



Structural Observability Determines When UAV-Based Structure-from-Motion Approximates LiDAR in Forests

Felix Morsdorf^{1,2}, Mauro Marty², Aline Bornand^{1,2}, Meredith C. Schuman¹, and Daniel Kükenbrink²

¹Spatial Genetics of Ecosystems, Remote Sensing Laboratories, Department of Geography, University of Zurich, Winterthurerstrasse 190, CH-8057 Zurich, Switzerland

²Swiss Federal Institute for Forest, Snow and Landscape Research (WSL), Zurichstrasse 111, 8903 Birmensdorf, Switzerland

Correspondence: Felix Morsdorf (felix.morsdorf@geo.uzh.ch)

Abstract. Accurate three-dimensional characterization of forest structure is essential for ecological monitoring and operational forest inventories, not least because vegetation structure fundamentally shapes remotely sensed observations. While UAV-based laser scanning (ULS) enables detailed reconstruction of canopy and terrain structure, Structure-from-Motion (SfM) photogrammetry offers a substantially lower-cost alternative using consumer-grade imaging systems. However, the performance of SfM in forests is strongly influenced by canopy occlusion, observation geometry, and forest structural complexity. Here, we evaluate under which conditions optimized UAV-based SfM produces structural representations comparable to ULS and investigate the role of structural observability in explaining similarities and differences between both sensing approaches.

We compared ULS with two image-based SfM acquisition strategies: (i) a standard nadir-oriented mapping workflow and (ii) a multi-angle acquisition employing oblique viewing geometries designed to improve canopy observability. Data were acquired during leaf-off and leaf-on conditions across three contrasting temperate forest plots in Switzerland representing deciduous-dominated, mixed, and conifer-dominated stand structures.

Datasets were compared visually and quantitatively using metrics characterizing canopy height, cover, and vertical structural complexity, together with assessments of ground visibility and individual-tree detection performance. The multi-angle SfM configuration consistently outperformed the standard nadir-oriented workflow and substantially improved the representation of canopy structural detail, the completeness of canopy surfaces, and vertical structure. Several structural metrics showed improvements approaching a factor of two relative to the standard SfM acquisition. Under favourable conditions, optimized SfM closely reproduced LiDAR-derived canopy height and plot-scale vertical canopy profiles and occasionally matched or exceeded LiDAR point frequencies within externally visible canopy layers.

Nevertheless, important limitations remained. SfM exhibited strongly reduced ground visibility beneath closed canopies and incompletely represented lower canopy layers, sub-canopy structures, and fine woody elements, particularly in structurally complex and fully foliated stands. Individual-tree detection performance also decreased markedly in dense and conifer-dominated forests, whereas ULS remained substantially more robust across conditions.

Overall, our results indicate that the principal limitation of UAV-based SfM in forests is not the geometric accuracy of reconstructed surfaces but the observability of structural elements that remain partially or completely occluded from the camera network. Observation geometry emerged as a key factor controlling this observability and therefore the degree of agreement



between SfM and ULS. Optimized UAV-based SfM can provide a cost-effective alternative for plot-scale characterization of canopy structure when high-quality terrain information is available and the structural elements of interest are sufficiently observable from the camera network.

1 Introduction

- 30 Forest ecosystems represent structurally complex three-dimensional environments (McElhinny et al., 2005) in which the visibility of canopy and sub-canopy elements is strongly constrained by occlusion, canopy density, and observation geometry (Seidel, 2018). Remote sensing methods that reconstruct three-dimensional point clouds therefore do not directly observe the complete forest structure, but rather sample the subset of vegetation elements that remain observable under a given sensing configuration (Schneider et al., 2019). As a consequence, structural metrics derived from point clouds are influenced not only by ecosystem properties themselves, but also by sensor characteristics, viewing geometry, and the spatial distribution of occluded canopy volumes (Kükenbrink et al., 2017). Understanding how sensing geometry and canopy occlusion shape structural observability is therefore critical for the interpretation of remotely sensed forest structure. This becomes particularly important in close-range applications, where forest structure is often characterized directly from reconstructed three-dimensional geometry rather than inferred through empirical statistical relationships (Morsdorf et al., 2018).
- 40 Recent advances in close-range remote sensing techniques have substantially improved the ability to capture detailed three-dimensional (3D) representations of forest structure. Among these approaches, Light Detection and Ranging (LiDAR) and Structure from Motion (SfM) photogrammetry are widely used for generating point clouds capable of characterizing variables such as canopy height, vertical foliage distribution, canopy cover, and forest biomass (Iglhaut et al., 2019; Filippelli et al., 2019). Although based on fundamentally different measurement principles, both approaches produce sensor-specific samples of the same underlying forest structure, whose completeness is governed by structural observability.

- Many of the concepts underlying remote sensing-based forest structural characterization were originally developed in the context of airborne laser scanning (ALS), including terrain modelling beneath forest canopies and the quantification of canopy height and vertical vegetation structure (Kraus and Pfeifer, 1998; Lefsky et al., 1999; Næsset and Okland, 2002; Lefsky et al., 2002). These developments established LiDAR as a cornerstone technology for forest structural analysis and laid the foundation for subsequent uncrewed aerial vehicle (UAV)-based laser scanning approaches. Advances in sensor miniaturization and UAV technology have enabled the deployment of UAV-based laser scanning (ULS) systems capable of acquiring high-resolution structural observations at local spatial scales. Early ULS systems relied on comparatively large and operationally complex platforms carrying miniaturized airborne laser scanners (Morsdorf et al., 2017; Kellner et al., 2019), while recent advances in sensor miniaturization and UAV integration have enabled the deployment of increasingly compact multirotor-based systems capable of acquiring high-density point clouds at local spatial scales (Mandlbürger et al., 2016; Wieser et al., 2017). However, despite substantial technological progress, ULS acquisition still requires comparatively complex sensor systems, precise trajectory reconstruction, and considerable operational expertise during data acquisition and processing.



In contrast, SfM and Multi-View Stereo (MVS) approaches reconstruct three-dimensional geometry from overlapping image observations through camera pose estimation and dense image matching. These approaches offer a comparatively low-cost and operationally flexible alternative (Iglhaut et al., 2019), as data can be acquired using consumer-grade cameras mounted on UAVs or handheld systems (Piermattei et al., 2019; Mokroš et al., 2021; Kükenbrink et al., 2022). However, because image-based reconstruction relies on passive optical observations, the completeness of reconstructed geometry is fundamentally constrained by viewing geometry, visibility, and occlusion (Petrovska and Jutzi, 2025a). In forest environments, competition for light produces vertically stratified and structurally complex canopies in which the very elements defining forest structure simultaneously obstruct their own observation, making canopy observability fundamentally dependent on viewing geometry.

Analogous to terrestrial laser scanning approaches, where occlusion effects are commonly mitigated through multi-scan acquisition from different observation positions (Bienert et al., 2010; Wilkes et al., 2017; Duncanson et al., 2021), increasing angular diversity in UAV-based image acquisition may improve the observability of structurally complex forest environments. Recent advances in UAV platforms, including longer flight endurance and improved imaging capabilities, now allow the operational implementation of highly-redundant multi-angle acquisition strategies. Such acquisition strategies may improve the structural completeness of SfM point clouds and potentially reduce the apparent performance gap relative to ULS.

Previous SfM-based sensitivity analyses demonstrated that image overlap, viewing geometry, and oblique image acquisition can substantially affect the completeness and stability of forest point cloud reconstructions (Frey et al., 2018; Mueller et al., 2023). Similar observations were also reported in exploratory multi-angle UAV photogrammetry studies focusing on forest canopy reconstruction (Hese, 2022). However, without an external structural reference such as LiDAR, it remains difficult to assess to what degree increasingly complex acquisition schemes actually improve the representation of forest structure.

At the same time, many comparisons between ULS and image-based point cloud reconstruction in forest environments were still based on acquisition strategies originally optimized for orthomosaic generation, frequently relying on predominantly nadir-oriented image observations (Winsen and Hamilton, 2023; Dhruva et al., 2024). Such acquisition geometries inherently limit angular sampling diversity and may therefore confound intrinsic methodological limitations of image-based reconstruction with incomplete structural observability caused by viewing geometry, potentially reinforcing the common view that photogrammetric point clouds primarily represent the upper canopy envelope (McNicol et al., 2021). In contrast, increasing angular diversity and multi-view coverage through oblique acquisitions can substantially expand the observable canopy surface, while remaining constrained to optically visible structures.

In this study, we compare a state-of-the-art ULS approach with two UAV-based image acquisition strategies: a conventional nadir-oriented workflow optimized primarily for standard aerial mapping applications and an enhanced multi-angle acquisition strategy with highly redundant oblique imagery designed to improve structural observability within forest canopies. The datasets were acquired across three 50 m × 50 m forest plots representing contrasting temperate forest structural conditions, including deciduous-dominated, mixed, and conifer-dominated stands. All LiDAR and image-based datasets were collected during both leaf-on and leaf-off conditions on the same acquisition dates, thereby minimizing temporal differences between datasets.



The objectives of this study are therefore to: (i) evaluate whether optimized multi-angle SfM can approximate ULS in terms of derived forest structural metrics and canopy representations across contrasting forest structural and phenological conditions; (ii) assess how acquisition geometry influences canopy representation, vertical structural metrics, and ground visibility; and
 95 (iii) identify forest conditions under which SfM provides a practical alternative to ULS for forest structural characterization.

2 Data and methods

2.1 Study site

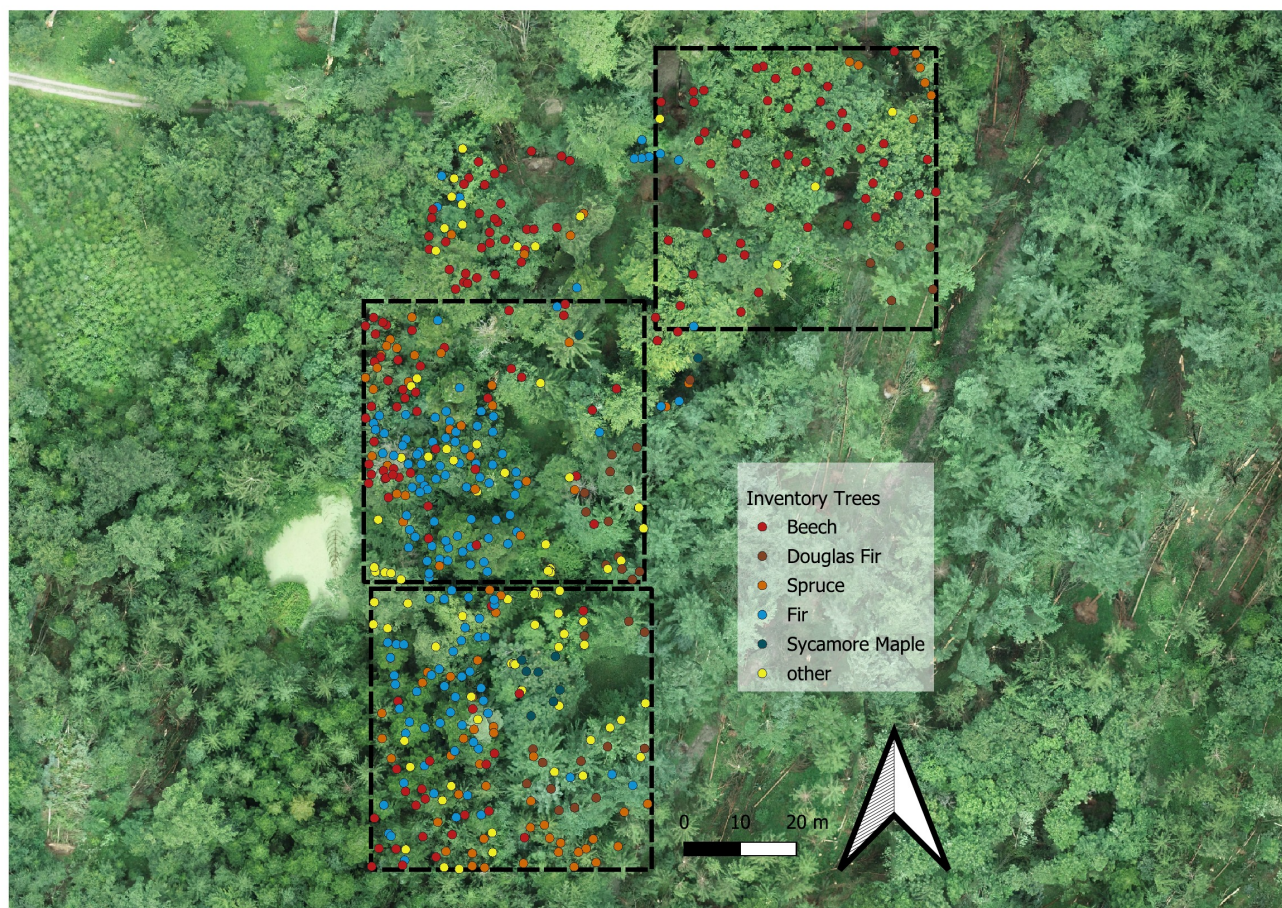


Figure 1. Study area with designated plots derived from an orthoimage acquired in July 2021 using a DJI Phantom 4 RTK. The analyses focus on three plots representing different forest types and structural conditions: deciduous-dominated (FP5), conifer-dominated (FP8), and mixed (FP10). Colored points indicate inventory trees, classified by species (beech, douglas fir, spruce, fir, sycamore maple, and other).



The experiment was conducted at the Ramerenwald site near the Swiss Federal Research Institute WSL main campus in Birmensdorf, Switzerland. The site is located at 47.3620° N, 8.4521° E and comprises three spatially distinct plots (50 m × 50 m) named FP5, FP8 and FP10. The selected plots represent contrasting forest structural conditions. FP5 is an older, deciduous-dominated stand with comparatively large trees, whereas FP8 and FP10 are denser stands with substantial conifer components. FP10 was included as an additional structurally complex case, characterized by higher species diversity and heterogeneity, rather than as an intermediate step along a predefined structural gradient.

Plot	DBH [cm]			Rich.	Shan.	Spec. dom.	P_{conifer}	Func. dom.
	mean	SD	CV					
FP5	31.9	12.6	0.40	7	1.02	0.72	0.22	0.78
FP10	22.3	15.1	0.68	11	1.91	0.30	0.60	0.60
FP8	18.5	14.3	0.77	10	1.62	0.40	0.61	0.61

Table 1. Summary of forest structural properties derived from field inventory data for the three study plots (FP5, FP10, FP8), representing contrasting stand structures. Diameter at breast height (DBH) is reported as mean, standard deviation (SD), and coefficient of variation (CV) in cm. Species richness, Shannon diversity, and species dominance (relative abundance of the most common species) were computed at the species level. The proportion of coniferous trees (P_{conifer}) and functional dominance were derived from functional grouping into deciduous and coniferous species.

