Revista Brasileira de Cartografia
ISSN 1808-0936 | https://doi.org/10.14393/revbrascartogr
Sociedade Brasileira de Cartografia, Geodésia, Fotogrametria e Sensoriamento Remoto

Terrestrial Laser Scanning (TLS): state-of-the-art and applications in forest plantations

Laser Scanner Terrestre (TLS): estado da arte e aplicações em plantios florestais

Adriane Avelhaneda Mallmann [1], Ana Paula Dalla Corte [2] Alexandre Behling [3], Lucas Henderson Oliveira dos Santos [4], Claiton Nardini [5], Jonathan William Trautenmüller [6], Kauana Engel [7], Carlos Roberto Sanquetta [8] and Rubén Manso [9]

1 University of Paraná - UFPR, Curitiba, PR, Brazil. mallmann.adriane@gmail.com.
ORCID: https://orcid.org/0000-0002-5588-9877
2 University of Paraná - UFPR, Curitiba, PR, Brazil. anapaulacorte@gmail.com.
ORCID: https://orcid.org/0000-0001-8529-5554
3 University of Paraná - UFPR, Curitiba, PR, Brazil. alexandre.behling@gmail.com.
ORCID: https://orcid.org/0000-0002-7032-2721
4 University of Paraná - UFPR, Curitiba, PR, Brazil. lucashendersonohs@gmail.com.
ORCID: https://orcid.org/0000-0002-0121-8752
5 University of Paraná - UFPR, Curitiba, PR, Brazil. claitonardini@gmail.com.
ORCID: https://orcid.org/0000-0001-5791-6720
6 "Luiz de Queiroz" College of Agriculture - ESALQ), University of São Paulo -USP, Piracicaba, SP, Brazil. jwtraute@gmail.com.
ORCID: https://orcid.org/0000-0002-1314-8026
7 University of Paraná - UFPR, Curitiba, PR, Brazil. kauanaeg@gmail.com.
ORCID: https://orcid.org/0000-0002-8171-0885
8 University of Paraná - UFPR, Curitiba, PR, Brazil. carlossanquetta@gmail.com.
ORCID: https://orcid.org/0000-0001-6277-6371
9 Forestry Research (UK). rmgforestal@hotmail.com.
ORCID: https://orcid.org/0000-0003-0667-8392
Received: 05.2024 | Accepted: 04.2026

Abstract: In forest inventories, obtaining accurate data from forest plantations is important for estimating the production of these areas. In this context, remote sensing plays a relevant role in forest inventory activities. TLS uses LiDAR technology to collect field data and facilitate rapid acquisition of this information. Therefore, this study aimed to conduct a literature review on the use of TLS technology in forest plantations over the last 10 years (2012–2022). In the bibliographic survey conducted during this period, 19 scientific publications published in 9 journals were selected. The year with the highest number of publications was 2022 (42.10%). In total, 12 different TLS sensors were identified among the analyzed studies, with the RIEGL VZ-400 being the most frequently used. In general, the studies addressed topics related to 3D point cloud registration, extraction of dendrometric metrics, and application of TLS in forest environments. The results indicated that the adoption of multiple scanning positions contributes to mitigating the effects of occlusion caused by tree density and understory vegetation, resulting in higher tree detection rates and more reliable estimates of DBH and tree height.
Keywords: Terrestrial Laser Scanning. Forest Inventory. Remote Sensing. Forest Point Cloud.

Resumo: No inventário florestal, a obtenção de dados precisos dos plantios florestais é importante para estimar a produção dessas áreas. Nesse contexto, o sensoriamento remoto desempenha papel relevante nas atividades de inventário florestal. O TLS utiliza a tecnologia LiDAR para coletar dados de campo e facilitar rápida aquisição dessas informações. Portanto, este estudo teve como objetivo realizar uma revisão da literatura sobre o uso da tecnologia TLS em plantios florestais nos últimos 10 anos (2012-2022). No levantamento bibliográfico realizado nesse período, foram selecionadas 19 publicações científicas publicadas em 9 periódicos. O ano com maior número de publicações foi 2022 (42,10%). Ao todo, foram identificados 12 diferentes sensores TLS entre os estudos analisados, sendo o RIEGL VZ-400 o mais utilizado. De modo geral, os estudos abordaram temas relacionados ao registro de nuvens de pontos 3D, extração de métricas dendrométricas e aplicação do TLS em ambientes florestais. Os resultados indicaram que a adoção de múltiplas posições de escaneamento contribui para mitigar os efeitos de oclusão causados pela densidade de árvores e vegetação do sub-bosque, resultando em maiores taxas de detecção de árvores e estimativas mais confiáveis do DAP e altura das árvores.
Palavras-chave: Varredura a Laser Terrestre. Inventário Florestal. Sensoriamento Remoto. Nuvem de Ponto Florestal.

1 INTRODUCTION

Forests worldwide cover a total area of approximately 4 billion hectares, of which 3.74 billion hectares are classified as native forests, representing about 93% of the total, while planted forests account for 291 million hectares, corresponding to approximately 7% (FAO, 2020). Since 1990, the area of planted forests has increased by around 123 million hectares, with approximately 44% of these plantations being predominantly composed of introduced species, defined as species that are not native to the region where they are cultivated and that originate from other countries or continents. These species are generally selected due to their rapid growth, high productivity, and suitability for intensive management systems, such as species of the genera *Eucalyptus* and *Pinus* (FAO, 2020).

Understanding the characteristics of trees in forest plantations is of paramount importance for calculating tree biometric variables and estimating production in these areas (Hunčaga et al. 2020). In this regard, remote sensing plays a significant role in the field of forest inventory. Terrestrial Laser Scanning (TLS) utilizes Light Detection and Ranging (LiDAR) technology for field data collection in forest inventories and can facilitate the rapid acquisition of this type of data.

LiDAR is an active remote sensing system that emits energy and records the signal returned after interacting with objects, allowing the generated information to be represented at large scales as three-dimensional surfaces (Fernández-Sarría et al., 2013). However, these approaches present limitations in the detailed characterization of stem structure and in the accurate estimation of individual-tree variables, particularly in dense forest stands.

In contrast, TLS enables the acquisition of ultra-high-density three-dimensional point clouds from ground level, allowing a detailed description of tree geometry, including diameter at breast height (DBH), stem form, and crown architecture, with millimeter-level accuracy (Hunčaga et al., 2020). For this reason, TLS has emerged as a promising tool for high-precision forest inventories and studies at the individual-tree scale.

Image-based methods, such as photogrammetry and 3D reconstruction using Structure-from-Motion (SfM), have also been applied in forest environments, mainly due to their lower operational costs. However, these approaches are highly dependent on lighting conditions and target visibility, and they present limitations in canopy penetration and in the acquisition of structural metrics in areas with high tree density (Iglhaut et al., 2019).

Therefore, for the acquisition of precise point cloud-based information from TLS in the field of forest inventory, it is necessary to search the literature that addresses this technology in the context of forest plantations. Thus, this study aimed to conduct a literature review to gather publications addressing the use of TLS technology in forest plantations over the last 10 years (2012-2022). This includes quantifying publications that discuss the use of TLS technology in forest plantations, listing the sensors used, and describing the applications and prospects of using TLS technology in forest plantations.

