Individual tree point clouds and tree measurements from multi-platform laser scanning in German forests

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Abstract. Laser scanning from different acquisition platforms enables collecting 3D point clouds from different perspectives and with varying resolutions. Such point clouds allow us to e.g., retrieve information about the forest structure and individual tree properties, or to model individual trees in 3D. We conducted airborne laser scanning (ALS), UAV-borne laser scanning (ULS) and terrestrial laser scanning (TLS) in German mixed forests with species typical for Central Europe. We provide the spatially overlapping, georeferenced point clouds of the different acquisitions. As a result of individual tree extraction, we furthermore present a comprehensive database of tree point clouds and corresponding tree metrics, both measured in the field and derived from the point clouds. Our dataset may be used for the creation of 3D tree models for radiative transfer modeling or LiDAR simulation studies or to fit allometric equations between point cloud metrics and forest inventory variables. It can further serve as a benchmark dataset for different algorithms and machine learning tasks, in particular automated individual tree segmentation, tree species classification or forest inventory metric prediction. The dataset and supplementary metadata are available for download on the PANGAEA data publisher at https://doi.org/10.1594/PANGAEA.933426 (Weiser et al., 2021b).

1 Introduction

Detailed 3D tree models are required for a plethora of applications. For example, 3D tree models derived from laser scans of real trees have been used to develop structural tree allometries to, e.g., non-destructively estimate the aboveground-biomass of tree individuals (Calders et al., 2015). Further, virtual forest scenes can be built from 3D tree models and used as input to radiative transfer models (e.g., DART, Gastellu-Etchegorry et al. 2015) or Light Detection and Ranging (LiDAR) simulators (e.g., HELIOS++, Winiwarter et al. 2022). Such simulations enable an improved understanding of the relation between forests' structural elements and electromagnetic radiation (Disney et al., 2010; Weiser et al., 2021; Widlowski et al., 2015). This is particularly relevant for improving remote sensing-assisted forest inventory approaches. 3D tree models can also be used to parameterize eco-physiological models (Sinoquet et al., 2001) to quantify shading effects and evapotranspiration properties of urban trees. Other applications of detailed tree models include their integration in 3D visualizations as, e.g., used in urban landscape planning projects or in computer games (Bournez et al., 2017).

Three common approaches to generate 3D tree models exist. The first approach is the use of simplified geometric objects such as cones and ellipsoids representing tree crowns. The tree crowns' geometries can then either be defined as fully opaque (Frazer et al., 2011; Lovell et al., 2005) or as a turbid-medium (Goodwin et al., 2007). Turbid medium tree models can either assume a homogeneous distribution of leaves in the entire crown or sub-divide the crown object space into smaller voxels with varied levels of penetrability. Simplifying the complex crown structures of trees to such geometric primitives may not be acceptable for all applications. The second approach is to generate 3D tree models using specialized software that grow artificial 3D trees based on initial tree species specific parameters that can be obtained using field measurements. Examples of these software include Arbaro (Weber and Penn, 1995), OnyxTree (Onyx Computing, 2020), AMAPstudio (Griffon and de Coligny, 2014), and xfrog (Deussen and Lintermann, 1997). Tree models created with Arbaro and AMAPstudio have been criticized to be not fully biologically realistic in some studies (Roberts et al., 2020) but were used successfully in others (Widlowski et al., 2015; Hämmerle et al., 2017). In the third approach, tree models are reconstructed from 3D point clouds obtained with terrestrial (TLS), UAV-borne (ULS) or airborne laser scanning (ALS). One key advantage of this approach is that the tree models originate from real trees and the morphological features of the initial point clouds are hence biologically realistic. (Semi-)automated methods to extract tree models from TLS point clouds are readily available (e.g., SimpleTree/SimpleForest, Hackenberg et al. 2015; TreeQSM, Raumonen et al. 2013) but data collection and extraction of high-quality tree point clouds is still very time-demanding because it requires manual interaction and control. This generally limits the acquisition and processing of very large numbers of trees in single projects and thus underlines the importance of publishing such datasets as open data for shared usage.

In this dataset, we present 1491 trees which were extracted from ALS, ULS and TLS point clouds acquired in 12 forest plots in Southwest Germany. Single tree metrics were measured in the field and/or derived from the point clouds. These include tree species, height, diameter at breast height (DBH) and crown metrics. The dataset is one of the biggest open-access collections of multi-platform tree point clouds with matching inventory data of common tree species of Central European forests. For 1285 trees, both ALS and ULS point clouds are available and for 1168 trees, ULS point clouds acquired under both leaf-off and leaf-on canopy conditions are available. For 249 trees, point clouds acquired from all three platforms are provided. For the leaf-on data, the maximum time period between ALS and TLS acquisitions is 60 days (70 days between ALS and ULS). In addition to the 3D coordinates, each point has attributes including reflectance, echo number, waveform deviation and time of recording. The dataset further exists of the larger area forest point clouds of the acquisitions and the flight trajectory or scan position information.

Such comprehensive datasets are extraordinary because field work, data processing and quality control are very costly and labor intensive. Figure 1 displays the workflow of the data acquisition and processing steps.

