Digital Forest Inventory Using Fused UAV and PLS Point Cloud Data

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Abstract

Accurate digital forest inventory (DFI) is essential for sustainable forest management, yet single-sensor LiDAR approaches often fall short in capturing the full vertical structure of forest stands. This study evaluates the performance of a fused dataset combining UAV-based LiDAR (ULS) and personal laser scanner (PLS) data to overcome platform-specific limitations. A mixed forest stand in northeastern Germany was surveyed using both ULS and PLS under consistent scanning patterns, supported by ground control points for georeferencing. Point cloud fusion was achieved through a dynamic marker-based alignment and refined using partial iterative closest point (ICP) registration. The fused dataset, processed in TreeLS, enabled detailed stem reconstruction and vertical canopy characterization. Comparative analysis against field-measured tree metrics revealed a mean deviation of -2.5% for diameter at breast height (DBH) and +4.9% for tree height, with RMSE values of 2.9 cm and 3.84 m, respectively. These results highlight the complementary strengths of ULS and PLS platforms, demonstrating that their integration significantly enhances the accuracy, completeness, and efficiency of forest inventories. The presented workflow supports scalable, repeatable, and ecologically informative forest assessments, offering substantial potential for precision forestry and long-term monitoring applications.

1. Introduction

Digital forest inventory (DFI) based on discrete point clouds has emerged as a critical area of research in remote sensing and is increasingly vital for forestry management, offering essential information to support decision-making processes (Fassnacht et al. 2024; Kellner et al. 2019; Murtiyoso et al. 2024). Integrating remote sensing technologies into forest inventory practices represents a paradigm shift from traditional field-based measurements to advanced, data-driven methodologies. This evolution allows for temporal monitoring, and the extraction of detailed structural attributes of forest ecosystems. Recent advancements have introduced methods for semantic segmentation (Krisanski et al. 2021), tree instance segmentation (Straker et al. 2023), and comprehensive process chains for DFI (Tockner et al. 2022; Wang and Bryson 2023; Wilkes et al. 2023; Xiang et al. 2024).

However, challenges remain in accurately capturing and reconstructing the full vertical structure of forests using individual sensing platforms. These limitations stem from the inherent constraints associated with single-sensor systems' spatial positioning and scanning capabilities. Point clouds generated below the canopy with terrestrial laser scanners (TLS), or personal laser scanners (PLS) provide high-resolution representations of stems and lower crown structures, but often lack detailed information on the upper crown (Lau et al. 2019; Terryn et al. 2022). This is primarily due to the occlusion caused by dense canopy layers that obstruct the upward view of ground-based sensors. Conversely, UAV-based point clouds effectively capture the upper crown but the lower crown and parts of the stems are often missing due to occlusions (Terryn et al. 2022). Especially in stands with closed canopies and dense understory this affects the measuring of the diameter at breast height which is an essential parameter for forest inventory, accurate tree modeling and biomass estimation.

A second challenge is georeferencing of point cloud data collected below the canopy and therewith, determining accurate tree foot positions (Fol et al. 2023). Precise georeferencing is crucial for longitudinal studies and change detection analysis, where consistent spatial referencing across time and platforms is necessary.

These limitations can be mitigated through the fusion of point clouds from both platforms, leveraging their complementary strengths (Chen et al. 2024; Guo et al. 2023; Wang et al. 2023). A multi-sensor fusion strategy can integrate the detailed stem representation from TLS/PLS with the upper crown depiction from UAV point clouds, thereby enhancing the overall completeness and accuracy of the forest structural model. The combination of different viewpoints and resolutions contributes to a more robust representation of the vertical forest profile, enabling improved characterization of forest heterogeneity and vertical layering. Furthermore, incorporating RGB, multispectral, or thermal sensor data alongside LiDAR enabling applications such as tree health monitoring and providing a holistic understanding of forest ecosystems to support sustainable forestry management (Jurado et al. 2022).

This study explores a novel approach for co-registering point cloud data collected from different platforms and sensors, employing dynamic markers for georeferencing and coarse alignment of the terrestrial point cloud and the iterative closest point algorithm for partially overlapping data (partial ICP) for fine registration.

The use of artificial or natural markers enables initial alignment between datasets with different acquisition geometries and spatial references. Subsequently, the partial ICP algorithm refines the registration by minimizing point-to-point distances and ensuring spatial coherence across the merged dataset.