2 MATERIALS AND METHODS

2.1 Bibliographic Survey

This literature review aimed to answer the following research question: What scientific knowledge has been produced in the last 10 years (2012-2022) regarding the use of TLS technology in forest plantations? To achieve this, it combines two types of review: a systematic review and a literature scoping review. The systematic review was used to obtain an initial set of articles for the survey, focusing on the year 2022. For this review, the following search query was formulated: TLS AND FOREST. The searches were conducted in the Web of Science (WoS) textual database, as it is one of the databases with a high number of indexed journals available.

Meanwhile, the scoping review was used to select a second set of articles, comprising publications from 2012 to 2022 that are cited by the authors of the first set of articles. The final set of articles in the survey combines the articles selected in both reviews.

The selection of articles for the survey was based on the following inclusion criteria: (1) scientific articles that are open access; (2) articles published from 2012 to 2022; (3) research articles; and (4) articles related to the use of TLS technology in forest plantations.

The following were excluded from the survey: (1) studies published in sources other than scientific articles; and (2) scientific articles in which TLS technology was used outside the context of forest plantations.

2.2 Bibliographic Survey Analysis

For the selected publications, the following tabular, graphical, textual, and image products were prepared: 1) Table with the list of articles, authors, publication year, and language used; 2) Graph showing the frequency of publications by year; 3) Graph depicting the journals and the number of publications in each journal; 4) Word cloud with the keywords used by the authors; 5) Map showing the locations of the study areas; 6) Summary table with publications, the TLS sensor used, and the species employed in the studies; and (7) the list of topics covered, which served as the basis for discussions.

3 RESULTS

3.1 Result of the Bibliographic Survey

In the systematic review, with the application of the search query on the Web of Science (WoS) platform, 504 scientific publications were found, of which 309 were open access. Among these, only 58 corresponded to scientific articles published in the year 2022. After reading the abstracts, 39 articles were pre-selected, and after reading the full articles, 7 articles were selected.

In the scoping review, out of the 389 references evaluated, 81 scientific articles that addressed the use of TLS technology were pre-selected based on abstracts, and after reading the articles, 12 articles were selected that described the use of TLS in forest plantations.

Thus, in the bibliographic survey, a total of 19 scientific articles produced between 2012 and 2022 that address the use of TLS technology in forest plantations were selected (Table 1).

Table 1 - Set of articles selected in the bibliographic survey on the use of TLS technology in forest plantation.

n	Author and Year	Title
1	Bayer et al. (2013)	Structural crown properties of Norway spruce (*Picea Abies* [L.] Karst.) and European Beech (*Fagus Sylvatica* [L.]) in mixed versus pure stands revealed by terrestrial laser scanning
2	Raumonen et al. (2013)	Fast automatic precision tree models from terrestrial laser scanner data
3	Hackenberg et al. (2015)	Non destructive method for biomass prediction combining TLS derived tree volume and wood density
4	Koreň et al. (2017)	Accuracy of tree diameter estimation from terrestrial laser scanning by circle-fitting methods
5	Puletti et al. (2019)	Evaluating the eccentricities of poplar stem profiles with terrestrial laser scanning
6	Pyörälä et al. (2019)	Assessing log geometry and wood quality in standing timber using terrestrial laser-scanning point clouds
7	Guan et al. (2020)a	A marker-free method for registering multi-scan terrestrial laser scanning data in forest environments
8	Guan et al. (2019)	A novel framework to automatically fuse multiplatform LiDAR data in forest environments based on tree locations
9	Yrttimaa et al. (2020)	Performance of Terrestrial Laser Scanning to characterize managed Scots Pine (*Pinus Sylvestris* L.) stands is dependent on forest structural variation
10	Demol et al. (2021)	Consequences of vertical basic wood density variation on the estimation of aboveground biomass with terrestrial laser scanning
11	Wan et al. (2021)	A novel and efficient method for wood–leaf separation from terrestrial laser scanning point clouds at the forest plot level
12	Dai et al. (2022a)	Multisource forest point cloud registration with semantic-guided keypoints and robust RANSAC mechanisms
13	Dai et al. (2022b)	A comparison of the performances of Unmanned-Aerial-Vehicle (UAV) and Terrestrial Laser Scanning for forest plot canopy cover estimation in *Pinus massoniana* forests
14	Demol et al. (2022)	Volumetric overestimation of small branches in 3D reconstructions of *Fraxinus excelsior*

Continues…

Conclusion

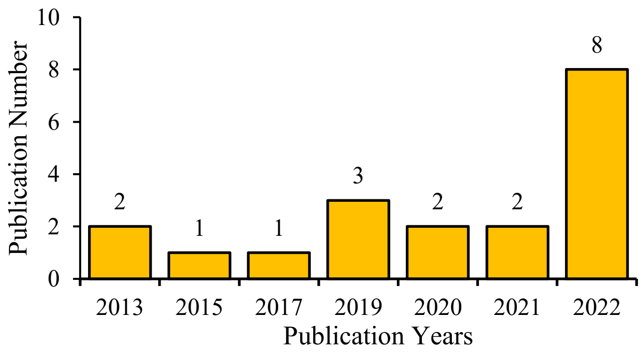
n	Author and Year	Title
16	Ronoud et al. (2022)	Terrestrial laser scanning in assessing the effect of different thinning treatments on the competition of Scots Pine (*Pinus sylvestris* L.) forests
17	Shimizu et al. (2022)	Integrating terrestrial laser scanning and unmanned aerial vehicle photogrammetry to estimate individual tree attributes in managed coniferous forests in Japan
18	Tienaho et al. (2022)	Assessing structural complexity of individual Scots Pine trees by comparing terrestrial laser scanning and photogrammetric point clouds
19	Zhang et al. (2022)	Simulating wind disturbances over rubber trees with phenotypic trait analysis using terrestrial laser scanning

Source: The authors (2024).

3.2 Analysis of Scientific Publications

The year 2022 had the highest number of publications on the use of TLS technology in forest plantations, with 8 publications (42.10%), followed by 2019 with 3 publications (15.79%), 2021, 2020, and 2013, each with 2 publications (10.53%) (Figure 1).

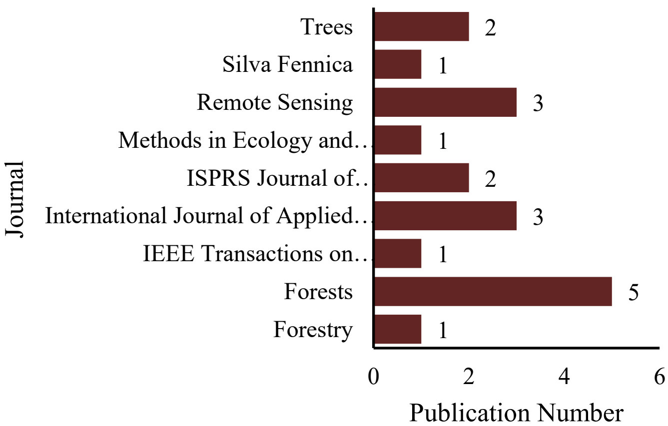
Figure 1 - Frequency of articles published annually about the use of TLS technology in the forest plantation.



Source: The authors (2024).

The 19 articles selected in the survey were published in 9 different journals (Figure 2). The journal Forests had the highest number of publications, with a total of 5 articles (26.32%). The remaining articles were published in other journals: Remote Sensing (15,79%), International Journal of Applied Earth Observation and Geoinformation (15,79%), Trees (10,53%), ISPRS Journal of Photogrammetry and Remote Sensing (10,53%), Forestry (5,26%), IEEE Transactions on Geoscience and Remote Sensing (5,26%), Methods in Ecology and Evolution (5,26%) and Silva Fennica (5,26%).