The dataset has a very high reuse value for numerous applications such as:

- to create 3D forest scenes for radiative transfer modeling or LiDAR simulation studies

- as a benchmark dataset for automated individual tree segmentation algorithms

- to develop allometries between 3D tree structure and forest inventory variables
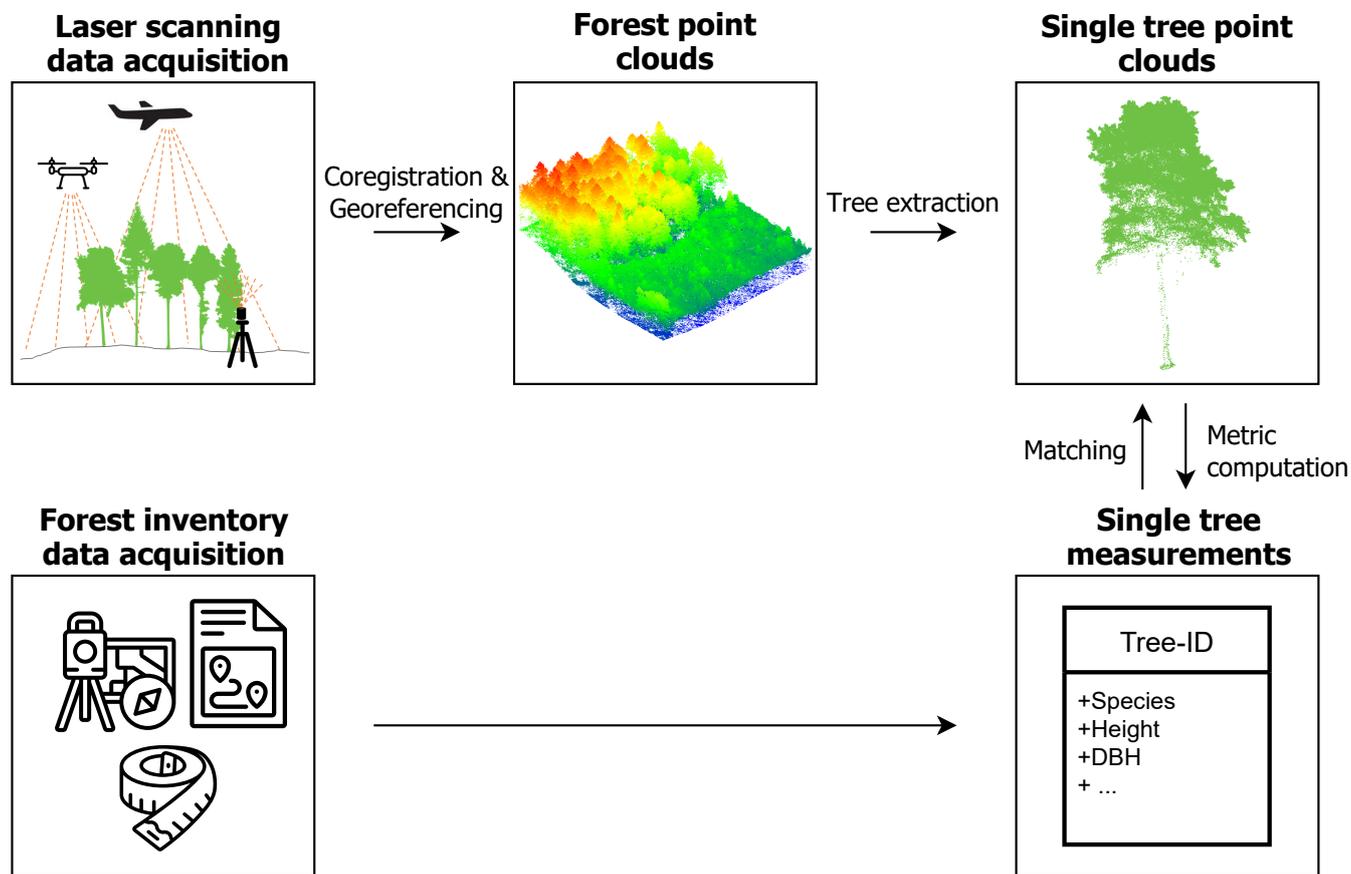
Figure 1. Workflow for the generation of the dataset, starting with the laser scanning data acquisition and forest inventory measurements and resulting in single tree point clouds and corresponding point cloud-derived and field-measured metrics. This figure has been designed using resources from http://www.flaticon.com/ (Smashicons, Freepik).

- as training data for algorithms focusing on automated extraction of tree metrics from individual tree point clouds

- as training data for machine learning applications, e.g., tree species classification

- to create detailed tree models for computer rendering

2   Methods

In this section, we introduce the study site, give an overview of the measurements taken in the field and document the LiDAR acquisitions from the three different platforms (airborne, UAV-borne, terrestrial) which were conducted in 2019 and 2020 under leaf-on and leaf-off canopy conditions. We describe how we extracted single tree point clouds from the LiDAR datasets to a) match them to the field measurements, and b) derive individual tree metrics directly from the point clouds.