Inventory data (Table 1) highlight clear differences in stand structure: FP5 is characterized by fewer but larger trees (high mean DBH, low variability), whereas FP8 exhibits higher stem density and smaller trees with greater variability in DBH. The mixed stand FP10 combines relatively high stem density with pronounced variability in tree size and species composition.

Each plot was centred on a permanently marked reference point, enabling repeated measurements and long-term monitoring. Across the study area, the dominant tree species are European beech (*Fagus sylvatica*), silver fir (*Abies alba*), and Norway spruce (*Picea abies*).

Together, these plots represent contrasting combinations of tree size, stem density, and structural heterogeneity, including varying levels of understory vegetation, and thus provide a suitable testbed to evaluate the performance of SfM and LiDAR across different forest structural conditions.

Within each plot, the position, species and diameter at breast height (DBH) of all trees exceeding a DBH threshold of 7 cm were recorded. Tree positions were determined using a Leica MS50 total station referenced to a network of permanent survey points established from differential GNSS measurements and a subsequent total-station traverse, resulting in sub-centimetre relative positioning accuracy. DBH was measured using a caliper in two orthogonal directions, while stem circumference was recorded for trees exceeding the caliper range.

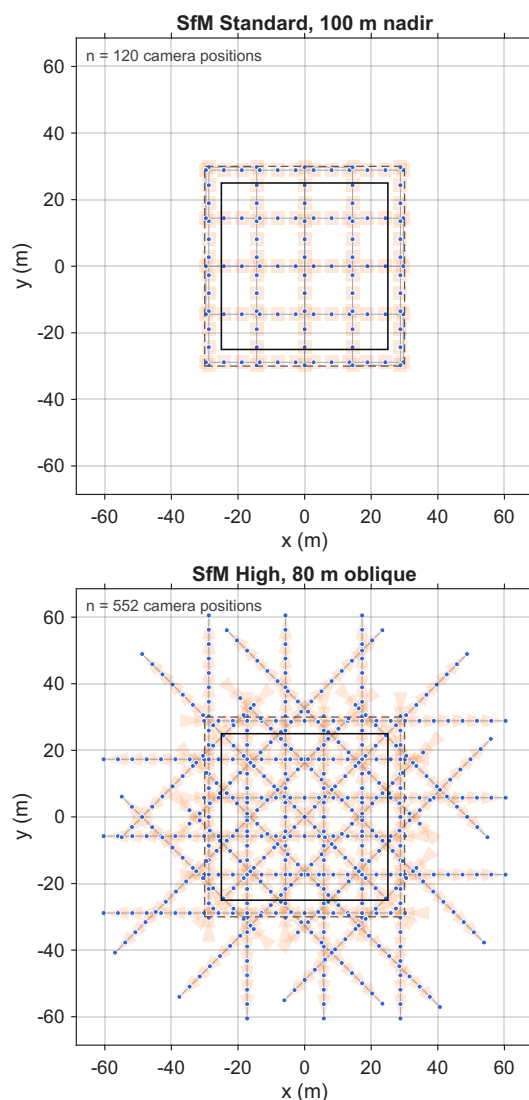


Figure 2. Image-acquisition geometries of the standard nadir-oriented SfM survey at 100 m AGL (top) and the multi-angle oblique survey at 80 m AGL (bottom). Blue points and grey lines represent nominal camera positions and flight paths, respectively; orange symbols schematically indicate nadir footprints or estimated oblique viewing directions. Black and dashed grey outlines indicate the 50×50 m analysis plot and its processing buffer.

2.2 UAV-based SfM data acquisition and processing

Two aerial campaigns were conducted under contrasting phenological conditions (leaf-off: 26 March 2024; leaf-on: 29 May 2024). During each campaign, ULS and UAV-based SfM datasets were acquired consecutively to minimise temporal differences.



Plot	SfM	Phenol.	No. img	GSD [cm]	Cam. err. [cm]	Points full	Points 2 cm	Alt. [m]	ICP offset [cm]		
									<i>x</i>	<i>y</i>	<i>z</i>
FP5	Std.	On	100	2.36	3.79	16,173,874	6,279,086	82.6	-12.7	29.8	18.1
FP5	Std.	Off	100	2.51	4.70	7,184,659	3,345,940	85.3	-19.6	37.2	32.6
FP5	High	On	445	1.83	6.02	45,902,825	14,222,487	59.2	-29.4	6.9	16.9
FP5	High	Off	440	2.10	6.97	24,261,122	9,077,639	73.7	-9.6	0.7	-1.1
FP8	Std.	On	99	2.22	3.24	20,381,100	8,082,331	81.8	-36.3	-20.8	47.4
FP8	Std.	Off	97	2.33	4.04	12,777,718	4,979,773	83.2	-34.6	-7.5	18.1
FP8	High	On	448	1.85	6.86	51,363,975	16,363,207	64.4	-8.6	9.3	5.8
FP8	High	Off	437	1.96	8.87	40,800,475	13,642,291	67.1	34.0	-5.0	-1.6
FP10	Std.	On	100	2.27	4.76	13,637,600	5,273,014	83.0	34.7	-25.8	4.8
FP10	Std.	Off	99	2.22	3.24	11,867,900	4,619,125	81.8	31.8	-36.2	-2.6
FP10	High	On	423	1.83	8.59	44,050,135	13,672,751	64.5	49.7	-25.2	7.0
FP10	High	Off	420	1.87	6.22	40,557,321	12,713,104	63.9	68.2	13.1	5.8

Table 2. Overview of the SfM datasets, acquisition settings, reconstruction characteristics, and ICP-derived registration shifts relative to the ULS reference. Shifts in *x*, *y*, and *z* were obtained by rigid ICP co-registration in CloudCompare with ULS as the reference, using default random subsampling of the complete point clouds. These shifts may also reflect differences in vegetation representation and are not independent estimates of geolocation error. “Full” denotes the original dense SfM reconstruction, whereas “2 cm” denotes subsampling to a minimum point spacing of 2 cm.

RGB imagery was acquired using a DJI Mavic 3 Multispectral (M3M) UAV equipped with a 20 MP RGB camera. Flight missions were planned in Drone Harmony and consisted of two acquisition configurations (Fig. 2). The standard configuration used a nadir-oriented double-grid flight pattern at a nominal flight altitude of 100 m above the take-off elevation, whereas the high-overlap multi-angle configuration combined two double grids rotated by 45° and acquired at an oblique viewing angle of 70° from a nominal altitude of 80 m above the take-off elevation. Terrain variation within the plots was small relative to the flight altitude, and all flights were conducted without terrain following.

Both configurations were designed to provide very high image overlap (95% forward and 90% side overlap). However, these values represent nominal overlaps calculated relative to the ground surface. In forest canopies, the effective overlap at canopy height is lower because image footprints decrease with decreasing sensor-object distance. The high nominal overlaps were therefore intentionally chosen to ensure sufficient image redundancy within structurally complex forest canopies.

All SfM processing was performed in Agisoft Metashape Professional (Version 2.2.0). Images were aligned using the High accuracy setting, while depth maps and dense point clouds were generated using the Ultra High setting. Mild depth filtering was applied to reduce the occurrence of spurious points below the terrain surface. For each flight configuration and phenological state, point clouds, orthomosaics and digital elevation models were generated.



2.3 ULS data acquisition and processing

Similar to the SfM data, LiDAR acquisitions were conducted in both leaf-off and leaf-on conditions using a DJI Matrice 600 (M600) hexacopter equipped with a RIEGL miniVUX-3 UAV laser scanner. Each LiDAR survey was carried out immediately prior to the corresponding SfM acquisition on the same day. The laser scanner operated at a pulse repetition frequency of 300 kHz and was mounted in nadir orientation, providing a full 90° field of view. Flights were performed at a nominal altitude of 60 meters above ground level with a forward speed of 3.1 m/s. To ensure complete coverage of all study plots and maximize canopy penetration from varying perspectives, a combined flight pattern was employed consisting of two double-grid trajectories rotated by 45 degrees, thereby providing an acquisition geometry comparable to the optimized multi-angle SfM survey. The resulting LiDAR point clouds were classified into ground and vegetation returns using LAStools lasground function (v241125). For each phenological condition (leaf-on and leaf-off), the classified point clouds were subsequently clipped to the plot boundaries.

2.4 Co-registration of LiDAR and SfM data

LiDAR and SfM point clouds were matched by phenological state and plot ID and co-registered in CloudCompare (Version 2.13) using the built-in iterative-closest-point (ICP) algorithm using the default values for number of random samples (50'000) and expected overlap (100%). The LiDAR point clouds served as the reference coordinate system, while the SfM point clouds were adjusted by translation and rotation only, with scale held constant. The resulting translation parameters are reported in Table 2. These values should be interpreted as pragmatic co-registration parameters rather than as absolute measures of positional accuracy, as ICP alignment is influenced by the subset of structures represented in both point clouds and by the presence of non-corresponding observations. For this reason, co-registration was performed only between LiDAR and SfM datasets acquired under the same phenological conditions.

Following registration, all point clouds were spatially subsampled using CloudCompare to a minimum point spacing of 2cm, reducing oversampling and partially harmonizing point densities across datasets (Table 2). The aim was not to equalize the point clouds completely, but to minimize density differences arising purely from differences in acquisition sampling density and thereby facilitate a more meaningful comparison of structural observability.

2.5 Terrain modelling and point-cloud normalization

All point clouds were first clipped to the true 50 × 50m plot extent in the original LV95 coordinate system. For numerical processing and visualization, a plot-wise translation was applied to shift the coordinate origin to a local coordinate system. This transformation was applied equally to all datasets of a plot and did not involve any rotation or scaling.

Ground returns extracted separately from the leaf-off and leaf-on ULS acquisitions were interpolated onto regular 0.25m grids using natural-neighbour interpolation, resulting in phenology-specific LiDAR-derived terrain models. Each LiDAR and SfM point cloud was subsequently normalized using the LiDAR DTM corresponding to the same phenological state. This



avoided additional uncertainty from cross-phenological co-registration while maintaining a common terrain reference within each LiDAR–SfM comparison.

The interpolated terrain elevation was subtracted from each point to derive normalized height-above-ground coordinates.
170 The ability of each acquisition strategy to directly observe the terrain surface was analysed separately based on ground-point density and spatial coverage (Section 2.6.3).

2.6 Multi scale structural analysis

The selected analyses were designed to characterize forest structure across multiple levels of spatial organization, ranging from plot-scale vertical canopy profiles and local structural metrics to ground visibility and individual-tree representations.

175 2.6.1 Vertical canopy profiles

Plot-level vertical point-height profiles were generated by aggregating all terrain-normalized point heights within the 50×50 m plot extent into 90 equally spaced height bins between 0 and 45 m. Histograms were intentionally expressed as absolute point counts to preserve differences in both vertical distribution and observation magnitude between sensing modalities. All profiles were derived from the spatially subsampled (2 cm) point clouds.

180 2.6.2 Structural metrics

To enable quantitative comparisons between LiDAR and SfM point clouds, we selected three structural metrics representing complementary dimensions of forest canopy structure. Following the conceptual framework of Fahey et al. (2019), temperate forest canopies can be described along three largely independent structural axes: canopy height, canopy openness, and vertical complexity. Although these dimensions are not strictly orthogonal, they capture complementary aspects of canopy organization
185 and therefore provide a useful framework for evaluating structural observability in 3D point clouds. Accordingly, we derived canopy height (CH), fractional cover (FCO), and foliage height diversity (FHD) as proxies for these three dimensions using a custom MATLAB-based processing workflow. These metrics have been widely used to characterize vegetation structure across spatial scales. Their interpretation, however, depends strongly on the unit of aggregation. While pixel-based implementations frequently reflect stand-level structural heterogeneity and spatial aggregation patterns (Schneider et al., 2017), individual-tree
190 implementations can act as crown morphological descriptors and proxies of tree architecture (Zheng et al., 2021). Accordingly, all metrics were calculated on a regular 2 m grid, representing a compromise between local canopy characterization and statistical robustness while maintaining sufficient returns per grid cell for stable metric estimation.

Canopy height (CH) was defined as the 99th percentile of normalized point heights within each grid cell. Fractional cover (FCO) was calculated as the proportion of returns above 0.5 m, representing canopy closure and openness. Foliage height



195 diversity (FHD) was used to characterize vertical structural complexity and was calculated from the relative distribution of
 returns above 0.5 m among height bins using the Shannon-Wiener entropy formulation:

$$FHD = - \sum_i p_i \log(p_i), \quad (1)$$

where p_i denotes the proportion of returns within height bin i .

For each plot, acquisition strategy, and phenological state, SfM-derived grid-cell metrics were compared against the corre-
 200 sponding LiDAR-derived values using the coefficient of determination (R^2), regression slopes, root mean square error (RMSE),
 normalized RMSE (nRMSE), and mean bias.

2.6.3 Ground visibility

Ground visibility was assessed by selecting all points with normalized heights of ≤ 0.1 m relative to the LiDAR-derived terrain
 surface for each phenological state. Ground observations were quantified using a regular grid with a cell size of 0.25 m. Spatial
 205 completeness was quantified as grid occupancy, *i.e.*, the proportion of 0.25 m grid cells containing at least one ground point.
 In addition, local ground-point density was characterized as the median number of ground points per occupied grid cell. These
 metrics were compared across sensing modalities and phenological states.

2.7 Individual tree detection and segmentation

To complement the plot- and grid-level structural analyses, individual tree detection and segmentation were evaluated as a tree-
 210 level application of the different point-cloud acquisition strategies using the *SegmentAnyTree* (Wielgosz et al., 2024) framework
 implemented on the ForestSens platform (<https://forestsens.com/>).

The segmentation workflow was applied consistently across all subsampled (2 cm) datasets without plot-specific parameter
 tuning. For the individual tree detection workflow, leaf-on and leaf-off SfM point clouds were merged prior to segmentation to
 increase the structural completeness of the reconstructed point cloud.

215 To maintain a consistent processing workflow across sensing approaches, the corresponding ULS point clouds were merged
 in the same manner before segmentation and matching. No additional post-filtering of segmented trees, such as removing
 segments based on minimum point count, segment size, or other geometric plausibility criteria, was applied prior to evaluation.
 Consequently, all segmentation artefacts, over-segmentation effects, and false detections produced by the respective point
 clouds were retained in the evaluation.

220 Segmentation results were then evaluated independently for LiDAR and SfM datasets against the same field inventory. Seg-
 mented trees were spatially matched to field-measured stem positions using a global one-to-one nearest-neighbour assignment
 based on horizontal distances and a maximum matching threshold of 2 m. Tree positions of segmented instances were defined
 as the horizontal centroid (mean x, y position) of all points belonging to the segment within a 1–2 m height-above-ground
 slice, providing an approximation of stem position rather than crown centroid. Each field tree and each detected tree could only
 225 be assigned once.



