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Terrestrial and mobile laser scanning for national forest inventories: From theory to implementation

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ABSTRACT

Light Detection and Ranging (LiDAR) has emerged as an important data source for monitoring forest resources. Terrestrial laser scanning (TLS) and Mobile laser scanning (MLS) have already shown high potential in further advancing forest inventory development. By enabling the retrieval of new forest attributes in addition to traditional ones, these technologies could drive forest inventories into a new paradigm by introducing innovative approaches to measuring and monitoring forests. The debate on the possible implementation of TLS and MLS in forest inventories, particularly in national forest inventories (NFIs), continues in both the scientific community and the public institutions. To date, few studies have evaluated the application of TLS and MLS technologies in large-scale forest inventories or assessed their practical operational limits. In this practice-oriented paper, we first detail TLS and MLS data acquisition and processing for tree attribute estimation, assessing their maturity and main limitations. We then explore three European case studies—from the French, Finnish, and Swiss National Forest Inventories (NFIs)—where these technologies have been tested. Based on these experiences, we identify the main constraints and challenges for operational implementation. Lastly, we discuss the prospects for TLS and MLS within the NFI context and the requirements for their successful adoption. We conclude that TLS and MLS should be viewed not as a replacement for, but as a complement to and enhancement of, traditional NFI practices. Emphasis should be placed on the new opportunities these technologies offer, rather than on direct comparisons with conventional methods.

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1. Introduction

A forest inventory accounts for trees and their related characteristics of interest over a well-defined land area (Scott and Gove, 2002). The term forest inventory can refer to the action of measuring forest variables, the data collected from such measurements, or the information thus gathered (Tomppo et al., 2010). Forest inventory is central to forest resources assessment and monitoring (Corona et al., 2011). In assessing the extent, condition, and productivity of forest resources, forest inventories are essential for forest management. They encompass both the assessment and the regulation of forest ecosystem services and timber production (Vidal et al., 2016; Rondeux, 2021).

Forest inventories are realised by first sampling defined portions of a forest (i.e., sample-based inventory), called forest plots, and then extrapolating these observations to a forest stratum of interest, such as forest stands delineated and classified according to species and maturity class (Loetsch et al., 1973). Inventory design features, including sampling design, plot design, survey intervals, geographical extent, criteria for selection site, variables measured, and inventory threshold, vary depending on the overall objectives to be attained (Kleinn et al., 2002; Scott and Gove, 2002).

Many countries worldwide have put into place large-scale national forest inventories (NFIs) that follow standardised, efficient sampling protocols across their territories (Vidal et al., 2016). NFIs in Europe were first introduced in Nordic countries with Norway in 1919, Finland in 1921, and Sweden in 1923 (Gschwantner et al., 2022). Traditionally, forest inventory field measurements focused on a limited set of variables, referring to tree position and size, with an emphasis on evaluation of forest timber resources (Loetsch et al., 1973; McRoberts et al., 2010). These inventories maintained their traditional characteristics until around fifteen years ago, when growing concerns about biodiversity, forest health, carbon storage, and ecosystem services led NFIs to expand their scope to include measurements and variables beyond traditional dendrometric data (McRoberts et al., 2010). These variables, including measures of tree regeneration, forest diversity, sanitary state, carbon stock, and stem quality (Gschwantner et al., 2022), also yield information about multiple forest ecosystem services (Corona et al., 2011; Borghi et al., 2024). In addition, forest monitoring requirements drawn up by international bodies and frameworks, such as the Food and Agriculture Organisation (FAO), the United Nations Framework Convention on Climate Change (UNFCCC), the Intergovernmental Panel on Climate Change (IPCC), and the Convention on Biological Diversity (CBD), highlight the need for consistent and comparable data collected at national scale on the changing state of forests themselves and their ecosystemic roles as resource and service providers (Corona et al., 2011).

Since the early 2000s, remote sensing data have been used to support national forest inventories for observation or measurement (McRoberts and Tomppo, 2007). Satellite imagery was successfully applied to improve efficiency and add value to national forest inventory reporting (Tomppo and Katila, 1991), demonstrating potential for large-area forest inventories (Tomppo et al., 1994). Soon afterwards, data acquired from airborne sensors, such as profiling radar (e.g., Hyyppä and Hallikainen, 1996) and imaging spectrometers (Hyyppä et al., 2000), were also used to monitor forest areas. Light Detection and Ranging (LiDAR, also called laser scanning) was first investigated in forest inventory studies in the 1980s (Nelson et al., 1988) and emerged as the dominant data source for estimating forest resources (e.g., Hollaus et al., 2009; Disney et al., 2018). Major campaigns of LiDAR data acquisition from sensors mounted on aircraft (Airborne Laser Scanning, ALS) were conducted over large territories, soon making it the gold standard for both large-scale forest inventories (Kangas et al., 2018) and NFIs (e.g., McRoberts et al., 2010; Astrup et al., 2019). Integrating LiDAR data into NFIs enhanced statistical and economic efficiency by reducing the need for field-measured plots while meeting precision requirements. It also added value by yielding new results besides traditional inventory summaries and analyses (White et al., 2025).

Demand for the collection of more detailed plot and tree-level variables has grown in recent decades, impelled by the emergence of close-range sensing as a novel means of gathering field measurements. In particular, terrestrial and mobile LiDAR, i.e., Terrestrial Laser Scanning (TLS) and Mobile Laser Scanning (MLS), respectively, have gained popularity in forest inventory applications (Liang et al., 2018a,b; Donager et al., 2021). TLS systems are mounted on static tripods, whereas MLS systems are carried by vehicles, robots, or human operators. Here we limit the scope of MLS to applications involving the use of backpack-mounted and handheld laser scanning systems, also known as Simultaneous Localisation and Mapping (SLAM)-based MLS, as these are the commonest and easiest to use in forest inventory applications.

TLS and MLS allow a close-up scan of the forest scene from underneath the canopy with a higher point density than ALS (Lefsky et al., 2002; Watt and Donoghue, 2005). TLS and MLS have demonstrated high potential to advance forest inventories by offering new ways to characterise forest resources (Liang et al., 2016) and influence strategic, tactical, and operational planning (White et al., 2016). The impact of TLS and MLS has fuelled ongoing debate on their applicability and usability in NFIs, both within the scientific community and among forest inventory institutions (Harpold et al., 2015).

To date, most studies have examined the use of TLS and MLS to retrieve forest attributes and assess the accuracy of estimates (Maas et al., 2008; Liang et al., 2016; Liang et al., 2018a,b; Abegg et al., 2023). However, few studies have evaluated the practical implementation and operationalisation of TLS and MLS in large-scale forest inventories. Thies and Spiecker (2004), Liang et al. (2016), and Cristea and Jocea (2015) evaluated the potential use of TLS in forest inventory practices by reviewing the scientific literature, while Liang et al. (2014) and Krok et al., (2020)contributed to the debate by conducting new experiments. Although all these studies have brought TLS and MLS closer to operationality in forest inventories, they are still seldom deployed in large-scale surveys and NFIs, and very few studies have a national or international scope (Liang et al., 2018a). It is thus relevant to identify the main constraints limiting the use of TLS and MLS in NFIs to understand why their high potential has yet to be fulfilled.

This practice-oriented paper is a response to the paucity of real-world examples of TLS and MLS usage in NFIs. Here we describe three instances where TLS and MLS have been experimented with in the existing NFI context of France, Finland and Switzerland. Through these experiences, we address the following questions: (i) What is the estimated accuracy and precision of the forest inventory attributes commonly obtained from TLS and MLS data? (ii) What are the main operational constraints and the lessons that have emerged from the French, Finnish and Swiss NFI examples of TLS and MLS application? Based on the answer to these questions, we make suggestions and propose guidelines to help make TLS and MLS fully operational in future NFIs.

To address these two questions, we first describe the traditional and enhanced tree attributes retrievable from TLS and MLS data. Then, from critical evaluation of the successes and failures of the French, Finnish and Swiss NFI experiences of TLS and MLS application in NFIs, we identify both the major advantages and the potential constraints of their use. Lastly, we make recommendations and state key points to consider when implementing TLS and MLS in NFIs.

2. Individual tree attribute extraction

In what follows, we describe tree attributes that can be retrieved from the tree point clouds. We distinguish between traditional attributes (i.e., the attributes that are traditionally measured or estimated during forest inventory field campaigns) and enhanced attributes, which cannot be directly acquired through manual measurements. The concept of "enhanced forest attributes" is drawn from the "enhanced forest inventories" concept introduced by White et al., (2016). We consider enhanced tree attributes to be those that can be used to support the development of improved management strategies for forest health and biodiversity, while at the same time improving wood utilisation and production efficiencies (White et al., 2017). We expand that definition to add attributes that cannot be directly measured from manual measurement but are quantifiable through TLS or MLS. These enhanced attributes, when already included in traditional forest inventories, are either estimated indirectly using other attributes, such as wood volume derived from height and DBH, or are estimated by expert knowledge (stem wood quality or microhabitats) or via labour-intensive measurements (crown dimension). All the attributes described in the following section are meant to be extracted from individual tree point clouds obtained through the segmentation of TLS and MLS data collected in sample plots.

2.1. Point cloud acquisition and pre-processing

To proceed with TLS and MLS tree measurements, data must first be acquired and pre-processed. Depending on plot characteristics and study goals, different scanning strategies can be applied. TLS involves either single or multiple scans from fixed positions. It offers high precision but faces occlusion issues. MLS, by contrast, allows faster acquisition through mobile systems but generally yields noisier data. Once acquired, the generated point cloud requires careful preprocessing steps including tree segmentation, denoising, and sometimes voxelization to facilitate tree attribute extraction (Fig. 1).

A full description of acquisition setups, noise filtering techniques, and voxelization strategies is provided in the Supplementary Material.

2.2. Segmentation of the point cloud into single trees

To retrieve single tree attributes, the complete 3D scene is typically classified and divided into classes based on the structure of the point cloud or common properties through a segmentation process. There are two types of segmentation: semantic and instance segmentation. Semantic segmentation of forest scenes discriminates different materials (e.g., wood and leaves) or different tree sections (e.g., stems, branches, and crowns) or other forest components (e.g., ground, lying deadwood, regenerating vegetation) (Krisanski et al., 2021a). Instance segmentation identifies and segments every tree into individual point clouds (Fig. 2).

Numerous methods have been proposed for segmenting point clouds into individual trees (e.g., Krisanski et al., 2021b). Many approaches begin with stem identification in a horizontal slice of the point cloud at a specific height above the ground. This requires the prior creation of a digital terrain model (DTM) from classified ground points. Ground points are typically identified by detecting the lowest points within a horizontal grid and classifying all points below a predefined *Z*-axis threshold as ground points. The DTM can then be constructed using either a grid-based resolution, where ground height in each cell is defined as the lowest or mean ground point height (Simonse et al., 2003), or a triangular irregular network (TIN) method (Aschoff et al., 2004).

Using the DTM, point clouds can be normalised and then sliced at specific heights above ground. Some segmentation algorithms use slices at a standard breast height (e.g., 1.30 m in Europe) (Koreň et al., 2017; Liu et al., 2018), which can then be fed to a stem identification algorithm (Chen et al., 2024). These identified stem slices serve as seeds for further segmentation, extending to the rest of the stem and branches (Hackenberg et al., 2015; Hackenberg et al., 2021).

More recent methods rely on a two-stage process. In the first stage, they use deep learning techniques for semantic segmentation and in the second phase, they exploit the semantic information to segment individual trees into instances. Because these methods remain computationally inefficient (Wielgosz et al., 2024), the latest research aims at processing both types of segmentation at once with deep learning algorithms (Xiang et al., 2024), improving the quality of both the segmentation and the computational processes.

2.3. Traditional forest inventory attributes

For the purpose of forest inventory, the use of TLS and MLS initially sought to obtain variables such as tree position, diameter at breast height (DBH), or tree height (Maas et al., 2008) which are traditionally directly measured in forest inventory field campaigns (for every tree or a sample of trees) or estimated with allometric equations (e.g., wood volume). The main purpose of using TLS and MLS was to replace manual measurement in the desire for efficiency. In the literature, these attributes are often compared with traditional measurements for accuracy.

2.3.1. Tree detection and positioning

The process of detecting and positioning trees is closely related to that of DBH extraction. The most relevant approaches proposed for the automatic detection of tree positions are the cluster algorithms and circle- or cylinder-fitting algorithms based on a thin slice of the trunk located 1.30 m above the ground, which corresponds to a standard breast height in Europe (Gollob et al., 2019). The tree position is then

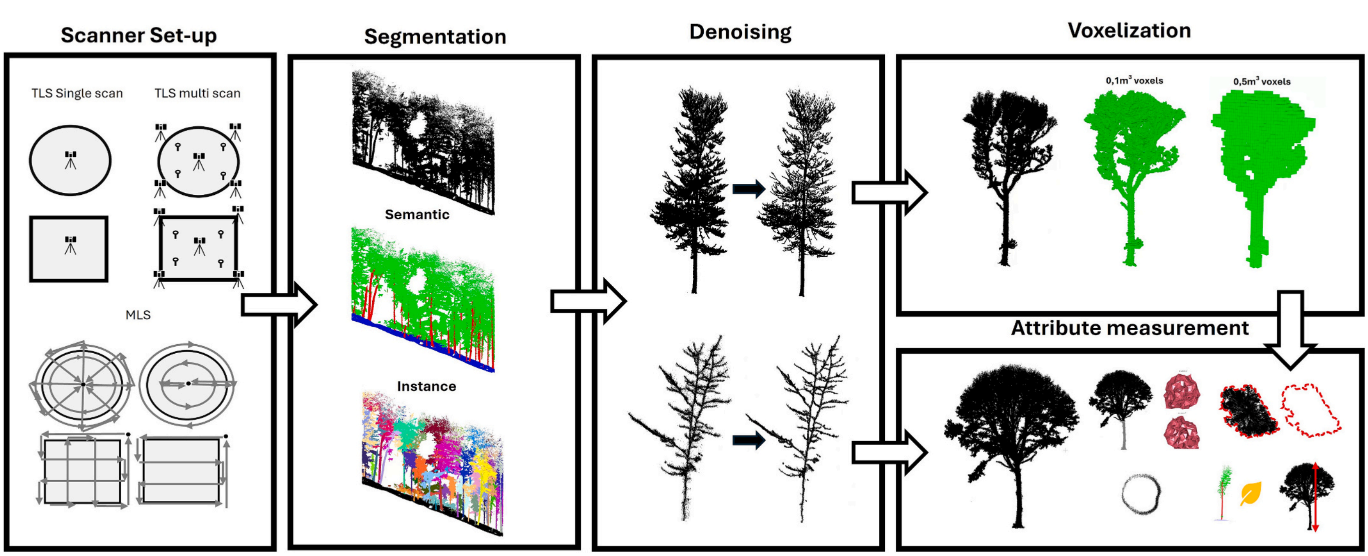

Fig. 1. TLS and MLS scan setup, point cloud segmentation, and pre-processing.