2.1 Study site

The two study study sites, the Bretten municipal forest (49°00'36"N 8°41'35"E) and the Hardtwald forest in Karlsruhe-Waldstadt (49°02'04"N 8°25'40"E), are located in a region of temperate forests in the federal state of Baden-Württemberg, Germany (Figure 2). Data acquisitions cover three forest plots in the Karlsruhe forest and nine in the Bretten municipal forest, totaling twelve forest plots (Figure 2). The Bretten site is characterized by the hilly landscape of the Kraichgau, and the Karlsruhe site is on flat terrain of the Upper Rhine Plain. The main tree species in the managed forest stands are Scots pine (*Pinus sylvestris* L.), European beech (*Fagus sylvatica* L.), common oak (*Quercus robur* L.), sessile oak (*Quercus petraea* (Matt.) Liebl.), red oak (*Quercus rubra* L.), European hornbeam (*Carpinus betulus* L.), Douglas fir (*Pseudotsuga menziesii* (Mirb.) Franco), and Norway spruce (*Picea abies* (L.) H. Karst). Most stands have multiple layers, a mixed species composition, and a dense forest cover. Karlsruhe plots are dominated by Scots pine, red oak and beech. Bretten plots are more diverse and characterized by beech, spruce, Douglas fir, oaks (mostly sessile oak) and European hornbeam.

2.2 Laser scanning data acquisition and co-registration

2.2.1 Airborne laser scanning (ALS)

MILAN Geoservice GmbH was commissioned by the Institute of Geography and Geoecology (IFGG) of Karlsruhe Institute of Technology (KIT) to carry out the ALS acquisitions. The flights were conducted on July 5, 2019 under leaf-on conditions with a *RIEGL* VQ780i (RIEGL Laser Measurement Systems, 2019) sensor mounted on an aircraft of type Cessna C207. Data were acquired in 38 parallel flight strips, plus two orthogonal strips, in Karlsruhe, covering an area of around $65\,\mathrm{km}^2$. In Bretten, data were acquired in 25 parallel flight strips, plus two orthogonal strips, covering an area of around $32\,\mathrm{km}^2$. Detailed acquisition parameters are listed in Table 1. The data were georeferenced and transformed into the coordinate reference system ETRS89 / UTM zone 32 (EPSG:25832) with ellipsoidal height (GRS80). Full-waveform data are available from the authors on reasonable request.

For quality control, seven small built-up areas surrounding the area of interest were recorded by the 3DGeo Research Group of Heidelberg University using ULS, for which georeferencing was carried out as described in the next section.

Flight strips were merged and the point clouds were clipped to the 12 forest plots, using a generously sized buffer to cover the other datasets (ULS, TLS, field measurements). This resulted in extracted ALS point clouds of $300\,\mathrm{m}\times300\,\mathrm{m}$, $200\,\mathrm{m}\times200\,\mathrm{m}$, or $120\,\mathrm{m}\times120\,\mathrm{m}$ extent (Figure 2). Pulse density grids with a cell size of $1\,\mathrm{m}$ were computed for each point cloud. Pulse density, averaged over all 12 plot point clouds, was $72.5\,\mathrm{pts/m}^2$ (standard deviation: $31.0\,\mathrm{pts/m}^2$).

2.2.2 UAV-borne laser scanning (ULS)

UAV-borne laser scanning point clouds were acquired with a *RIEGL* miniVUX-1UAV (RIEGL Laser Measurement Systems, 2020b) sensor mounted on a DJI Matrice 600 Pro Hexacopter (DJI, 2018). Flights were conducted in August and September 2019, in December 2019, and in March and April 2020 to obtain data of trees under both leaf-on and leaf-off conditions. Table 2
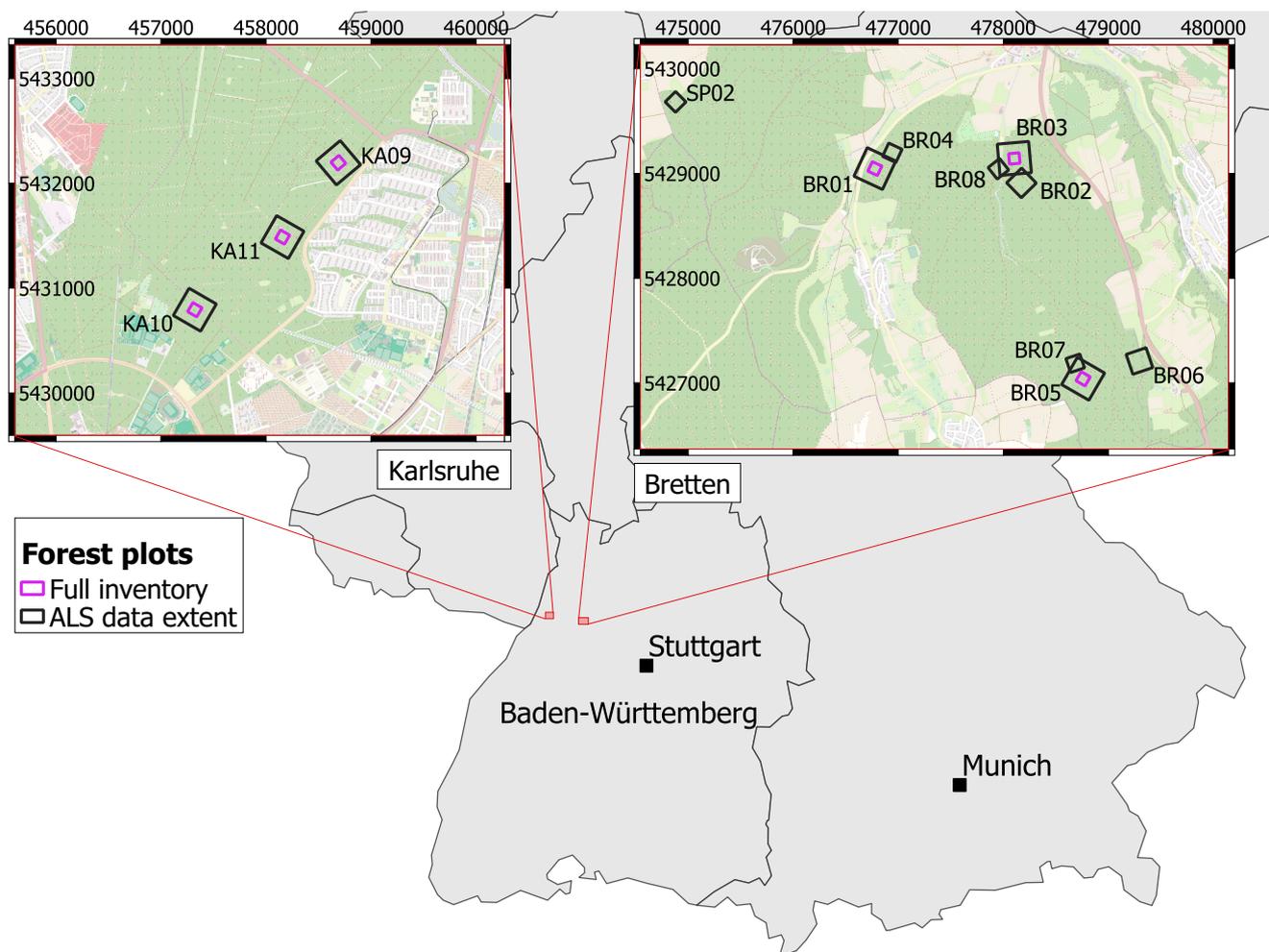
Figure 2. Map of the forest plots in Karlsruhe (left) and Bretten (right) in the federal state of Baden-Württemberg, Germany. The extent of the extracted ALS data is outlined in black, areas for which field measurements were conducted are outlined in purple ("Full inventory"). All plots except BR04 are covered by the ULS acquisitions. TLS was performed in selected locations within the plots. Coordinates are given in the projected coordinate system ETRS89 / UTM zone 32N (EPSG:25832). Map data: © OpenStreetMap contributors 2021. Distributed under the Open Data Commons Open Database License (ODbL) v1.0. Administrative boundaries: © EuroGeographics (2021).