Detection performance was quantified using recall and precision. Recall was defined as the proportion of field-inventory trees successfully detected in a given point-cloud dataset:

$$\text{Recall} = \frac{TP}{TP + FN}$$

where TP represents detections matched to field-inventory trees and FN represents field trees not detected in the point cloud.

Precision was defined as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

where FP represents segmented trees without a corresponding field-inventory tree within the matching threshold.

The harmonic mean of precision and recall was additionally summarized using the F1-score:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

3 Results

3.1 Point cloud comparison under varying observation geometry and phenology

We first compare ULS and SfM point clouds visually to highlight differences in canopy representation under varying observation geometries and phenological conditions. Consequently, the figures primarily serve to compare geometric completeness and structural representation rather than visual appearance. The animated supplementary videos provide additional visual context and can aid the interpretation of structural differences apparent in the static figures.

For FP5 (Figure 3), ULS shows continuous canopy surfaces, clearly visible stems, and structural elements throughout the canopy profile. SfM High (multi-angle oblique acquisition) reconstructs substantially more woody and canopy structure than SfM Standard (standard nadir acquisition), particularly under leaf-off conditions, but both SfM configurations lose structural information below dense crowns during leaf-on conditions.

For FP8 and FP10 (Figure A1), visual differences between leaf-off and leaf-on conditions are less pronounced, consistent with the substantial conifer component of both stands. SfM High again produces a more complete and vertically continuous reconstruction than SfM Standard, while ULS maintains the most complete representation across canopy layers.

Across all plots, ULS produced a more volumetric representation of forest structure, including interior crown points and persistent representation of stems and lower canopy elements. SfM point clouds were dominated by externally visible canopy and woody surfaces, with SfM High showing greater canopy continuity and representation of woody elements than SfM Standard. Differences among acquisition strategies were most pronounced in the deciduous-dominated FP5 plot under leaf-on

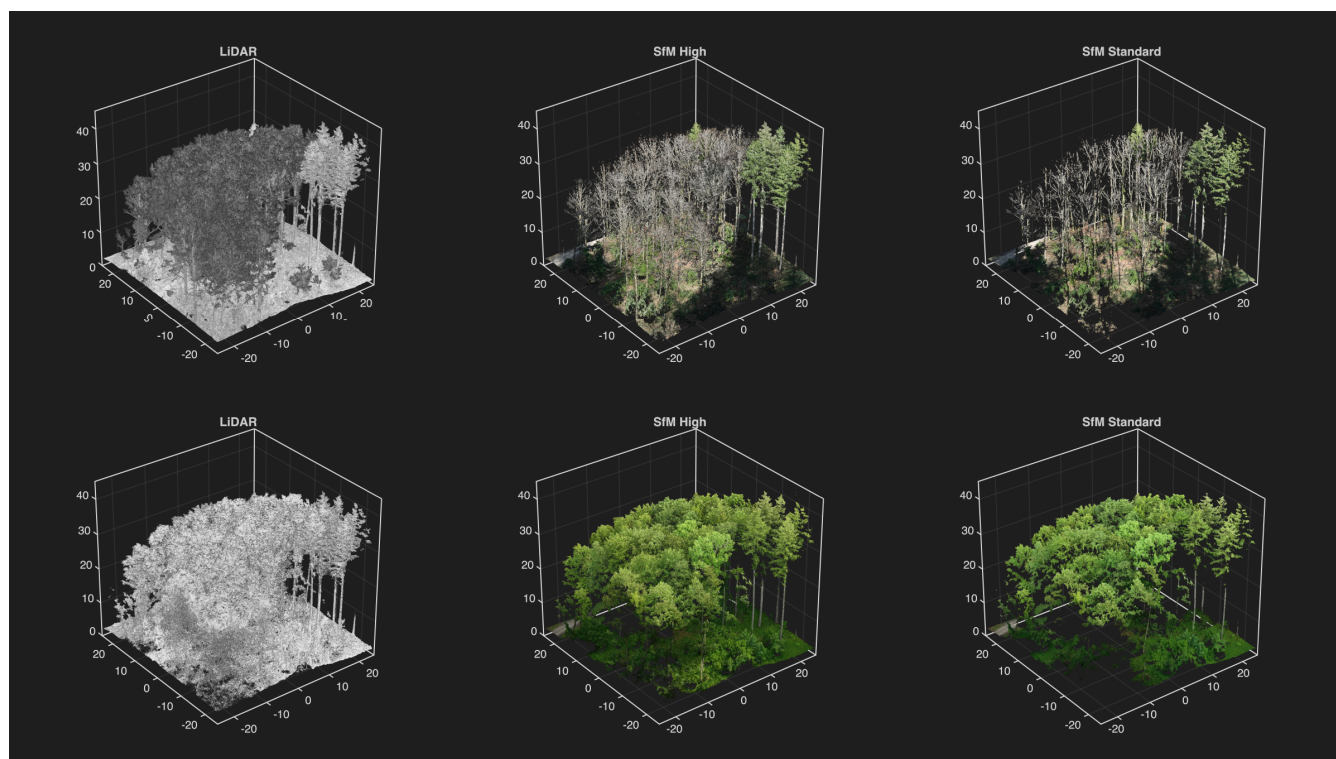


Figure 3. 3D visualization of the deciduous-dominated plot FP5 under leaf-off (top row) and leaf-on (bottom row) conditions. Columns show ULS (left), SfM High (middle), and SfM Standard (right). The SfM High configuration improves the representation of canopy structure compared to the Standard configuration, while ULS captures finer structural detail throughout the canopy. Animated version is available at <https://youtu.be/ojkl9tJARA>.

conditions. These relative differences between SfM Standard and SfM High remained clearly visible after spatial subsampling to a common point spacing, indicating that they were not solely attributable to differences in point density.

255 3.2 Vertical canopy structure

In FP5, ULS exhibits a pronounced peak of canopy material around 25 m under leaf-off conditions (Figure 4). This peak is only partially represented by SfM High and is largely absent in SfM Standard. Visual inspection indicates that this discrepancy is primarily associated with the incomplete reconstruction of fine woody elements in the upper canopy. Under leaf-on conditions, however, SfM High closely reproduces the dominant canopy peak and locally even exceeds ULS point frequencies within the canopy layer.

In FP8 and FP10, SfM High again shows substantially closer agreement with ULS than SfM Standard. Across both phenological conditions, the general shape and position of the dominant canopy peaks are reproduced remarkably well at plot scale, and several secondary peaks and shoulder structures indicative of vertically stratified canopies are also partially recovered.

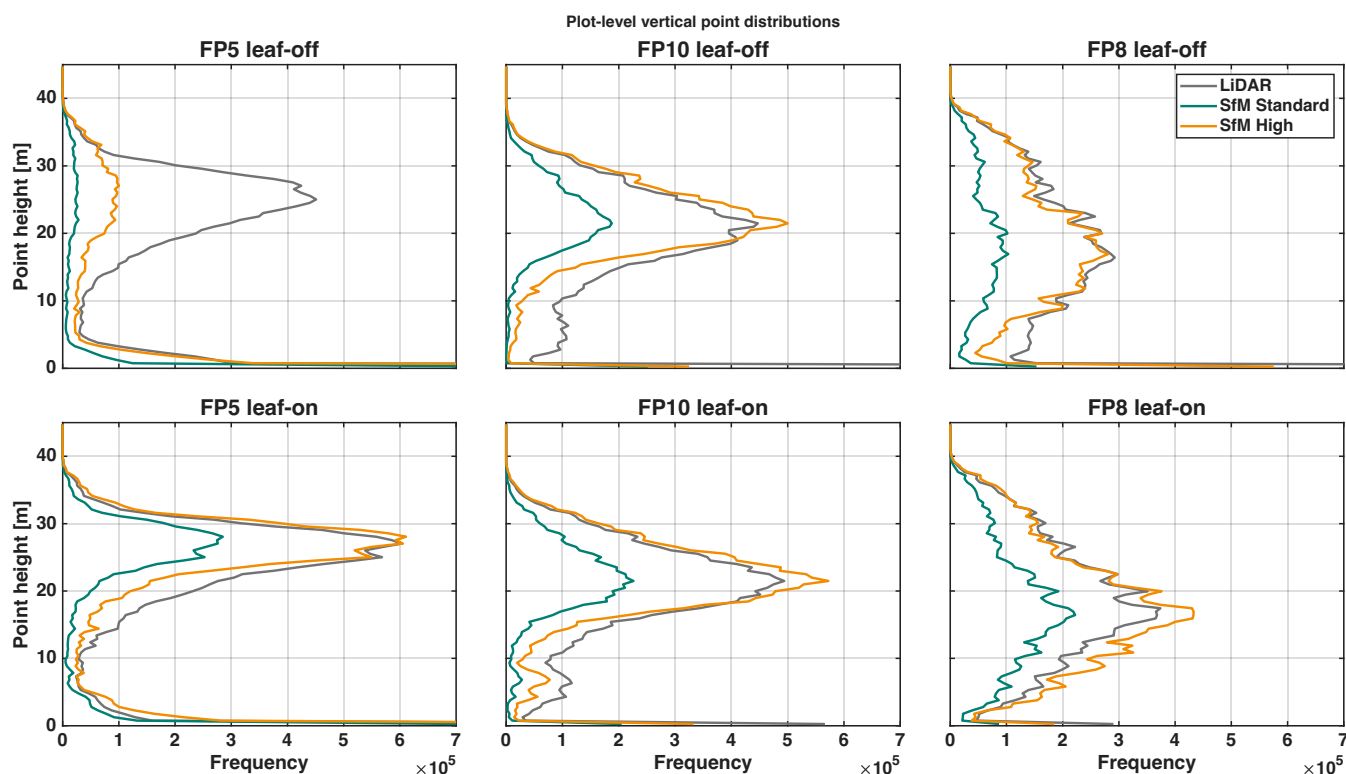


Figure 4. Plot-level height–frequency distributions of point cloud returns within the 50 m × 50 m plots FP5 (deciduous-dominated), FP8 (conifer-dominated), and FP10 (mixed/structurally heterogeneous), shown for leaf-off (top row) and leaf-on (bottom row) conditions. Solid grey, teal, and orange lines indicate LiDAR, SfM Standard, and SfM High, respectively.

Nevertheless, below the dominant canopy layers, SfM profiles frequently decline more rapidly than the corresponding ULS
 265 profiles, indicating reduced observability of lower canopy structure.

Overall, SfM High reproduced plot-scale vertical point distributions remarkably closely and substantially reduced differences relative to ULS. Even when considering absolute point frequencies, SfM High often reached point counts within the same order of magnitude as ULS while closely matching the position of the dominant canopy peaks.

3.3 Comparison of derived canopy structure metrics

270 We further evaluated the agreement between ULS and SfM-derived canopy metrics, including canopy height (CH), fractional cover (FCO), and foliage height diversity (FHD).

For FP5, canopy height shows strong agreement across methods, particularly under leaf-on conditions (Figure 5). Fractional cover and foliage height diversity exhibit larger deviations between ULS and SfM. Across the FP5 comparisons, SfM High generally shows higher agreement with ULS than SfM Standard.

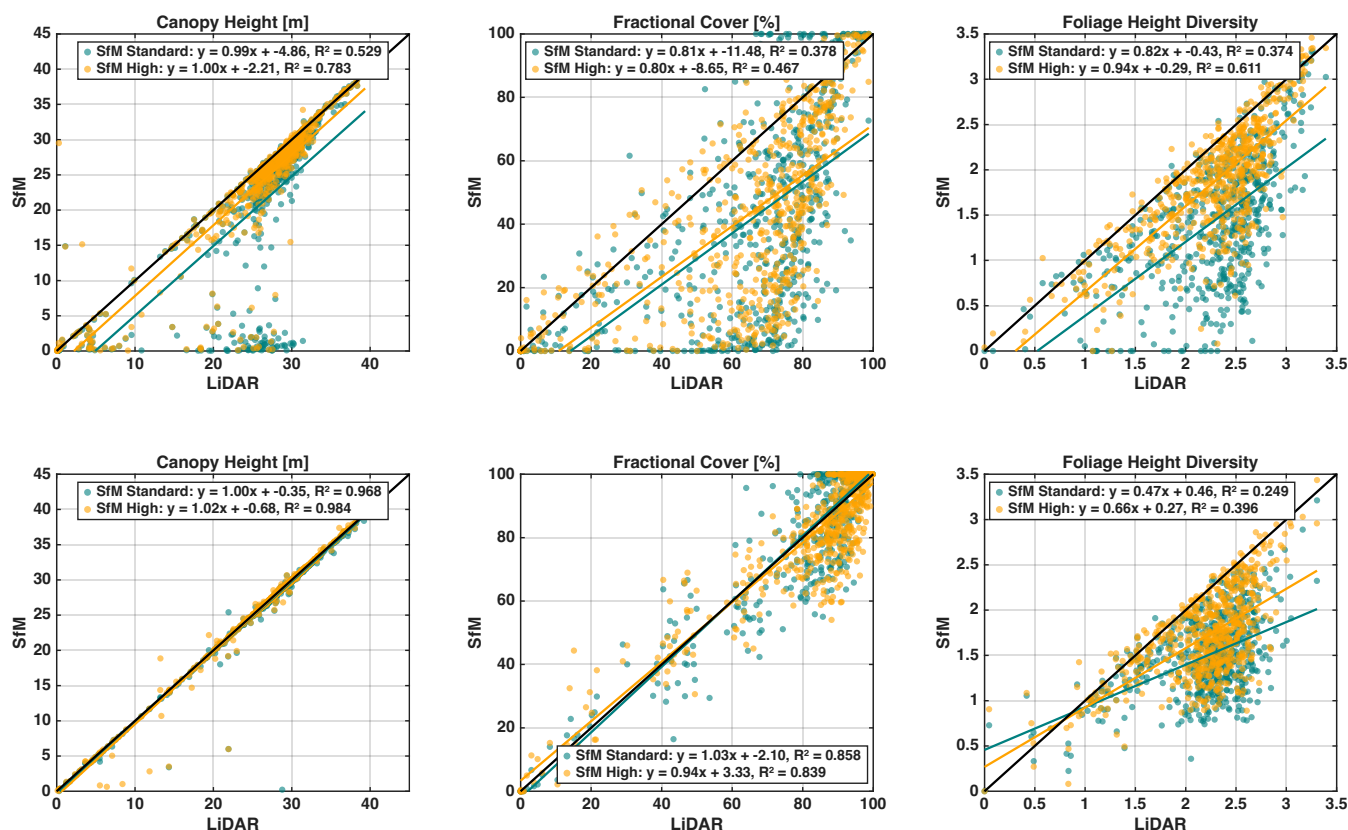


Figure 5. Comparison of ULS and SfM-derived canopy metrics for the deciduous-dominated plot FP5. Top row: leaf-off; bottom row: leaf-on. Metrics include canopy height (left), fractional cover (middle), and foliage height diversity (right).