The focus of this research is to evaluate the performance of fused UAV and PLS point clouds in reconstructing vertical forest structures and deriving key forest inventory metrics. By addressing the limitations of individual platforms, this study aims to advance methods for digital forest inventory and inform sustainable forestry practices. Ultimately, such integrated approaches facilitate better-informed decision-making processes and promote adaptive forest management strategies in response to climate change and ecosystem degradation.

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2. Materials and Methods

2.1 Study area

The scanning activity was carried out in a mixed forest stand near the village of Haselberg in north-eastern Germany, one of Eberswalde University for Sustainable Development's Martelescope application sites.

2.2 Data collection

As preparation of the site, 5 ground control points (GCPs) were evenly distributed in canopy opening across the investigation site in order to extract their coordinates from the ULS point cloud for georeferencing of the PLS point cloud in the consecutive step described in 2.3.
The PLS point cloud was collected with a GreenValley LiGrip H300 (GreenValley, Berkeley, USA) PLS which has 300 meters range and 640000-point scattering capacity per second. A parallel scanning pattern with a distance between the scanning lines of 20 m was applied. After the last line, a diagonal calibration path which ended at the starting point was conducted to enable closed loop error correction. The position of the distributed GCPs were marked in the PLS point cloud using stop-and-go referencing during the scanning process (FARO).
UAV-based lidar acquisition (ULS) was carried out with the same scanner by mounting it on a DJI M350 RTK. The same scanning pattern was applied in a flight height of 50 m.
Additionally, conventional field methods were employed, utilizing measuring tape, calipers, and a vertex hypsometer to collect ground reference data.

2.3 Data processing, georeferencing and co-registration

PLS and ULS scanner data were converted into point clouds using the LiFuser BP software and then cropped into the specified area of interest. Thereby the coordinates of the GCPs were extracted from the ULS point cloud and applied to the PLS point cloud for georeferencing.
This approach integrates the GCPs directly into the calculation of the scan trajectory of the PLS scan and, thereby, enhancing the spatial coherence between the PLS and ULS scans.
After the PLS point cloud was georeferenced, it was co-registered to the ULS point cloud with the partial ICP algorithm in Cloud Compare. The final overlap of the point cloud was estimated with 20% and the threshold for the outlier filtering was set accordingly that only the best 20% of pairs were used for the registration.
For a proper result, it is crucial that the final overlap is not overestimated, and the initial alignment of the point cloud has an offset of only a few cm which was ensured by the used georeferencing approach. Otherwise, the partial ICP can also result in incorrect registrations results as local minima.
After co-registration, the point clouds were merged and a scalar field containing the point cloud origin was generated (Figure 1).

2.4 Digital forest inventory and field reference data collection

The generation of the inventory table for the specified area was accomplished through the utilisation of TreeLS, an open-source software package utilising the R programming language. The point clouds were categorized into ground and above-ground points using the Progressive Morphological Filter (PMF) approach (Zhang et al. 2003). From the classified ground points, a Digital Terrain Model (DTM) was produced through the Inverse Distance Weighting (IDW) interpolation technique. The terrain was subsequently normalized based on the process described by (Liu et al. 2017). Advanced algorithms, including the Hough transformation, eigende-composition with clustering, and RANSAC with cylinder fitting, were applied to accurately process and model tree stems for detailed analysis (Conto et al. 2017). The classification and segmentation of stem points were conducted automatically within TreeLS, following standardized processing routines.

2.5 Evaluation

Forest metrics derived from each data type were evaluated by comparing them to ground-truth data from the area of interest. Subsequently, a regression analysis was performed in order to investigate the average diameter at breast height (DBH) and the height of individual trees. The aim was to ascertain whether these metrics varied between point cloud datasets obtained from UAV-LiDAR and PLS-LiDAR, as well as their fused counterparts. Furthermore, the study sought to quantify any observed variations.