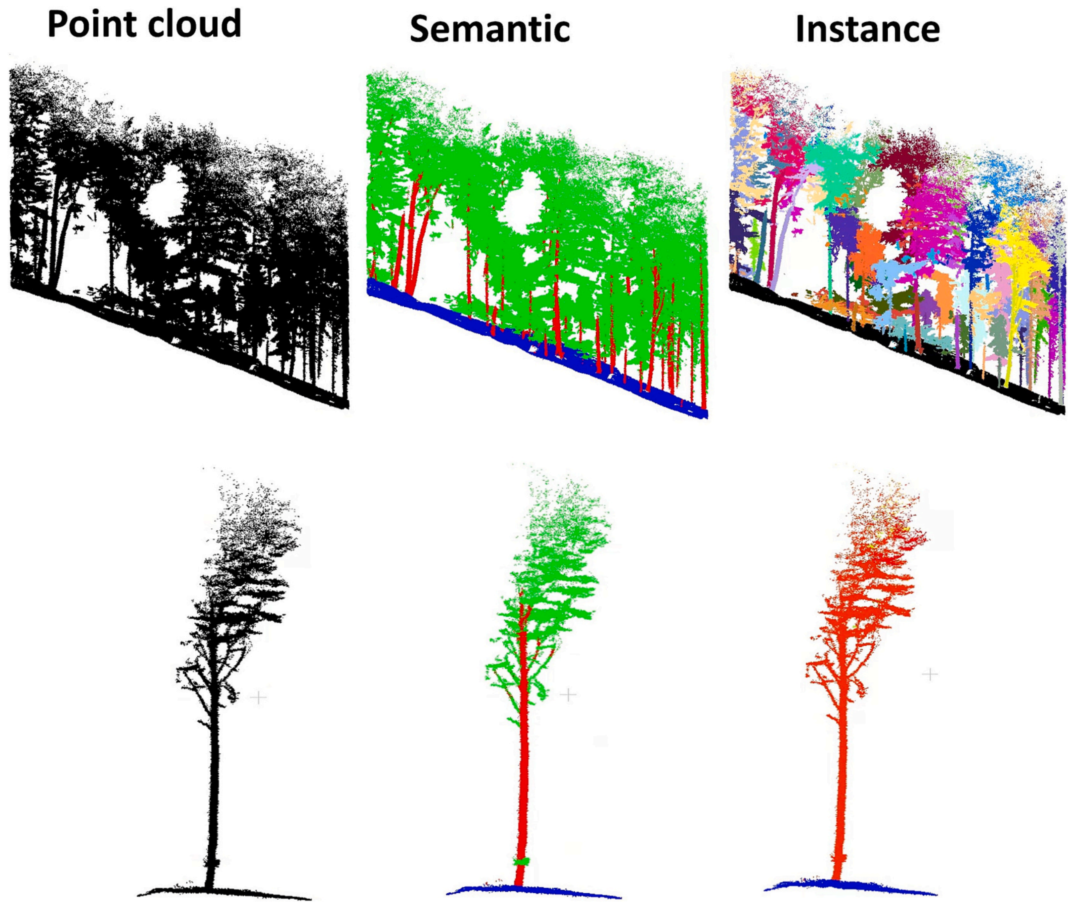

Fig. 2. The results from the semantic and the instance segmentation of the same trees scanned in a Swiss forest using the Segmentanytree algorithm (Wielgosz et al., 2024).

defined as the coordinates (x, y) of the centre of the slice. To increase the efficiency of computation in processing large point cloud data for stem positioning, the point cloud is often discretised into voxels, or else clustering is subsequently applied to subsamples from multiple vertical layers (Gollob et al., 2019).

Several studies have focused on the performance of the automatic detection and positioning of trees in a forest inventory context according to scanning setup (i.e., the number of scans and the position of the scanner), the size of the tree diameter, and forest structure. The main variables influencing tree detection are plot coverage, structure of the plot (i.e., tree density and lower vegetation density), and occlusion. The literature shows that single-scan TLS tends to have a lower detection rate than multi-scan, and MLS has the highest detection rate (Table 1).

When using single-scan TLS, plot size has been shown to have a major impact on tree detection, because the further from the scanner position, the more occlusion there is. With a radius of 15 m or less, tree detection was estimated at between 73 % and 100 % (Maas et al., 2008; Murphy et al., 2010). It decreased to 62.9 % and 68 % for a 30 m radius (Brolly and Király, 2009; Lovell et al., 2011) and to between 40 % and 52 % for a 50 m radius (Strahler et al., 2008; Lovell et al., 2011).

2.3.2. *Diameter at breast height*

The most common methods to extract DBH from the point cloud include circle fitting, cylinder fitting and the Hough transformation. The first method calculates the diameter of a circle obtained by a procedure that fits a circle to a thin slice of the stem point cloud extracted at the standard breast height (Koreň et al., 2017; Liu et al., 2018) (Fig. 3). The second method fits cylinders to the stem point cloud and calculates the diameter of the cylinder fitted at height 1.30 m (Brolly and Király, 2009; Čerňava et al., 2017). The last method uses the Hough transformation to detect a circle in a rasterised point cloud and retrieve the diameter of that circle (Tansey et al., 2009; Zhou et al., 2019a).

The typical DBH accuracy (bias) achieved by the three scanning methods is reported in Table 2. Multi-scan TLS displays the best performance in terms of both precision (Root Mean Square Error, RMSE) and accuracy. MLS is the second most accurate, but tends to underestimate the DBH.

A flaw in all these approaches is the assumption of stem slice circularity, which is not exactly fulfilled (Pulkkinen, 2012). Even so, previous studies have demonstrated that the measurement accuracy of diameters is similar to when it is measured with traditional instruments, such as callipers. In their 2017 study, Wang et al. (2017a,b) demonstrated that a combined Fourier series and circle fitting, which allows more non-circularity, can improve the diameter measurement precision, reducing the RMSE by 12.4 % from 37.1 % down to 24.7 %, but it did not significantly improve accuracy. The accuracy of the estimation depends mostly on the completeness of the point cloud, which in turn is influenced by the coverage of the forest scene during the scan (Liu et al., 2018), and the shape and texture of the trunk: deeply textured bark will cause LiDAR to systematically underestimate DBH compared to manual measurements (Brolly and Király, 2009).

2.3.3. *Tree height*

Tree height is usually obtained by either calculating the difference between the highest and lowest Z-axis value of the point cloud of the segmented tree or by previously normalising the height of the point cloud and extracting the highest value for each point cloud. The accuracy of the estimate depends on the forest scene coverage (Liu et al.,

Table 1
Individual tree detection rate range for the different scanning methods. "/" indicates that the information was not found.

Method	Detection rate (%)	Number of scans	Plot size (m^2)	Forest Type	Location	Species composition	Tree Density (stems/ha)	Authors
Single-scan TLS	86.7–100	1	/	Temperate Softwood and hardwood	Germany, Austria, Ireland	*Picea abies* Abies spp. *Fagus sylvatica* Larix spp. *Pseudotsuga menziesii*	/	Maas et al., 2008
	40.2	1	7854	Pine plantation/ native forest	Tumbarumba (NSW, Australia)	*Pinus ponderosa*/Eucalyptus delagatensis *Eucalyptus dalrympleana*	128	Strahler et al., 2008
	62.9–72.3	1	2827	Temperate mixed forest	Hidegvíz-völgy (Hungaria)	Quercus patrea *Carpinus betulus* *Fagus sylvatica* *Larix decidua* Piea abies	753	Brolly and Király, 2009
	59–82	1	1000	Pine plantation	South Australia/ Western Australia	Pinus spp.	153–570	Murphy et al., 2010
	54–68	1	7854	Pine plantation/ native forest	Tumbaruma (NSW, Australia)	*Pinus ponderosa*/Eucalyptus delagatensis *Eucalyptus dalrympleana*	128	Lovell et al., 2011
	73	1	314	Temperate mixed	Evo (Finland)	Pinus spp. *Picea abies* Betula spp.	509–1432	Liang et al., 2012
	73.4	1	314	Temperate mixed	Evo (Finland)	*Pinus sylvestris Picea abies* Betula spp.	605–1210	Liang and Hyyppä, 2013
	73.3	1	1257	Hemi-boreal forest	Remningstorp (Sweden)	*Picea abies Pinus sylvestris* Betula spp.	358–1042	Olofsson et al., 2014
Multi-scan TLS	100	5		Temperate softwood	Southern Finland	Pinus silvestris Betula spp.	278	Liang et al., 2015
	84.6–97.4	5	500	Temperate mixed and softwood	Grisons (Switzerland)	*Picea abies* *Fagus sylvatica* *Larix decidua* *Pinus sylvestris*	/	Heinzel and Huber, 2018
	66–100	5	1024	Boreal forests	Evo (Finland)	*Picea abies* *Betula pendula* *Betula pubescens*	592–2021	Liang et al., 2018a,b
MLS	100	/	900	Mixed temperate forest	Masala (Finland)	*Pinus sylvestris*	278	Liang et al., 2015
	90.9	/	300	/	Haidian District (China)	*Styphnolobium japonicum* Betula spp. *Pinus tabuliformis*	1100	Chen et al., 2019
	67.5	/	1963	Temperate mixed forest	Kremnica mountains (Slovakia	*Fagus sylvatica, Picea abies*	416–864	Mokroš et al., 2021
	70	/	400	Temperate hardwood	Saint Quentin (NB, Canada)	*Acer saccharum* *Betula alleghaniensis* Abies balamea	500	Vandendaele et al., 2022

2018), the forest structure, and tree density: a dense canopy cover will result in a lower probability that a laser pulse reaches the top of the tree (Moskal and Zheng, 2011). Therefore, to properly extract tree height, it is advised to scan the plot during leaf-off conditions, when possible, and to cover the plot fully during the scan.

Studies comparing tree height measurement using TLS and MLS technologies with measurements using traditional instruments (i.e., clinometer) report that it typically estimates tree heights to be lower than traditional measurements. The accuracy and precision for the three methods, single-scan TLS, multi-scan TLS and MLS, as found in the literature, are reported in Table 3. Of the three methods, multi-scan TLS shows the lowest RMSE when estimating height, followed by MLS then single-scan TLS. Stereńczak et al. (2019) noted that traditionally estimated tree height bias could be up to 5 m when using a clinometer, indicating that, depending on the situation, point cloud estimations can be more accurate. In their study, Chiappini et al. (2022) compared the MLS estimated height to felled tree measurements on 50 pines. They identified a mean 1.48 m underestimation bias of the total tree height by the MLS. They also noted that the accuracy decreased as the tree height increased. They attributed this to the occlusion effect worsening with the dense canopy.

2.3.4. Tree species identification

In NFIs, the tree species is a key information item reported for every tree. From the perspective of TLS and MLS-driven forest inventory, the species is usually identified by the operator in the field and attributed to the point clouds afterwards. This limitation considerably hinders the capacity of TLS and MLS to give critical information by species without additional human intervention. Accordingly, the development of automatised classification based on TLS and MLS scans has received growing attention since the beginning of the 2020s (Terryn et al., 2020, Xi et al., 2020; Liu et al., 2021; Liu et al., 2022a; Hui et al., 2023; Puliti et al., 2025). The first studies to automatically identify species were based on the analysis of bark texture (Mizoguchi et al., 2017). Other studies focused on the retrieval of tree structural attributes such as branch angle or crown-to-stem proportion to feed these variables to a classification algorithm (Puttonen et al., 2010; Lin and Herold, 2016; Terryn et al., 2020; Hui et al., 2023). More recently, deep learning techniques, using either the 3D point cloud or simulated 2D pictures of the point cloud taken at different angles, were developed and trained to predict species of individually segmented point clouds (Puliti et al., 2025). A summary of the accuracy of these different methods is given in Table 4.

The main constraint of these approaches is the need for a large amount of data to train the algorithms and obtain reliable results. This

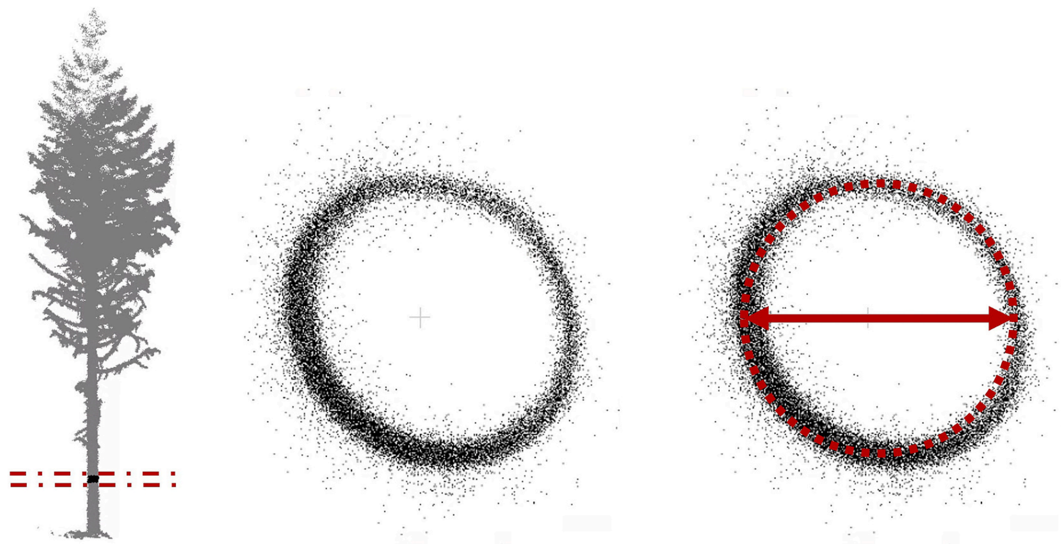

Fig. 3. Circle fitting method to retrieve DBH applied to a Norway spruce point cloud. Left, slice extraction at 1.30 m height. Middle, point cloud of the slice. Right, circle fitting.

results in developed algorithms fitting only the specific conditions represented in the training dataset (e.g., climate, forest structure, population age and size, species composition).