Figure 2 - Number of publications on the use of TLS technology in forest plantation, from 2012 to 2022, organized by Journal.



Source: The authors (2024).

The word cloud, generated based on the keywords used by authors when addressing the use of TLS in forest plantations, presented the following 10 most frequent keywords: Forest; Terrestrial Laser Scanning; LiDAR; Point Cloud; Tree; Registration; Unmanned Aerial Vehicle; Crown; Forest Inventory; and Forest Management (Figure 3).

Figure 3 - Word cloud based on the keywords used by the authors of the scientific publications selected in the bibliographic survey on the use of TLS in forest plantation.

Source: The authors (2024).

The 19 publications selected in the survey had their study areas distributed across 9 locations (Figure 4). China (CN) was the country with the highest number of research involving the topic; out of the 19 articles selected in the survey, 6 had their study areas located in this country. Finland (FI) had 4 publications conducted in its territory, and Belgium (BE) had 2 publications. In the territory of South Korea (KOR), Slovakia (SK), Italy (IT), Japan (JP), Germany (DE), and Norway (NO), 1 research was conducted in each of these locations (Table 2). Two publications did not have their study area defined (ND).

Figure 4 - Study locations used in publications on the use of TLS in forest plantation, from 2012 to 2022.

Source: The authors (2024).

With regard to the species used in the 19 studies, 18 different species were identified (Table 2). Pinus sylvestris appeared as the subject of study in 8 publications, *Fagus sylvatica* and *Pinus massoniana* in three publications, and *Cryptomeria japonica*, *Fraxinus excelsior*, *Picea abies*, and *Pinus tabuliformis* in two publications. The remaining species, such as: *Acer platanoides*, *Betula papyrifera*, *Chamaecyparis pisifera*, *Erythrophleum fordii*, *Hevea brasiliensis*, *Larix decidua*, *Larix gmelinii*, *Populus nigra*, *Quercus petraea*, *Styphnolobium japonicum* and *Taxodium distichum* appear in only one publication.

Table 2 - Set of articles selected in the bibliographic survey on the use of TLS technology in forest plantation.

n	Author and Year	TLS	Species	Study Locations
1	Bayer et al. (2013)	RIEGL LMS-Z420i	*Picea abies* *Fagus sylvatica*	NO
2	Raumonen et al. (2013)	Leica HDS6100	*Picea abies* *Pinus sylvestris* *Acer platanoides*	ND
3	Hackenberg et al. (2015)	Z+F IMAGER 5010	*Pinus massoniana*, *Erythrophleum fordii* *Quercus petraea*	CN
4	Koreň et al. (2017)	FARO Focus 3D 120	*Fagus sylvatica*	SK
5	Puletti et al. (2019)	FARO Focus 3D 130	*Populus nigra*	IT
6	Pyörälä et al. (2019)	Trimble TX5	*Pinus sylvestris*	FI
7	Guan et al. (2020) a	RIEGL VZ-400i	*Pinus sylvestris* *Pinus tabuliformis*	CN
8	Guan et al. (2019)	RIEGL VZ-400	*Pinus tabuliformis* *Pinus sylvestris*	CN
9	Yrttimaa et al. (2020)	Trimble TX5	*Pinus sylvestris*	FI
10	Demol et al. (2021)	RIEGL VZ-1000 RIEGL VZ-400	*Pinus sylvestris*, *Fraxinus excelsior* *Fagus sylvatica* *Larix decidua*	BE
11	Wan et al. (2021)	RIEGL VZ-1000	*Betula papyrifera* *Larix gmelinii* *Styphnolobium japonicum*	ND
12	Dai et al. (2022a)	RIEGL VZ-400	*Pinus massoniana*	CN
13	Dai et al. (2022b)	RIEGL VZ-400	*Pinus massoniana*	CN
14	Demol et al. (2022)	RIEGL VZ-400	*Fraxinus excelsior*	BE
15	Ko et al. (2022)	Leica RTC360	*Cryptomeria japonica* *Chamaecyparis pisifera* *Taxodium distichum*	KOR
16	Ronoud et al. (2022)	Trimble TX3	*Pinus sylvestris*	FI
17	Shimizu et al. (2022)	UTM-30LX-EM	*Cryptomeria japonica*	JP
18	Tienaho et al. (2022)	Trimble TX5	*Pinus sylvestris*	FI
19	Zhang et al. (2022)	HS450	*Hevea brasiliensis*	CN

Source: The authors (2024).

In the studies selected in the survey, the most commonly used TLS sensors were from the RIEGL brand (http://www.riegl.com/), present in 8 studies (42%), including: RIEGL LMS-Z420i; RIEGL VZ-1000; RIEGL VZ-400; and RIEGL VZ-400i. Of these, the most widely used was the RIEGL VZ-400, present in 5 studies (Table 2 and 3). The second most used brand was Trimble® (https://trimble.com.br/), used in 4 publications (21%), with the Trimble TX5 sensor. Less frequently used in the studies were the Leica brand (https://leica-geosystems.com/pt-br), with Leica HDS6100 and Leica RTC360 sensors, and the FARO brand (https://www.faro.com/pt-BR), with FARO Focus 3D 120 and FARO Focus 3D 130 sensors. The Zoller+Fröhlich (https://www.zofre.de/), HOKUYO (https://www.hokuyo-aut.jp/), and Hi-Target (https://en.hi-target.com.cn/) brands were each present in one study.

Table 3 - Technical specifications of TLS sensors used in the articles selected in the bibliographic survey.

n	TLS	Accuracy (mm)	Field of View	Measurement Rate (pts.s^{-1})	Range (m)
1	RIEGL VZ-400	5	360° x 100°	122,000	600
2	RIEGL LMS-Z420i	4	360° x 80°	11,000	1,000
3	RIEGL VZ-400i	3	360° x 100°	500,000	800
4	RIEGL VZ-1000	5	360° x 100°	120,000	1,400
5	Trimble TX5	2	360° x 300°	976,000	0.6-120
6	Leica HDS6100	2-3	360° x 310°	508,000	-
7	Leica RTC360	1.9-5.3	360° x 300°	2,000,000	0.5-130
8	FARO Focus 3D 120	2-10	360° x 300°	976,000	0.6-120
9	FARO Focus 3D 130	2	360° x 300°	976,000	0.6-130
10	Zoller+Fröhlich IMAGER 5010	0.5	360° x 320°	1,016,027	187
11	HOKUYO UTM-30LX-EW	50	360° x 270°	1,940,000	0.1-30
12	Hi-Target HS450D	8	360° x 60°	500,000	-

Source: The authors (2024).

In general, the topics covered in the articles involve the registration of 3D point clouds, extraction of metrics from point clouds, and applications of TLS. For a better understanding, they were classified into the following categories: (1) Registration of 3D point clouds; (2) Separation of wood and leaves; (3) Tree detection; (4) Tree height; (5) Diameter at breast height (DBH); (6) Canopy structure; (7) Estimation of volume and biomass; and (8) Other applications.

4 DISCUSSION

4.1 Applications and Perspectives of Using TLS Technology

In forest resource inventory, the use of laser scanning devices allows for the acquisition of three-dimensional spatial data through point clouds with coordinates (Ko et al. 2022). Laser scanning is widely recognized as a non-destructive technique that serves as an alternative for the establishment and monitoring of forest inventories, and it is one of the primary techniques that enhance the accuracy and efficiency of measurements (Ko et al. 2022).