275 Under leaf-off conditions, canopy height was systematically underestimated by SfM. The standard nadir acquisition exhibited a canopy height bias of approximately -4.9 m, whereas the multi-angle oblique acquisition substantially reduced this bias to approximately -2.2 m.

For FP8, canopy height agreement is high for both SfM configurations and phenological states (Figure A2). Fractional cover also shows comparatively high agreement under leaf-on conditions. FHD shows larger scatter and lower agreement than canopy height, with differences between SfM Standard and SfM High configurations remaining visible. FP10 showed consistently high canopy-height agreement, while fractional cover and particularly FHD showed greater sensitivity to phenological condition and acquisition strategy.

Canopy height showed the strongest overall agreement between SfM- and ULS-derived metrics across all study plots and acquisition settings (Figure 6). For FP8 and FP10, canopy height agreement was consistently high ($R^2 > 0.9$) for both SfM Standard and SfM High acquisitions under leaf-on and leaf-off conditions, with regression slopes remaining close to unity.

Fractional cover agreement varied more strongly with phenological condition. Across all plots, leaf-on acquisitions resulted in higher agreement with ULS than leaf-off acquisitions. The highest fractional cover agreement was observed for FP8, where

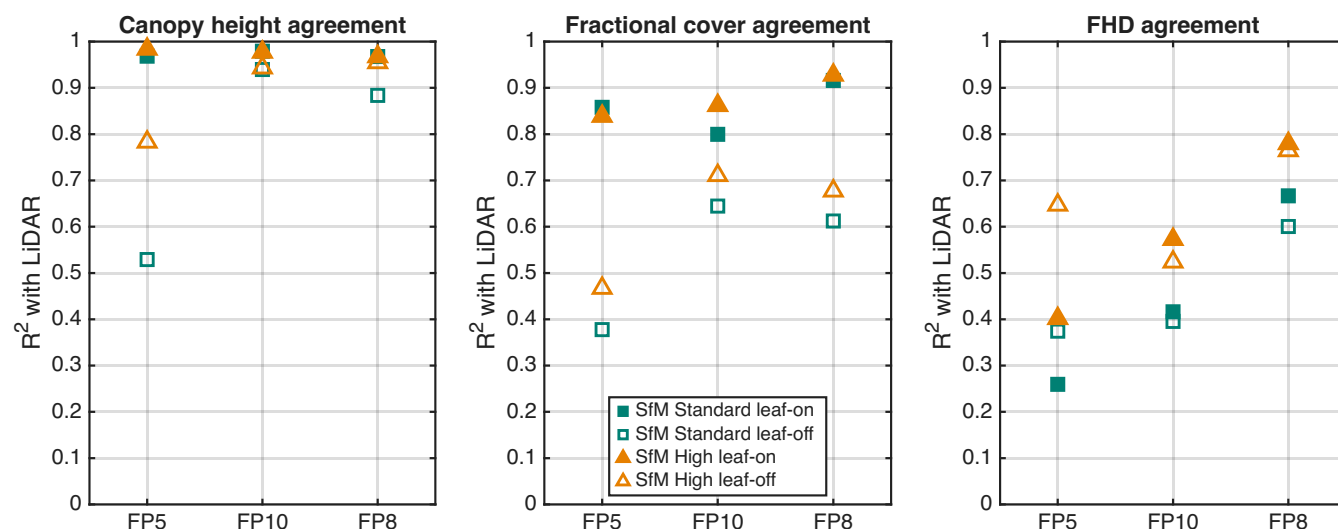


Figure 6. Agreement of structural metrics derived from SfM and ULS point clouds across three forest plots (FP5, FP8, FP10) and phenological conditions. Filled symbols indicate leaf-on acquisitions, while open symbols indicate leaf-off acquisitions. Circles represent SfM Standard acquisitions and squares represent SfM High acquisitions; colours are retained for visual guidance.

R^2 values exceeded 0.9 for both SfM acquisition strategies during leaf-on conditions. Agreement was consistently lower under leaf-off conditions, particularly for FP5.

290 Foliage height diversity (FHD) showed lower overall agreement with ULS than canopy height or fractional cover and exhibited stronger variability among plots, phenological conditions, and acquisition strategies. SfM High consistently showed stronger FHD agreement than SfM Standard. The strongest agreement was observed for FP8 under leaf-on conditions using SfM High ($R^2 \approx 0.78$). A pronounced effect of acquisition strategy was also observed for FP5 under leaf-off conditions, where SfM High reached relatively high agreement ($R^2 \approx 0.65$), while SfM Standard showed substantially lower agreement. The

295 lowest agreement occurred for FP5 with SfM Standard in leaf-on conditions ($R^2 \approx 0.26$).

3.4 Ground point availability and terrain representation

To assess differences in terrain observability between acquisition methods, we analyzed the spatial distribution of ground returns and ground-like SfM points under different phenological conditions.

For FP5, ground point availability is high in the ULS data under both phenological conditions (Figure 7). In the SfM datasets, ground-like points are more spatially clustered and decrease strongly under leaf-on conditions, particularly in areas below closed crowns.

300

For FP8, SfM-derived ground-like points are sparse and spatially discontinuous relative to ULS (Figure A3). The difference is visible under both phenological conditions and is especially apparent in the standard SfM configuration.

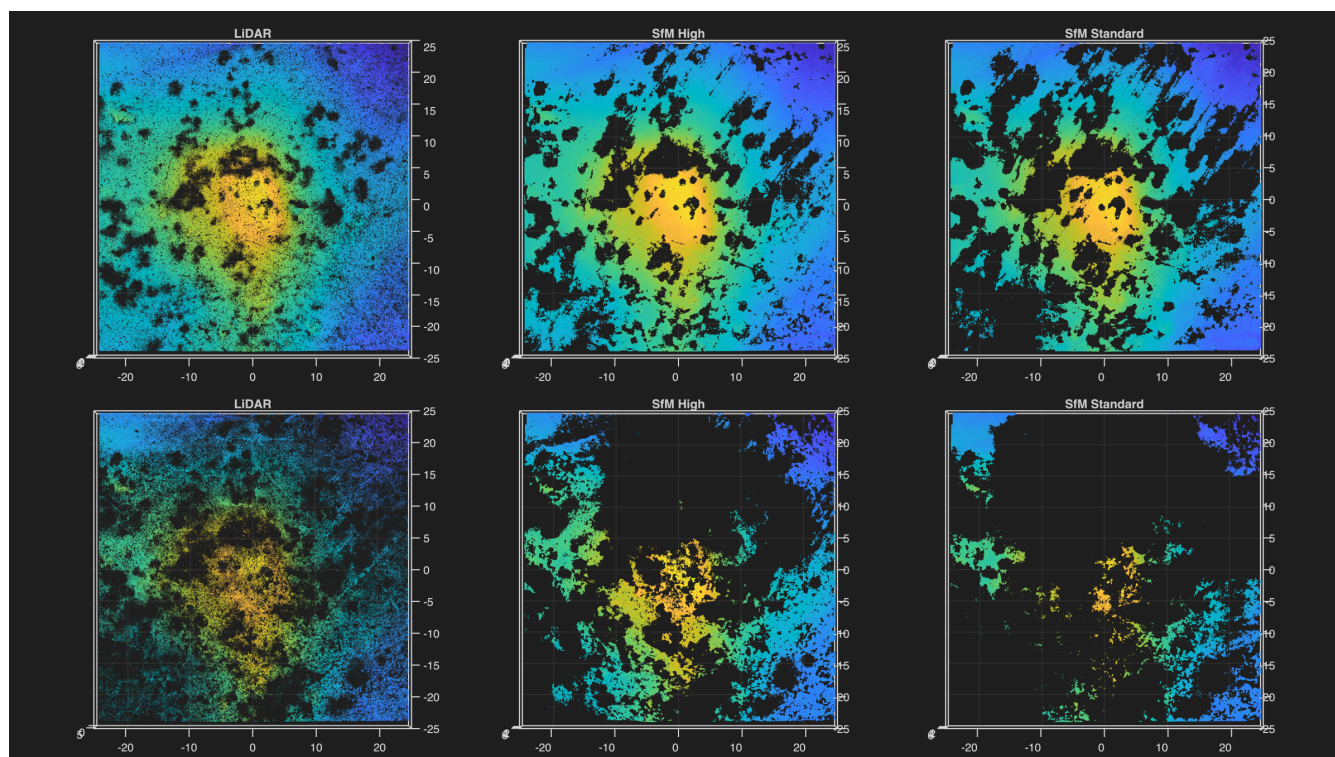


Figure 7. Spatial distribution of ground points for the deciduous-dominated plot FP5 under leaf-off (top row) and leaf-on (bottom row) conditions. Columns correspond to ULS, SfM High, and SfM Standard (from left to right).

Ground visibility differed strongly between ULS and SfM datasets and was sensitive to phenological state and acquisition geometry (Figure 8). ULS maintained consistently high ground visibility across all plots, with more than 80% of the ground area remaining observable even under leaf-on conditions. In contrast, SfM reconstructions showed substantial reductions in observable ground area, particularly in FP10 and FP8. Leaf-on conditions reduced both the spatial extent and local density of ground observations for all methods, including ULS, although the strongest reductions were observed for SfM.

SfM High increased the proportion of observed ground area relative to SfM Standard in all plots, with the strongest improvements observed in FP5 under leaf-off conditions. In addition to spatial coverage, marked differences in local ground-point density were observed. ULS frequently exhibited lower median numbers of ground points per occupied grid cell despite substantially larger overall ground coverage, whereas SfM ground observations were concentrated in localized canopy gaps and open areas. Consequently, high local densities of SfM ground points did not translate into good terrain representation at the plot scale.

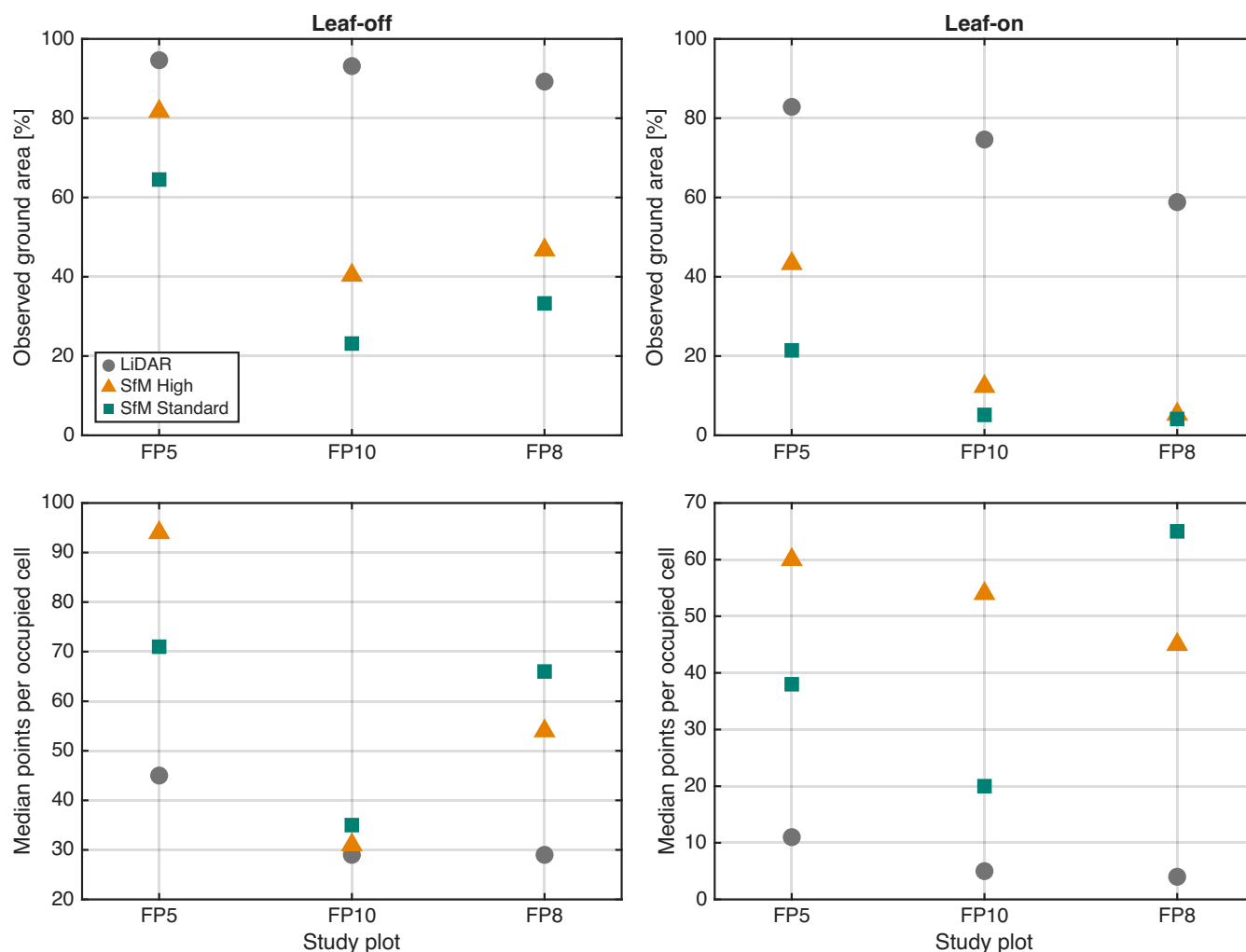


Figure 8. Ground visibility metrics derived from terrain-normalized point clouds. The upper panels show spatial completeness, expressed as the proportion of grid cells containing at least one ground point. The lower panels show local ground-point density, expressed as the median number of ground points per occupied grid cell. Results are shown separately for leaf-off and leaf-on conditions across the deciduous-dominated (FP5), mixed (FP10), and conifer-dominated (FP8) plots. Circles indicate ULS, triangles indicate the multi-angle oblique acquisition (SfM High), and squares indicate the standard nadir acquisition (SfM Standard); colours are retained for visual guidance.

315 3.5 Single tree detection

Individual tree detection performance varied strongly among forest plots and acquisition strategies (Figure 10). The highest detection rates were observed in the deciduous-dominated plot FP5, where SfM High achieved recall values close to ULS and substantially higher recall than SfM Standard. In contrast, recall was markedly lower in the mixed FP10 and conifer-dominated FP8 plots, where even SfM High detected substantially fewer field trees than ULS.



Table 3. Individual tree detection performance across plots and acquisition strategies. Shown are the number of field-observed trees (n_{field}), the total number of detected tree segments (n_{detected}), true positives (TP), false negatives (FN), false positives (FP), recall (TP / field trees), precision (TP / detected trees), and the F1-score, representing the harmonic mean of recall and precision.