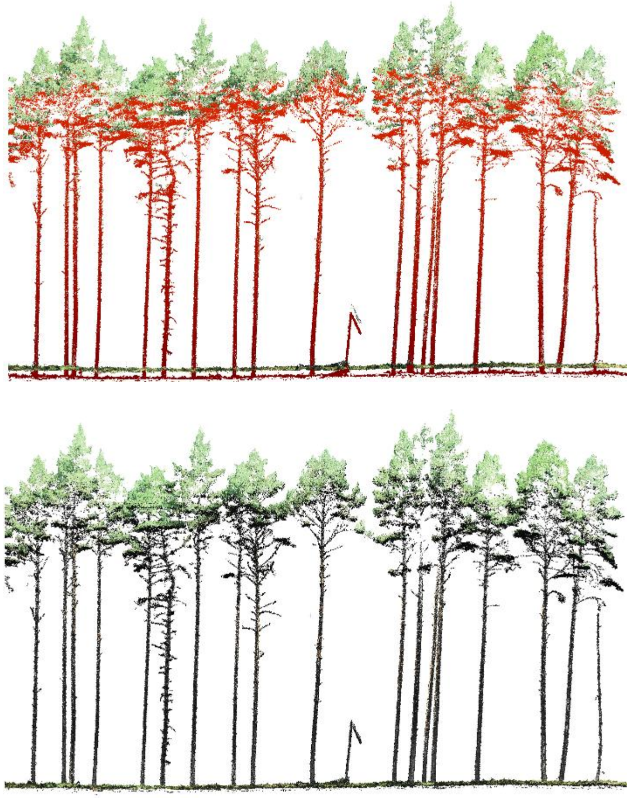

Figure 1 Example visualisation of data fusion workflow with UAV and PLS. Top: UAV dataset (red) and PLS dataset which was georeferenced by dynamic makers obtained from the UAV data. Bottom: UAV and PLS data after co-registration with partial ICP.

3. Results and Discussion

The comparison between PLS-LiDAR and UAV-LiDAR point cloud captures revealed distinct patterns in the distribution of points by height (Figure 2). The PLS-LiDAR capture exhibited a more uniform distribution of points across lower height ranges, accurately capturing details of stems and understory vegetation. This dense representation at lower canopy strata facilitated accurate reconstruction of ground-level forest structures, which are essential for deriving key forest inventory metrics such as diameter at breast height (DBH), stem form (Liang et al. 2018).

In contrast, the UAV-LiDAR dataset displayed a higher density of points concentrated in the canopy height range, reflecting its stronger capability in characterizing upper tree structures. This pattern corresponds to the top-down scanning geometry of UAV-LiDAR systems. However, due to limited penetration of laser pulses through dense foliage, UAV-based captures showed lower point density in the stem and understory zones. These limitations hinder detailed reconstruction of lower strata, particularly in closed-canopy conditions (Calders et al. 2020).

recorded, compared to 14% of the UAV returns at that same height. By contrast, from the last 10 meters height, starting from 170-172 me altitude intervals the UAV captures half of its total points while PLS has already captured its more than 96% of total points. Additionally, the UAV captured a much larger share of points in the highest canopy layer in the 174-176 m bin approximately one-fifth of the UAV's points occur, versus about 1% of the PLS points. These differences are clearly illustrated by the cumulative distribution curves (Figure 2)