Based on the type of sensor used, there are various types of LiDAR, which can be mounted on satellites, airplanes, vehicles, or ground-based equipment. In the forested area, airborne laser scanning (ALS) and TLS are commonly applied (Ko et al. 2022).

TLS is an effective technology for collecting dense and highly detailed three-dimensional (3D) point clouds of trees (Wan et al. 2021; Demol et al. 2021), enabling quantitative tree analysis and the reconstruction of quantitative tree models. This type of data can be used to develop improved statistical models for tree attributes (Raumonen et al. 2013).

Ronoud et al. (2022) explain that the accuracy of TLS in characterizing the 3D structure of a forest depends on several factors, including scan configuration, algorithms used for tree detection and reconstruction, and the integrity of point clouds, as these are the main sources of error that limit the application of TLS in forest measurements. Below, some of the applications and prospects of using TLS technology in forest plantations are described.

4.2 Registration of 3D Point Clouds

A significant bottleneck for the large-scale application of TLS in forest management and studies is the automatic registration of high-precision multi-scan TLS data (Guan et al. 2020). The authors note that for forest applications of multi-scan TLS, the registration of TLS point clouds is a prerequisite.

External features are typically necessary to register point clouds collected from different scanning locations (Guan et al. 2019). Currently, there are three commonly used point cloud registration frameworks, including target-based, feature-based, and point-based methods. One of the most commonly used methods is to manually set up registration targets in the scanning environment and register TLS scans by identifying and manually matching these targets from point clouds (Guan et al. 2020).

Guan et al. (2020) explain that numerous efforts have been made in the development of markerless methods for registering multi-scan TLS data in forest environments. These methods typically use individual tree attributes. However, as promising as these methods may be, they require specific individual tree attributes (location, height, DBH, and stem maps) obtained through a series of post-processing steps (Guan et al. 2020, Dai et al. 2022a).

In this context, Guan et al. (2020) proposed a markerless algorithm to accurately register multi-scan TLS data in forested areas without the need to process raw TLS data to extract individual tree attributes. The authors explain that the principle of the proposed algorithm is to identify and use shadowed areas in raw TLS point clouds as the main feature to match adjacent TLS scans.

The authors' study was conducted using the RIEGL VZ-400 terrestrial laser scanner and tested in six plots with different types of vegetation. As a result, they found that the registration accuracy was equivalent to the results of manual registration using high-reflectance registration targets, and the slight difference between these two methods could be caused by random errors from the TLS scanner and the Iterative Closest Point (ICP) algorithm used. The authors believe that the proposed method has significant potential to reduce the time and cost of TLS data collection and expand the application of TLS technique in large-scale forest studies.

Multi-platform registration is also an option for registering point clouds that is gaining traction in the forestry field. Dai et al. (2022a) point out that aerial laser scanning (ALS) is highly efficient and flexible in mapping the forest canopy layer but captures insufficient points from the understory layer. On the other hand, the TLS can provide complementary observations of the understory layer in the vertical direction but suffers from occlusions in the horizontal direction when using a single scan, which can be problematic when characterizing forest structure.

In this regard, Dai et al. (2022a) state that multi-platform point cloud registration, including TLS-TLS registration of different terrestrial scans and ALS-TLS registration of terrestrial-airborne scans, is a prerequisite for accurately understanding the horizontal and vertical configurations of the forest.

In the study by DAI et al. (2022a), the terrestrial LiDAR RIEGL VZ-400 and the airborne LiDAR R-Fans-16 were used for multi-platform point cloud registration without the use of markers. The authors proposed a new keypoint detector (WRI) for registration, and based on these keypoints, they introduced the RANSAC algorithm to enhance the efficiency and accuracy of registration.

They concluded that the proposed method performed well in both registration accuracy and efficiency, surpassing the traditional method. Additionally, the WRI detector showed reliable repeatability and descriptiveness in TLS-TLS and ALS-TLS registrations. The modified RANSAC algorithm was also able to find matches efficiently and effectively.

In the study by GUAN et al. (2019), the authors proposed a new multi-platform LiDAR data registration framework for forest applications based on the unique spatial distribution of trees in a forest stand, with tree pairs identified from multi-platform LiDAR data as the only required resources in the registration process. The study was conducted in three study areas within a forest plantation where the dominant species were Pinus sylvestris and Pinus tabuliformis. Three widely used LiDAR platforms were used for point cloud registration, including terrestrial LiDAR (RIEGL VZ-400i), airborne LiDAR, and a backpack LiDAR.

In response to this registration proposal, the authors found that the fusion of backpack LiDAR and ALS-LiDAR datasets achieved vertical accuracy better than 20 cm and horizontal accuracy better than 30 cm in two of the three study locations. The accuracy of the multi-scan TLS data registration was much higher than that of the backpack LiDAR and ALS-LiDAR data registration. This suggests that the performance of the proposed framework can be improved by increasing the accuracy of the LiDAR data.

The authors pointed out that although the accuracy of TLS data registration is still lower than that of the manual target-based registration method, it can be used as a preliminary step before manual registration to increase efficiency. They also suggested that future studies could consider using reference targets as external information to further improve registration accuracy.

4.3 The Separation of Wood and Leaves

Determining the characteristics and quality attributes of trees is important in forest management. These attributes are geometric and statistical characteristics of trees, such as the height of the crown base, total volume above ground, distribution of branch sizes, and branch structure (Raumonen et al. 2013).

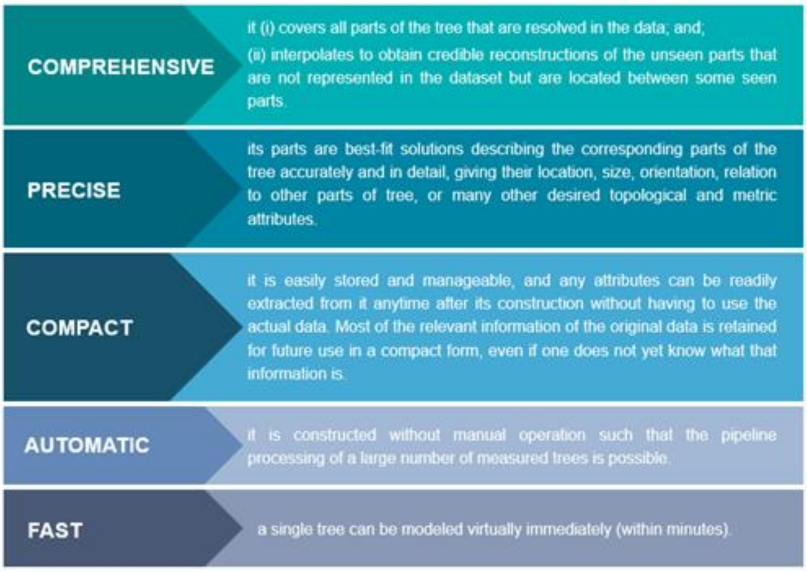
For the authors, wood-leaf separation is a prerequisite step to reconstruct quantitative tree models from TLS data. However, accurate and efficient separation of wood and leaf points from TLS data remains a challenging task (Wan et al. 2021).