Plot	Method	Conf.	n_{field}	n_{det}	TP	FN	FP	Recall	Precision	F1
FP5	LiDAR	Ref.	69	158	66	3	92	0.957	0.418	0.582
FP5	SfM	Std.	69	79	40	29	39	0.580	0.506	0.541
FP5	SfM	High	69	108	59	10	49	0.855	0.546	0.667
FP10	LiDAR	Ref.	179	255	154	25	101	0.860	0.604	0.710
FP10	SfM	Std.	179	36	16	163	20	0.089	0.444	0.149
FP10	SfM	High	179	84	49	130	35	0.274	0.583	0.373
FP8	LiDAR	Ref.	187	227	121	66	106	0.647	0.533	0.585
FP8	SfM	Std.	187	66	42	145	24	0.225	0.636	0.332
FP8	SfM	High	187	119	67	120	52	0.358	0.563	0.438

320 The difference between SfM Standard and SfM High was most pronounced in FP5. In this plot, SfM Standard detected only about half of the field-observed trees (recall = 0.58), whereas the multi-angle oblique acquisition recovered most trees (recall = 0.86) and approached the ULS detection rate (recall = 0.96). In FP10 and FP8, SfM High also achieved higher recall than SfM Standard, but the remaining difference to ULS was substantially larger (FP10: 0.27 vs. 0.86; FP8: 0.36 vs. 0.65).

The spatial matching examples support this pattern (Figure 9). In FP5, ULS and SfM High produced broadly similar spatial
 325 patterns of matched tree positions. The main difference was that ULS produced a larger number of unmatched detections, whereas SfM High achieved a more balanced trade-off between recall and precision. In FP8, both ULS and SfM High showed lower matching performance, with the SfM result containing a larger number of unmatched field trees.

The detailed matching results confirm the plot-level patterns (Table 3). In FP5, SfM High achieved substantially higher recall than SfM Standard and approached the ULS detection performance. Precision was also higher for SfM High than for
 330 ULS in this plot, resulting in the highest F1-score among the FP5 configurations. In FP10 and FP8, SfM High showed higher recall than SfM Standard, but recall remained substantially below ULS. Precision nevertheless remained comparatively high, indicating that the lower detection performance of SfM was primarily associated with increasing numbers of false negatives rather than excessive false-positive detections.

4 Discussion

335 4.1 Observation geometry and point cloud completeness

The visual point-cloud comparison demonstrates that image acquisition geometry is a primary factor controlling the completeness of UAV-SfM forest reconstructions. Increasing angular diversity through highly redundant oblique image acquisitions substantially improved canopy continuity, the reconstruction of woody elements, and the representation of lower canopy layers compared with the standard nadir-dominated acquisition. This indicates that part of the performance gap between UAV-based

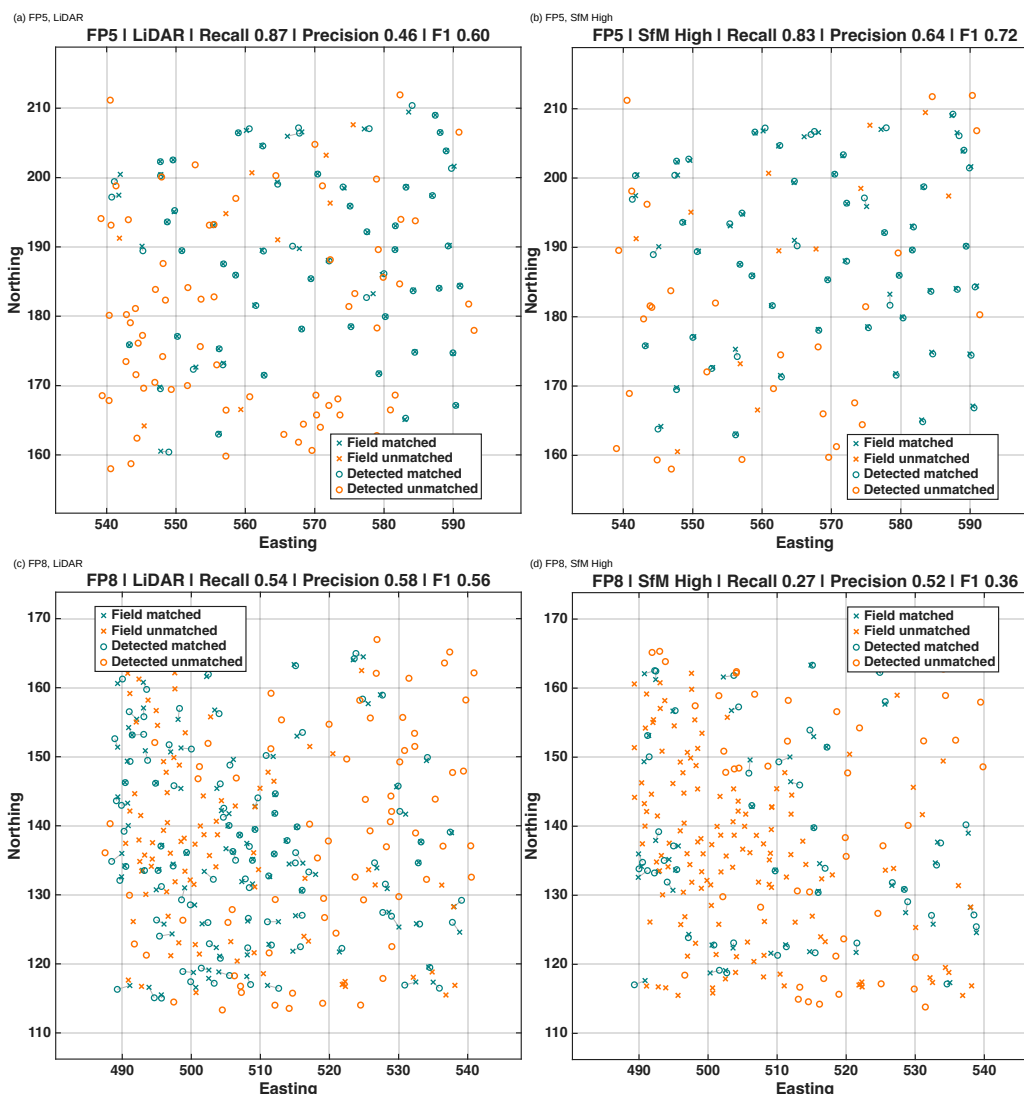


Figure 9. Individual tree detection examples for the deciduous-dominated FP5 and conifer-dominated FP8 plots. Crosses indicate field-inventory tree positions and circles indicate detected tree centroids. Teal symbols represent matched trees, while orange symbols indicate unmatched field trees or unmatched detections.

340 SfM and ULS is not only caused by the passive imaging principle itself, but also by the extent to which the acquisition geometry samples canopy elements from multiple viewing directions.

This finding is consistent with previous studies on UAV-based photogrammetry in forests, which demonstrated that increased image overlap and multi-angular acquisition geometries improve canopy reconstruction by increasing viewpoint diversity and reducing occlusion effects (Smith et al., 2016; Nesbit and Hugenholtz, 2019). The present study extends these findings by
 345 showing that the benefit of multi-angle acquisition is not limited to increasing point density. Instead, additional viewing direc-

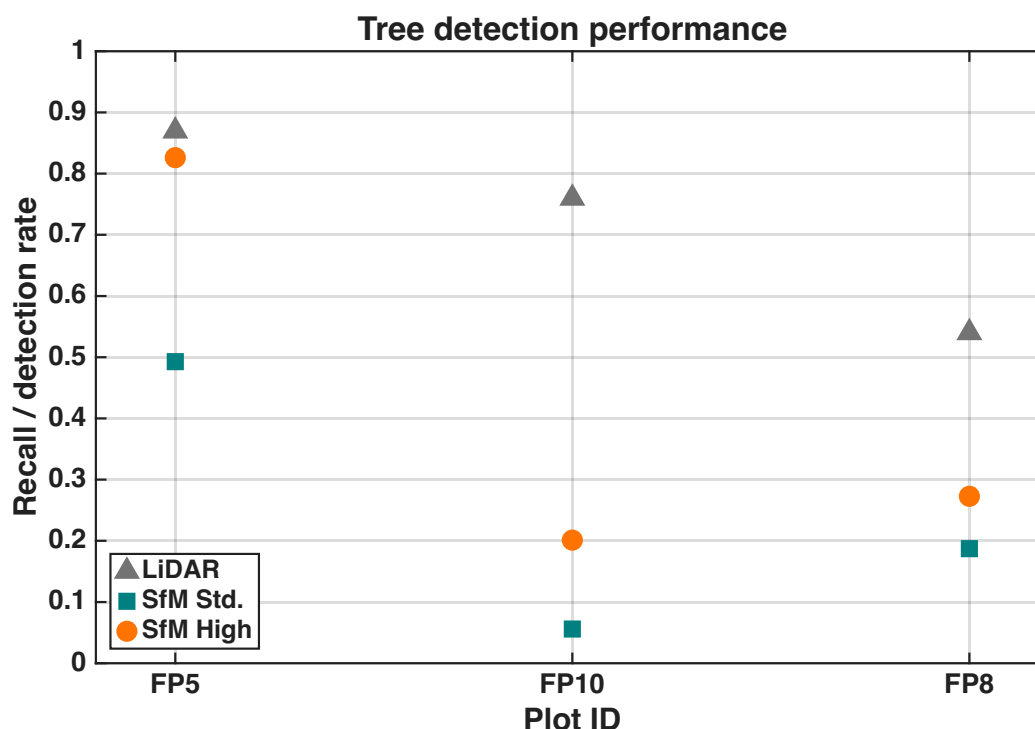


Figure 10. Aggregated individual tree detection performance across the three study plots (FP5, FP10, FP8) and acquisition strategies. Recall (detection rate) is shown for ULS, SfM High (multi-angle oblique acquisition), and SfM Standard (standard nadir acquisition).

tions improve structural observability by changing which canopy components can be reconstructed. Similar effects have been demonstrated for active laser scanning systems, where observations from different viewing geometries reveal complementary structural information and substantially alter the apparent representation of vegetation structure (Schneider et al., 2019). More generally, previous work on image-based point clouds has emphasized that viewing geometry and occlusion can substantially influence reconstruction completeness, particularly in structurally complex environments (Iglhaut et al., 2019).

The persistence of structural differences between SfM Standard and SfM High after spatial subsampling further supports this interpretation. If the improvement of SfM High were primarily a point-density effect, harmonizing point spacing should have reduced most differences between the two SfM configurations.

4.2 Vertical canopy structure and canopy observability

The comparison of vertical canopy profiles demonstrates that the agreement between SfM and ULS is primarily controlled by structural observability rather than point density alone. High-redundancy multi-angle SfM produced plot-level vertical profiles that closely resembled those derived from ULS, despite the fundamental differences between passive image matching and active laser ranging. This indicates that canopy representations are strongly governed by sampling geometry and by the probability that vegetation elements are observed from suitable viewing directions.



360 The close agreement of plot-level vertical profiles can partly be explained by the fact that both sensing approaches provide observation-weighted representations of forest structure rather than complete volumetric descriptions. Although ULS provides improved penetration through canopy gaps, the majority of returns are still generated from the most observable canopy elements. Consequently, vertical profiles are dominated by well-sampled structures, whereas differences in less observable regions contribute less to the overall profile shape.

365 However, similar vertical profiles should not be interpreted as identical sampling of forest structure. Photogrammetric point clouds remain constrained by image-based visibility and therefore provide less information on poorly observable canopy regions. Similar behaviour has been reported previously for image-based forest reconstructions, where photogrammetric point clouds predominantly captured canopy surfaces while providing comparatively limited information on lower canopy structure (Dandois and Ellis, 2013; Dandois et al., 2015). Likewise, UAV photogrammetry in tropical forests reproduced upper-canopy
 370 structure reasonably well but remained less sensitive to hidden structural components, although these studies were based mainly on nadir-oriented acquisition designs (McNicol et al., 2021).

The beech-dominated FP5 plot in leaf-off condition represents a special case because fine woody elements limited the photogrammetric reconstruction of the upper canopy. However, the resulting discrepancy should not be interpreted solely as a failure of SfM. Simulation studies suggest that objects approaching or falling below the footprint size can generate spurious
 375 LiDAR returns and distort the apparent representation of canopy structure (Abegg et al., 2023). Complementary experimental evidence indicates that the representation of fine branches in LiDAR point clouds is highly dependent on footprint size and sampling geometry (Morhart et al., 2024). Given the relatively large footprint and dense sampling used here, the pronounced differences in FP5 leaf-off likely reflect different sensor-specific realizations of fine woody canopy structure rather than reconstruction errors alone.

380 Furthermore, the two sensing modalities differ fundamentally in how repeated observations affect point-cloud density. In SfM, additional images do not necessarily produce additional points because new observations only contribute when stable image matches can be established. LiDAR, by contrast, can continue to accumulate returns on fine woody elements with increasing observation density, potentially amplifying the representation of small structures.

The agreement between ULS and the high-redundancy multi-angle SfM configuration may partly result from the fact that
 385 both acquisitions provided high angular diversity, increasing the probability of observing canopy elements through available gaps and from multiple directions. While ULS retains a fundamental advantage through active ranging, both approaches remain affected by occlusion and therefore represent geometry-dependent samples of vegetation structure. This suggests that differences previously reported between image-based and LiDAR-derived canopy profiles may partly reflect differences in acquisition geometry rather than sensor-specific limitations alone.

390 **4.3 Reliability and implications of derived canopy metrics**

Canopy height showed the strongest agreement between UAV-based SfM and ULS across most plots and acquisition settings. Regression slopes were generally close to unity and biases were small in most cases, indicating that SfM reconstructed the geometry of observable canopy surfaces with high fidelity when normalized with a common ULS-derived terrain model. This



suggests that the dominant limitation of SfM in forests is not necessarily geometric accuracy, but whether relevant structural components are represented in the reconstruction. Similar findings have been reported previously, with canopy height generally showing among the strongest agreement between UAV photogrammetry and LiDAR-derived structural metrics (McNicol et al., 2021).

The deciduous-dominated FP5 plot under leaf-off conditions represents an important boundary case. Here, canopy height was systematically underestimated by SfM, even in the high-redundancy acquisition, although the bias was substantially reduced compared with the standard configuration. This indicates that structural observability can become limiting even for generally robust metrics such as canopy height when relevant canopy components are insufficiently represented.

Fractional cover agreement was highest under leaf-on conditions, consistent with its dependence on the continuity of the observable canopy envelope rather than detailed information on internal canopy organization. In contrast, foliage height diversity was more sensitive to acquisition geometry and phenological state because it depends on the vertical distribution of reconstructed points throughout the canopy.