One current initiative to overcome this limitation is to establish a large database of individual trees captured by TLS or MLS and then use the database to test and benchmark the algorithms. The initiative is available at https://github.com/stefp/FOR-species. At the time of writing, the database comprises approximately 20000 individual trees of 33 tree species from three continents. Seven classification solutions have been tested using the database. The results show that using a 2D representation of a point cloud and feeding it to a Convolutional Neural Network (CNN) is currently the most accurate method (Puliti et al., 2025). The authors of the study state that the better result of 2D compared to 3D analysis might come from the greater maturity of 2D image prediction in comparison with 3D point cloud predictions, such as the deep learning architecture PointNet++ (Qi et al., 2017).

2.4. Enhanced forest inventory attributes

As the horizon of TLS and MLS technology applications began to expand (Calders et al., 2020), attributes concerning tree crowns, foliage, wood quality, and tree microhabitats became accessible. Enhanced forest attributes contribute to data-rich, efficient, and modern forest management for addressing today's environmental, economic, and operational challenges in forestry (White et al., 2017).

2.4.1. Stem and branch volume

By sampling the position and shape of the stem and branches of a tree, TLS and MLS enable direct measurement of the volume of the stem and branches, as opposed to indirect allometric equations. In this case, their main advantage is that they enable volume estimates fitted at the individual tree level with potentially greater accuracy. With the proper method and algorithms, LiDAR-derived wood volumes can be more accurate than by allometric equations, effectively improving wood volume and carbon stock monitoring (Vandendaele et al., 2022).

A common method for estimating stem volume derived from the point cloud is by the use of Quantitative Structural Models (QSMs) (Raumonen et al., 2013; Hackenberg et al., 2015; Demol et al., 2021). A QSM is designed to model the stem using geometric shapes, mostly cylinders, fitted to the stem point cloud. By summing the volume of the cylinders belonging to the stem, its wood volume can be estimated (Raumonen et al., 2013). Many QSM algorithms rely on a series of hyperparameters that often need to be fine-tuned, tree by tree, hindering automation.

Other methods to compute stem volume use diameters extracted along the stem (Hyyppä et al., 2020a; Pitkänen et al., 2021). The volume is then obtained either by deriving the stem taper equation and integrating it with the total tree height (Hyyppä et al., 2020a) (Fig. 4) or by using Huber's or Smalian's formula for summing the trunk sections (Pitkänen et al., 2021).

The accuracy of stem volume estimates compared to destructive measurements for multi-scan TLS and MLS is reported in Table 5. Multi-scan TLS stem volume measurements are more accurate than MLS estimates in terms of both RMSE and bias. This is mainly due to device-specific accuracy differences. It is still important to note that the quality of multi-scan TLS will depend closely on the scan coverage of the forest plot. Single-scan TLS for stem volume estimation is less widely reported on in the literature, being more challenging due to unavoidable occlusion (Liang et al., 2018a). Single-scan TLS estimates tend to be less accurate than multi-scan and MLS (Astrup et al., 2014) as occlusion causes the stem to be incomplete.

Branch wood volume can also be estimated using QSMs: branch cylinders can be extracted from the complete QSM (Fig. 5), and their volume computed and summed. Compared to stem wood volume accuracy, branch wood volume tends to be overestimated (Demol et al., 2021; Vandendaele et al., 2022) owing to a combination of increased distance from the scanner, decreased branch size and noise caused by wind-induced movement of the branches during the scan. The scan often results in the branches being less clearly defined and blurred, leading to an overestimation of their diameter. This effect is more marked the smaller the branches and the higher they are located up the crown.

2.4.2. Crown attributes

Crown attributes are rarely measured in traditional NFIs, mainly because of the time required by traditional methods to sample each tree. These are nevertheless desirable attributes because measurement of the crown volume and crown projected area can serve as proxies of either competition or wood productivity (Pretzsch et al., 2015; Saarinen et al., 2022).

To extract a crown attribute from a point cloud representing a single tree, it is necessary to first identify the points of the crown. This can be done by building a horizontal convex hull along the *Z*-axis and detecting the break point at which the maximum distance between the points and the centre of the convex hull increases significantly (Schneider et al.,

Table 2
Root Mean Square Error (RMSE) range and Bias range of DBH estimations by the different scanning methods. "/" indicates that the information was not found.

Method	RMSE range (cm)	Bias range (cm)	Number of scans	Plot size (m^2)	Forest type	Location	Species composition	Tree density (stems/ha)	Authors
Single-scan TLS	[3.4, 7.0]	[−1.6, 0.5]	1	2827	Temperate mixed forest	Hidegvíz-völgy (Hungaria)	Quercus patrea *Carpinus betulus* *Fagus sylvatica* *Larix decidua* *Picea abies*	753	Brolly and Király, 2009
	1.8	[−0.67, 1.58]	1	/	Temperate Softwood and hardwood	Germany, Austria, Ireland	*Picea abies* Abies spp. Faguss spp. Larix spp. Pseudotsuga meziesii	/	Maas et al., 2008
	1.3	0.2	1	314	Temperate mixed	Evo (Finland)	Pinus spp. *Picea abies* Betula spp.	509–1432	Liang et al., 2012
	3.8	0.2	1	6400	/	Remningstorp (Sweden)	*Picea abies* Betula spp.	1519	Lindberg et al., 2012
	[0.7, 2.4]	[−0.2, 1.9]	1	314	Temperate mixed	Evo (Finland)	*Pinus sylvestris* *Picea abies* Betula spp.	605–1210	Liang and Hyyppä 2013
	[1.47, 1.58]	[−0.13, −0.07]	1	5000	Mixed temperate forest	Kaiserslautern (Germany)	*Fagus sylvatica* Pseudotsuga meziesii	579–1032	Pueschel et al., 2013
	[2.0, 4.2]	0.6	1	1257	Hemi-boreal forest	Remningstorp (Sweden)	*Picea abies* *Pinus sylvestris* Betula spp.	358–1042	Olofsson et al., 2014
	1.83	/	1	40/404	/	College Station (TX, US) / Huntsville (TX, US)	*Quercus stellata* *Pinus taeda*	/	Srinivasan et al., 2015
Multi-scan TLS	7, 8	−2	5	10,000	Softwood and hardwood forests	New England (USA)	*Tsuga canadensis* *Picea rubens* *Pinus strobus* *Quercus rubra* *Acer rubrum* *Fagus sylvatica* *Betula alleghaniensis*	1020–3281	Yao et al., 2011
	[0.66, 0.97]	[−0.16, 0]	6	5000	Mixed temperate forest	Kaiserslautern (Germany)	*Fagus sylvatica* Pseudotsuga meziesii	579–1032	Pueschel et al., 2013
	2.38	/	5	1024	Temperate softwood	Southern Finland	Pinus silvestris Betula spp.	278	Liang et al., 2015
	2.17	−1.53	5	400	Temperate hardwood	Saint Quentin (NB, Canada)	*Acer saccharum* *Betula alleghaniensis* Abies balamea	500	Vandendaele et al., 2022
MLS	2.92	/	/	900	Mixed temperate forest	Masala (Finland)	*Pinus sylvestris*	278	Liang et al., 2015
	[0.9, 1.3]	[−0.39, −0.44]	/	1024	Boreal forest	Evo (Finland)	*Picea abies* Pinus spp. Betula spp.	690–1470	Hyyppä et al., 2020b
	/	−2.5	/	1225	Poplar plantation	Opwijk (Belgium)	*Populus x canadensis*	245	Stal et al., 2021
	[1.72, 2.61]	[0.98, 1.27]	/	20,000	Pinus plantation	Island of Aotearoa (New Zealand)	*Pinus radiata*	~442	Hartley et al., 2022
	[2.4, 3.8]	/	/	2500	Mixed Temperate forest	Zurich (Switzerland)	*Fagus sylvatica* *Picea abies* Abies spp. *Pseudotsuga menziesii* *Carpinus betulus*	360–760	Kükenbrink et al., 2022
	2.93	−2.49	/	400	Temperate hardwood	Saint Quentin (NB, Canada)	*Acer saccharum* *Betula alleghaniensis* Abies balamea	500	Vandendaele et al., 2022
	1.25	−0.4	/	2500	/	Harvard Forest (USA)	*Acer rubrum* Pinu strobus *Quercus rubra* *Tsuga canadensis*	/	Stovall et al., 2023

2020). The height of this break point is defined as the crown base height and all points above it pertain to the crown (Fig. 6). These algorithmic approaches are being increasingly replaced by semantically segmented point clouds where living and dead branches are separated (see Section 2.3), thus allowing direct computation of crown metrics (Xiang et al., 2024).

In traditional manual measurements, the crown projection area has often been quantified by measuring the crown's maximum extent in

Table 3
RMSE and bias range of height estimation for the different scanning methods. "/" indicates that the information was not found.

Method	RMSE range (m)	Bias range (m)	Number of scans	Plot size (m^2)	Forest type	Location	Species composition	Tree density (stems/ha)	Authors
Single-scan TLS	[1.51, 4.9]	[−0.1, 0.6]	1	314	Temperate mixed	Evo (Finland)	*Pinus sylvestris* *Picea abies* Betula spp.	605–1210	Liang and Hyyppä, 2013
	4.6	−0.6	1	/	Temperate softwood and hardwood	Germany, Austria, Ireland	*Picea abies* Abies spp. Fagus spp. Larix spp. Pseudotsuga meziesii	/	Maas et al., 2008
	4.9	−0.1	1	1257	Hemi-boreal forest	Remningstorp (Sweden)	*Picea abies* *Pinus sylvestris* Betula spp.	358–1042	Olofsson et al., 2014
	1.51	0.3	1	40/404	/	College Station (TX, US)/ Huntsville (TX, US)	*Quercus stellata* *Pinus taeda*	/	Srinivasan et al., 2015
Multi-scan TLS	/	−0.5	5	1225	Pinus plantation and hardwood forest	Southern Ontario (Canada)	*Acer saccharum* *Pinus resinosa*	465–661	Hopkinson et al., 2004
	2.4	/	22	3575	Mixed broadleaf forest	Hainich National Park (Germany)	*Tilia cordata* *Tilia platyphyllos* *Carpinus betulus* *Quercus robur*	392	Fleck et al., 2011
	[2.0, 6.5]	[0.6, 1.3]	5	314	Temperate mixed	Evo (Finland)	*Pinus sylvestris* *Picea abies* Betula spp.	605–1210	Liang and Hyyppä, 2013
	0.76	−0.3	16	1225	Hardwood forest	Culai Mountain (China)	Quercus liaotungensis *Robinia pseudoacacia*	212	Huang et al., 2011
MLS	[1.4, 2.0]	[−1.1, −0.16]	/	1024	Boreal forest	Evo (Finland)	*Picea abies* Pinus spp. Betula spp.	690–1470	Hyyppä et al., 2020b
	1.11	0.45	/	707	Lowland deciduous forest	Northern Croatia	*Quercus robur* *Carpinus betulus* *Alnus glutinosa* *Fraxinus excelsior*	305	Jurjević et al., 2020
	2.78	−1.18	/	20,000	Pinus plantation	Island of Aotearoa (New Zealand)	*Pinus radiata*	~442	Hartley et al., 2022

Table 4
Overall accuracy of the tree species prediction algorithms by method. "/" indicates that the information was not found.