Table 1. Airborne laser scanning acquisition parameters. Laser beam divergence is specified as the points where the energy drops to $1/e^2$ of the maximum.

Date	2019-07-05
Aircraft	Cessna C207
Sensor	*RIEGL* VQ-780i
Laser beam divergence	0.25 mrad
Pulse repetition frequency	1000 kHz
Scan frequency	225 lines per second
Altitude above ground	650 m
Off-nadir scan angle	$\pm 30°$
Flight line distance	175 m
Flight line overlap	76 %
Speed	100 kn

shows the general settings used in all 21 flights. For plots KA10 and KA11 in Karlsruhe, only leaf-on data were acquired in summer. Two overlapping double grid patterns, offset by $45°$ in orientation were employed for all flights (Figure 3). In the 2019 flights, adaptive banked turns were flown, while in the 2020 flights, the UAV was operated in stop and turn-mode, i.e., stopped in each corner to turn without inclining about the roll axis. Flying altitude, speed and flight line distance varied across the different flight campaigns and are listed in Table 3. Note that for the 2019 flights of plots BR03 and BR08, the two parts of the double cross were flown at different speeds.

Table 2. Constant UAV-borne laser scanning acquisition parameters. Laser beam divergence is specified as full angle measured at 50 % peak intensity (full width at half maximum; FWHM).

UAV	DJI Matrice 600 Pro
Sensor	*RIEGL* miniVUX-1UAV
Laser beam divergence	1.6 mrad $\times$ 0.5 mrad
Pulse repetition frequency	100 kHz
Scan frequency	50 lines per second
Off-nadir scan angle	$\pm 90°$