The contrasting behaviour of FHD among plots suggests that this metric is not simply more difficult for SfM, but depends on the spatial scale and type of structures contributing to vertical complexity. This interpretation is consistent with previous work showing that the ecological meaning of FHD depends strongly on the spatial unit of analysis (Schneider et al., 2017; Zhang et al., 2021).

In FP8, where many small conifer crowns created a vertically heterogeneous but externally observable canopy envelope, SfM reproduced FHD comparatively well. Interestingly, the high-redundancy SfM acquisition also achieved moderate agreement in the deciduous FP5 plot under leaf-off conditions, indicating that multi-angle image observations can recover part of the woody crown structure when occlusion is reduced and sufficient viewing geometry is available.

The substantially lower agreement of the standard acquisition in the same plot highlights that this capability is strongly acquisition-dependent. FHD therefore appears most reliable when vertical complexity is expressed through observable canopy structures, while its interpretation becomes increasingly dependent on acquisition geometry for less accessible canopy components.

4.4 Terrain modelling and ground visibility

The ground-visibility results highlight one of the clearest limitations of SfM in forest environments. While SfM can reconstruct exposed terrain surfaces where optical access is available, ground representation remained strongly constrained by canopy occlusion. In contrast, ULS provided substantially more continuous terrain sampling across different forest structures and phenological conditions.

SfM frequently produced high local densities of ground-like points in observed areas, sometimes exceeding LiDAR densities within individual grid cells. However, these dense local reconstructions did not translate into reliable terrain representation at the plot scale because only a small fraction of the forest floor was observed. Ground-point density and spatial coverage were therefore partly decoupled: SfM can densely reconstruct visible terrain patches, but cannot recover surfaces that remain inaccessible to the camera network.



Increasing angular diversity improved terrain observability relative to the standard SfM acquisition, particularly in the more open FP5 leaf-off case. However, the high-redundancy multi-angle configuration did not overcome the fundamental limitation imposed by canopy occlusion. Under leaf-on conditions and in structurally dense stands, observable ground area remained very limited despite the increased number of viewing directions. This indicates that additional image redundancy can improve ground visibility where openings exist, but cannot compensate for the absence of optical access to the forest floor. Similar dependencies of ground-return availability on canopy structure and foliage conditions have also been reported for airborne and UAV-based laser scanning systems (Wallace et al., 2012, 2016).

The LiDAR observations themselves illustrate that terrain visibility in forests is observation-dependent rather than absolute. Under leaf-on conditions, the number and density of ground returns decreased substantially relative to leaf-off acquisitions, showing that even active ranging systems are affected by canopy occlusion. Nevertheless, under the highly redundant multi-angle ULS acquisition employed in this study, the remaining ground observations were sufficiently well distributed to support reliable terrain modelling. This should not be interpreted as a general property of airborne laser scanning, as ground visibility under dense foliage also depends strongly on acquisition geometry and sampling density.

In this study, canopy metrics were normalized using ULS-derived terrain models to isolate differences in canopy reconstruction from terrain-related errors. The ground-visibility results indicate that SfM-only workflows remain strongly limited in dense or fully foliated forests where reliable terrain reconstruction is required. However, existing ALS terrain products, increasingly available from regional and national mapping campaigns, can provide suitable external terrain references for UAV photogrammetry. Previous studies have similarly shown that the utility of image-based forest structure assessment strongly depends on accurate terrain information (St-Onge et al., 2008; Puliti et al., 2020).

4.5 Implications for individual-tree detection

The individual-tree detection results show that improved point-cloud completeness does not automatically translate into uniformly high tree-detection performance. While increased angular diversity improved SfM-based tree detection, object-level applications require not only accurate surface reconstruction but also sufficient representation and separation of individual tree structures.

The FP5 results demonstrate that successfully detected trees in SfM High were generally located at spatial positions comparable to those obtained from ULS and field inventory. The dominant limitation in more complex stands was omission: many field trees were not detected from SfM point clouds, whereas detected trees often corresponded to real field trees. Similar relationships between stand structure, observation geometry, and object detectability have been demonstrated for terrestrial laser scanning, where additional viewing positions substantially reduced, but did not completely eliminate, occlusion-driven omissions (Abegg et al., 2017).

The different error characteristics of ULS and SfM are also important. ULS provided higher recall but also produced more detections not matched to field inventory trees, particularly in FP5. Some of these apparent false positives may represent trees below the field inventory DBH threshold or segmentation artefacts caused by the highly detailed representation of forest structure. SfM, in contrast, produced fewer detections in structurally complex plots, but precision remained comparatively



high. This indicates that SfM-based tree detection was primarily limited by omissions rather than excessive false detections. Similar limitations of image-based forest point clouds have been reported previously (Dandois and Ellis, 2013; Dandois et al., 2015; McNicol et al., 2021).

465 Part of the reduced tree-detection performance of SfM should also be interpreted in relation to the employed segmentation workflow. Although SegmentAnyTree is described as sensor-agnostic, it was primarily developed using LiDAR-type point clouds with more complete three-dimensional object representations. Therefore, lower detection rates may partly reflect a mismatch between the assumptions of the segmentation algorithm and the structural characteristics of SfM-derived point clouds rather than a general inability of image-based reconstruction to support individual-tree detection.

470 This interpretation is consistent with the high agreement observed for canopy height metrics, suggesting that methods relying mainly on canopy-surface information, such as local-maximum or watershed-based approaches, may yield more comparable performance between SfM and ULS.

4.6 Limitations

Several limitations of the present study should be considered. First, the analysis was based on three selected plots representing 475 contrasting structural cases rather than a statistically replicated gradient of forest complexity. FP5, FP8, and FP10 should therefore be interpreted as examples of contrasting stand structures rather than as a formal low-to-high complexity sequence. Future work should test whether the observed patterns generalize across larger numbers of plots, forest types, phenological states, and acquisition settings.

Second, all canopy metrics were normalized using ULS-derived terrain models. This deliberate design decision separated 480 vegetation-structure observability from terrain reconstruction performance, but also means that the results do not represent the complete error budget of an entirely SfM-based workflow.

Third, the individual-tree detection analysis was performed without additional post-filtering or method-specific tuning of segmented trees. This preserves comparability between acquisition strategies but also retains segmentation artefacts, over-segmentation, and detections below or outside the field inventory definition. The stem-centred detection and matching approach 485 may additionally disadvantage SfM, where stems and lower-canopy structures are less consistently reconstructed. Crown-centred detection approaches might therefore yield different relative performance, but would introduce additional uncertainty when matched against field-measured stem positions.

An additional limitation relates to the specific UAV-LiDAR system used in this study. The RIEGL miniVUX sensor has its own footprint geometry, beam divergence, ranging behaviour, and return-detection characteristics. The observed differences 490 between LiDAR and SfM therefore reflect not only the contrast between active and passive sensing, but also the sampling characteristics of the specific LiDAR instrument and acquisition design used here. Beyond these study-specific limitations, the results also suggest that acquisition design should be treated as an integral component of forest structural remote sensing rather than a purely operational preprocessing step. Acquisition geometry determines which structures become observable and therefore which ecological or structural metrics can be retrieved reliably.



495 5 Conclusion and Outlook

This study demonstrates that optimized UAV-based SfM can reproduce several LiDAR-derived forest structural properties remarkably well when acquisition geometry is specifically designed for three-dimensional canopy reconstruction. Highly redundant multi-angle image acquisition substantially improved point-cloud completeness and enabled close agreement with ULS for metrics dominated by externally visible canopy geometry, particularly canopy height and plot-scale vertical canopy profiles.

More fundamentally, our results indicate that the principal limitation of UAV-based SfM in forests is not the geometric accuracy of reconstructed surfaces but the observability of structural elements that remain partially or completely occluded from the camera network. Across visual comparisons, vertical profiles, canopy metrics, ground analyses, and individual-tree detection, the same pattern emerged: structures that were sufficiently visible from multiple viewing directions were reconstructed with high spatial fidelity, whereas lower canopy layers, terrain surfaces, fine woody structures, and suppressed trees remained incompletely reconstructed or omitted.

The results further suggest that LiDAR and SfM should not be interpreted simply as providing better or worse representations of forest structure. Instead, both sensing approaches generate sensor-specific realizations of observable forest geometry. Although ULS provides a widely used reference for above-canopy, plot- to stand-level three-dimensional forest structure retrieval, LiDAR observations are likewise shaped by acquisition geometry, footprint characteristics, ranging behaviour, and occlusion effects.

Practically, the results indicate considerable potential for UAV-based SfM in plot-based forest structural monitoring. Modern multirotor UAVs equipped with high-resolution cameras permit efficient acquisition of dense multi-angle image datasets at comparatively low cost and with substantially lower hardware requirements than ULS systems. For applications focused on canopy height, crown-surface properties, plot-scale structural comparisons, or monitoring relative structural change, optimized UAV-based SfM therefore represents a valuable complement and, where forest structure and acquisition conditions provide sufficient observability, a potential alternative to ULS.

However, substantial limitations remain for applications requiring reliable terrain retrieval, lower-canopy representation, fine woody structure characterization, or robust individual-tree detection in dense and vertically heterogeneous forests. In these applications, ULS retained clear advantages due to its superior ability to sample canopy volumes and partially occluded structures.

Future work should therefore move beyond simple point-cloud comparisons and explicitly address forest observability as a central concept of structural remote sensing. In particular, further research is needed to better understand how sensor physics, acquisition geometry, canopy occlusion, and forest architecture jointly determine which structural components become observable and how these observable components propagate into derived ecological metrics. This includes the development of quantitative approaches to characterize sensor-specific visibility, for example through explicit occlusion mapping, allowing structural observability to be assessed independently of the reconstructed point clouds themselves. Rather than asking whether SfM can replace LiDAR in forests, our results establish structural observability as a conceptual framework for identifying



the structural and observational conditions under which both sensing modalities converge or diverge in their representation of
530 forest structure.

Appendix A: Additional comparisons

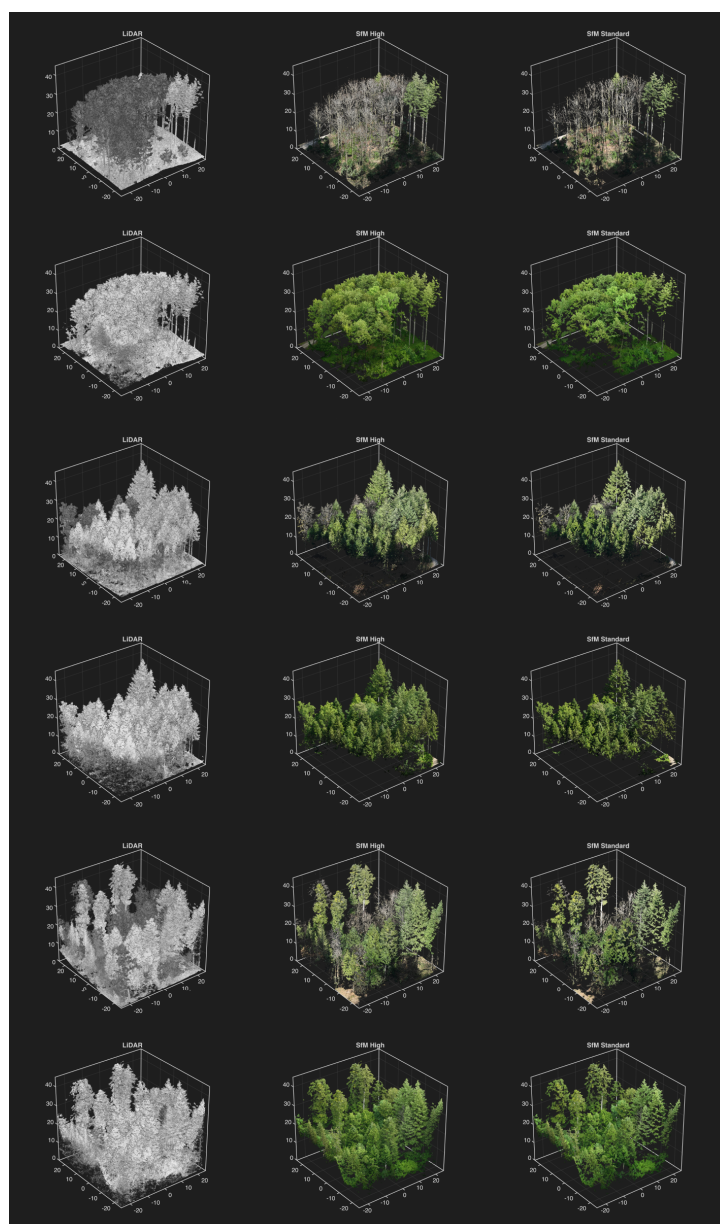


Figure A1. Comparative 3D visualizations of the three study plots (FP5, FP10, and FP8) under leaf-off (top rows within each panel) and leaf-on (bottom rows within each panel) conditions. Animations (FP5, FP10, FP8): <https://youtu.be/ojkjL9tJARA>, <https://youtu.be/uxWHfRyTKXY>, https://youtu.be/FR_0xZf78-k. Columns show ULS (left), SfM High (middle), and SfM Standard (right).

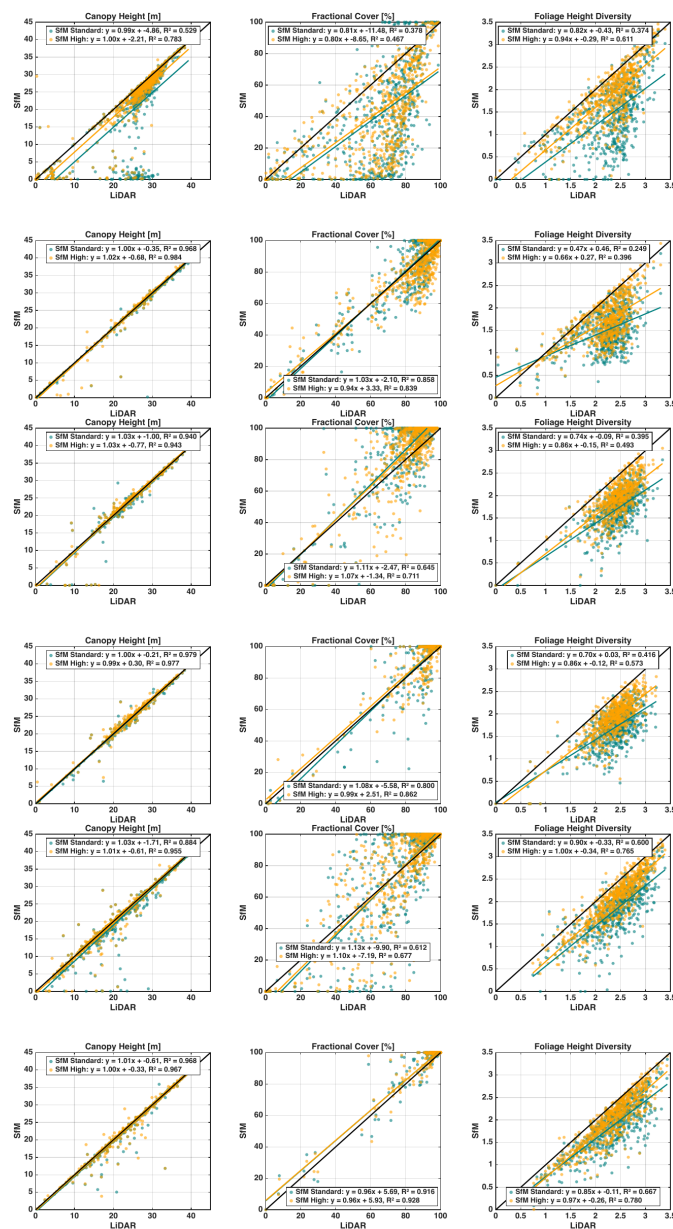


Figure A2. Comparison of ULS- and SfM-derived canopy metrics across the three study plots. The plots are arranged from top to bottom as FP5, FP10, and FP8, with two rows per plot: leaf-off above and leaf-on below. Columns show canopy height (left), fractional cover (middle), and foliage height diversity (right).