Method	Overall accuracy (%)	Number of Species	Number of trees	Forest type	location	Authors
Structural feature	90	3	24	/	Measurement in the laboratory	Puttonen et al., 2010
	83.5	10	133	Urban garden	Espoo (Finland)	Puttonen et al., 2011
	77.5–90	4	40	Unmanaged mixed forest	Seurasaari Island (Finland)	Lin and Herold, 2016
	80	5	758	Mixed deciduous forest	Wytham Woods (UK)	Terryn et al., 2020
	96.65–98.06	5	568	Mixed Central European forest	Baden-Württemberg (Germany)	Hui et al., 2023
2D images of point clouds	92	2	600	Natural and planted hardwood forests	Saihanba forest – Laougou forest (China)	Chen et al., 2021
	86	7	690	Managed and unmanaged temperate forests	Germany, Oregon (USA)	Seidel et al., 2021
	81	5	2478	Softwood riparian zones, Mixed forest	Central Spain	Allen et al., 2023
	90.6	33	20,158	/	Canada, Europe, Australia	Puliti et al., 2025
3D point cloud	93.1–95.6	4	181	/	San Joaquin Experimental Range (CA, USA)	Zhou et al., 2017
	95.8	9	771	Monospecific and near-monospecific forests	Canada, Finland	Xi et al., 2020
	92	2	1200	/	Saihanba forest (China)	Liu et al., 2021
	95	8	1312	Unmanaged, planted and semi-natural forests	Greater Khingan Station, Huailai, Gaofeng forest (China)	Liu et al., 2022a
	88	8	1312	Unmanaged, planted and semi-natural forests	Greater Khingan Station, Huailai, Gaofeng forest (China)	Liu et al., 2022b

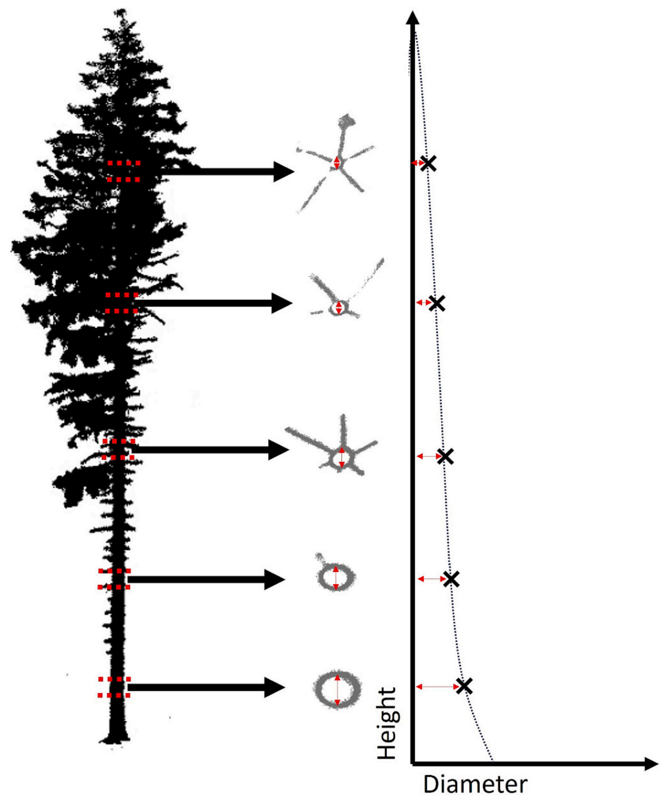

Fig. 4. Extraction of stem diameters from the point cloud and development of the stem taper equation for the estimation of the volume by integrating the equation along the total height of the stem.

several directions, averaging these distances (to give the mean diameter of the crown) and finally calculating the area with the mean radius. The point cloud allows the crown projected area to be estimated by fitting a convex (α-) hull to the crown points (Fleck et al., 2011; Terryn et al., 2023). The choice of the α-value significantly impacts the shape of the polygon that envelops the crown. An α-value of 1 results in a crown projection area similar to the conventional eight-point crown projection area, whereas an α-value of 0.1 generates a polygon that frames the crown tightly, resulting in a crown projection area smaller than the conventional eight-point crown projection area (Fig. 7). To avoid the variation of the estimation due to the α-value, Liang et al. (2024) proposed deriving crown contours that automatically and adaptively search key contour points to faithfully depict the crown projection. The accuracy of the estimation will also depend on the quality of the single tree segmentation and the accuracy of the derived crown contour (Liang et al., 2024).

Crown volume, defined as the three-dimensional space occupied by the tree crown (Zhu et al., 2021), can be estimated by the 3D α-shape around the crown points (Schneider et al., 2020), allowing the creation of a bounding volume that envelops a set of 3D points, or by the space occupied by the voxelised crown point cloud (Liang et al., 2024). The volume of the α-shape then corresponds to the crown volume (Gardiner et al., 2018; Terryn et al., 2023; Zhu et al., 2021) (Fig. 8).

Crown volume is sensitive to occlusion, and its accuracy decreases as the size and complexity of the crown increase (Terryn et al., 2022; Vandendaele et al., 2022). Changes in the parameters used for deriving the bounding α-shape can also have a strong impact on the final estimated volume. This raises challenges for mixed-species stands where it is difficult to develop a single set of optimised parameters that effectively capture crown dimensions for all species.

2.4.3. *Foliage attributes*

Leaf-related attributes, though not currently measured in traditional NFIs, can provide valuable insights into the health and productivity of

Table 5
Relative RMSE and bias range of stem volume estimation for the different scanning methods. “/” indicates that the information was not found.

Method	Relative RMSE (%)	Bias (%)	Number of scans	Plot size	Forest type	Location	Species composition	Tree density (stems/ha)	Authors
Multi-Scan TLS	9.47	−5.87	7	314	/	Evo (Finland)	*Pinus sylvestris* *Picea abies*	600	Liang et al., 2014
	5–10	/	5	1024	/	Spread over Finland	*Pinus sylvestris Picea abies* *Betula pubescens* *Betula pendula*	600–200	Pitkänen et al., 2021
	12.74	8.86	5	400	Temperate hardwood	Saint Quentin (NB, Canada)	*Acer saccharum* *Betula alleghaniensis* Abies balamea	500	Vandendaele et al., 2022
	7.77–24.57	[−4.68, 11.33]	/	/	Mixed managed temperate forests		*Fagus sylvatica* *Picea abies* *Acer pseudoplatanus* *Fraxinus excelsior*	/	Bornand et al., 2023
	28.3–77.1	[28, 81]	5	1024	Boreal forests	Evo (Finland)	*Picea abies* *Betula pendula* *Betula pubescens*	592–2021	Liang et al., 2018b
MLS	8.9–11.5	[0.6, 6.1]	/	1024	Boreal forest	Evo (Finland)	*Picea abies* Pinus spp. Betula spp.	690–1470	Hyyppä et al., 2020b
	12.4	−4.1	/	5000		Cesane regional forest (Italy)	*Pinus nigra* Quercus pubescens *Acer pseudoplatanus* *Cotinus coggygria*	800	Chiappini et al., 2022
	10.16	/	/	20,000	Pinus plantation	Island of Aotearoa (New Zealand)	*Pinus radiata*	~442	Hartley et al., 2022
	12.7–21.3	[−9.3, 5.7]	/	/	Boreal softwood forest	Lappeenranta (Finland)	*Picea abies*	690	Hyyppä et al., 2022
	21.82	14.55	/	400	Temperate hardwood	Saint Quentin (NB, Canada)	*Acer saccharum* *Betula alleghaniensis* Abies balamea	500	Vandendaele et al., 2022

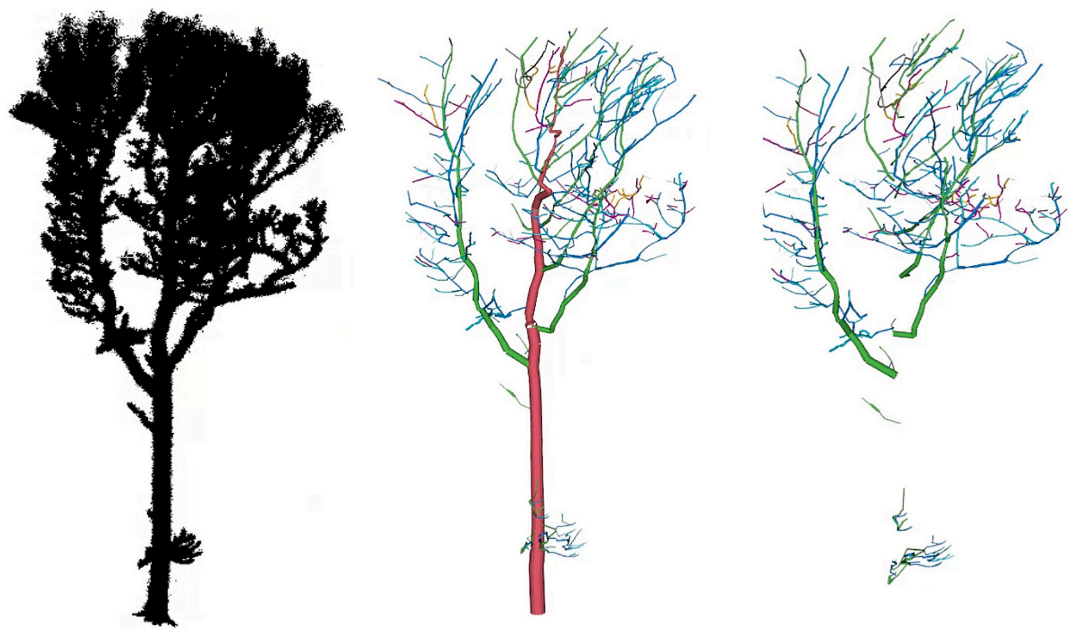

Fig. 5. Quantitative structural model built with TreeQSM 2.4.1 (Raumonen et al., 2013; Åkerblom et al., 2017): the different colours in the tree in the centre and to the right are associated with different hierarchical levels of the branches.

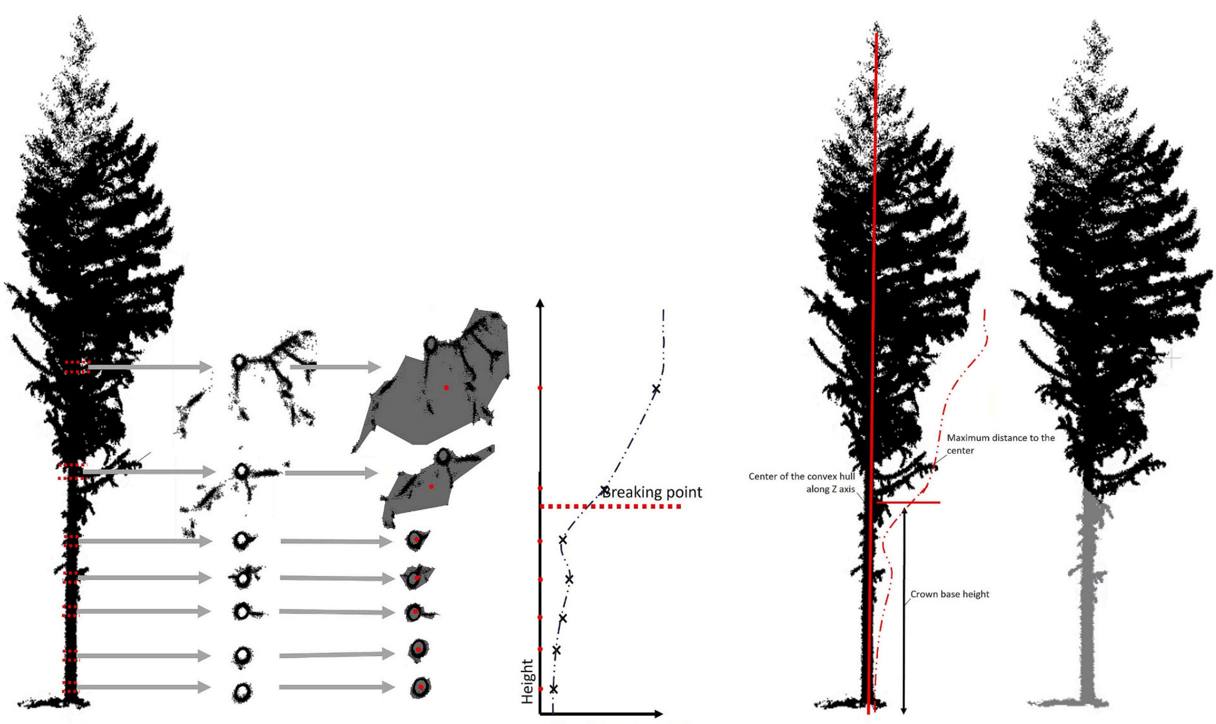

Fig. 6. Crown base identification process. From left to right: slice extraction at regular interval, convex hulls and their centre fitted to the slices, identification of the "breaking point", identification of crown base height and identification of crown points.

sampled trees. Leaf shape, quantity, and distribution reflect past and present stress, providing critical information on environmental impacts and aiding early detection of potential crises, such as bark beetle infestation or ash dieback outbreaks.

Extracting foliage attributes from TLS and MLS point clouds requires distinguishing between leaf and wood points. This is typically achieved through planar form detection or with complementary data such as visual spectrum colorised returns. Existing methods for this separation are summarised in Zhou et al. (2019b), with additional approaches detailed in Wang et al. (2017a) and Wan et al. (2021). However, these methods often involve high computational demands, as noted by Wan et al. (2021). Some semantic segmentation algorithms also integrate leaf-point identification as part of their process.

Key attributes such as Leaf Area Index (LAI), Leaf Area Density (LAD), and Total Leaf Area (TLA) assess both the quantity and distribution of photosynthetic material, enabling a comprehensive evaluation of tree foliage and overall health.

LAI, defined as the ratio of total leaf area to ground surface area, is

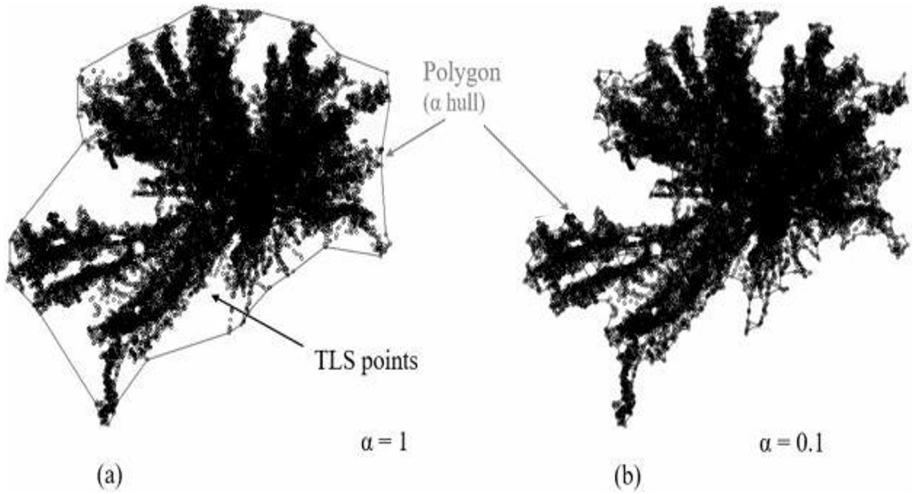

Fig. 7. Estimation of the crown projected Area using Apha polygons with respectively an α value of 1 (a) and 0,1 (b).