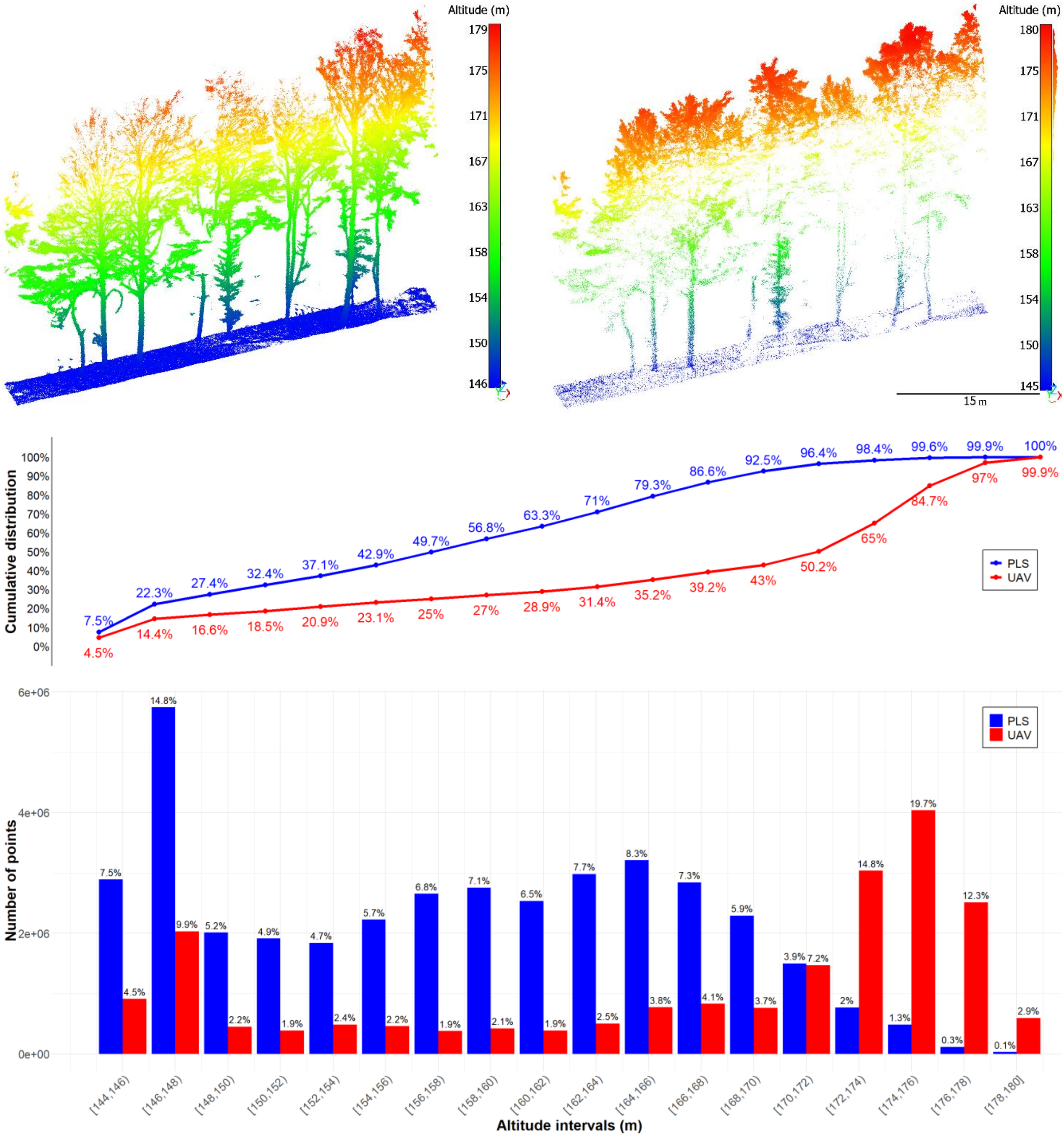

Figure 2 Vertical distribution of PLS-UAV LiDAR points. a) Top-left: Example of a 5-meter width section of the PLS point distribution by height. b) Top-right: Example of a 5-meter width section of the UAV point distribution by height. c) Middle: Cumulative distribution of points for whole area of interest. d) Bottom: Number of points by altitude intervals by 2 meters for whole area of interest.

The UAV LiDAR points are heavily concentrated in the upper canopy, whereas the PLS points are more uniformly distributed through lower heights. For example, the first 4 meters height from the ground level roughly 22% of all PLS returns were

This indicates that the UAV predominantly samples the upper canopy, while the PLS provides denser sampling of the sub-canopy and ground level. The numerical trends highlight how each platform captures a different slice of the vertical forest structure, the UAV from the top-down, capturing the outer canopy surface, and the PLS from the bottom-up, capturing understory vegetation and lower tree stems (Neuville et al. 2021). These results highlight the inherently complementary nature of the two acquisition methods. PLS-LiDAR excels in the detailed detection of lower forest structures, including stem profiles and ground-level vegetation, while UAV-LiDAR provides superior coverage of upper canopy layers. Their integration through data fusion techniques enables a more complete and structurally continuous representation of vertical forest profiles. This synergy is especially valuable in forest inventory applications where both lower and upper structural components are required for accurate parameter estimation.

Figure 3 illustrates the fused point cloud dataset, combining PLS-LiDAR and UAV-LiDAR captures. In this visualization, blue points represent PLS-LiDAR data, while red points represent UAV-LiDAR data. The fused dataset demonstrates the clear vertical complementarity between the two sources, with PLS-LiDAR dominating the lower forest structure and UAV-LiDAR representing the canopy layers. The combined dataset thus enables a holistic 3D spatial representation of the forest stand, improving the spatial continuity and accuracy of structural analysis (Brede et al. 2019).