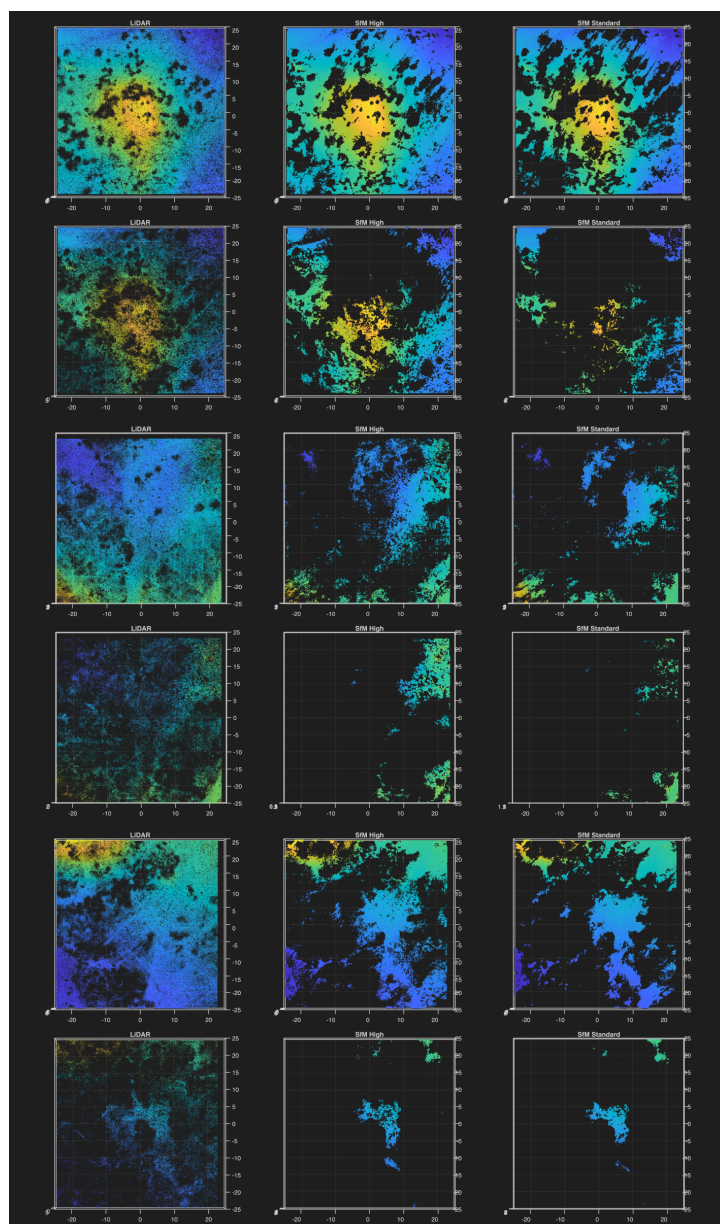


Figure A3. Spatial distribution of ground points across the three study plots (FP5, FP10, and FP8) under leaf-off (top rows within each panel) and leaf-on (bottom rows within each panel) conditions. Columns correspond to ULS (left), SfM High (middle), and SfM Standard (right).



Code and data availability. The data underlying the results and figures presented in this study and the MATLAB scripts used for processing and analysis are currently available from the corresponding author upon request and can be provided to reviewers during the review process. Public archiving of these materials in a suitable repository is planned. Repository details and persistent identifiers will be added to the manuscript once the materials have been deposited.

Author contributions. FM conceptualized the study, developed the methodology and software, performed the formal analysis, and wrote the original manuscript draft. DK contributed to the conceptualization and methodology development. MM collected data, and AB produced data. MCS contributed to the conceptualization. All authors contributed to reviewing and editing the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. Parts of the research workflow and manuscript preparation were supported using the generative AI system ChatGPT Pro (OpenAI, San Francisco, CA, USA), primarily based on the GPT-5.5 large language model architecture (accessed May 2026). The system was used interactively as a computational assistance and ideation tool during data analysis and manuscript development. Typical use cases included support for MATLAB code structuring and refactoring, debugging assistance, organization of project notes and action items, exploratory discussion of methodological concepts, restructuring of result narratives, and language refinement of manuscript text. The AI system was not used to autonomously generate scientific results, perform independent analyses, or make final methodological decisions. All analyses, interpretations, figures, statistical evaluations, and conclusions were designed, verified, and validated by the authors. All code and manuscript content were critically reviewed, modified where necessary, and executed under full author supervision and responsibility. The use of AI tools is therefore best understood as a form of interactive computational assistance integrated into the iterative research workflow, comparable to an advanced conversational coding and editing environment.



550 References

- Abegg, M., Kükenbrink, D., Zell, J., Schaepman, M. E., and Morsdorf, F.: Terrestrial Laser Scanning for Forest Inventories—Tree Diameter Distribution and Scanner Location Impact on Occlusion, *Forests*, 8, 184, <https://doi.org/10.3390/f8060184>, 2017.
- Abegg, M., Bösch, R., Kükenbrink, D., and Morsdorf, F.: Tree volume estimation with terrestrial laser scanning - testing for bias in a 3D virtual environment, *Agricultural and Forest Meteorology*, 331, 109–134, <https://doi.org/10.1016/j.agrformet.2023.109348>, 2023.
- 555 Aguilar, F. J., Rivas, J. R., Nemmaoui, A., Peñalver, A., and Aguilar, M. A.: UAV-Based Digital Terrain Model Generation Under Leaf-Off Conditions to Support Teak Plantations Inventories in Tropical Dry Forests. A Case of the Coastal Region of Ecuador, *Sensors*, <https://doi.org/10.3390/s19081934>, 2019.
- Alexiou, S., Deligiannakis, G., Pallikarakis, A., Papanikolaou, I., Psomiadis, E., and Reicherter, K.: Comparing High Accuracy T-LiDAR and UAV-SfM Derived Point Clouds for Geomorphological Change Detection, *Isprs International Journal of Geo-Information*, <https://doi.org/10.3390/ijgi10060367>, 2021.
- 560 Anders, N., Valente, J., Masselink, R., and Keesstra, S.: Comparing Filtering Techniques for Removing Vegetation From UAV-Based Photogrammetric Point Clouds, *Drones*, <https://doi.org/10.3390/drones3030061>, 2019.
- Bernyk, K.: Evaluation of Remotely Piloted Aircraft Systems (RPAS)-based Structure-from-Motion (SfM) Photogrammetry for Characterizing Microtopography and Vegetation Structure in a Southeastern Ontario Peatland, <https://doi.org/10.22215/etd/2023-15439>.
- 565 Bienert, A., Queck, R., Schmidt, A., Bernhofer, C., and Maas, H.-G.: Voxel space analysis of terrestrial laser scans in forests for wind field modeling, *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 38, 92–97, 2010.
- Bornand, A., Abegg, M., Morsdorf, F., and Rehush, N.: Completing 3D point clouds of individual trees using deep learning, *Methods in Ecology and Evolution*, 15, 2010–2023, <https://doi.org/10.1111/2041-210x.14412>, 2024.
- Carvajal-Ramírez, F., Serrano, J., Agüera-Vega, F., and Martínez-Carricondo, P.: A Comparative Analysis of Phytovolume Estimation Methods Based on UAV-Photogrammetry and Multispectral Imagery in a Mediterranean Forest, *Remote Sensing*, <https://doi.org/10.3390/rs11212579>, 2019.
- 570 Coverdale, T. C. and Davies, A. B.: Unravelling the Relationship Between Plant Diversity and Vegetation Structural Complexity: A Review and Theoretical Framework, *Journal of Ecology*, <https://doi.org/10.1111/1365-2745.14068>, 2023.
- Dandois, J. P. and Ellis, E. C.: High Spatial Resolution Three-Dimensional Mapping of Vegetation Spectral Dynamics Using Computer Vision, *Remote Sensing of Environment*, 136, 259–276, <https://doi.org/10.1016/j.rse.2013.04.005>, 2013.
- 575 Dandois, J. P., Olano, M., and Ellis, E. C.: Optimal Altitude, Overlap, and Weather Conditions for Computer Vision UAV Estimates of Forest Structure, *Remote Sensing*, 7, 13 895–13 920, <https://doi.org/10.3390/rs71013895>, 2015.
- Dhruva, A., Hartley, R. J. L., Redpath, T. A. N., Estarija, H. J. C., Cajes, D., and Massam, P. D.: Effective UAV photogrammetry for forest management: New insights on side overlap and flight parameters, *Forests*, 15, <https://doi.org/10.3390/f15122135>, 2024.
- 580 Dietenberger, S., Mueller, M. M., Bachmann, F., Nestler, M., Ziemer, J., Metz, F., Heidenreich, M. G., Koesch, F., Hese, S., Dubois, C., and Thiel, C.: Tree stem detection and crown delineation in a structurally diverse deciduous forest combining leaf-on and leaf-off UAV-SfM data, *Remote Sensing*, 15, <https://doi.org/10.3390/rs15184366>, 2023.
- Duncanson, L., Armston, J., Disney, M., Avitabile, V., Barbier, N., Calders, K., Carter, S., Chave, J., Herold, M., et al.: Aboveground Woody Biomass Product Validation Good Practices Protocol, <https://doi.org/10.5067/doc/ceoswgcv/lpv/agg.001>, 2021.



- 585 Enterkine, J., Hojatimalekshah, A., Vermillion, M., Der Weide, T. V., Arispe, S. A., Price, W. J., Hulet, A., and Glenn, N. F.: Voxel Volumes and Biomass: Estimating Vegetation Volume and Litter Accumulation of Exotic Annual Grasses Using Automated Ultra-High-Resolution SfM and Advanced Classification Techniques, *Ecology and Evolution*, <https://doi.org/10.1002/ece3.70883>, 2025.
- Fahey, R. T., Atkins, J. W., Gough, C. M., Hardiman, B. S., Nave, L. E., Tallant, J. M., Nadehoffer, K. J., Vogel, C., Scheuermann, C. M., Stuart-Haëntjens, E., Haber, L. T., Fotis, A. T., Ricart, R., and Curtis, P. S.: Defining a spectrum of integrative trait-based vegetation canopy structural types, *Ecology Letters*, 22, 2049–2059, <https://doi.org/10.1111/ele.13388>, 2019.
- 590 Fawcett, D., Blanco-Sacristán, J., and Benaud, P.: Two Decades of Digital Photogrammetry: Revisiting Chandler’s 1999 Paper on “Effective Application of Automated Digital Photogrammetry for Geomorphological Research” – A Synthesis, *Progress in Physical Geography Earth and Environment*, <https://doi.org/10.1177/0309133319832863>, 2019.
- Filippelli, S., Lefsky, M., and Rocca, M.: Comparison and integration of LiDAR and photogrammetric point clouds for mapping pre-fire forest structure, *Remote Sensing of Environment*, 224, 154–166, <https://doi.org/10.1016/j.rse.2019.01.029>, 2019.
- 595 Fletcher, A. and Mather, R.: Hypertemporal Imaging Capability of UAS Improves Photogrammetric Tree Canopy Models, *Remote Sensing*, <https://doi.org/10.3390/rs12081238>, 2020.
- Frey, J., Kovach, K. R., Stemmler, S., and Koch, B.: UAV Photogrammetry of Forests as a Vulnerable Process. A Sensitivity Analysis for a Structure from Motion RGB-Image Pipeline, *Remote Sensing*, <https://doi.org/10.3390/rs10060912>, 2018.
- 600 Guimarães, N., Pádua, L., Marques, P., Silva, N., Peres, E., and Sousa, J. J.: Forestry Remote Sensing From Unmanned Aerial Vehicles: A Review Focusing on the Data, Processing and Potentialities, *Remote Sensing*, <https://doi.org/10.3390/rs12061046>, 2020.
- Hartley, R. J. L., Leonardo, E. M., Massam, P., Watt, M. S., Estarija, H. J., Wright, L., Melia, N., and Pearse, G. D.: An Assessment of High-Density UAV Point Clouds for the Measurement of Young Forestry Trials, *Remote Sensing*, 12, 4039, <https://doi.org/10.3390/rs12244039>, 2020.
- 605 Hese, S.: Oblique and cross-grid UAV imaging flight plans – a sneak preview of the analysis of resulting 3D point cloud properties for deciduous forest surfaces, <https://jenacopterlabs.de/?p=1711>, accessed: 2026-05-22, 2022.
- Iglhaut, J., Cabo, C., Puliti, S., Piermattei, L., O’Connor, J., and Rosette, J.: Structure from Motion photogrammetry in forestry: a review, *Current Forestry Reports*, 5, 155–168, <https://doi.org/10.1007/s40725-019-00094-3>, 2019.
- Karthigesu, J., Owari, T., Tsuyuki, S., and Hiroshima, T.: UAV Photogrammetry for Estimating Stand Parameters of an Old Japanese Larch Plantation Using Different Filtering Methods at Two Flight Altitudes, *Sensors*, <https://doi.org/10.3390/s23249907>, 2023.
- 610 Kellner, J. R., Armston, J., Birrer, M., Cushman, K. C., Duncanson, L., Eck, C., Fallegger, C., Imbach, B., Král, K., Krůček, M., Trochta, J., Vrška, T., and Zraggen, C.: New Opportunities for Forest Remote Sensing Through Ultra-High-Density Drone Lidar, *Surveys in Geophysics*, 40, 959–977, <https://doi.org/10.1007/s10712-019-09529-9>, 2019.
- Kesselring, J., Morsdorf, F., Kükenbrink, D., Gastellu-Etchegorry, J.-P., and Damm, A.: Diversity of 3D APAR and LAI dynamics in broadleaf and coniferous forests: Implications for the interpretation of remote sensing-based products, *Remote Sensing of Environment*, 306, 114 116, <https://doi.org/10.1016/j.rse.2024.114116>, 2024.
- 615 Kraus, K. and Pfeifer, N.: Determination of terrain models in wooded areas with airborne laser scanner data, *ISPRS Journal of Photogrammetry & Remote Sensing*, 53, 193–203, 1998.
- Kükenbrink, D., Schneider, F. D., Leiterer, R., Schaepman, M. E., and Morsdorf, F.: Quantification of hidden canopy volume of airborne laser scanning data using a voxel traversal algorithm, *Remote Sensing of Environment*, 194, 424 – 436, 2017.
- 620