ULS data was processed using the software RiProcess (RIEGL Laser Measurement Systems 2020a, version 1.4.2). GNSS reference measurements were retrieved as a virtual base station from SAPOS Baden-Württemberg (https://www.sapos-bw.de), and were used to post-process the trajectory using Applanix PosPac MMS 8.3 (Applanix Corporation, 2018). The trajectory and the point cloud data from the scanner were imported to RiProcess. At import, the point cloud data were filtered for reflectance between -22 dB and 10 dB, scan angle $\leq \pm 90°$ off-nadir, and ranges between 5 m and 150 m to filter outliers from the data.
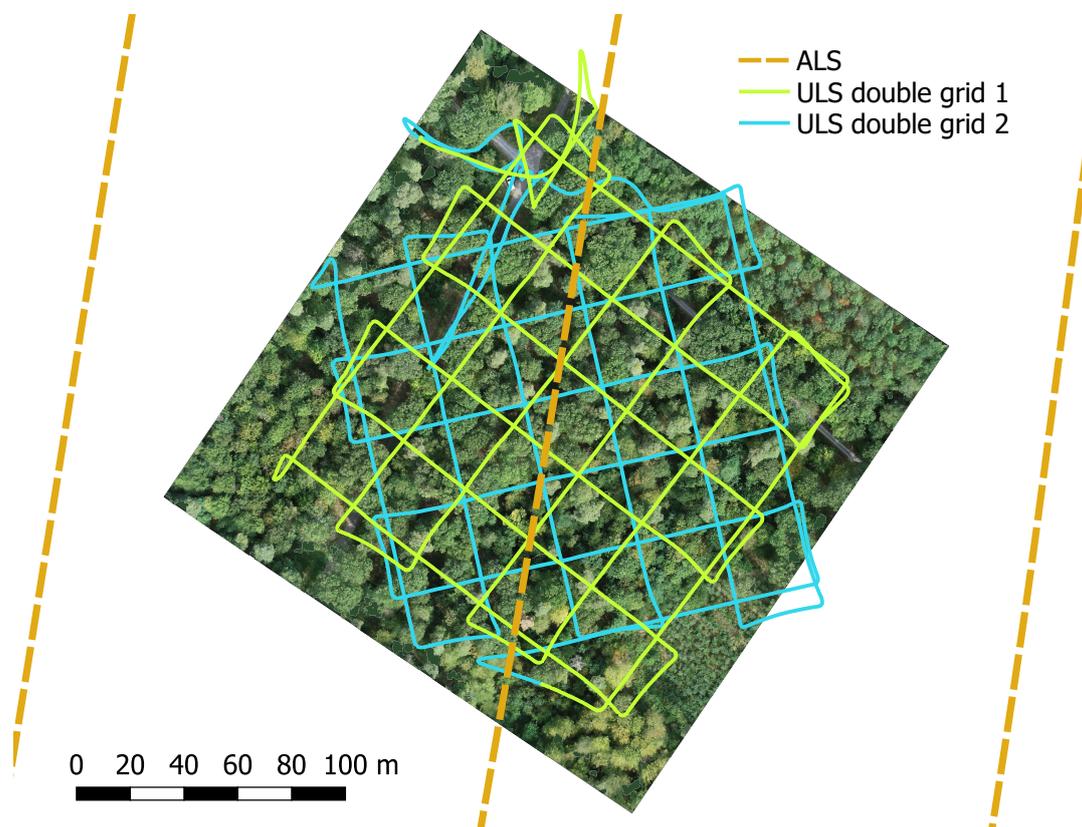
Figure 3. UAV-borne laser scanning (ULS) and airborne laser scanning (ALS) flight trajectories of plot KA10. Background: Orthophoto of the forest plot.

The point cloud data were converted from the scanner (SDCImport) and then transformed from local polar to world coordinates (ETRS89/UTM Zone 32N) using the flight trajectory (RiWorld). For the subsequent strip adjustment, only points with a scan angle $\leq \pm 45°$ off-nadir were considered, because larger off-nadir angles constitute almost only of within-canopy returns which we presumed to be less accurate and/or less suitable for strip adjustment. Finally, each flight strip (with the full scan angle range) was exported in LAZ format including intensity information (signal amplitude and reflectance) and waveform information (pulse shape deviation). Using LAStools (Rapidlasso GmbH 2020, version 200509), the single flight strips were merged and the information on the flight lines was encoded in the LAS field "Point Source ID".

Pulse density grids were computed for extracted 1-ha point clouds of the 12 plots (i.e., excluding the edges of the flight lines) with a cell size of $1\,\mathrm{m}$. The mean pulse densities derived for these grids are shown in Table 3.

2.2.3 Terrestrial laser scanning (TLS)

TLS acquisitions were performed at selected spots within the 12 forest plots. Our focus was on the most common species in our study site. In total, we conducted 31 TLS surveys on 20 days between June and September 2019 under leaf-on conditions.

Table 3. UAV-borne laser scanning acquisition parameters per flight and resulting approximate pulse densities, quantified on extracted point clouds of 1 ha, thereby excluding points on the flight line edges.

Plot	Date	Canopy condition	Altitude above ground [m]	Speed [m s^{-1}]	Flight line distance [m]	Mean pulse density [pt m^{-2}]
	2019-09-12	leaf-on	68.3, ± 2.4	5.0	30	936
BR01	2019-12-04	leaf-off	62.3, ± 1.7	5.0	30	859
	2020-03-27	leaf-off	72.4, ± 1.9	5.0	27	824
BR02	2019-08-24	leaf-on	72.1, ± 3.4	5.0	26	1091
	2020-04-01	leaf-off	62.4, ± 3.9	5.0	26	1026
BR03	2019-08-24	leaf-on	62.5, ± 1.3	5.0 / 4.0	26	1262
	2020-03-31	leaf-off	67.7, ± 2.9	5.0	27	1114
BR05	2019-09-12	leaf-on	70.8, ± 4.7	5.0	30	909
	2020-03-26	leaf-off	74.5, ± 5.0	5.0	27	988
BR06	2019-09-12	leaf-on	61.2, ± 2.8	5.0	30	953
	2020-03-27	leaf-off	61.2, ± 3.3	5.0	26	1023
BR07	2019-08-24	leaf-on	70.1, ± 5.7	4.4	26	1115
	2020-03-26	leaf-off	71.4, ± 5.4	5.0	27	1050
BR08	2019-08-24	leaf-on	63.9, ± 2.2	5.0 / 4.0	26	1205
	2020-03-31	leaf-off	69.3, ± 2.3	5.0	27	1024
SP02	2019-09-03	leaf-on	64.0, ± 2.5	4.0	25	797
	2020-04-01	leaf-off	66.2, ± 3.1	5.0	26	919
KA09	2019-09-13	leaf-on	65.6, ± 0.8	5.0	30	941
	2019-12-10	leaf-off	60.9, ± 0.8	5.0	30	987
KA10	2019-09-13	leaf-on	64.9, ± 0.8	4.8	30	1036
KA11	2019-09-06	leaf-on	64.4, ± 1.0	3.0	25	1554