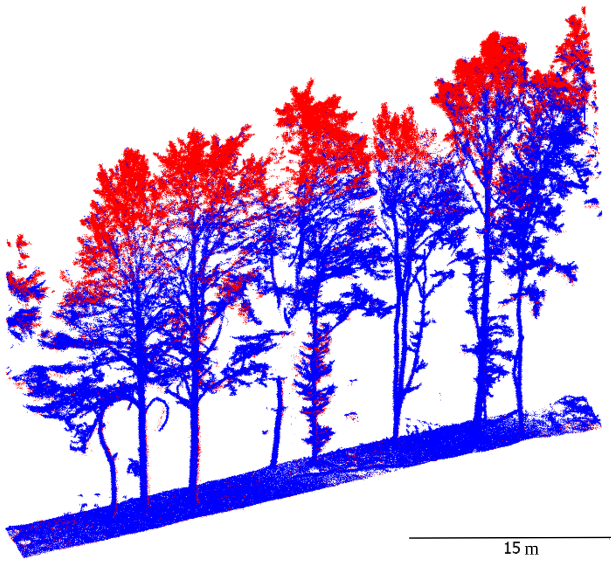

Figure 3 Visual example of a 5-meter width section of fused PLS-UAV point cloud data. Red indicates UAV while blue indicates PLS.

Following the data integration, forest inventory parameters such as DBH and tree height were extracted from the fused dataset and compared against reference values obtained through conventional field-based measurements. This comparison provides a quantitative assessment of the accuracy and reliability of LiDAR-based inventory methods.

According to Table 1, the mean DBH obtained from the fused dataset was 34.5 cm, while the field-based reference mean was 35.4 cm. Similarly, the mean tree height derived from the fused LiDAR data was 26.75 m, compared to 25.50 m in the field reference data. The corresponding percentage differences were -2.5% for DBH and +4.9% for height, indicating a strong overall agreement between remote sensing-derived and manually measured values.

The standard deviation (SD) values were also consistent between datasets. The fused dataset showed a DBH standard deviation of 14.2 cm, compared to 15.3 cm in the field data. The height standard deviation was 7.06 m in the fused dataset and 5.96 m in the reference dataset. These values suggest that the fused dataset captured a comparable range of variability in tree size distributions, further supporting its applicability for structural forest analysis.

The Root Mean Square Error (RMSE) values were 2.9 cm for DBH and 3.84 m for height, corresponding to relative errors of 8.2% and 15.1%, respectively. These error margins are within the expected range for operational forest inventory applications using LiDAR technology. In addition, the Mean Absolute Error (MAE) was 2.2 cm (6.2%) for DBH and 2.35 m (9.2%) for height. These metrics demonstrate good predictive performance and confirm that the fused LiDAR dataset provides reliable quantitative outputs.

Table 1 Statistical Comparison Between Fused LiDAR Data and Reference Data

	DBH [cm]	**Height [m]**	**DBH $_{ref}$[cm]**	**Height $_{ref}$[m]**
Mean	34.5	26.75	35.4	25.50
SD	14.2	7.06	15.3	5.96
RMSE	2.9	3.84		
MAE	2.2	2.35		
Bias	-0.8	1.26		

Bias values were also calculated to assess systematic deviations between LiDAR-derived and reference measurements. The DBH bias was -0.8 cm, representing a relative bias of -2.3%, indicating a slight underestimation by the fused dataset. In contrast, the height bias was +1.26 m, equivalent to a relative bias of +4.9%, suggesting a moderate overestimation of tree height. These results are consistent with previous studies, where tree height derived from UAV-LiDAR often tends to be slightly overestimated due to canopy point scattering (Bing et al. 2025), while DBH estimations derived from ground-based point clouds are generally more conservative due to modeling constraints at the lower stem level (Ye et al. 2020).

Despite these biases, the high level of correspondence between fused LiDAR outputs and field measurements demonstrates the effectiveness and operational relevance of integrating ground-based and aerial LiDAR platforms. The fusion of these datasets not only improves vertical structural representation but also strengthens confidence in the inventory metrics derived by mitigating the limitations inherent to each individual method (Panagiotidis et al. 2022).