Wan et al. (2021) point out that the difficulty in separating wood and leaf components is related to two aspects. First, thin branches, twigs, and leaves in the crown mix together, making it difficult to distinguish them. Second, TLS scans trees from outside the canopy, so branches may be obscured by foliage or by each other, resulting in discontinuous and missing branches in the point cloud.

Generally, the types of classification features used in wood-leaf separation include radiometric features, waveform features, and geometric features (Wan et al. 2021). More recently developed methods rely on geometric characteristics. Geometric features are the size, shape, location, density, roughness, curvature and other characteristics of a set of points, calculated from the 3D coordinates of the points (Wan et al. 2021).

For Raumonen et al. (2013), many issues in forestry, biomass estimation, forest research, and forest remote sensing could be more easily resolved if it were routinely possible to fit tree models to TLS measurements, so that a model would be comprehensive, accurate, compact, automatic, and fast (Figure 5).

Figure 5 - Assumptions for a statistical model according to Raumonen et al. (2013).



Source: Raumonen et al. (2013).

Taking these premises into consideration, Raumonen et al. (2013) proposed a new method that generates 3D tree models from TLS data acquired by the Leica HDS6100 sensor. The study targeted a tree of the species Picea abies, two trees of Pinus sylvestris, and one tree of Acer platanoides. Based on this method, it was possible to perform quantitative analyses of the structural and size properties of the tree.

In this study, trunk and branch profiles, or statistical distributions such as branching angle distribution, could be determined. Furthermore, this model allowed for the production of branch size distributions.

Validation with an artificial point cloud with a known volume revealed complete modeling of the stem and up to 90% of the branches. In current literature, the method is commonly known as Quantitative Structure Modeling (QSM) (Hackenberg et al. 2015).

According to Wan et al. (2021), although some geometric-based and Machine Learning-based methods have achieved good accuracy in wood-leaf separation, these methods have computational disadvantages when processing TLS data at the plot level.

In this regard, the authors proposed a segment-based classification method for accurate and efficient wood-leaf separation at the plot level. The authors tested the method on three forest plots of *Betula papyrifera*, *Larix gmelinii*, and *Styphnolobium japonicum*, using data from the RIEGL VZ-1000 terrestrial laser scanner, and compared the results with two other methods (Canupo and LeWoS).

Wan et al. (2021) found that in terms of overall classification accuracy, the proposed method achieved better results when compared to the CANUPO and LeWoS methods. For all datasets, the average classification accuracy reached 94.05%. In terms of speed, the authors noted that the proposed method was 10 times faster than the compared methods while maintaining comparable or even higher accuracy.

Demol et al. (2022) investigated the underlying mechanisms of inaccurate branch reconstructions and formulated strategies to improve wood volume estimates of trees based on TLS. To do this, they used a unique dataset of over 250 manually measured branch diameters, distributed across two Fraxinus excelsior individuals, which were paired with diameters extracted by the QSM algorithm.

The diameters derived from TLS for small branches (d <10 cm) of leafed trees were generally larger than manually measured diameters, with smaller branches having larger relative errors. These estimation errors resulted in an initial overestimation of wood volume ranging from 38% to 52%.

Some strategies were employed in an attempt to improve the accuracy of branch diameter and wood volume estimates for trees. The authors found that the most effective strategy was the reflectance dispersion filter procedure or an improved fine alignment of the point cloud, which reduced the original overestimation by half. However, it was not possible to improve the diameter estimates for branches with d < 2.5 cm. They also found that misalignment and scattering errors were the main causes of inaccuracies in the QSM tree reconstructions.

4.4 Tree Detection

With regard to tree detection, Ko et al. (2022) explain that the occlusion problem prevents the complete collection of point clouds, and that one of the advantages of the TLS single-scan method is that data can be obtained quickly. However, the loss of point clouds caused by occlusion and the resulting low accuracy mean that the method is less applicable.

Ko et al. (2022) compared and analyzed the efficiency and accuracy of backpack laser scanning (BPLS) and TLS (Leica RTC360) in acquiring data in three forest plots containing *Cryptomeria japonica*, *Chamaecyparis pisifera*, and *Taxodium distichum*. Regarding tree detection, the authors pointed out that when only a single laser scan was used, the detection rate of TLS was 95% (*C. japonica*), 88.46% (*C. pisifera*), and 100% (*T. distichum*). However, in the case of multiple scans, the TLS detection rate was 100% in all plots.

In the study conducted by Tienaho et al. (2022) in *Pinus sylvestris* stands, the authors used multiple scans from the TLS (Trimble TX5 3D) and achieved an average tree detection rate of 98.5%. In sparser plots, the detection rate was 100%. However, in denser plots, the detection rate was 96%, primarily due to occlusion. These results are consistent with the study by Yrttimaa et al. (2020), who, in *P. sylvestris* stands, using the same TLS sensor with multiple scans, achieved a tree detection rate of 98.8%, also influenced by occlusion caused by tree density and undergrowth vegetation.

Shimizu et al. (2022), in a study conducted in *Cryptomeria japonica* plantations, when using TLS (UTM-30LX-EM) with multiple scans in two plots, observed that, when compared to field measurements, although all trees were correctly detected, false tree detections also occurred, leading to a correct detection rate of 96.2% (thinned plot) and 80.4% (unthinned plot) for the two plots. These false detections resulted from the presence of dead trees in the study area.

4.5 Tree Height

In the study by Ko et al. (2022), the authors point out that when multiple scans were used, the TLS method compared to the BPLS method showed higher quality of fits for height measurements. Yrttimaa et al. (2020) observed that when compared to field measurements, on average, tree heights were underestimated by 0.3 m, with a Root Mean Square Error (RMSE) of 1.6 m (8.4%).

Tienaho et al. (2022) observed a mean difference of 34 cm between tree heights measured in the field and tree heights measured by TLS. In general, tree heights derived from TLS were underestimated. Compared to field measurements, the RMSE of tree heights derived from point clouds was 1.32 m for TLS. The RMSE was higher in untreated plots and lower in plots with intensive thinning.

In their study, Shimizu et al. (2022) used TLS (UTM-30LX-EM) along with a UAV (DJI Phantom 4 Pro) and proposed three approaches for height estimation: (A1) tree height was obtained directly from TLS estimates; (A2) tree height was estimated from the locations of trees in the Digital Canopy Height Model (DCHM) and TLS data. The DCHM values that matched the tree locations were treated as the heights of individual trees in this approach; and (A3) tree height was estimated by detecting tree canopies based on the locations of DCHM and TLS. The assumption of this approach was that tree canopies were not always directly above the location of each tree but rather near the corresponding tree locations.

As results of the first approach (A1), the authors found that when compared to field measurements, tree height was significantly underestimated by TLS, with a bias of 8.80 m (-27.7%) in thinned plots and 7.45 m (-26.2%) in unthinned plots. The RMSE was 9.16 m (28.9%) in thinned plots and 8.17 m (28.8%) in unthinned plots, respectively. And the Concordance Correlation Coefficient (CCC), which ranges from -1 to +1, was only 0.024 and 0.085 in thinned and unthinned plots, respectively. In this study, the average tree height was relatively high (30.7 m) compared to the detection range of the TLS laser (0.1 - 30 m). In this regard, the capability of the TLS laser sensor made it challenging to detect tree canopies.

