	Urban forests / parks	9 (16%)	Expedited inventories of individual trees and green infrastructure management
Dendrometric Variables	Diameter (*DBH*)	56 (100%)	Key variable; reported RMSE values typically range between 1 and 3 cm depending on the device and conditions
	Total height (*TH*)	42 (75%)	Limited by the 5 m range on smartphones; systematic negative biases in MLS

Note: Frequency (*n*) and percentages are derived from the final sample of selected studies (n = 56) after applying the PECO inclusion criteria and the PRISMA method. The technology categories include both professional-grade equipment and low-cost prototypes. The sum of the evaluated variables may exceed the total number of studies due to studies that report multiple dendrometric parameters simultaneously.

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 [2, 61].

3.4. Technical Comparison: Professional PLS versus 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 [59, 60]. In contrast, smartphone-based LiDAR sensors (including the 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 [19, 60]. Despite these differences in operational range and point density, both professional PLS instruments and smartphones with LiDAR sensors can utilise advanced point cloud comparison techniques (such as M3C2) to identify structural changes in forests over time, providing higher accuracy than traditional methods [31, 64]. A detailed comparison is provided in Table 3.

Technical Comparison: PLS versus Smartphone LiDAR Table 3

Feature	Personal Laser Scanning (PLS)	Smartphone/Tablet LiDAR
Measurement principle	High-performance SLAM (LiDAR + IMU)	Short-range LiDAR + ARKit/ARCore
Effective range	30-100 metres (depending on model)	5-10 m (depending on model and app)
Range accuracy	±1-3 cm	±3-5 cm
Point density	Very high (>300,000-1.2 M pts/sec)	Medium-Low (depends on the app and AR)
Approximate cost	$15,000 - $50,000 + USD	$800 - $1,500 USD
Processing	Traditional / real-time post-processing in RT models	Instant processing using specialised apps
Limitations	High cost; weight; drift over long distances	Short range; obstruction by underbrush; battery consumption

Note: The comparison is based on this systematic review evaluating accuracy, operational efficiency, and affordability. The ranges include both low-cost prototypes and high-end commercial systems. “Instant” processing on smartphones relies on specialised apps (e.g., ForestScanner, Arboreal Forest), and the flexibility of PLS has increased, as advanced models (ZEB-REVO-RT, Stonex X120GO) enable real-time visualisation and analysis on mobile devices, reducing reliance on post-processing on PCs.

3.5. Dendrometric Accuracy and Temporal Efficiency

3.5.1. 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 [4, 34, 54]. When measuring tree *DBH* using traditional methods, the measurement is taken at one location with a calliper [63]; 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 [57, 61]. A comparison is shown in Table 4.

Table 4

Comparison of measurement accuracy by technology and dendrometric variable

Sensor category	Variable	RMSE	Bias	R^2	Operational conditions	Sources
HMLS (professional)	*DBH*	1.11-1.92	-0.08 to +0.21	0.95-0.99	Dense deciduous/conifer forest; mixed terrain; standard plot sizes	[4, 34]
	TH	0.87-2.85	-2.34	0.71-0.97	Same forest types and terrain; canopy occlusion may affect height measurement	[3, 41]
LC-MLS (low cost)	*DBH*	1.40-3.50	+1.24 to +1.62	0.94-0.98	Semi-open forest; low-complexity terrain; handheld or mobile scanning	[3, 61]
	TH	0.36-2.47	-2.16	0.90-0.98	Same forest types; limited range may affect tree height	
Smartphone LiDAR	*DBH*	2.27-5.30	-0.15 to -2.49	0.84-0.98	Small plots; low canopy occlusion; short-range scanning; app-dependent	[16, 24, 53]
	TH	1.19-5.07	-3.52	0.89	Same plots; height estimation affected by occlusion and limited range	
Photogrammetry (CRP)	*DBH*	0.42-1.40	-0.01 to +0.28	0.99	Leaf-off conditions; high-resolution imagery; small/medium plots	[42, 61]

Note: *DBH* values (RMSE and Bias) are expressed in centimetres (cm), while tree height (*TH*) values are expressed in metres (m). All values are based on studies published between 2015 and 2026. Accuracy depends on device type, algorithm, and environmental conditions.

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 to limited coverage around the full circumference of the trunk [24, 53]. 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 metres for taller trees due to limitations in accurately capturing the true apex of the canopy [2, 41].

3.5.2. 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, as shown in Table 5 [32, 33]. The use of tablets and smartphones enables faster LiDAR data acquisition, reducing field time by approximately two to four times compared to traditional methods, depending on the study [43, 46, 59].