Importantly, the fused LiDAR approach substantially enhances data acquisition efficiency compared to traditional field methods. While conventional inventories require manual measurement of each tree's DBH and height, an effort-intensive and time-consuming process LiDAR-based methods enable rapid data collection over large areas (Melville et al. 2015). Once the fusion workflow is established, the process can be repeated at regular intervals for forest monitoring, enabling time-series analysis, change detection, and the modeling of forest dynamics under different management scenarios (Apostol et al. 2019).

In addition to inventory applications, the improved vertical representation obtained from fusion datasets supports broader ecological assessments. For example, the combined data allow for more accurate quantification of vertical foliage distribution, crown base height, and forest stratification, which are essential for biodiversity studies and habitat modeling. The fine-resolution vertical structure also aids in carbon stock estimation, as accurate DBH and height measurements are fundamental inputs for allometric equations used in biomass modeling (Ferraz et al. 2016).

Furthermore, the successful fusion of PLS-LiDAR and UAV-LiDAR demonstrates a scalable workflow that can be adapted to various forest types and terrain conditions. The approach is especially valuable in heterogeneous forest environments where single-platform data collection may fail to capture complete structural variation. By leveraging the strengths of both ground and aerial perspectives, the fusion technique contributes to enhanced spatial data quality and supports precision forestry approaches.

4. Conclusions

This study demonstrates the effectiveness of fusion PLS-LiDAR and UAV-LiDAR data for forest inventory analysis. While PLS-LiDAR effectively captured detailed stem structures and understory vegetation, UAV-LiDAR provided comprehensive coverage of canopy architecture. The fusion of both datasets enabled a structurally complete and vertically continuous representation of the forest stand.

The fused dataset exhibited strong agreement with reference field measurements, with errors, 2.2 cm for diameter at breast height (DBH) and 2.35 m for tree height, and low bias values. These results confirm the accuracy and reliability of the fused point cloud compared to conventional field-based inventory methods. Moreover, this approach significantly reduces the time and manual effort required for data collection, without compromising measurement precision.

By leveraging the complementary strengths of ground-based and aerial platforms, LiDAR data fusion offers a scalable, efficient, and replicable solution for forest monitoring and inventory. The methodology supports not only operational forest assessments but also broader applications in ecological modeling and sustainable forest management. Future research could expand its application to diverse forest types and structural conditions, further enhancing the adaptability and utility of this approach in forestry science.

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References

Apostol, Bogdan; Chivulescu, Serban; Ciceu, Albert; Petrila, Marius; Pascu, Ionut-Silviu; Apostol, Ecaterina Nicoleta et al. (2019): Data collection methods for forest inventory: a comparison between an integrated conventional equipment and terrestrial laser scanning. In *Ann. For. Res.* 61 (2), p. 189. DOI: 10.15287/afr.2018.1189.

Bing, Qi; Zhang, Ruirui; Zhang, Linhuan; Li, Longlong; Chen, Liping (2025): UAV-SfM Photogrammetry for Canopy Characterization Toward Unmanned Aerial Spraying Systems Precision Pesticide Application in an Orchard. In *Drones* 9 (2), p. 151. DOI: 10.3390/drones9020151.

Brede, Benjamin; Calders, Kim; Lau, Alvaro; Raumonen, Pasi; Bartholomeus, Harm M.; Herold, Martin; Kooistra, Lammert (2019): Non-destructive tree volume estimation through quantitative structure modelling: Comparing UAV laser scanning with terrestrial LIDAR. In *Remote Sensing of Environment* 233, p. 111355. DOI: 10.1016/j.rse.2019.111355.

Calders, Kim; Adams, Jennifer; Armston, John; Bartholomeus, Harm; Bauwens, Sebastien; Bentley, Lisa Patrick et al. (2020): Terrestrial laser scanning in forest ecology: Expanding the horizon. In *Remote Sensing of Environment* 251, p. 112102. DOI: 10.1016/j.rse.2020.112102.

Chen, Junhua; Zhao, Dan; Zheng, Zhaoju; Xu, Cong; Pang, Yong; Zeng, Yuan (2024): A clustering-based automatic registration of UAV and terrestrial LiDAR forest point clouds. In *Computers and Electronics in Agriculture* 217, p. 108648. DOI: 10.1016/j.compag.2024.108648.

Conto, Tiago de; Olofsson, Kenneth; Görgens, Eric Bastos; Rodriguez, Luiz Carlos Estraviz; Almeida, Gustavo (2017): Performance of stem denoising and stem modelling algorithms on single tree point clouds from terrestrial laser scanning. In *Computers and Electronics in Agriculture* 143, pp. 165–176. DOI: 10.1016/j.compag.2017.10.019.