In each survey, a group of selected trees was scanned from 5 to 8 scan positions (SPs), regularly distributed around the target
120 trees. Depending on the size of the scan area, the terrain, and the forest density, the number and the exact positions of the SPs
were adjusted. The scans were acquired with a *RIEGL* VZ-400 terrestrial laser scanner, which has a wavelength of $1550\,\mathrm{nm}$
and a beam divergence of $0.3\,\mathrm{mrad}$ (full angle, measured at the $1/\mathrm{e}^2$ points; RIEGL Laser Measurement Systems 2017). Scans
were performed with a pulse repetition frequency (PRF) of $300\,\mathrm{kHz}$ and vertical and horizontal angle increments of $0.017°$
($0.3\,\mathrm{mrad}$). This results in $3\,\mathrm{mm}$ point spacing at $10\,\mathrm{m}$ range for a single scan and ensures non-overlapping footprints. Only
125 in three acquisitions on June 3, 2019 and June 4, 2019, the vertical resolution was erroneously set to $0.099°$ ($1.73\,\mathrm{mrad}$). Each
scan had a vertical field of view of $60°$ (-20/+40° from the horizontal plane) and a horizontal field of view of $60°$ to $100°$
facing the target trees. If the distance between scanner and target trees was low in relation to the tree height, we performed an
additional tilted scan at respective SPs to increase the vertical extent of the scan. Five cylindrical reflective targets mounted
on tripods were positioned in the area to be scanned. They serve as tiepoints in the tiepoint-based co-registration of multiple
130 scans. Further circular reflectors were pinned onto trees of interest to later facilitate their identification in the point cloud.

For each campaign, RTK GNSS measurements from one scan position, referred to as the *main stable position*, and one
tiepoint were used for initial georeferencing of the respective scan. Remaining scans were registered to the main stable position
in the software RiSCAN Pro (versions 2.8.0, 2.8.2, 2.9.0) using the cylindrical and circular reflective targets in the scene. After
the tiepoint-based registration, a fine alignment was performed using the Multi Station Adjustment (MSA) function of RiSCAN
135 Pro, which uses a variant of the iterative closest point (ICP) algorithm based on planar areas in the point cloud. Because of the
weak GNSS signal below the leaf canopy, the positional measurements taken in the forest only allowed coarse georeferencing
of the TLS point clouds. Therefore, TLS point clouds were registered to the ULS point clouds by tree matching and subsequent
ICP-alignment. Because stems are sampled better in the leaf-off point clouds due to the higher penetrability of the defoliated
crowns, we used the ULS leaf-off point clouds for stem detection where available. TLS point clouds were downsampled for the
140 stem detection using the RiSCAN octree filter with a voxel size of $0.05\,\mathrm{m}$. We calculated normal vectors, linearity and 3D point
densities in corresponding TLS and ULS point clouds using OPALS (Pfeifer et al. 2014, version 2.3.1). By filtering for these
three attributes, stem points were extracted and then segmented. To derive the final stem positions, each segment was projected
to the horizontal plane and the center of gravity was computed. For each pair of overlapping point clouds, TLS-derived tree
positions were manually matched to ULS-derived tree positions and the resulting rigid transformation was applied to the TLS
145 point cloud. The height offset was estimated by selecting corresponding points in a vertical profile in both point clouds. After
correcting the height offset, a fine alignment between TLS and ULS point clouds was performed with the ICP implementation
of OPALS. A visual assessment of the alignment between ALS, ULS and TLS is presented in Figure 4.