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 [57], while several studies report substantial reductions in labour requirements [29, 43]. Recent studies using the TreeScanner 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 [43]. This agility in operation allows for a higher sampling density to ensure the statistical representativeness of forest inventories at the stand level.

Data collection efficiency and inventory times Table 5

Method	Time per tree [second]	Time per plot add [minutes]	Improvement / advantage	Sources
Manual (tape)	55-70	20-32	Gold standard for reliability; labour-intensive	[13, 62]
TLS (static)	N/A	30-75	High accuracy; very slow due to multiple configurations	[18, 33, 34, 60]
HMLS / PLS	15-51	3.76-15	Up to 4.7x faster than TLS; reduces occlusion	[17, 29, 43, 46]
Smartphone (LiDAR App)	9-21	0.83-7.51	On-site processing; instant digitisation	[19, 20, 43, 57]

Note: TLS acquisition times include instrument setup and multiple scan positions. Reported times represent ranges across different forest conditions, including vegetation density, forest types, plot sizes, and levels of operator experience.

3.5.3. Seasonal Effects on Data Quality and Forest Detection

Seasonal environmental variability is recognised 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 [28] report tree detection rates of up to 100%, this figure drops dramatically during the growing season. Research done in dense stands [28] 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. [65] 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. [28], 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, RMSE increases due to interference from surrounding vegetation [28, 53, 65]. Tree height is the most sensitive variable. Wu et al. [65] 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. [28], the 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. [27] 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). Studies by Ko et al. [28] and Zhang et al. [67] 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. This also was noted by Holvoet et al. [22] and Zhang et al. [67] in structurally complex forests, as summarised in Table 6.

Seasonal effects on LiDAR-derived structural parameters (HMLS/PLS platform) Table 6

Parameter	Winter condition (leaf-off)	Summer condition (leaf-on)	Source
Detection rate [%]	High (100 approx.)	Moderate (81-90% approx.)	[28]
RMSE DBH [cm]	0.87-3.26	1.43-7.75	[28]
RMSE TH [m]	1.27-1.50	5.07-7.38	[65]
Ground visibility [%]	High (84% approx.)	Very Low (7-14% approx.)	[28]

Note: Ground visibility refers to the proportion of LiDAR pulses reaching the forest floor. Values vary with forest structure, leaf cover, and seasonal conditions.

3.5.4. 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 [28, 65]. 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 [28]. 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 subannual changes in tree structure and branch dynamics. This differs from multi-temporal LiDAR surveys, which are acquired seasonally or annually [5, 9]. Hyper-temporal monitoring may allow the detection of tree responses to environmental factors such as precipitation and temperature, allowing for more detailed forest monitoring.

3.6. Multi-temporal Point Cloud Analysis and Forest Dynamics

3.6.1. Algorithms for Multi-Temporal Comparison

The use of mobile LiDAR can provide a transformative way for forest inventories [5, 9]. The detection of changes depends on the accuracy of the algorithm applied and on the quality of point cloud registration and alignment between successive scans [50, 64]. 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 neighbour [7, 31]. 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 [7, 41, 64]. This approach is mainly suited for identifying large and sudden changes (typically greater than 0.5 m), such as tree removal or terrain displacement [50, 64]. The Multiscale Model-to-Model Cloud Comparison (M3C2) method has been widely accepted as a very reliable technique for monitoring forests [31, 50], since it measures distances between two-point clouds along their respective local surface normal, thus decreasing the potential effect of point density and creating a statistically valid threshold for detecting change [31, 64]. 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 modelling process to help reduce false positives in locations where the surfaces are highly complex or uneven [64]. A comparison is provided in Table 7.

3.6.2. Detection of Phenological Changes versus 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 [52]. Studies using hyper-temporal datasets show that these technologies can detect shifts in leaf phenology to within centimetres, including temporal differences among trees of the same species, up to approximately 12 days [5, 9]. 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 [5]. 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 [47]. 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% [47].