In contrast, the bias and other accuracy metrics improved when combined with UAV data. Using the combined two plots, the bias became -0.46 m (-1.5%) and 0.36 m (1.2%) in approaches (A2) and (A3), respectively. The RMSE was 1.89 m (6.2%) and 1.77 m (5.7%) in approaches (A2) and (A3), respectively. And CCC increased to 0.73 in approach (A2) and 0.78 in approach (A3). Estimating tree height with crown detection (A3) generally showed higher precision compared to estimating tree height based on tree location (A2), revealing that tree crowns were not always directly above tree locations and needed to be detected for accurate estimation.

4.6 Diameter at Breast Height (DBH)

Regarding the estimation of diameter at breast height (DBH), Yrttimaa et al. (2020) observed that TLS underestimated DBH by 0.1 cm, with an RMSE of 0.7 cm (3.4%) when compared to field measurements. In Ko et al. (2022), reported that in comparison to TLS, height measurements were more accurate than DBH measurements, as TLS accuracy is often affected by occlusion.

In the work conducted by Shimizu et al. (2022), when comparing field-measured DBH estimates to DBH measured by TLS, they obtained an RMSE of 2.27 cm (5.0%) in the thinned plot and 2.54 cm (7.4%) in the unthinned plot. The authors suggest that the high stand density in the unthinned plot may have reduced point clouds on the stems, leading to lower precision in the estimates.

Puletti et al (2019), used the Trimble TX5 TLS sensor with multiple scans in poplar plantations. The statistical analysis of DBH quantitatively documented the effects of stand density and anisotropic competition. Compared to traditional methods of stem profile measurement, TLS provided much greater precision and accuracy.

The authors pointed out that the average diameter for the 4 m spacing was over 38 cm. When the distance between the trees along the row was 4.5 m, the average diameter was 40.6 cm, while with a 5 m spacing, the average diameter was only one millimeter larger than with the 4.5 m spacing. Furthermore, the analysis revealed that, on average, the cross-sections at breast height were compressed in the row direction; they were about 1.6 cm smaller than the orthogonal ones.

In the study by Koreň et al. (2017), the authors compared five methods for estimating the diameter at breast height (DBH) in plots of *Fagus sylvatica* using FARO Focus 3D 120 TLS data. The circle-fitting methods from cross-sections of a TLS point cloud were divided by the authors into initial methods and refinement methods.

The initial methods included: Minimum Bounding Box Method (MBB), Centroid Method (CEN), and Maximum Distance Method (MDS). The refinement methods included: Monte Carlo Method (MC) and Optimal Circle Method (OC).

Koreň et al. (2017) analyzed the behavior of different DBH estimation methods in two distinct situations, single-scan and multi-scan. In the case of a single scan, MBB results in incorrect size and position, leading to errors in DBH estimation; CEN shifts the tree center towards the higher point density reflected on the trunk, also resulting in DAP estimation error; MDS is less sensitive to irregular point distributions on the trunk's perimeter. It seeks the farthest points, and only a few reflected points from opposite sides of a trunk are sufficient to correctly estimate the tree's position and DBH.

On the other hand, the MC and OC methods are also affected by the irregular trunk coverage by the point cloud. However, the optimization function minimizes the sum of squared distances from TLS points to a circle that approximates the trunk's cross-section. Consequently, there is a significant shift of the approximation circle towards a cross-section of the trunk with a higher point density, which improves position and DBH estimates.

In the case of trees scanned with multiple scans, approximately the same DBH estimate was achieved by all fitting methods. However, the authors pointed out that such situations are rare in real forest conditions. The irregular spatial distribution of trees, terrain obstacles, and understory vegetation does not allow for regular scans of all trees in the research plot.

Overall, the authors concluded that the Optimal Circle Method (OC) proved to be the most accurate fitting method for estimating DBH from point clouds in both scan modes. They also noted that fitting algorithms in combination with advanced point cloud processing procedures, such as point cloud filtering, shadow reduction, Digital Elevation Model (DEM) extraction, spatial clustering, and tree identification, can lead to effective use of TLS in forestry, forest inventory, forest harvesting, and forest research.

4.7 Crown Structure

The extraction of a description of the structure of TLS point clouds, such as a collection of connected lines, is called Skeletonization and allows for a detailed analysis of morphological features such as branch angles, branch length, branch curvature, crown volume, and branch occupancy within the canopy space (Bayer et al. 2013).

Bayer et al. (2013), in a skeletonization study, used data collected by the ground-based laser scanner sensor RIEGL LMS-Z420i to determine the morphological characteristics of the species Picea abies and Fagus sylvatica, thereby obtaining information about the crown structures of these species. To do so, they applied a new semi-manual skeletonization method using software specifically developed for this purpose.

The authors pointed out that the semi-manual skeletonization approach facilitates the recovery of crown structures from imperfect TLS point cloud data regardless of the tree species. However, occlusion, non-uniform point densities, and noise in the dataset can still be issues. Bayer et al. (2013) suggest that establishing more scan positions and using a more advanced TLS device, such as a full waveform scanner, can help overcome this problem.

Dai et al. (2022b) conducted a comparison of the performance of unmanned aerial vehicles (UAV), using ALS (Airborne Laser Scanning) technology, and TLS for canopy cover estimation in forest plots of Pinus massoniana. They tested two methods, both based on the canopy height model (CHM) and individual tree delineation (ITD).

Compared to the reference data, the ALS_CHM method was the most accurate, with an R^2 of 0.996 and an RMSE of 0.59%, followed by the ALS_ITD method, with an R^2 of 0.992 and an RMSE of 0.82%. The TLS_ITD method had an R^2 of 0.846 and an RMSE of 3.64%, while the TLS_CHM method had an R^2 of 0.541 and an RMSE of 6.30%.

When the ALS estimates were directly compared to the TLS estimates, most of the ALS estimates were higher than the TLS estimates, with an average difference of 6.91%.

The ALS estimates were lower than the TLS estimates; this occurred when the canopy boundaries were complete in the ITD method in the single plots due to the more detailed and suppressed canopy in the intermediate and understory than in the ALS. In the CHM-based method, the reasonable CHM pixel sizes for canopy coverage estimates ranged from 0.07 to 1.2 m for ALS and 0.07 to 1.5 m for TLS. Within these ranges, the estimates were marginally influenced by pixel size.

4.8 Volume and Biomass Estimation

Hackenberg et al. (2015) introduced a non-destructive method to estimate aboveground biomass for the species *Pinus massoniana*, *Erythrophleum fordii*, and *Quercus petraea*. The predictions were based on density measurements combined with volume assessments derived from Z+F IMAGER 5010 TLS data. The authors found that the proposed method yielded good aboveground biomass estimation results for tree compartments without leaves with a diameter above 10 cm. Biomass estimation using the total volume derived from TLS was satisfactory for the species *P. massoniana*, with the mean error being less than 3%.

Hackenberg et al. (2015) pointed out that in volume estimation, errors occurred in the thinner tree compartments located in the tree canopies. The lower quality of point clouds in the crown, mainly due to occlusion, wind, and precipitation, led to a significant overestimation of branch volume in leafless *Q. petraea* and an underestimation in evergreen *E. fordii*. In this regard, the authors suggest that scanning operations should be conducted under good weather conditions to achieve the highest data quality.