- Kukkonen, M., Maltamo, M., Korhonen, L., and Packalen, P.: Evaluation of UAS LiDAR data for tree segmentation and diameter estimation in boreal forests using trunk- and crown-based methods, *Canadian Journal of Forest Research*, 52, 674–684, <https://doi.org/10.1139/cjfr-2021-0217>, 2022.
- Kükenbrink, D., Marty, M., Bösch, R., and Ginzler, C.: Benchmarking laser scanning and terrestrial photogrammetry to extract forest inventory parameters in a complex temperate forest, *International Journal of Applied Earth Observation and Geoinformation*, 113, 102999, <https://doi.org/10.1016/j.jag.2022.102999>, 2022.
- Lefsky, M. A., Cohen, W. B., Acker, S. A., Parker, G. G., Spies, T. A., and Harding, D.: Lidar Remote Sensing of the Canopy Structure and Biophysical Properties of Douglas-Fir Western Hemlock Forests, *Remote Sensing of Environment*, 70, 339–361, 1999.
- Lefsky, M. A., Cohen, W. B., Parker, G. G., and Harding, D. J.: Lidar Remote Sensing for Ecosystem Studies, *BioScience*, 52, 19–30, 2002.
- 625 Li, L., Chen, J., Mu, X., Li, W., Yan, G., Xie, D., and Zhang, W.: Quantifying Understory and Overstory Vegetation Cover Using UAV-Based RGB Imagery in Forest Plantation, *Remote Sensing*, <https://doi.org/10.3390/rs12020298>, 2020.
- 630 Lines, E. R., Fischer, F. J., Owen, H., and Jucker, T.: The Shape of Trees: Reimagining Forest Ecology in Three Dimensions With Remote Sensing, *Journal of Ecology*, <https://doi.org/10.1111/1365-2745.13944>, 2022.
- Mandlbürger, G., Wieser, M., Hollaus, M., and Pfeifer, N.: ULS LiDAR Supported Analyses of Laser Beam Penetration from Different ALS Systems into Vegetation, in: *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. III-3, pp. 233–239, <https://doi.org/10.5194/isprs-annals-III-3-233-2016>, 2016.
- 635 Mandlbürger, G., Wieser, M., Pfennigbauer, M., and Riegl, U.: UAS-borne LiDAR for Mapping Complex Terrain and Vegetation Structure, *GIM International*, 2017.
- Mandlbürger, G., Kölle, M., Pöpl, F., and Cramer, M.: Evaluation of Consumer-Grade and Survey-Grade UAV-LiDAR, *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 2023.
- 640 McElhinny, C., Gibbons, P., Brack, C., and Bauhus, J.: Forest and woodland stand structural complexity: Its definition and measurement, *Forest Ecology and Management*, 218, 1 – 24, 2005.
- McGlade, J., Wallace, L., Reinke, K., and Jones, S.: The Potential of Low-Cost 3D Imaging Technologies for Forestry Applications: Setting a Research Agenda for Low-Cost Remote Sensing Inventory Tasks, *Forests*, <https://doi.org/10.3390/f13020204>, 2022.
- 645 McNicol, I. M., Mitchard, E. T. A., Aquino, C., Burt, A., Carstairs, H., Dassi, C., Modinga Dikongo, A., and Disney, M. I.: To What Extent Can UAV Photogrammetry Replicate UAV LiDAR to Determine Forest Structure? A Test in Two Contrasting Tropical Forests, *Journal of Geophysical Research: Biogeosciences*, 126, e2021JG006586, <https://doi.org/10.1029/2021JG006586>, 2021.
- Mokroš, M., Mikita, T., Singh, A., Tomašík, J., Chudá, J., Wężyk, P., Kuželka, K., Surový, P., Klimánek, M., Zięba-Kulawik, K., Bobrowski, R., and Liang, X.: Novel low-cost mobile mapping systems for forest inventories as terrestrial laser scanning alternatives, *International Journal of Applied Earth Observation and Geoinformation*, 104, 102512, <https://doi.org/10.1016/j.jag.2021.102512>, 2021.
- 650 Moreira Perez, B. H., Goyanes, G., Pina, P., Vassilev, O., and Heleno, S.: Assessment of the Influence of Survey Design and Processing Choices on the Accuracy of Tree Diameter at Breast Height (DBH) Measurements Using UAV-Based Photogrammetry, *Drones*, <https://doi.org/10.3390/drones5020043>, 2021.
- Morhart, C., Schindler, Z., Frey, J., Sheppard, J. P., Calders, K., Disney, M., Morsdorf, F., Raunonen, P., and Seifert, T.: Limitations of estimating branch volume from terrestrial laser scanning, *European Journal of Forest Research*, 143, 687–702, <https://doi.org/10.1007/s10342-023-01651-z>, 2024.
- 655 Morsdorf, F., Eck, C., Zraggen, C., Imbach, B., Schneider, F., and Kükenbrink, D.: UAV-based LiDAR acquisition for the derivation of high-resolution forest and ground information, *Leading Edge*, 36, 566–570, <https://doi.org/10.1190/tle36070566.1>, 2017.



- Morsdorf, F., Kükenbrink, D., Schneider, F. D., Abegg, M., and Schaepman, M. E.: Close-range laser scanning in forests: towards physically
660 based semantics across scales, *Interface Focus*, 8, <https://doi.org/https://doi.org/10.1098/rsfs.2017.0046>, 2018.
- Mueller, M. M., Dietenberger, S., Nestler, M., Hese, S., Ziemer, J., Bachmann, F., Leiber, J., Dubois, C., and Thiel, C.: Novel UAV flight
designs for accuracy optimization of Structure from Motion data products, *Remote Sensing*, 15, <https://doi.org/10.3390/rs15174308>, 2023.
- N. Young, D. J., Koontz, M. J., and Weeks, J.: Optimizing Aerial Imagery Collection and Processing Parameters for Drone-Based Individual
Tree Mapping in Structurally Complex Conifer Forests, <https://doi.org/10.32942/osf.io/p7ygu>, 2021.
- 665 Næsset, E. and Okland, T.: Estimating tree height and tree crown properties using airborne scanning laser in a boreal nature reserve, *Remote
Sensing of Environment*, 79, 105–115, 2002.
- Nasiri, V., Darvishsefat, A. A., Arefi, H., Pierrot, F., Namiranian, M., and Bris, A. L.: Unmanned Aerial Vehicles (UAV)-based Canopy
Height Modeling Under Leaf-on and Leaf-Off Conditions for Determining Tree Height and Crown Diameter (Case Study: Hyrcanian
Mixed Forest), *Canadian Journal of Forest Research*, <https://doi.org/10.1139/cjfr-2020-0125>, 2021.
- 670 Nesbit, P. R. and Hugenholtz, C. H.: Enhancing UAV–SfM 3D Model Accuracy in High-Relief Landscapes by Incorporating Oblique Images,
Remote Sensing, 11, 239, <https://doi.org/10.3390/rs11030239>, 2019.
- Pessacg, F., Gómez-Fernández, F., Nitsche, M., Chamo, N., Torrella, S. A., Ginzburg, R., and Cristóforis, P. D.: Simplifying UAV-
Based Photogrammetry in Forestry: How to Generate Accurate Digital Terrain Model and Assess Flight Mission Settings, *Forests*,
<https://doi.org/10.3390/f13020173>, 2022.
- 675 Petrovska, I. and Jutzi, B.: Seeing beyond vegetation: A comparative occlusion analysis between Multi-View Stereo, Neural Radi-
ance Fields and Gaussian Splatting for 3D reconstruction, *ISPRS Open Journal of Photogrammetry and Remote Sensing*, p. 100089,
<https://doi.org/10.1016/j.ophoto.2025.100089>, 2025a.
- Petrovska, I. and Jutzi, B.: 3D Gaussian Splatting Methods for Real-World Scenarios, *ISPRS Annals of the Photogrammetry, Remote Sensing
and Spatial Information Sciences*, 2025b.
- 680 Piermattei, L., Karel, W., Wang, D., Wieser, M., Mokroš, M., Surový, P., Koreň, M., Tomašík, J., Pfeifer, N., and Hollaus, M.: Terrestrial
Structure from Motion Photogrammetry for Deriving Forest Inventory Data, *Remote Sensing*, 11, 950, <https://doi.org/10.3390/rs11080950>,
2019.
- Puliti, S., Dash, J. P., Watt, M. S., Breidenbach, J., and Pearse, G. D.: A comparison of UAV laser scanning, photogrammetry and airborne
laser scanning for precision inventory of small-forest properties, *Forestry: An International Journal of Forest Research*, 93, 150–162,
685 <https://doi.org/10.1093/forestry/cpz057>, 2020.
- Sanz-Ablanedo, E., Chandler, J. H., Rodríguez Pérez, J. R., and Ordóñez, C.: Accuracy of Unmanned Aerial Vehicle (UAV) and
SfM Photogrammetry Survey as a Function of the Number and Location of Ground Control Points Used, *Remote Sensing*,
<https://doi.org/10.3390/rs10101606>, 2018.
- Schneider, F. D., Morsdorf, F., Schmid, B., Petchey, O. L., Hueni, A., Schimel, D. S., and Schaepman, M. E.: Mapping
690 functional diversity from remotely sensed morphological and physiological forest traits, *Nature Communications*, 8, 1441,
<https://doi.org/https://doi.org/10.1038/s41467-017-01530-3>, 2017.
- Schneider, F. D., Kükenbrink, D., Schaepman, M. E., Schimel, D. S., and Morsdorf, F.: Quantifying 3D structure and occlu-
sion in dense tropical and temperate forests using close-range LiDAR, *Agricultural and Forest Meteorology*, 268, 249–257,
<https://doi.org/10.1016/j.agrformet.2019.01.033>, 2019.
- 695 Seidel, D.: A holistic approach to determine tree structural complexity based on laser scanning data and fractal analysis, *Ecology and
Evolution*, 8, 128–134, 2018.



- Simonson, W. D., Allen, H., and Coomes, D. A.: Applications of Airborne LiDAR for the Assessment of Animal Species Diversity, *Methods in Ecology and Evolution*, <https://doi.org/10.1111/2041-210x.12219>, 2014.
- Smith, M. W., Carrivick, J. L., and Quincey, D. J.: Structure from Motion Photogrammetry in Physical Geography, *Progress in Physical Geography*, 40, 247–275, <https://doi.org/10.1177/0309133315615805>, 2016.
- St-Onge, B., Hu, Y., and Vega, C.: Mapping the height and above-ground biomass of a mixed forest using lidar and stereo Ikonos images, *International Journal of Remote Sensing*, 29, 1277–1294, 2008.
- Swinfield, T., Lindsell, J., Williams, J., Harrison, R. D., Agustiono, Habibi, H., Gemita, E., Schönlieb, C.-B., and Coomes, D. A.: Accurate Measurement of Tropical Forest Canopy Heights and Aboveground Carbon Using Structure from Motion, *Remote Sensing*, <https://doi.org/10.3390/rs11080928>, 2019.
- Wallace, L., Lucieer, A., Malenovsky, Z., Turner, D., and Vopěnka, P.: Assessment of Forest Structure Using Two UAV Techniques: A Comparison of Airborne Laser Scanning and Structure from Motion (SfM) Point Clouds, *Forests*, 7, 62, <https://doi.org/10.3390/f7030062>, 2016.
- Wallace, L. O., Lucieer, A., and Watson, C. S.: Assessing the Feasibility of UAV-Based LiDAR for High Resolution Forest Change Detection, in: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XXXIX-B7, pp. 499–504, Melbourne, Australia, <https://doi.org/10.5194/isprsarchives-XXXIX-B7-499-2012>, 2012.
- Wielgosz, M., Puliti, S., Xiang, B., Schindler, K., and Astrup, R.: SegmentAnyTree: A sensor and platform agnostic deep learning model for tree segmentation using laser scanning data, *Remote Sensing of Environment*, 313, 114 367, <https://doi.org/10.1016/j.rse.2024.114367>, 2024.
- Wieser, M., Mandlbürger, G., Hollaus, M., Otepka, J., Glira, P., and Pfeifer, N.: A Case Study of UAS Borne Laser Scanning for Measurement of Tree Stem Diameter, *Remote Sensing*, 9, 1154, <https://doi.org/10.3390/rs9111154>, 2017.
- Wilkes, P., Lau, A., Disney, M., Calders, K., Burt, A., de Tanago, J. G., Bartholomeus, H., Brede, B., and Herold, M.: Data acquisition considerations for terrestrial laser scanning of forest plots, *Remote Sensing of Environment*, 196, 140–153, <https://doi.org/10.1016/j.rse.2017.04.030>, 2017.
- Winsen, M. and Hamilton, G.: A Comparison of UAV-Derived Dense Point Clouds Using LiDAR and NIR Photogrammetry in an Australian Eucalypt Forest, *Remote Sensing*, 15, 2423, <https://doi.org/10.3390/rs15092423>, 2023.
- Xiang, T.-Z., Xia, G.-S., and Zhang, L.: Mini-Unmanned Aerial Vehicle-Based Remote Sensing: Techniques, Applications, and Prospects, *Ieee Geoscience and Remote Sensing Magazine*, <https://doi.org/10.1109/mgrs.2019.2918840>, 2019.
- Yin, T., Zeng, J., Zhang, X., and Zhou, X.: Individual Tree Parameters Estimation for Chinese Fir (*Cunninghamia Lanceolata* (Lamb.) Hook) Plantations of South China Using UAV Oblique Photography: Possibilities and Challenges, *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, <https://doi.org/10.1109/jstars.2020.3038819>, 2021.
- Zhang, H., Bauters, M., Boeckx, P., and Oost, K. V.: Mapping Canopy Heights in Dense Tropical Forests Using Low-Cost UAV-Derived Photogrammetric Point Clouds and Machine Learning Approaches, *Remote Sensing*, <https://doi.org/10.3390/rs13183777>, 2021.
- Zheng, Z., Zeng, Y., Schneider, F. D., Zhao, Y., Zhao, D., Schmid, B., Schaepman, M. E., and Morsdorf, F.: Mapping functional diversity using individual tree-based morphological and physiological traits in a subtropical forest, *Remote Sensing of Environment*, 252, <https://doi.org/10.1016/j.rse.2020.112170>, 2021.