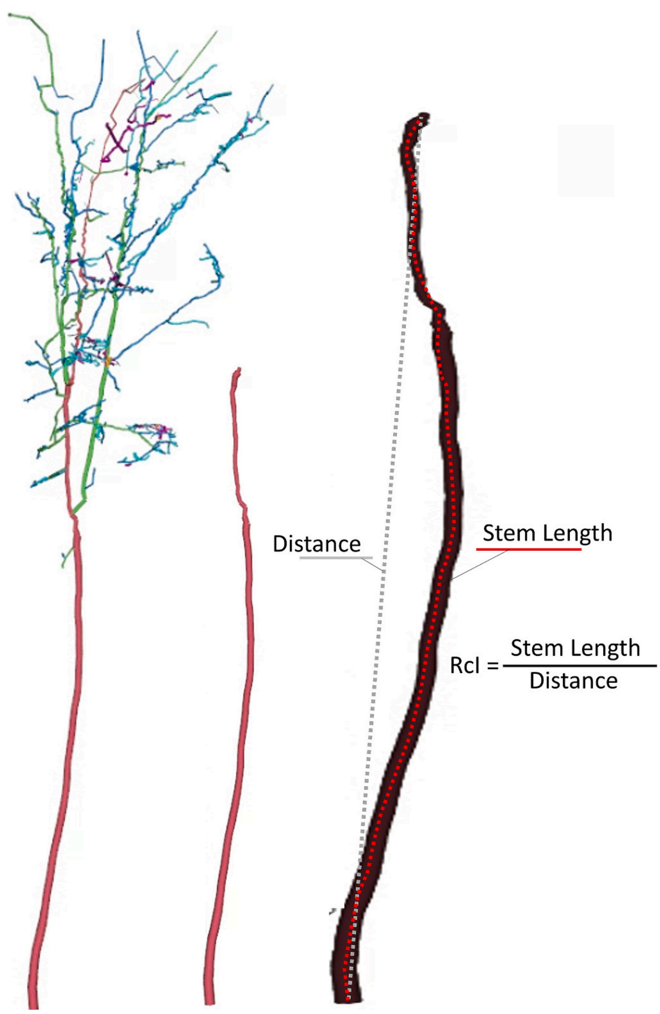

Fig. 9. Calculation of the rectitude index (RcI). Left, complete Quantitative structural model (QSM). Middle, merchantable wood QSM. Right, calculation of the RcI.

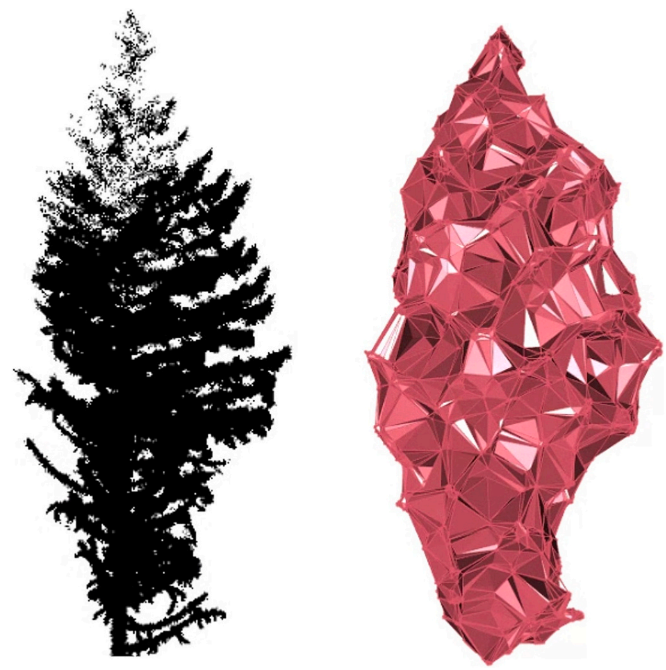

Fig. 8. The crown volume of a Norway spruce tree. The crown dimension has been computed using the ITSMe R package (Terryn et al., 2023) using the default parameter values. Left: crown points. Right: crown volume.

one of the most widely studied foliage attributes owing to its importance in predicting photosynthetic production, evapotranspiration, and growth at the stand level. LAI is derived primarily from TLS and MLS data through its correlation with the gap fraction (i.e., the proportion of empty volume within a canopy), based on the Beer-Lambert law, which describes beam attenuation through semi-permeable materials. Point cloud voxelisation and density within voxels are commonly used to estimate permeability. Though effective, these methods are hindered by clumping, occlusion, voxel size, and the presence of woody material (Wang and Fang, 2020). Full reconstruction of the tree crown at individual-leaf scale is technically possible but computationally demanding, and evidence suggests that direct gap fraction estimates derived this way do not differ markedly from Beer-Lambert projections (Zhu et al., 2023).

LAD is defined as total one-sided leaf area per unit volume of canopy [m^2/m^3] (Béland et al., 2014). LAD can be obtained from the TLS and MLS point cloud transformed into voxels (Eichhorn et al., 2017). However, the combined effects of vegetation occlusion and the shooting pattern of TLS and MLS scanners lead to highly heterogeneous sampling. This limits the reliability of estimates, since many voxels are either not explored or only poorly covered by laser beams. In response to these limitations (i.e., wood and foliage properties, laser effective footprint, and occlusion effects), algorithms have been developed to take account of the space occupied by woody materials, leaf clumping and unvisited voxels (Pimont et al., 2019; Soma et al., 2020).

TLA offers additional insights into gas exchange surfaces and resource availability compared to LAD. TLA can be estimated by converting LAD into a total surface area based on point density, although this method has similar constraints to LAD. Alternative approaches involve reconstructing planar leaf surfaces using triangulation (Yun et al., 2019) or great circle algorithms (Zhu et al., 2021). Another technique uses the total grid area (TGA) derived from the first and second echoes of LiDAR sensors (Li and Xue, 2023).

Overall, LAI, LAD and TLA estimations with LiDAR can correspond closely to non-destructive measurements with hemispherical photos (Patočka et al., 2020). Compared to manual measurements, TLS can make a close estimation of these variables (Hosoi and Omasa, 2006; Tang et al., 2012) and offer more detailed structural information than traditional non-destructive measurements, including measures of vertical distribution and heterogeneity.

2.4.4. *Wood quality attributes*

Wood quality assessment in national and management forest inventories is crucial from a silvicultural perspective. Its assessment allows estimations of the potential monetary value of standing timber. On a national scale, this enables forestry stakeholders, such as loggers, sawmill owners, and others, to project future resource availability and plan their actions accordingly. Following wood quality over time also allows the impact of environmental forces and silvicultural operations to be evaluated (Kint et al., 2009; Rudnicki et al., 2017).

In most NFI surveys, the quality of stem timber is assessed for the portion extending from the base of the trunk to the first large or living branch, or the first major defect, as this is the most valuable part of the tree. The commonest approach is to visually assess the stem shape, potential knots, branching structure, defects on the trunk and signs of rot or decay (Bosela et al., 2016).

Stem rectitude, or sweep, can be expressed through the rectitude index (RcI), calculated as the ratio of stem length to stem distance (Thies et al., 2004) (Fig. 9). Using QSMs, the first can be calculated by summing the length of the individual cylinders constituting the main stem, and the second using the first and last cylinder coordinates. Seeking to retrieve log-specific tapering and sweep, Pyörälä et al. (2019) obtained a mean difference of −3 % and 78 % respectively, compared to the sawmill reference measurement. The large sweep overestimation was mainly due to a difference in the estimation of the stem centre point.

Regarding branching structure, the height of the first living branch is estimated using the method described in Section 3.2.2. Pyörälä et al. (2018) identified whorl positions using TLS. Leveraging deep learning techniques, Puliti et al. (2023) have shown that the vertical position of whorls, even in dense UAV laser scanning point clouds, can be identified using CNN-based bounding box detection. Using the same data, Cattaneo et al. (2024) further demonstrated the possibility of estimating the diameter of the largest knot per whorl. Though applicable only to coniferous trees, such techniques can provide useful information not only on individual stem quality but also on tree growth and thus site productivity. We consider that TLS and MLS, which offer a denser and more complete point cloud, should achieve higher accuracy.

Knots and defects in tree trunks can be detected using high-density TLS point clouds by analysing surface patterns and irregularities (Schütt et al., 2004; Kretschmer et al., 2013). The process involves computing each stem point's distance to the centre, normalising it to assess trunk roughness, and then identifying patterns (Fig. 10). Detection can be threshold-based or use neural networks. Using a semi-automated method based on a similar principle, Thomas and Thomas (2011) identified 53 of 64 defects on 14 logs with only 9 false positives. Nguyen et al. (2021) combined segmentation and random forest

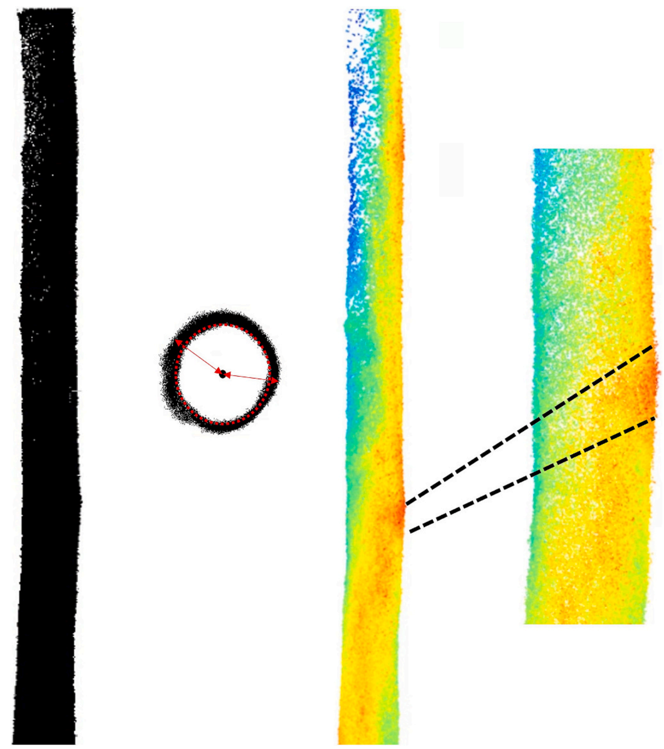

Fig. 10. Extraction of the surface structure of the trunk from point clouds and detecting patterns and irregularities on it.

classification to detect and locate 115 of 141 manually observed defects, with omitted ones averaging under 20 mm in width and 69 false positives. They noted a general overestimation of the defect surface and observed that a classification by quality category could be made, but led to an overall underestimation of the stem quality when compared to manual evaluation.

Wood decay is traditionally estimated in the field with decay levels, where the categories are defined according to quantifiable indicators (e.g., depth at which a knife can penetrate a log). Hrdina and Surový (2023) used deep learning to train a neural network to estimate the level of decay of scanned tree trunks with close-range photogrammetry and iPhone LiDAR. The validated accuracies of the models showed the method to be promising, with accuracy ranging from 57.7 % to 65.5 % compared to acoustic tomography. We consider that TLS and MLS, which offer better resolution and coverage, should achieve higher accuracy.

The difficulties in properly assessing wood quality using TLS and MSL lie in the need for a combination of multiple approaches to estimate more than one variable (sweep, branching structure, stem defects and signs of rot). Besides the accuracy of the estimates taken separately, the weighting of each attribute in the final wood quality assessment must be carefully defined to provide quality categories that meet market expectations.

2.4.5. *Tree-related microhabitat attributes*

The growing demand for the evaluation of forest biodiversity has promoted tree-related micro-habitat evaluation. A tree-related microhabitat (TREM) is defined as a distinct, well-delineated structure occurring on living or standing dead trees that constitutes a particular and essential substrate or life site for species or species communities during at least a part of their life cycle to develop, feed, shelter or breed (Larrieu et al., 2018). Larrieu et al. (2021) give a complete overview of tree-related microhabitats, which include cavities, concavities, tree injuries and exposed wood, crown deadwood, excrescences, fruiting bodies of saproxylic fungi and slime moulds, fresh exudates, moss, ivy/

liana, micro-cavities, and fungi. The trees that host tree-related microhabitats can be counted and integrated into biodiversity indicators (Asbeck et al., 2021).

Some methods to retrieve TREM from TLS and MLS point clouds have already been described in the previous section on wood quality attributes. Rehush et al. (2018) used TLS data to retrieve moss, ivy/liana, micro-cavities and fungi at the stem level by rasterising the tree stems into 2D "pictures" representing surface roughness and then feeding them to a neural network to be trained. This approach requires training the neural network with manually segmented point clouds where microhabitats are identified and marked. The final user and producer accuracy ranged from 60 % to 90 % depending on the TREM under consideration. The main factors influencing the identification of microhabitats were occlusion, point cloud quality, spatial resolution, and spectral information.

The small number of studies published on the extraction of tree-related microhabitat attributes from TLS data (Rehush et al., 2018; Frey et al., 2020; Fol et al., 2022; Fol et al., 2023) reflects the fact that the tree-related microhabitat concept is still recent, with many knowledge gaps that challenge its robustness and applicability. It remains promising for biodiversity and nature conservation, but is still underused (Martin et al., 2022).

3. Cases of explorative implementation of MLS and TLS technologies in national forest inventories

In the following section, we look closely at three examples of explorative assessment of TLS and MLS in NFIs: the French, Finnish and Swiss NFIs. In these three cases, TLS and MLS have been or are currently being evaluated for operational inclusion in the protocol of field surveys of NFI.

It is important to keep in mind that, given the need to cover the variability of all forest types, NFI plots are spread throughout the forest areas of the country under study, sometimes far from the major roads and in challenging terrain. The survey is usually carried out regardless of the time of year, even in windy and rainy conditions, and sometimes in snow-covered plots. In addition, NFIs often have to meet a schedule, and so the time spent to survey each plot is carefully considered. All these aspects have to be taken into consideration when trying to implement TLS or MLS in NFIs, especially if the 3D survey has to coincide with the NFI field survey. A summary of the main characteristics of the three cases is reported in Table 6.

3.1. French NFI

The French NFI follows a continuous two-phase sampling design with semi-permanent plots (Duong et al., 2025), surveying 14,000 plots annually-half newly measured and half remeasured after five years. Trees are recorded within concentric plots of 6, 9, and 15 m radius, depending on diameter class (Vidal et al., 2007; Duong et al., 2025).

Recognising TLS as a valuable tool for non-destructive tree mensuration, the French NFI conducted TLS acquisitions from 2010 to 2019 to improve tree species stem volume equations. The goal was to compile a database of 10,000 tree point clouds covering key species, diameter classes, and forest conditions. A subsample of NFI plots was selected to be scanned with the TLS by dividing the national territory into 40 sectors, scanning 100–200 plots annually using FARO Focus scanners (FARO Technologies, Lake Mary, FL, USA, formerly GeoSLAM Ltd., Nottingham, UK). This choice was motivated by their portability, allowing them to be taken to remote forest areas more easily, and their fast-scanning capabilities. Up to five scanners were used simultaneously in the field across the country, handled by specialised NFI crews trained in TLS acquisition and manual measurements.