Comparison of multi-temporal detection capabilities by algorithm Table 7

Algorithm	Robustness to noise	Sign detection capability	Key Forestry Application and Source
C2C	Low (sensitive to point density)	No (absolute distance/unsigned)	Detection of large changes such as tree removal, mortality or major structural loss [7, 14, 31]
M3C2	High (uses local surface normal)	Yes (+ / -) (allows distinguishing growth/loss)	Monitoring of annual growth and phenology, detecting moderate structural changes [31, 64]
M3C2-EP	Very High (incorporates error propagation)	Yes (+ / -) (detects changes below noise level)	Detecting fine-scale changes and branch dynamics in complex structures [64]
DoD (2.5D)	Medium (limited to vertical projection)	Yes (+ / -) (height/DEM differences)	Large-scale height change and terrain/soil change detection [31, 50]

Note: Robustness to Noise refers to the algorithm's ability to handle variations in point density and sensor errors. Sign Detection Capability (+/−) means that the algorithm can distinguish between increases and decreases in volume or height. DoD stands for DEM of Difference (2.5D) and is limited to vertical changes. Forestry applications are typical examples, and actual accuracy depends on the quality of the LiDAR and the registration of the point clouds.

3.6.3. 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 [12, 50]. A typical level of detection (LoD95) for datasets that have been registered correctly is between 2-4 cm [50]. Differences smaller than this threshold are usually due to uncertainty in registration, noise from the sensor or external factors such as wind [50, 64]. 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 [3, 35]. 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 [35]. 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 [52].

3.6.4. 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 the 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 [41]. 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* (L.) or *Quercus petraea* [(Matt.) Liebl.], have a broader residual band in the point cloud, which often causes overestimation of the *DBH* in circle fitting algorithms [4, 22, 61]. Conversely, species with smooth bark, such as *Abies alba* (Mill.) or *Fagus sylvatica* (L.), present specific challenges for consumer-grade devices [61]. 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 [61]. 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 [4, 65].

The quality of SLAM mapping results is highly dependent on user behaviour and the geometry of the paths taken [10, 49]. 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 [18, 60]. The way people walk influences the angles at which objects are scanned and the uniformity of scene coverage [10, 15]. Ensuring multiple scanning angles around each tree, including circular or randomised 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 [16]. Finally, operator skill is critical to the overall success of the mission plan mainly due to professional user capabilities to provide effective scanning solutions in more dense or occluded landscapes [10, 49].

The accuracy of dendrometric variables depends on achieving minimum density thresholds. If point density falls below these thresholds, RMSE rises sharply, compromising the accuracy of the measurements. Point densities of between 600 and 700 points/m^3 are required to stabilise the error below 1 cm for *DBH* assessments [27, 61]. Densities below 200 points/m^3 result in incomplete stem profiles that may invalidate the automatic fit [27]. For tree height, the requirement is less restrictive, reaching a plateau in accuracy (*RMSE* < 1 m) starting at 300 points/m^3, provided that the sensor successfully captures the actual tree top [27, 61]. Table 8 provides a summary of the influencing factors and their effects.

Influencing factors and their impact on measurement quality Table 8

Determining factor	Impact on the point cloud	Dendrometric consequence	Sources
Rough bark	Increased surface noise	Overestimation of *DBH*	[4, 22]
Low texture (Smooth)	Instability in *ToF* alignment	Variable bias in smartphones	[61]
Drift	Geometric distortion of the plot	Cumulative positional error	[10, 60]
Low density	Incomplete stem profiles	Failure in automatic detection	[27]
Wind / Movement	Ghosting effect in tree crowns	Error in branch architecture	[52, 60]

4. Discussion

The technological transition from static terrestrial laser scanning (TLS) to dynamic platforms and consumer-grade devices represents the most significant paradigm shift in forest measurement over the past decade [4, 35]. The results of this review have shown that the accuracy gap between professional-grade systems and low-cost systems has significantly decreased for *DBH* measurement. Although smartphone-based LiDAR systems still exhibit higher variability compared to TLS, recent developments indicate that their accuracy has reached a level that can support operational forest inventory applications under appropriate conditions [15, 53]. This level of performance makes these tools increasingly applicable to operational forest inventory workflows, particularly in contexts where cost and efficiency are prioritised over millimetric precision [49, 61]. Nevertheless, system reliability is strongly influenced by SLAM algorithm performance and processing workflows, with applications such as ForestScanner or 3D Scanner App mitigating sensor limitations through real-time processing and augmented reality integration [16, 57].