FARO. Available online at https://knowledge.faro.com/Software/GeoSlam/GeoSLAM_Connect/Control_Point_File_Format_for_Stop-And-Go_Georeferencing_in_GeoSLAM_Connect, checked on 4/9/2025.

Fassnacht, Fabian Ewald; White, Joanne C.; Wulder, Michael A.; Næsset, Erik (2024): Remote sensing in forestry: current challenges, considerations and directions. In *Forestry: An International Journal of Forest Research* 97 (1), pp. 11–37. DOI: 10.1093/forestry/cpad024.

Ferraz, António; Saatchi, Sassan; Mallet, Clément; Jacquemoud, Stéphane; Gonçalves, Gil; Silva, Carlos et al. (2016): Airborne Lidar Estimation of Aboveground Forest Biomass in the Absence of Field Inventory. In *Remote Sensing* 8 (8), p. 653. DOI: 10.3390/rs8080653.

Fol, C. R.; Murtiyoso, A.; Kükenbrink, D.; Remondino, F.; Griess, V. C. (2023): TERRESTRIAL 3D MAPPING OF FORESTS: GEOREFERENCING CHALLENGES AND SENSORS COMPARISONS. In *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.* XLVIII-1/W3-2023, pp. 55–61. DOI: 10.5194/isprs-archives-XLVIII-1-W3-2023-55-2023.

Guo, Lijie; Wu, Yanjie; Deng, Lei; Hou, Peng; Zhai, Jun; Chen, Yan (2023): A Feature-Level Point Cloud Fusion Method for Timber Volume of Forest Stands Estimation. In *Remote Sensing* 15 (12), p. 2995. DOI: 10.3390/rs15122995.

Jurado, Juan M.; López, Alfonso; Pádua, Luís; Sousa, Joaquim J. (2022): Remote sensing image fusion on 3D scenarios: A review of applications for agriculture and forestry. In *International Journal of Applied Earth Observation and Geoinformation* 112, p. 102856. DOI: 10.1016/j.jag.2022.102856.

Kellner, James R.; Albert, Loren P.; Burley, John T.; Cushman, K. C. (2019): The case for remote sensing of individual plants. In

American journal of botany 106 (9), pp. 1139–1142. DOI: 10.1002/ajb2.1347.

Krisanski, Sean; Taskhiri, Mohammad Sadegh; Gonzalez Aracil, Susana; Herries, David; Turner, Paul (2021): Sensor Agnostic Semantic Segmentation of Structurally Diverse and Complex Forest Point Clouds Using Deep Learning. In *Remote Sensing* 13 (8), p. 1413. DOI: 10.3390/rs13081413.

Lau, Alvaro; Martius, Christopher; Bartholomeus, Harm; Shenkin, Alexander; Jackson, Tobias; Malhi, Yadvinder et al. (2019): Estimating architecture-based metabolic scaling exponents of tropical trees using terrestrial LiDAR and 3D modelling. In *Forest Ecology and Management* 439, pp. 132–145. DOI: 10.1016/j.foreco.2019.02.019.

Liang, Xinlian; Hyyppä, Juha; Kaartinen, Harri; Lehtomäki, Matti; Pyörälä, Jiri; Pfeifer, Norbert et al. (2018): International benchmarking of terrestrial laser scanning approaches for forest inventories. In *ISPRS Journal of Photogrammetry and Remote Sensing* 144, pp. 137–179. DOI: 10.1016/j.isprsjprs.2018.06.021.

Liu, Jing; Skidmore, Andrew K.; Heurich, Marco; Wang, Tiejun (2017): Significant effect of topographic normalization of airborne LiDAR data on the retrieval of plant area index profile in mountainous forests. In *ISPRS Journal of Photogrammetry and Remote Sensing* 132, pp. 77–87. DOI: 10.1016/j.isprsjprs.2017.08.005.

Melville, Gavin; Stone, Christine; Turner, Russell (2015): Application of LiDAR data to maximise the efficiency of inventory plots in softwood plantations. In *N.Z. j. of For. Sci.* 45 (1). DOI: 10.1186/s40490-015-0038-7.