Between 2010 and 2019, two distinct TLS acquisition periods were

Table 6
Features of the three explorative implementations of TLS and MBL technologies in NFI.

	France	Finland	Switzerland
Period of implementation	2010–2019	2017–2018	2019 – ongoing (evaluation phase), 2027 – (planned inclusion of MLS in the 6th cycle of the Swiss NFI)
Sampling season	2010–2016: leaf-on and leaf-off 2016–2019: leaf-off only (November–March)	May–November (mostly leaf-on time)	March–October (leaf-on time)
Synchronisation with the NFI field survey	2010–2016: ~207 days lag 2016–2019: 0 days lag	TLS synchronised with partial NFI field measurements	MLS synchronised with NFI field measurements
Plot shape and size	Circular 6, 9 or 15 m radius depending on tree size	Circular 9 m radius	Square 50 m side
Total number of surveyed plots	~1529	253	~6500 (expected over the full 9 years Swiss NFI cycle)
Device used	Focus (FARO Technologies, Lake Mary, FL, USA, formerly GeoSLAM Ltd., Nottingham, UK)	ScanStation P40 (Leica Geosystems AG, Heerbrugg, Switzerland)	GeoSLAM ZEB Horizon handheld MLS (FARO Technologies, Lake Mary, FL, USA, formerly GeoSLAM Ltd., Nottingham, UK)
Scanning setup	2010–2016: 4 scans per plot (variable size) 2016–2019: 9–12 scans per plot (fixed size)	Normally, 5 scans per plot	Regular parallel path covering 50 m × 50 m
Duration of the acquisition per plot	~2.5 h (including the planning of scanning locations and target positioning)	Normally 1–2 h (including preparations, scanning and field measurements)	15 min
Data processing platform	FARO Scene for scan alignment and export CloudCompare for visualisation and segmentation Computree for visualisation and processing, including stem reconstruction MATLAB tested for stem reconstruction, and R for additional post-processing	Leica Geosystems Cyclone 9.1 software for initial point cloud co-registration, MATLAB for QSM development and R for additional processing	GeoSLAM connect, Cloudcompare, LASTools, Python
TLS and MLS target attributes	DBH, stem diameters, tree height, stem volume, total tree volume	Tree position, DBH, stem volume, stem taper curve, crown information, stand-level variables	Tree position, DBH, crown information, forest structure (canopy layering, coverage, etc.), lying deadwood, forest regeneration, etc.

identified based on field protocol. From 2010 to 2016, scans occurred year-round in both leaf-on and leaf-off conditions. Each plot was covered by four scans, lasting about seven minutes each. Five spherical targets were placed for co-registration (Fig. 11). TLS acquisition was separate from traditional NFI surveys, resulting in an average lag of 207 (±126) days. During this period, around 1400 plots were scanned, representing more than 20000 trees from nearly 200 species (of which 13 species had more than 500 trees scanned). In 2016, data analysis revealed inconsistencies in point cloud density and completeness, prompting a revised TLS protocol. Scanning was restricted to a fixed 10 m radius in hardwood stands during leaf-off conditions. The number of scans increased from 4 scans to 9 to 12 scans, with optimised positions to minimise occlusion in the crown (Fig. 11). Black and yellow tape were added at breast height to identify measured trees, understory vegetation was partially removed to reduce occlusion, and scanning time was reduced from 7 to 4 min to offset the increased number of scan and reduce wind impact on the point cloud. Additional field measurements (i.e., diameter along the stem up to a diameter of 7 cm, DBH and total tree height) were taken for validation purposes. This new protocol allowed two plots per day to be acquired, for a total of 200 plots scanned (∼ 2000 trees, 50 species, of which 4 species with at least 200 trees).

Data processing started in 2015 as part of the H2020 DIABOLO project (Hackenberg et al., 2017; http://diabolo-project.eu/). The FARO Scene software (FARO Technologies, Lake Mary, FL, USA, formerly GeoSLAM Ltd., Nottingham, UK) was used to co-register TLS point clouds and export them into a standard format. A plot-level processing chain was implemented in the Computree platform (Othmani et al., 2011). It comprised (i) point filtering algorithms to remove noise and harmonise point density, (ii) DTM development to identify the ground level and separate tree points from ground points (Morel et al., 2017), (iii) tree localisation, by circle fitting in a slice between 1.20 m and 1.40 m above the ground, (iv) tree segmentation using a Dijkstra based shortest path algorithm to associate points with one of the tree seeds extracted in the previous step (Chen, 2003), (v) geometric reconstruction of the trees using the SimpleTree cylinder fitting algorithm (Hackenberg et al., 2015). The processing steps are detailed in Hackenberg et al. (2017).

The entire processing chain was evaluated as part of a EuroSDR benchmark study of TLS methods for forestry applications (Liang et al., 2018a). Tree-level assessment was also conducted on 25 NFI plots acquired through the TLS protocol used in the period 2016–2019. Four regular NFI attributes were evaluated for 114 trees (101 hardwood and 13 conifers): DBH, diameter at 2.6 m, total tree height and height at 7 cm diameter. Relative RMSEs were 5.8 %, 8.9 %, 13.4 % and 27.9 % respectively. The above-ground volume, estimated with SimpleTree (Hackenberg et al., 2015), was evaluated using an independent tree dataset of 76 trees, including conifers and hardwoods. The assessment produced a relative RMSE of 23.5 %, explaining 98 % of the observed variance on a sample.

Following this initial work, a set of 275 trees was manually extracted from 36 plots of the second-period acquisition protocol. The dataset was used to evaluate an alternative tree reconstruction approach (Raumonen et al., 2013). Assessment for DBH, total tree height and stem volume performed comparably, with relative mean absolute errors for hardwoods and conifers, respectively, of 3.84 % and 3.91 %, 7.11 % and 9.5 % and 15.83 % and 21.09 %.

Despite a processing chain being successfully implemented in Computree, increasing the technological maturity of the various steps toward operational use was held back by remaining data quality issues, the lack of dedicated permanent personnel and the difficulties in finding persons with the required competencies at that time. For these reasons, it was decided to suspend local methodological development and instead explore more technologically mature data processing algorithms. The tree volume estimations and allometric equation modelling are expected to resume once adequate processing solutions are found.

3.2. Finnish NFI

The Finnish NFI is based on clusters of 8–11 circular sample plots located close to each other and placed in a country-wide region-specific systematic grid (Korhonen et al., 2024). Some of these clusters are permanent with repeated measurements, while the rest are temporary and measured only once. About 20 simultaneously working inventory groups visit approximately 10,000 field plots yearly between May and October, covering the whole country in a 5-year cycle. The fieldwork includes measuring various tree-, stand- and plot-level variables. Tally trees are measured based on their DBH: trees with at least 9.5 cm DBH are included in a radius of 9 m, trees with 4.5–9.4 cm DBH in a radius of 4 m, and trees with DBH below 4.5 cm based on angle count sampling with a basal area factor of 1.5.

A large-scale TLS data acquisition was conducted to evaluate the feasibility of TLS-derived point clouds for improving or partially replacing Finnish NFI measurements and refining volume equations and taper curve models. Fieldwork took place in 2017–2018, with data processing and analysis over the following two years. Altogether, 568 plots were selected, although this was expected to exceed the currently available fieldwork resources capacity. The standard scanning protocol used five stations: one at the centre and four outside the plot, with adjustments made based on local conditions to minimise occlusions. For co-registration, 3–6 target spheres were strategically placed to ensure visibility from at least three stations (Fig. 12). TLS data were acquired using the ScanStation P40 (Leica Geosystems AG, Heerbrugg,

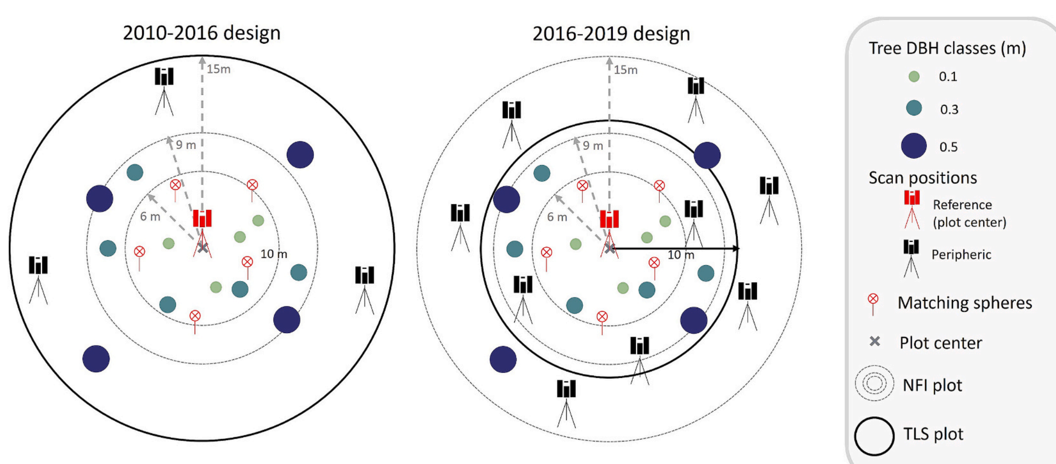

Fig. 11. TLS scanning setups in the French NFI explorative implementation in the two acquisition periods.

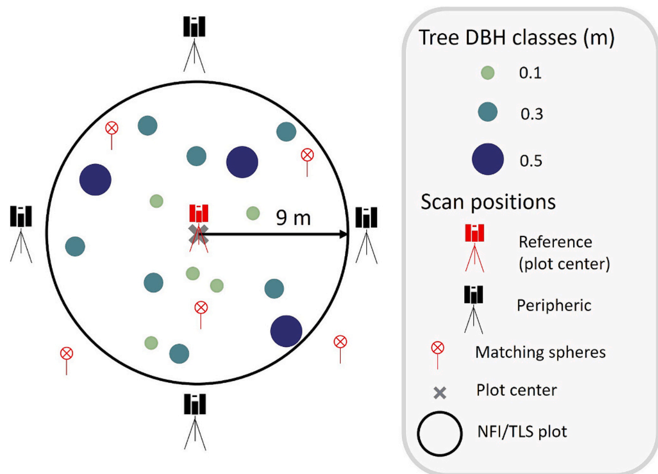

Fig. 12. TLS scanning setups in the Finnish NFI explorative implementation.

Switzerland) scanner with a point spacing of 3.1 mm at 10 m distance. Each plot required 1–2 h of fieldwork, including setting up and scanning the plot, and measuring field references. This was done by a crew of two experienced NFI fieldworkers trained to use the scanner. Each scan took about 3.5 min.

Manual tree measurements were made during the same visit, consisting of a selected subset of the operational NFI measurements. They included tree location, species, DBH, height, crown class and potential damage, site conditions and recent forest management operations. Tally trees were selected by relascope-based angle count sampling, using a basal area factor of 2 and a maximum radius of 9 m, thereby excluding some of the trees that would be part of the operational NFI protocol but simultaneously increasing the pace of the fieldwork. Additionally, stem curves of 76 sample trees from 19 plots were destructively measured (i.e., felling followed by diameter measurements from 16 different predefined proportional heights).

The entire campaign yielded scans from 253 plots across various parts of Finland and field reference measurements from 2168 tally trees. These included 971 Scots pines, 687 Norway spruces, 405 birch, and 105 trees of other species. After the acquisition, the individual scans of a plot were co-registered using Cyclone 9.1 software (Leica Geosystems, Heerbrugg, Switzerland).

Stems were identified, and their cylinder-derived QSMs were extracted using Matlab-based methods (Raumonen et al., 2013). Due to occlusions and wind-induced inaccuracies, a complementary approach was adopted to improve diameter modelling by splitting data into single scans and applying a circle-fitting procedure (Pitkänen et al., 2019). TLS-based stem volume estimates were further refined by incorporating field-measured dimensions and taper curves, reducing relative RMSE to under 5 % compared to destructively measured trees (Pitkänen et al., 2021). These results were first used to estimate calibrated stem volume functions, which indicated significant changes in the stem form compared to earlier models (Kangas et al., 2020) and then further applied to construct taper curve models (Kangas et al., 2022). Additionally, 113 Scots pines and 96 Norway spruces from 24 plots were manually segmented into good-quality single-tree clouds and used to quantify the inter-tree competition effects (Pitkänen et al., 2022).

Generally, TLS data collected during the campaign was sufficient to fulfil the initial purposes of improving the existing volume functions and taper curve models. Although the added value of TLS data for producing detailed structural information on trees was obtained, it was considered insufficient to meet the current requirements for operational NFI results or provide practical possibilities for equipping field crews with scanners that could be operated in addition to normal measurements. The NFI fieldwork, therefore, continues contemporarily based on traditional plot-wise manual measurements.

In conclusion, the collected data permitted the generation of updated stem volume and taper curve models, together with the assessment of the inter-tree competition effects. However, this explorative implementation relied strongly on time-consuming post-processing of the data from selected plots and trees, which also included manual computer work. Additionally, problems of correctly detecting and measuring all the trees increased substantially at higher tree densities because of occlusion, and more scanning stations would have been required. There also remained the important question of whether certain tree species or forest types were more prone to random errors or bias, which could be an issue from the perspective of NFI.

3.3. Swiss NFI

The Swiss NFI consists of more than 6500 plots regularly distributed on a grid of side 1.4 km over the whole country, visited at least once in a nine-year cycle. Fieldwork occurs annually from March to October, with approximately 750 plots assessed by three NFI field teams. Each plot features two concentric circles: a 200 m^2 area with a 7.98 m radius and a 500 m^2 area with a 12.62 m radius, along with a concentric 50 m × 50 m square. Tree measurements (position, species, DBH, and, for selected trees, total tree height and diameter at 7 m above ground) are made inside the two concentric circles. In the smaller 200 m^2 circle, all trees with a minimum DBH of 12 cm are measured. In the larger 500 m^2 circle, trees with a minimum DBH of 36 cm are measured. No tree measurements are performed outside these circular plots. The 50 m × 50 m square area is used to evaluate general forest stand structure, including canopy layering, coverages, and development stage, primarily based on expert knowledge.