2.3 Tree point cloud extraction

We used different procedures to extract single tree point clouds from the laser scanning data (Figure 5). The full TLS point
150 clouds were automatically segmented into individual tree point clouds (subsubsection 2.3.1). For the trees of interest in the cen-
ter of the acquired scene, the segmentation was improved by manual editing. ULS and ALS tree point clouds were delineated
manually in the point clouds. Because our multi-platform laser scanning point clouds are georeferenced and spatially overlap-
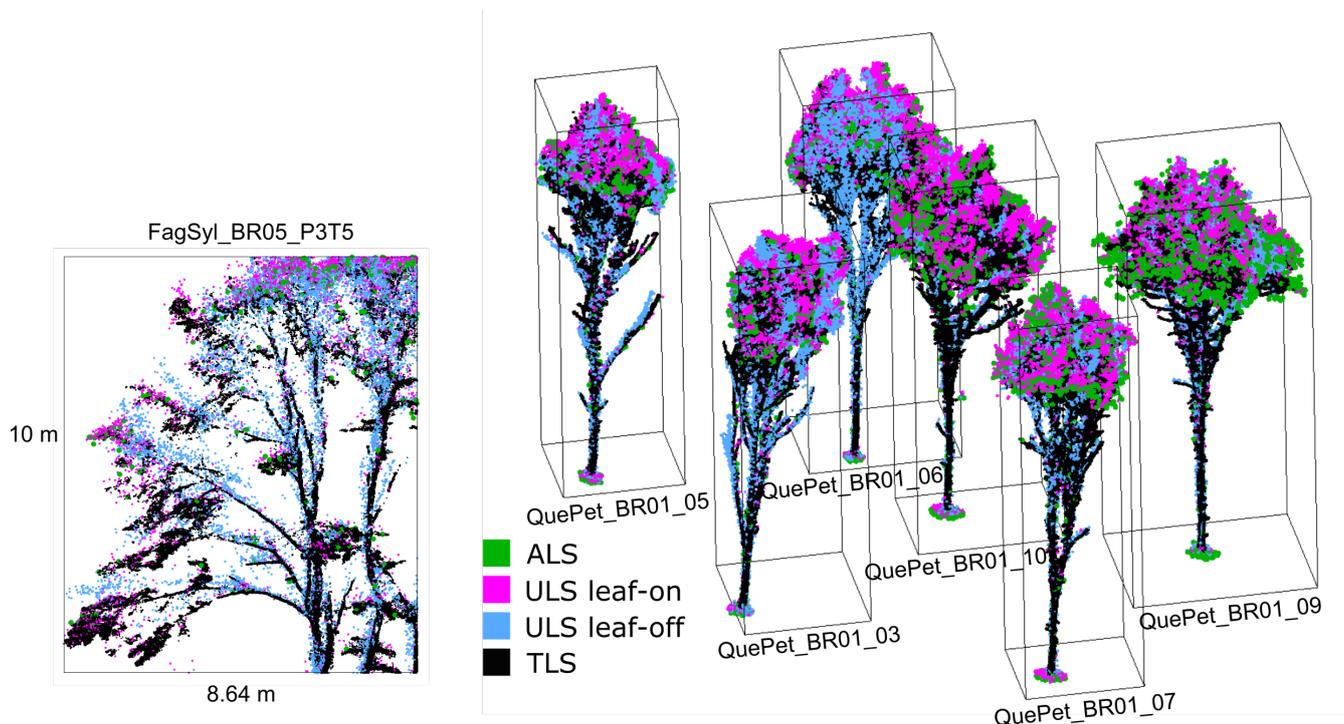
Figure 4. Point cloud visualizations showing the different point density and coverage for each platform. Left: Section of point clouds of a beech tree in plot BR05. The section has a depth of 1 m. Right: Point clouds of oaks in plot BR01. The trees are 16 m to 18 m tall. Point clouds are labeled by their tree ID in the dataset.

ping, it was possible to extract trees from one point cloud using already extracted tree point clouds from another platform or acquisition. This way, we only had to delineate each tree in one of the overlapping point clouds.

2.3.1 Automatic tree segmentation from TLS point clouds and manual post-processing

264 trees were extracted from the TLS point clouds. We first automatically segmented each TLS plot and then refined the segmentation result for our selected trees by manually editing the point clouds.

Automatic segmentation was performed with CompuTree software (Computree Group 2017, version 5.0.054b). The workflow consists of an Euclidean clustering approach combined with a competitive Dijkstra's algorithm and relies largely on the SimpleTree plugin (Hackenberg 2017, Beta version 4.33.06). After importing the point cloud of the forest scene, a digital terrain model (DTM) is computed. Next, a slice of the point cloud is extracted between 1.0 m and 1.6 m above the DTM. The sliced point cloud is spatially clustered to derive one seed cluster per tree stem. Each point in a stem seed is assigned a cluster ID and an initial distance of 0. A competitive Dijkstra's algorithm is run, where each vegetation point is connected to one of the clusters and receives the according cluster ID. A graph is built from the connected points. If there are multiple possible paths between a seed point and a target point, the shortest path is chosen.
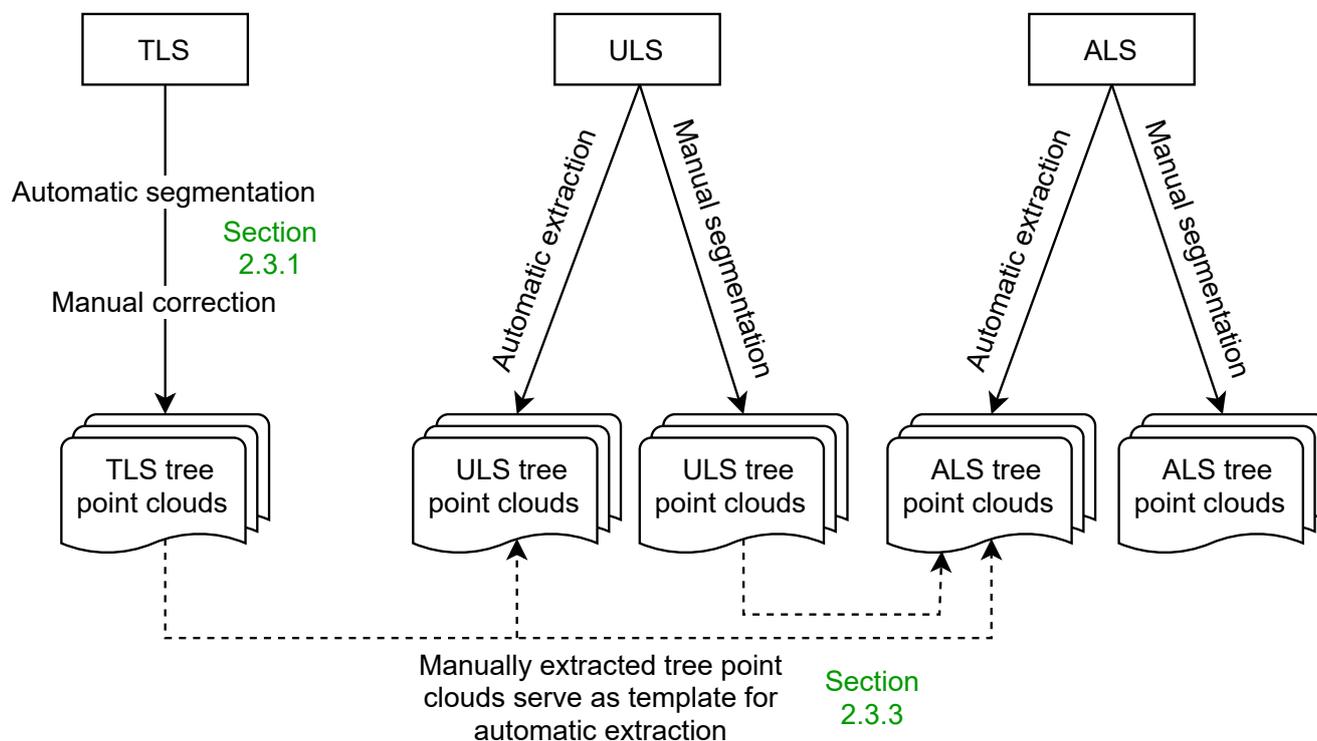
Figure 5. The different ways of single tree extraction. TLS point clouds were extracted with a combination of automatic segmentation and manual correction. ULS and ALS point clouds were partly segmented manually and partly extracted using a higher resolution point cloud from another platform (i.e., TLS and ULS).