Murtiyoso, Arnadi; Holm, Stefan; Riihimäki, Henri; Krucher, Anna; Griess, Holger; Griess, Verena Christiane; Schweier, Janine (2024): Virtual forests: a review on emerging questions in the use and application of 3D data in forestry. In *International Journal of Forest Engineering* 35 (1), pp. 29–42. DOI: 10.1080/14942119.2023.2217065.

Neuville, Romain; Bates, Jordan Steven; Jonard, François (2021): Estimating Forest Structure from UAV-Mounted LiDAR Point Cloud Using Machine Learning. In *Remote Sensing* 13 (3), p. 352. DOI: 10.3390/rs13030352.

Panagiotidis, Dimitrios; Abdollahnejad, Azadeh; Slavík, Martin (2022): 3D point cloud fusion from UAV and TLS to assess temperate managed forest structures. In *International Journal of Applied Earth Observation and Geoinformation* 112, p. 102917. DOI: 10.1016/j.jag.2022.102917.

Straker, Adrian; Puliti, Stefano; Breidenbach, Johannes; Kleinn, Christoph; Pearse, Grant; Astrup, Rasmus; Magdon, Paul (2023): Instance segmentation of individual tree crowns with YOLOv5: A comparison of approaches using the ForInstance benchmark LiDAR dataset. In *ISPRS Open Journal of Photogrammetry and Remote Sensing* 9, p. 100045. DOI: 10.1016/j.ophoto.2023.100045.

Terryn, Louise; Calders, Kim; Bartholomeus, Harm; Bartolo, Renée E.; Brede, Benjamin; D'hont, Barbara et al. (2022): Quantifying tropical forest structure through terrestrial and UAV laser scanning fusion in Australian rainforests. In *Remote Sensing of Environment* 271, p. 112912. DOI: 10.1016/j.rse.2022.112912.

Tockner, Andreas; Gollob, Christoph; Kraßnitzer, Ralf; Ritter, Tim; Nothdurft, Arne (2022): Automatic tree crown segmentation using dense forest point clouds from Personal Laser Scanning (PLS). In *International Journal of Applied Earth Observation and Geoinformation* 114, p. 103025. DOI: 10.1016/j.jag.2022.103025.

Wang, Feiyu; Bryson, Mitch (2023): Tree Segmentation and Parameter Measurement from Point Clouds Using Deep and Handcrafted Features. In *Remote Sensing* 15 (4), p. 1086. DOI: 10.3390/rs15041086.

Wang, Xufei; Yang, Zexin; Cheng, Xiaojun; Stoter, Jantien; Xu, Wenbing; Wu, Zhenlun; Nan, Liangliang (2023): GlobalMatch: Registration of forest terrestrial point clouds by global matching of relative stem positions. In *ISPRS Journal of Photogrammetry and Remote Sensing* 197, pp. 71–86. DOI: 10.1016/j.isprsjprs.2023.01.013.

Wilkes, Phil; Disney, Mathias; Armston, John; Bartholomeus, Harm; Bentley, Lisa; Brede, Benjamin et al. (2023): TLS2trees : A scalable tree segmentation pipeline for TLS data. In *Methods Ecol Evol* 14 (12), pp. 3083–3099. DOI: 10.1111/2041-210X.14233.

Xiang, Binbin; Wielgosz, Maciej; Kontogianni, Theodora; Peters, Torben; Puliti, Stefano; Astrup, Rasmus; Schindler, Konrad (2024): Automated forest inventory: Analysis of high-density airborne LiDAR point clouds with 3D deep learning. In *Remote Sensing of Environment* 305, p. 114078. DOI: 10.1016/j.rse.2024.114078.

Ye, WenFang; Qian, Chuang; Tang, Jian; Liu, Hui; Fan, XiaoYun; Liang, Xinlian; Zhang, HongJuan (2020): Improved 3D Stem Mapping Method and Elliptic Hypothesis-Based DBH Estimation from Terrestrial Laser Scanning Data. In *Remote Sensing* 12 (3), p. 352. DOI: 10.3390/rs12030352.

Zhang, Keqi; Chen, Shu-Ching; Whitman, D.; Shyu, Mei-Ling; Yan, Jianhua; Zhang, Chengcui (2003): A progressive morphological filter for removing nonground measurements from airborne LIDAR data. In *IEEE Trans. Geosci. Remote Sensing* 41 (4), pp. 872–882. DOI: 10.1109/TGRS.2003.810682.