Implementing proximal sensing technologies to support the Swiss NFI began to be considered in 2019. The aim was to include the chosen technology alongside conventional NFI plot assessments starting in 2027 with the sixth Swiss NFI cycle. The operational maturity of proximal sensing technology for the Swiss NFI was assessed based on a set of predefined constraints that had to be met. First, data acquisition should be performed by the usual NFI field teams during the conventional plot evaluations (i.e., from March to October in the leaf-on season). Secondly, including the selected remote sensing technology in the NFI plot evaluation protocol should not significantly increase the time spent on each plot: a maximum of 15 min of additional time on average over all NFI plots was set. Thirdly, the chosen instrument should not weigh more than 4 kg. Lastly, data acquisition should result reliably in an analysis-ready point cloud even under challenging conditions (e.g., steep terrain, dense understorey).

A benchmark study in Switzerland evaluated the suitability of TLS, MLS, and terrestrial photogrammetry in NFI operations, where MLS showed the highest potential for an operational implementation in the Swiss NFI while conforming to the set limitations (Kükenbrink et al., 2022). After the benchmark study, TLS was excluded from further evaluation due to its time requirements for complete coverage of the 50 m × 50 m square area. Terrestrial photogrammetry, though favourable in terms of acquisition time and hardware costs, was not further considered owing to the limited vertical coverage of the acquired point clouds (maximum up to 5 m above ground) and the reduced reliability in successfully producing an analysis-ready point cloud, especially for plots with higher understorey densities (Kükenbrink et al., 2022).

The goal of including MLS within the Swiss NFI was not to replace any currently measured forest variables, but to expand the scope of the information that could be obtained from each plot. Tree measurements, currently conducted only on smaller 200 m^2 and 500 m^2 circular plots, were intended to be expanded to cover the entire 50 m × 50 m square plot. This increase would be especially beneficial for evaluating the protective functions of mountain region forests, where the smaller plots pose limitations for such assessments. Additionally, forest structure assessments, primarily based on expert knowledge, which is prone to observer bias (Morrison, 2016) and shows limited reproducibility

(Traub et al., 2019), could be enhanced by MLS technologies capable of accurately reproducing the three-dimensional structure, thereby improving the monitoring of changes in forest structure with higher reproducibility than conventional methods.

The goal of the MLS implementation in the Swiss NFI is to cover all 6500 NFI plots. However, topographic or weather conditions might hinder the successful acquisition of all plots, mainly owing to safety concerns. The number of plots affected by this and the associated consequences are currently being investigated.

The protocol of the MLS data acquisition for each 50 m × 50 m square plot follows a regular path starting from the centre of the plot (Fig. 13). The operator should try to replicate this theoretical pattern as closely as possible through a slow walking pace (around 2 km/h). The terrain morphology and the undergrowth influence the acquisition time, which ranges from 10 min for a flat and easy plot to slightly above 15 min for very steep slopes (>90 %) and rugged terrain. Tree measurements (position, DBH, etc.) are made on the circular 200 m^2 and 500 m^2 plots. Forest structural assessment, together with MLS acquisitions, is performed on the 50 m × 50 m plot, shown as a grey dashed square in Fig. 13.

Currently, the GeoSLAM ZEB Horizon handheld MLS (FARO Technologies, Lake Mary, FL, USA, formerly GeoSLAM Ltd., Nottingham, UK) is being evaluated. However, it is already clear that completing an NFI cycle with the same instrument used at the start is unlikely due to the rapid evolution of laser scanning technologies, with new instruments entering the market almost annually. Evaluations are currently underway to assess the implications of changing instruments mid-cycle.

Because the implementation of MLS in the Swiss NFI is still being evaluated, the processing solutions and methods used are also continuously evolving. The processing chain currently uses the GeoSLAM proprietary software for processing the raw data and a combination of self-developed Python processing scripts in combination with LAStools (https://rapidlasso.de/) and CloudCompare (v 2.1.3, https://cloudcompare.org). Currently, the retrieved attributes include tree position and DBH, determined using an in-house developed tree detection algorithm called TreeDetector (Rehush et al., 2023), together with the amount of occluded volume during acquisition, calculated using a voxel traversal algorithm (Kükenbrink et al., 2017). Additional attributes of interest include lying deadwood, forest structure, forest regeneration, and light availability.

Until the planned implementation of MLS in the Swiss NFI in 2027, extensive testing is being conducted to identify best practices and assess reliability under various conditions using different devices. Additionally, efforts are underway to develop data archiving systems and processing pipelines. A study reporting on the performance of handheld MLS on 29 NFI plots distributed over the entire country and covering typical forest characteristics found in Switzerland, with a focus on challenging conditions (i.e., steep terrain, dense understorey vegetation), is currently under revision (Kükenbrink et al., 2025). This study showed promising results, highlighting high reliability in producing an analysis-ready point cloud also under challenging conditions. However, strategies to mitigate incomplete acquisitions due to terrain or dense vegetation have to be developed.

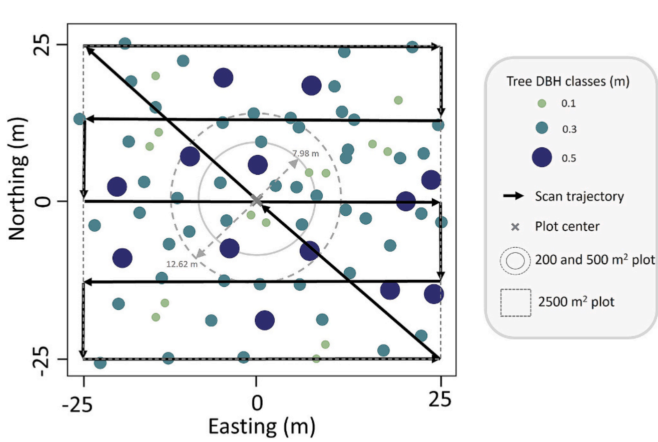

Fig. 13. MLS scanning design applied in the Swiss NFI explorative implementation.

3.4. Identified constraints for the operational inclusion of TLS and MLS technologies in NFI

NFIs are an ever-ongoing process for assessing the current state of forest resources and monitoring their dynamics over time. Most NFIs have been maintained for more than 30 years, building up a long-time series of measurements made with the same methods and tools (Breidenbach et al., 2021). The NFI field measurements of individual tree attributes represent only a small part of the overall NFI monitoring workflow, and any changes in the way the measurements are made would impact other processes, such as data processing, planning, and statistical analysis. Despite this, the high potential of TLS and MLS, both in terms of data quality and the opportunities they offer, motivated the French, Finnish, and Swiss NFIs to explore their utilisation within their monitoring systems. Through the experience gained from the exploratory implementation, new challenges specific to the integration of TLS and MLS technologies into NFI protocols for field surveys and data processing became more apparent. We have categorised these challenges into four groups: logistical challenges, data quality challenges, economic challenges, and challenges related to the perception and acceptance of new technologies.

3.4.1. Logistical challenges

Transporting and deploying TLS and MLS tools in a forest environment can be challenging. NFI plots are often located far from accessible roads, requiring field crews to carry all equipment on foot from the nearest access point to the plot. Increasing the volume and weight of the equipment already in use may thus be undesirable. Lighter and more compact scanners may be preferred even at the cost of lower scanner performance.

TLS and MLS tend to be less accurate in harsh weather conditions such as heavy rain or high-speed wind (Vaaja et al., 2016; Filgueira et al., 2017). Although avoiding such conditions might be feasible in isolated studies, it is impractical for NFIs, where field crews must proceed with data collection regardless of the weather to comply with the survey schedule. This will lead to cases where manual measurement is carried out, but TLS or MLS acquisition cannot be performed optimally because waiting for weather to improve is impossible owing to economic and scheduling constraints, forcing field teams to skip 3D data acquisition. This can introduce additional issues, because missing plots can lead to statistical bias (see Section 6.4.2).

NFI field crews work on tight schedules, and adding TLS and MLS surveys increases the time required per plot, potentially delaying campaigns. To mitigate this, institutions may need to deploy additional dedicated teams or reduce scanning durations, which could lower point density. Understanding how scan density affects point cloud quality is essential for both TLS and MLS. Vandendaele et al. (2024) found that while MLS scanning patterns did not significantly impact the accuracy of tree height, DBH, or crown attributes, sparser scans were preferable for estimating volume, particularly for smaller branches, as it reduces wind-induced noise. For TLS, Wilkes et al. (2017) showed that denser scans result in more uniform point clouds, improving segmentation and measurement accuracy. To address inconsistencies in point density across forest types, operators, and scanners, research increasingly focuses on sensor-agnostic algorithms for point cloud segmentation and tree attribute estimation (e.g., Krisanski et al., 2021a).

Scanning also requires field crews to attend to other tasks, such as charging batteries and extracting point cloud data from the scanners, which is typically then uploaded to a processing server. In an operational context, weak network connections can hinder data uploads, creating bottlenecks in fieldwork and potentially resulting in large data volumes being transmitted simultaneously. The considerable time required to process the data and extract tree attributes must also be considered. The NFI office crew regularly monitors the progress of the field crew and verifies the quality of the obtained data to minimise errors and prevent them during the field survey campaign. A time lag between 3D data acquisition and processed results could result in issues being noticed much later, potentially leading to missing plot information or significant time loss if the plot must be revisited, which is often not possible.

3.4.2. Data quality constraints

When forest plots cannot be fully or partially scanned with TLS or MLS due to difficult conditions (e.g., dense vegetation, rough terrain, or adverse weather), the resulting omissions must be accounted for to avoid bias. NFIs rely on aggregated plot data rather than individual plots, meaning missed plots can often be compensated for if they are representative of the same population. Random omissions, such as those caused by weather, generally have minimal impact, whereas systematic omissions within specific forest types or terrains pose a greater challenge. To mitigate this, it is crucial to identify the characteristics of unscanned plots during an initial test phase, analysing factors such as slope, forest structure, and location. If the omitted plots differ significantly from those successfully scanned, further manual measurements or targeted TLS/MLS experiments may be needed to refine estimates.

Point cloud-derived attributes should be accurate, unbiased, and representative of the full variability of interest. While automated extraction performs well for basic features like tree locations and DBH, retrieving detailed structural attributes, such as branch or crown characteristics, is more error-prone due to occlusions and wind-induced co-registration issues. Occlusion is particularly problematic in dense forests with overlapping crowns, leading to underestimations of tree height and branch wood volume. Increasing scanning coverage, by intensifying the number of scans per plot, or scanning during the leaf-off period, can help, but challenges remain in softwood-dominated regions where the leaf-off period without snow cover is brief. Further research is needed to assess how forest structure and weather affect TLS and MLS accuracy, especially across diverse forest types. Seasonal variations also impact measurements, as scans conducted during leaf-on and leaf-off periods may yield different results. Understanding and quantifying these errors is crucial for accurate reporting. Studies have shown mixed findings: Tupinambá-Simões et al. (2024) found no significant differences in DBH, tree height, or stem volume between leaf-on and leaf-off MLS measurements, whereas Arseniou et al. (2023) observed no impact on stem volume but significant differences in branch volume using TLS in a North American deciduous forest.

Given the rapid evolution of TLS and MLS scanners, it is probable that scanner models will change at some point. The impact of changing instruments on the derived forest attributes must therefore be evaluated and accounted for. However, several studies have shown that instruments with varying levels of precision and accuracy (e.g., TLS vs. MLS) can yield similar results for attributes such as tree position and DBH (Gollob et al., 2020; Mokroš et al., 2021; Kükenbrink et al., 2022), suggesting that some robustness to instrument changes is possible.

A significant data quality concern arises from the monitoring role of NFIs, which rely on repeated measurements over time to study the evolution of forest resources. If we were to use TLS or MLS to replace some previously sampled attributes, the accidental and unrecognised introduction of bias (or the removal of a previously existing bias) in the estimation could impact the conclusions drawn from monitoring. For instance, if TLS and MLS data were to estimate wood volume slightly higher or lower than conventional methods, the predicted trend in wood volume over time could be inaccurate, potentially leading to a false impression of declining wood productivity. To avoid such scenarios and identify potential biases, both traditional and new measurement tools must be employed during a transition phase to ensure continuity across years.

Additionally, potential errors due to a difference in acquisition patterns, operators, or acquisition period should be controlled or minimised to prevent fallacious interpretations of forest resource evolution.

3.4.3. Economic constraints

From an economic perspective, the implementation of TLS and MLS will need a significant investment in equipment, software, database maintenance, and qualified personnel. Field crews will also require training to ensure the proper use of the equipment.

NFIs often operate with multiple crews collecting field data simultaneously, meaning each crew will need to be equipped with scanners. Additional scanners will have to be procured to ensure backup for any equipment failure.

Processing the data will require high-performance computers with substantial processing power and large storage systems. The infrastructure will need regular maintenance and oversight to ensure its reliability and efficiency, adding to the regular costs of the implementation.

Data processing requires highly qualified personnel with expertise in both forestry science and computer programming. Additionally, they will need to stay updated on the latest algorithms and methods for processing point clouds, which may necessitate regular training. All these factors taken together must be considered when planning the implementation of TLS or MLS because the costs of setting up the process and maintaining it are both high. The budget to keep a TLS and MLS campaign running must be assured in the long term to prevent acquisitions from being abandoned partway through.

3.4.4. Constraints linked to the perception of new technologies

The adoption and implementation of a new technology never relies solely on efficiency gain and direct benefit of implementation (Nitoslawski et al., 2021; Haber and Carmeli, 2023). Both the perceived usefulness and ease of use, and the users' propensity to accept new technologies affect its implementation (Godoe and Johansen, 2012). NFIs rely on traditional means of measuring that have been tried, tested and used for a long time and so consolidated. NFI protocols and practices have evolved gradually over time, with the tools used slowly adapting in step. Up to the present, this slow evolution was based on already applied principles and tools, such as the transition from cross-staff to electronic clinometer to retrieve total tree height. The form and use of the instrument have changed significantly, but the trigonometric principle underlying the measurement remains the same. On the other hand, the principles underlying measurements made with TLS and MLS technologies are substantially different from those of traditional instruments.