According to Shimizu et al. (2022), stem volume was underestimated by the TLS approach (A1) due to the underestimation of tree height, with an RMSE of 0.76 m^3 (33.2%) in thinned stands and 0.39 m^3 (30.5%) in unthinned stands. In approach (A2), where heights were obtained based on the location of trees with the DCHM and TLS, the RMSE was 0.22 m^3 (9.8%) in thinned stands and 0.19 m^3 (14.7%) in unthinned stands. In approach (A3), where tree positions were identified based on the tree canopies in the DCHM and TLS, the RMSE was 0.22 m^3 (9.5%) and 0.19 m^3 (14.7%) in thinned and unthinned stands, respectively. The authors concluded that with the integration of drone-based photogrammetry and TLS, the accuracies improved in both thinned and unthinned stands, primarily due to better tree height estimates.

4.9 Other Applications

In the study conducted by Tienaho et al. (2022), when comparing TLS (Trimble TX5 3D) with Unmanned Aerial Vehicle (UAV), the authors pointed out that the point density of TLS was 15 times higher than that of the UAV. Point density is an important metric for characterizing the structural complexity of trees (Yrttimaa et al. 2020). Therefore, Tienaho et al. (2022) presumed that TLS described the structural complexity of trees with higher resolution and more precise details because the UAV could not penetrate denser vegetation.

Ronoud et al. (2022) studied the effect of different types and intensities of thinning on competition in *Pinus Sylvestris* stands. To this end, they used stem and canopy data extracted from TLS point clouds (Trimble TX5). From the point clouds classified as stem and non-stem, seven metrics characterizing tree stem and crown structure were calculated, including: location, diameter at breast height (DBH); total height (H); maximum crown diameter (MCD); canopy projection area (CA); canopy volume (CV); and canopy surface area (CS). Based on these metrics, competition indices (CI) were calculated.

The authors explained that the CIs are mainly derived from easily measurable variables such as DBH and H, while crown characteristics of trees are difficult to obtain. Additionally, distance-dependent CIs are rarely studied due to the difficulty in creating tree-level maps. To fill this gap, the authors evaluated the CIs using TLS point clouds and found significant differences in the competition status of individual trees compared to control plots.

Demol et al. (2021) investigated the errors associated with estimates of above-ground biomass from the vertical variation of basic wood density within the tree and did not aim to evaluate the metrics extracted from TLS point clouds.

The study was conducted in five forest stands with four of the most abundant and commercially important tree species in Europe. Two TLS sensors (RIEGL VZ-1000 and VZ-400) were used for volume estimation, as TLS has the potential to reliably estimate standing tree volume (Demol et al. 2021). Wood basic density was used to convert tree volume into biomass.

In their study with *Pinus Sylvestris*, Pyörälä et al. (2019) assessed log geometry and its relationship with wood quality using data obtained through TLS and at a sawmill. The TLS (Trimble TX5) sensor was employed. The average relative difference for estimates of variables such as top diameter, volume, and conicity was up to -3.0%, while for the scan, the difference was 78%. These authors found that diameters along the logs can be accurately estimated using high-density terrestrial point clouds scanned under favorable conditions.

Pyörälä et al. (2019) emphasize that the approach used in their study should be used with caution due to the non-uniformity in scan setup. The authors suggest that in future work to assess these studied variables, additional information from 3D point clouds should be included. Furthermore, they indicate that mobile platforms are likely more suitable for data acquisition than stationary ones.

In a study conducted by Zhang et al. (2022), the effects of hurricane-level winds (up to 17.5 m/s) on rubber tree plantations were assessed. To evaluate these effects, data were collected using two high-precision 3D laser scanners, HS450. The authors mentioned that the leaf area index increased after conducting tests with different wind speeds, whereas a decrease in leaf area was expected. These authors suggested that a combination of TLS data with deep learning networks can help remove noisy points, thus improving the accuracy of the algorithm used by the researchers. Another point mentioned was the recommendation to use a laser scanner with faster and more accurate data acquisition to maximize the accuracy of the estimates.

In the development of this review, some limitations were identified, one of the main ones being related to the article selection process, which may have introduced bias associated with language and publication availability. Priority was given to studies published in indexed journals with accessible full texts, which may have limited the inclusion of relevant works published in other languages, grey literature, or databases not covered. In addition, the heterogeneity of methodologies among the analyzed studies, including differences in the TLS sensors used, point cloud density, scanning configurations, and types of forest plantations, hampers direct comparisons and the generalization of the results.

As future perspectives, there is a clear need for studies that integrate TLS with other remote sensing technologies, such as airborne laser scanning, unmanned aerial vehicles and multispectral or hyperspectral imagery. In addition, the incorporation of artificial intelligence and machine learning techniques may contribute to the automation of point cloud processing, improving tree detection and the estimation of dendrometric variables. Advances in this direction are expected to expand the applicability of TLS in operational forest inventories, reducing costs and processing time while increasing the robustness of the estimates.

5 CONCLUSIONS

Based on the publications analyzed:

Laser scanning is widely recognized as a non-destructive technique that serves as an alternative for forest inventory construction and monitoring. Additionally, it is one of the main techniques that enhance measurement accuracy and efficiency. TLS is an effective technology for collecting dense and highly detailed three-dimensional (3D) point clouds of trees.

For forestry applications of multi-scan TLS, point cloud registration is a prerequisite. Research has been conducted to improve the point cloud registration step, using methods such as multi-platform registration or even registration without the use of markers.

The separation of wood and leaves is a prerequisite step for reconstructing quantitative tree models from TLS data. However, accurate and efficient separation of wood and leaf points from TLS data remains a challenging task, where the use of the QSM algorithm has gained prominence.

The use of multiple scans can help overcome the problem of occlusion caused by tree density and undergrowth vegetation. It can also ensure higher tree detection rates and more reliable estimates of DBH and height.

The extraction of a description of the structure from TLS point clouds, such as a collection of connected lines, is called Skeletonization and allows for a detailed analysis of morphological characteristics such as branch angle, branch length, branch curvature, crown volume, and branch occupancy within the crown space. It is necessary to carry out scanning operations under favourable meteorological conditions to achieve the maximum data quality and ensure the reliability of the metrics extracted from 3D point clouds and forest volume and biomass estimates, for example.

Authors' Contribution

AAM: conceived of the study, participated in its design and coordination and drafted the manuscript. APDC: coordination and helped to draft the manuscript. AB: revised the manuscript, contributed substantially to revisions and edited the manuscript. LHOS: contributed substantially to revisions and edited the manuscript. CN: contributed substantially to revisions and edited the manuscript. JWT: contributed substantially to revisions and edited the manuscript. KE: contributed substantially to revisions and edited the manuscript. CRS: revised the manuscript, contributed substantially to revisions and edited the manuscript. RM: revised the manuscript, contributed substantially to revisions and edited the manuscript.

Conflict of interest

The authors declare no conflict of interest.

References

Bayer, D., Seifert, S. & Pretzsch, H. (2017). Structural crown properties of Norway spruce (Picea abies [L.] Karst.) and European beech (Fagus sylvatica [L.]) in mixed versus pure stands revealed by terrestrial laser scanning. *Trees*. 27, 1035-1047 https://doi.org/10.1007/s00468-013-0854-4.

Dai, W., Kan, H., Tan, R., Yang, B., Guan, Q., Zhu, N., Xi. & Dong, Z. (2022). Multisource forest point cloud registration with semantic-guided keypoints and robust RANSAC mechanisms. *International Journal of Applied Earth Observation and Geoinformation*. 115, p. 103105 https://doi.org/10.1016/j.jag.2022.103105.