A key operational advantage identified in the studies analysed is time efficiency. The capacity to digitise the entire plot in a fraction of the time required by conventional manual methods, depending on the forest conditions and workflow, compared to conventional manual processing, has transformed inventory from a laborious task to a streamlined digital acquisition [43]. In recent studies employing the TreeScanner app, effective measurement of a single tree was reported to take roughly 10-15 seconds, which is faster than the speed of professional PLS systems owing to the absence of complex in-office post-processing steps [43, 57]. However, this increase in productivity, does not resolve the problem of the tree height challenge. The evidence under consideration indicates a negative bias in terrestrial sensors, which may be up to 2 m or even higher in tall stands due to occlusion by the canopy and to the limited range of *ToF* sensors [2, 41]. Studies indicate that, under current technological constraints, ground-based mobile scanning is most effective when combined with complementary approaches in which airborne or UAV-based LiDAR systems capture the upper canopy structure [41, 51]. While tree height readings may be affected by occlusions in dense, multi-layered canopies, the results of [53, 57] indicate reasonable accuracy for mobile LiDAR apps. The study of Morocho et al. [43] reports very low bias, suggesting that mobile LiDAR applications are a viable option for measuring tree heights. Continued validation will include different forest types.

Data quality and metric accuracy are strongly influenced by phenological and environmental conditions affecting point cloud acquisition. Specifically, seasonal changes have been shown to significantly affect data quality, as well as tree metrics accuracy, from point clouds. Evidence consistently shows higher tree detection rates and improved *DBH* accuracy during leaf-off seasons, particularly in late autumn in temperate forests [5-28]. In contrast, dense understory vegetation and foliage during the growing season can obstruct laser penetration, reduce the number of usable stem points and increase noise levels that interfere with reliable cylinder fitting [22, 65]. Additionally, species-specific characteristics, such as bark roughness in *Pinus sylvestris* (L.), may introduce systematic overestimation of *DBH* when point densities fall below critical thresholds [4, 27]. Therefore, there is a clear need to develop standardised acquisition protocols that incorporate both acquisition trajectory and seasonal conditions to ensure consistent and comparable results.

In addition to serving as a traditional static inventory, these technologies have strong potential for multi-temporal monitoring and producing high-detail digital models of the changes within forest dynamics. Robust point cloud comparison techniques are essential for the detection of subtle changes in the structure of trees, including small branch movements and short-term growth [5, 9]. M3C2 is one of the most widely accepted methods among point cloud comparison techniques because it is less sensitive to point density changes and can identify statistically significant changes, even when using detection thresholds on the order of several centimetres [50, 64].

Even though significant advancements have been made in the area of applying LiDAR technology to forest inventory, many challenges remain (e.g., lack of standardisation with scanning approaches, and limited trials of low-cost sensors for complicated ecosystems such as tropical forests). Looking ahead, further integration of artificial intelligence and real-time processing capabilities is expected, improving on-device processing for smartphone-based applications and enabling a shift from stand-alone tools to integrated forest monitoring systems [32, 35]. To support the transition toward digital forest inventories, researchers should expand validation efforts to include deep learning models capable of handling noisy and occluded point cloud data [61]. At the organizational level, forestry practitioners and agencies should develop standardised data collection protocols and training procedures to reduce systematic drift in SLAM-based systems and improve measurement reliability [22, 29].

Technological development should prioritise real-time processing tools on the device (edge computing) and open-source architectures that support algorithmic transparency and interoperability. Finally, the maturity of the technology is expected to depend on the adoption of hybrid workflows, where the capability of mobile LiDAR for detailed stem mapping is combined with the panoramic coverage of airborne or drone-based LiDAR to capture the complete structure of the upper canopy. The reported ranges reflect heterogeneous studies with different forest types, acquisition protocols, and sensor configurations, and should therefore not be directly comparable.

This study synthesises results from various studies on professional and low-cost LiDAR systems [4, 35, 61]. It differs from previous reviews by focusing on the differences among device types, methodologies, and environmental factors, providing practical implementation guidance rather than only describing research findings. The paper integrates accuracy assessment with operational considerations, offering a framework for the effective use of mobile LiDAR technology in precision forestry.

5. Conclusions

The digitisation 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 democratisation 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.

Acknowledgements

The author would like to thank the Department of Forest Engineering, Forest Management Planning and Terrestrial Measurements, the Faculty of Silviculture and Forest Engineering, Transilvania University of Brasov, for providing the infrastructure required to carry out this study. The infrastructure refers to access to the scientific databases and software used throughout the study.

Funding

This study was supported by the SINTETIC project funded by the European Union's Horizon Europe research and innovation programme under grant agreement No. 101082051. This manuscript reflects only the author's views and opinions, and neither the European Union nor the European Commission can be considered responsible for them. Part of this work was supported by two grants of the Romanian Ministry of Education and Research, CNCS–UEFISCDI, project numbers PN-IV-P8–8.1-PRE-HE-ORG-2023-0141 and PN-IV-P8–8.1-PRE-HE-ORG-2024-0186, within PNCDI IV.

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