TLS and MLS are seen by some forest actors as disruptive (Christensen et al., 2016) and groundbreaking technologies (Affan Ahmed et al., 2021) that threaten to slowly replace traditional tools and expertise and render them obsolete. Although the scientific community has already demonstrated the quality of the TLS and MLS measurements, not all forest actors are ready to rely on 3D observations to support conclusions on forest resource state and evolution. In contrast, other actors view TLS and MLS as consolidated technology and expect it to replace traditional measurement (Torresan et al., 2020), with more efficient and accurate results and time saving in the overall inventory process. Still others see it as a supplementary tool that could co-exist with previous methods and could bring new possibilities without replacing current practices. These conflicting views make it sometimes difficult to set the right expectations for TLS and MLS implementation, and the resulting debate can slow down the approval of the technology.

4. Discussion

4.1. Benefits drawn from TLS and MLS in NFIs

TLS and MLS enable forest managers to assess tree position, height, volume, and wood quality from a single set of scans, providing a comprehensive understanding of the woody resource with a single tool (Moskal and Zheng, 2011). Moreover, attributes that are either very complex or impossible to measure manually, such as LAI, crown surface, and volume, can already be retrieved from TLS and MLS point clouds. Emerging attributes, such as the retrieval of microhabitats on individual trees (Rehush et al., 2018; Fol et al., 2023), offer even more opportunities. These advancements could enable the assignment of biodiversity values to individual trees (Asbeck et al., 2021).

One significant benefit of TLS and MLS systems is their potential to enhance the reproducibility and objectivity of measurements derived from point clouds. Algorithms applied to point cloud data can be reprocessed to yield consistent results, reducing operator-induced variability. This is particularly relevant for metrics such as tree height, which are prone to inconsistencies in manual assessments (Yanai et al., 2022). Additionally, several attributes traditionally measured in NFI campaigns, such as vegetation coverage, potential fire fuel, and dominance, rely on expert judgment. While this approach balances efficiency and robustness, it remains inherently subjective and susceptible to operator bias (Frey et al., 2019; Yanai et al., 2022). Although early research suggests that TLS- and MLS-based methods could mitigate these limitations and improve measurement consistency (Frey et al., 2019), their full operability in NFIs must be confirmed through further testing. Comprehensive evaluations across diverse forest conditions and larger-scale campaigns are still needed to determine whether these methods can fully replace or should instead complement expert-driven assessments.

Another benefit is the long-term value of scan data as a resource for retroactive monitoring. Data acquired at a specific point in time can be preserved and reprocessed using updated algorithms to address emerging research needs. For example, 3D data collected in 2018 could be used retrospectively to measure tree diameters at a height of 7 m or to apply new algorithms for detecting individual tree microhabitats for that specific year, which is not feasible with traditional manual field measurements. This parallels the evolution of technologies such as aerial LiDAR and satellite imagery, where the full potential of early data was initially underappreciated but later acknowledged as research advanced and new applications emerged. Over time, older data became invaluable for retrospective analysis, even as scanning technologies continued to improve in capacity and resolution. Similarly, TLS and MLS data are expected to follow this trajectory, increasing in utility as they become integrated with new techniques and applications.

For time and practical reasons, NFI plots are often limited to dimensions approximating 600–1000 m^2. Increasing the surface manually sampled would proportionally increase the time spent on each plot. However, while initial TLS setup and scan can be time-consuming, MLS facilitates larger sampled areas without drastically increasing scanning time. Bauwens et al. (2016) took 13 min with a ZEB1 to cover a 700 m^2 plot (close to the NFI plot size), Hyyppä et al. (2020a, 2020b) covered 1000 m^2 in 10 min with a ZEB Horizon, while Kükenbrink et al. (2022) used a ZEB Horizon MLS to scan 2500 m^2 in only 15 min. These examples show how increasing the sample surface area does not necessarily drastically increase scanning time. Hence, MLS could potentially increase the extension of the area of the sample units and make the plots more representative of the forest. The monitoring process could then be more accurate if the measurement accuracy is maintained. In their study on the effect of scanning patterns using a Hovermap MLS (Emesent Pty Ltd., Milton, QLD, Australia), Vandendaele et al. (2024) found that a 20 m × 20 m grid pattern could prove more accurate than a denser 9 m circular plot pattern. This is possibly due to the oversampling of the scene, increasing the noise around the sampled trees. On the other hand, an underscanned plot would mean more occlusion, reducing overall accuracy. We still recommend expanding the surface beyond the traditional NFI plot limits to take full advantage of the MLS capacities.

In NFI plots, not all variables are estimated on the same area. Many NFIs are based on concentric circular plots of various radii, where smaller trees are measured only in the smallest circles while large trees are measured in the larger ones. This approach can introduce statistical uncertainties because the influence of individual trees on the overall forest assessment varies depending on their size and position within the plot. The use of TLS and MLS could solve this problem as the surface would be sampled uniformly, giving each tree the same representative value.

4.2. Practical considerations for the implementation

In case an NFI desires to implement TLS or MLS on a regular basis, we recommend the following steps.

First, we believe NFIs should familiarise themselves with TLS and MLS through a preliminary campaign which would last at least one year. We advise this campaign to be set on a representative subsample of the NFI plots, which should be scanned at least twice in different weather and seasonal conditions. This preliminary campaign will allow the NFI to set up the proper computation chain, train the field crew to operate the scanners and quantify the impact of the forest type, seasonality and weather on the measurement within the country's specific forest types. Furthermore, the preliminary campaign could also help build a foundational database for species recognition algorithms.

Once this test phase is over, the implementation can begin alongside the traditional measurement. Even if the end goal is to entirely replace dendrometric measurements, it is crucial to maintain both methods concurrently for a period ranging from one year to a full NFI cycle. This overlap will ensure continuous data comparability. Given the monitoring nature of NFIs studying forest evolution, the switch from traditional measurements to TLS or MLS must be gradual. This gradual shift is essential to ensure that comparisons between consecutive inventory instances (e.g., year to year, or cycle to cycle) are made using the same tools. This will permit the mitigation of any bias introduction or removal in the measurements. For instance, to properly assess changes from year T–1 to T + 1, physical measurements will be available for T–1 and T, and LiDAR measurements for T and T + 1, hence ensuring consistent overlap. To obtain the total evolution between T–1 and T + 1, the change observed in the physical measurements between T–1 and T should be added to the change observed in the LiDAR measurements between T and T + 1. However, as authors, we recommend not aiming for a complete replacement of traditional measurements with TLS/MLS in the short term. This is due to various constraints and inherent risks associated with TLS/MLS use. There remain too many uncertainties regarding the impact of weather conditions and forest structure, and the quality and reliability of TLS/MLS measurements may not yet consistently meet all expectations. As it stands today, TLS/MLS is an excellent tool for enabling new types of measurements, expanding plot coverage, and making expert assessments more rigorous across all scanned plots.

Should manual measurements be entirely replaced by TLS or MLS scans, it will be essential to maintain a smaller, representative subsample of plots where traditional measurements are still performed for validation purposes after the implementation phase. This practice would also help mitigate the potential introduction of long-term bias.

The choice between TLS and MLS will primarily depend on the specific objectives. TLS offers higher precision but is more complex and time-consuming to deploy in the field, and it is also more susceptible to occlusions. If the goal is to evaluate volume equations or monitor allometric changes through targeted use within the NFI, then TLS deployed on a subsample of plots is ideal.

On the other hand, MLS offers simplicity and speed of acquisition, and generally results in less occlusion than TLS, although it is less accurate. In cases where LiDAR scanning is to be applied systematically across all plots, MLS would be the preferred option.

Regarding leaf-on and leaf-off scans, in case of complete implementation of TLS or MLS, the scans will need to be performed in both conditions to follow the NFI schedule. In case of punctual use, the preferred condition will depend on the overall objective and the desired measurements. E.g., precise volume estimation, total tree height and diameter estimations will perform better in leaf-off conditions, while all leaf-related attributes will need leaf-on conditions. Additionally, in some countries, leaf-off conditions may coincide with unfavourable seasonal weather such as snow, rain, or strong winds. In such cases, leaf-on scanning might be preferred regardless of the specific measurements desired.

On a more practical note, the need for qualified personnel should not be underestimated. Even though more and more user-friendly and semi-automated algorithms and methods are being developed, processing point cloud data still requires a high level of expertise to process properly, and even automated processes still need to be supervised to ensure data quality. It is important to note that advancements are being made toward real-time, fully automated MLS data processing to retrieve DBH (Li et al., 2023), tree crown (Li and Xue, 2023) and species identification (Puliti et al., 2025).

Employing TLS and MLS technologies for NFI demands technical expertise and adequate infrastructure. It is therefore important to nurture close collaboration among technology experts, scanner manufacturers, and forest management professionals. Likewise, sharing experiences and communicating with other TLS and MLS users, whether other NFIs or researchers, can be most valuable. Exchanging insights, challenges, and recommendations with other users can provide practical tips and help avoid common pitfalls, thereby improving the efficiency and effectiveness of the TLS and MLS implementation.

Lastly, while TLS and MLS technologies are impressive and valuable, it is important to keep in mind that at the current time, they will not reduce the workload of field and office crews, nor will they reduce the overall cost of data acquisition. The implementation of TLS or MLS, whether as a periodic tool for specific reasons, such as for the French or Finnish NFIs, or for continuous use as planned in the Swiss NFI, can overcome traditional measurement limitations if carefully planned. We recommend setting clear goals for the TLS and MLS implementation at the start of the field campaign, as it is essential for defining the modus operandi for both field operations and the data processing chain. This clarity will streamline the entire process, ensuring that all parties are aligned and that adequate resources are used efficiently.

5. Conclusion

In this practice-oriented paper, first, we demonstrate the potential of TLS and MLS in NFIs, describing standard practices and listing individual tree attributes that can be recovered from the point cloud. We highlighted the possibilities and benefits offered by TLS and MLS technologies in forest inventories. Both TLS and MLS have a high potential in the NFI context, notably by allowing the measurement of new forest attributes or by increasing the accuracy and precision of other attributes, such as tree height and wood volume. While standard scanning protocols have been proposed for plots of 0.1 ha, which represent the approximate area for tree measurements in NFI, this standard plot surface and scanning protocol can easily be adapted to specific conditions and contexts and should not be constrained by historical standards.

Second, we analysed three practical cases, i.e., French, Finnish and Switzerland NFIs, where TLS and MLS technologies have been implemented and tested, and we identified the main constraints as experienced by users. Many implementation challenges come from logistical and data quality considerations, with a particular focus on the uncertainties in scheduling, weather impact and potentially unscannable plots.

Lastly, we made recommendations for the implementation of TLS or MLS in NFIs. The main recommendations are to consider TLS and MLS as an addition and enhancement to traditional measurements rather than a replacement, to start with a smaller test phase on a representative set of plots, to consider increasing the area of sampled plots relative to standard NFI plots, and to maintain close collaboration with other TLS and MLS users to benefit from rapidly advancing developments in this field. We believe that the benefits of data will increase over time, so there is an incentive to begin collecting data now in anticipation of more powerful analytical approaches, which remain in development, and which can take advantage of temporal information.

While we focused on French, Finnish and Swiss experiences of TLS and MLS technology implementation in the NFI, many countries are evaluating the potential benefit of adding TLS and MLS to their NFI protocol. For example, as this is being written, Slovenia, Belgium and Luxembourg are experimenting with MLS in subsamples of their NFI plots. Continuing to explore the feasibility of implementing TLS and MLS technologies in NFI will gradually bring TLS and MLS-enhanced forest inventories closer to operationalisation. Given the great potential of TLS and MLS and the ever-growing sum of research it attracts, we are confident that it will become increasingly available and easy to use for practitioners.

Investment in TLS and MLS technologies by NFI programs should be guided by clearly defined objectives and realistic expectations. Rather than simplifying or replacing all measurements, these technologies excel in enhancing the accuracy of specific attributes while enabling new measurement capabilities and future opportunities. Although the initial cost of adoption is significant, the return on investment will increase over time. However, such an investment is advisable only if NFIs can ensure long-term maintenance and guarantee the necessary financial and technical resources to support it.

Adopting TLS and MLS will position NFIs as leaders in forestry innovation, fostering collaboration with research institutions, universities, and other NFIs. This investment also enables participation in ongoing research. If coordinated, it can promote the standardisation of NFI methodologies across countries. For instance, algorithms developed for one nation’s data could be applied to the point clouds acquired through scans in other countries, addressing the critical challenge of measurement harmonisation, of great current relevance in Europe. Therefore, to maximise the impact of this investment, NFIs should prioritise collaboration and knowledge-sharing initiatives.

Despite the identified constraints and the difficulties arising in its use, the potential information provided by TLS and MLS data will support more sustainable and informed forest management practices in silviculture, biodiversity and restoration.

Credit authorship contribution statement

Justin Holvoet: Writing – review & editing, Writing – original draft, Visualization, Investigation, Data curation, Conceptualization. **Markus P. Eichhorn:** Writing – review & editing, Investigation, Conceptualization. **Francesca Giannetti:** Writing – review & editing, Investigation, Conceptualization. **Daniel Kükenbrink:** Writing – review & editing, Visualization, Resources, Investigation, Data curation, Conceptualization. **Xinlian Liang:** Writing – review & editing, Investigation, Conceptualization. **Martin Mokroš:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Conceptualization. **Jan Novotný:** Writing – review & editing, Visualization, Investigation, Conceptualization. **Timo P. Pitkänen:** Writing – review & editing, Visualization, Resources, Investigation, Data curation, Conceptualization. **Stefano Puliti:** Writing – review & editing. **Mitja Skudnik:** Writing – review & editing. **Krzysztof Stereńczak:** Writing – review & editing. **Louise Terryn:** Writing – review & editing. **Cédric Vega:** Writing – review & editing, Visualization, Resources, Investigation, Data curation. **Chiara Torresan:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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Appendix A. Supplementary data

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