Dai, W., Guan, Q., Cai, S., Liu, R., Chen, R., Liu, Q., Chen, C. & Dong, Z. A Comparison of the Performances of Unmanned-Aerial-Vehicle (UAV) and Terrestrial Laser Scanning for Forest Plot Canopy Cover Estimation in Pinus massoniana Forests. *Remote Sensing*. 14(5), 1188, 2022. https://doi.org/10.3390/rs14051188.

Demol, M., Calders, K., Krishna Moorthy, S. M., Van Den Bulcke, J., Verbeeck, H. & Gielen, B. (2021). Consequences of vertical basic wood density variation on the estimation of aboveground biomass with terrestrial laser scanning. *Trees*. 35, 671-684, https://doi.org/10.1007/s00468-020-02067-7.

Demol, M. & Wilkes, P.; Raumonen, P.; Krishna Moorthy Parvathi, S.; Calders, K.; GIELEN, B.; VERBEECK, H. (2022). Volumetric overestimation of small branches in 3D reconstructions of Fraxinus excelsior. *Silva Fennica*. 56(1), https://doi.org/10.14214/sf.10550.

Fernández-Sarría, A., Martínez, L., Velázquez-Martí, B., Sajdak, M., Estornell, J. & Recio, J. A. (2013). Different methodologies for calculating crown volumes of Platanus hispanica trees using terrestrial laser scanner and a comparison with classical dendrometric measurements. *Computers and electronics in agriculture*. 90, 176-185 https://doi.org/10.1016/j.compag.2012.09.017.

Food and Agriculture Organization (FAO). Global Forest Resources Assessment 2020 – Key findings. Rome. Available in: <https://doi.org/10.4060/ca8753en>. Accessed on: 20 Aug. 2023.

Guan, H., Su, Y., Hu, T., Wang, R., Ma, Q., Yang, Q., Sun, X., Li, Y., Jin, S., Zhang., J., Ma. Q., Liu, M., Wu, F. & Guo, Q. (2019). A novel framework to automatically fuse multiplatform LiDAR data in forest environments based on tree locations. *IEEE Transactions on Geoscience and Remote Sensing*. 58(3), 2165-2177 https://doi.org/10.1109/TGRS.2019.2953654.

Guan, H., Su, Y., Sun, X., Xu, G., Li, W., Ma, Q., Wu, X., Wu, J., Liu, L. & Guo, Q. (2020). A marker-free method for registering multi-scan terrestrial laser scanning data in forest environments. ISPRS Journal of Photogrammetry and Remote Sensing. 166, 82-94 https://doi.org/10.1016/j.isprsjprs.2020.06.002.

Hackenberg, J., Wassenberg, M., Spiecker, H. & Sun, D. (2015). Non destructive method for biomass prediction combining TLS derived tree volume and wood density. *Forests*. 6(4), 1274-1300 https://doi.org/10.3390/f6041274.

Hunčaga, M., Chudá, J., Tomaštík, J., Slámová, M., Koreň, M. & Chudý, F. (2020). The comparison of stem curve accuracy determined from point clouds acquired by different terrestrial remote sensing methods. *Remote Sensing.* 12(17), 2739 https://doi.org/10.3390/rs12172739.

Ko, C., Lee, J., Kim, D. & Kang, J. (2022). The Application of Terrestrial Light Detection and Ranging to Forest Resource Inventories for Timber Yield and Carbon Sink Estimation. *Forests.* 13(12), 2087 https://doi.org/10.3390/f13122087.

Koreň, M., Mokroš, M. & Bucha, T. (2017). Accuracy of tree diameter estimation from terrestrial laser scanning by circle-fitting methods. *International Journal of Applied Earth Observation and Geoinformation*. 63, 122-128 https://doi.org/10.3390/f10030239.

Pyörälä, J., Kankare, V., Liang, X., Saarinen, N., Rikala, J., Kivinen, V. P., Sipi, M., Holopainen, M., Hyyppä, J. & Vastaranta, M. (2019). Assessing log geometry and wood quality in standing timber using terrestrial laser-scanning point clouds. *Forestry: An International Journal of Forest Research.* 92(2), 177-187 https://doi.org/10.1093/forestry/cpy044.

Raumonen, P., Kaasalainen, M., Åkerblom, M., Kaasalainen, S., Kaartinen, H., Vastaranta, M., Holopainen, M., Disney, M. & Lewis, P. (2013). Fast automatic precision tree models from terrestrial laser scanner data. *Remote Sensing*. 5(2), 491-520 https://doi.org/10.3390/rs5020491.

Ronoud, G., Poorazimy, M., Yrttimaa, T., Luoma, V., Huuskonen, S., Hynynen, J., Hyyppä, J., Saarinen, N., Kankare, V. & Vastaranta, M. (2022). Terrestrial laser scanning in assessing the effect of different thinning treatments on the competition of Scots Pine (Pinus sylvestris L.) forests. *Remote Sensing.* 14(20), 5196 https://doi.org/10.3390/rs14205196.

Shimizu, K., Nishizono, T., Kitahara, F., Fukumoto, K. & Saito, H. (2022). Integrating terrestrial laser scanning and unmanned aerial vehicle photogrammetry to estimate individual tree attributes in managed coniferous forests in Japan. *International Journal of Applied Earth Observation and Geoinformation.* 106, 102658 https://doi.org/10.1016/j.jag.2021.102658.

Tienaho, N., Yrttimaa, T., Kankare, V., Vastaranta, M., Luoma, V., Honkavaara, E., Koivumäki, N., Huuskonen, S., Hynynem, J., Holopainen, M., Hyyppä, J. & Saarinen, N. (2022). Assessing structural complexity of individual Scots pine trees by comparing terrestrial laser scanning and photogrammetric point clouds. *Forests*. 13(8) 1305 https://doi.org/10.3390/f13081305.

Wan, P., Shao, J., Jin, S., Wang, T., Yang, S., Yan, G. & Zhang, W. (2021). A novel and efficient method for wood–leaf separation from terrestrial laser scanning point clouds at the forest plot level. *Methods in ecology and evolution*. 12(12) 2473-2486 https://doi.org/10.1111/2041-210X.13715.

Yrttimaa, T., Saarinen, N., Kankare, V., Hynynen, J., Huuskonen, S., Holopainen, M., Hyyppä, J. & Vastaranta, M. (2020). Performance of terrestrial laser scanning to characterize managed Scots pine (Pinus sylvestris L.) stands is dependent on forest structural variation. *ISPRS Journal of Photogrammetry and Remote Sensing*. (168), 277-287 https://doi.org/10.1016/j.isprsjprs.2020.08.017.

Zhang, B., Wang, X., Yuan, X., An, F., Zhang, H., Zhou, L., Shi, J. & Yun, T. (2022). Simulating wind disturbances over rubber trees with phenotypic trait analysis using terrestrial laser scanning. *Forests*. 13(8), 1298 https://doi.org/10.3390/f13081298.

 DOI: http://dx.doi.org/10.14393/rbcv78n0a-73631

Biography of the lead author

Forest Engineer, graduated from the Federal University of Santa Maria (UFSM). Holds a Master's and a Ph.D. in Forest Engineering, with a focus on Forest Management and Geotechnologies, from the Federal University of Paraná (UFPR). Researcher with over 10 years of experience in Remote Sensing, Cartography, Geoprocessing, and Geographic Information Systems (GIS). Has experience in Forest Inventory and Geospatial Data Processing applied to environmental planning, forest management, and biomass and carbon analysis in native and planted forests.