The result of this automatic approach is error-prone, i.e., the Dijkstra's algorithm cannot guarantee the assignment of each point to the correct tree cluster. This is due to overlapping tree crowns and occlusions in the crown. Furthermore, errors in the clustering of stems seeds can lead to false labeling of points.

We applied a manual correction procedure. Selected tree point clouds were compared to surrounding segmented trees to
170 identify erroneous or missing points and correct them manually. This was done in two stages by independent editors using the interactive segmentation tool of CloudCompare (CloudCompare, 2019). Human experts can take into account the morphology of the crowns in ways which are barely feasible automatically. A combined approach of automatic segmentation and manual correction is therefore a good solution to precisely delineate trees.

2.3.2 Manual tree extraction from ALS and ULS point clouds

175 From ALS and ULS point clouds, we delineated trees manually in the point cloud using the interactive segmentation tool of CloudCompare or we used already manually delineated trees as templates for automatic extraction (subsubsection 2.3.3).

2.3.3 Automatic tree extraction from ALS and ULS point clouds using extracted template tree point clouds

Because our laser scanning point clouds are spatially overlapping and co-registered, we were able to use already extracted tree point clouds from one dataset to query points from another dataset. For each point in the source tree point cloud, we queried all nearest neighbors within a given search radius in the larger area target point cloud to extract the same tree in the target point cloud. This was done with a k-nearest neighbor (kNN) search using a kDTree. We ensured that the source point clouds were of equal or higher resolution than the target point clouds to avoid extrapolation. For instance, we extracted ULS point clouds using TLS source point clouds but not ALS source point clouds because this could lead to missing points if, e.g., the stem was not completely captured in the ALS point cloud. When using TLS point clouds as source point clouds, we used search radii of $0.3\,\mathrm{m}$, $0.5\,\mathrm{m}$ and $1.0\,\mathrm{m}$ in the nearest neighbor search. We then visually examined the extracted ALS and ULS point clouds and chose the search radius achieving the best trade-off between errors of omission and errors of commission. For the extraction using ULS template point clouds, we always used a search radius of $1.0\,\mathrm{m}$.

2.3.4 Tree positions

We define the tree position as the intersection of the tree stem center with the terrain. To derive the tree positions, we first computed digital terrain models (DTMs) from the ALS point clouds. We then cut a slice through the bottom of the tree point cloud, preferably the TLS or ULS point clouds, if available. We determined the x-y position of the stem as the means of the x and y coordinates of all points in the slice. At this position, we queried the elevation of the DTM to retrieve the matching z-value. For quality control, the derived positions were visually investigated. In some cases, they had to be corrected either because of DTM errors or because the point cloud did not have enough stem points. If not enough stem points were present to determine the tree stem center at ground level, the x-y positions of the lowest visible stem point was used.

2.4 Tree measurements

Tree measurements were recorded in the field and/or derived from the point clouds. Table 4 gives an overview of the metrics and the data source they were derived from.

2.4.1 Field measurements

Field measurements were conducted in six plots of $1\,\mathrm{ha}$ (Figure 2): BR01, BR03 and BR05 in Bretten and KA09, KA10 and KA11 in Karlsruhe. For each tree, the diameter at breast height (DBH) was measured with a measuring tape at $1.3\,\mathrm{m}$ above ground. To determine the crown diameter (CD), the diameter of the estimated dripline (i.e., the line right under the outer circumference of the crown) was measured in two orthogonal directions using a Haglöf Vertex-IV hypsometer. Mean CD was then calculated as the mean of these two distance measures. We define crown base height (CBH) as the height of the lowest branch with a minimum length of $1\,\mathrm{m}$ and crown base height green (CBH green) as the height of the lowest green (living) branch with a minimum length of $1\,\mathrm{m}$. We selected the branches fulfilling these conditions by visual estimation and then measured their heights above ground using the hypsometer. Since measuring tree height with the hypsometer is difficult

Table 4. Tree measurements and the source(s) they were recorded or computed from. Tree height was only measured from TLS point clouds for understory trees, for which tree height measurements from ALS or ULS would not be reliable. Tree height was only recorded in FM for smaller trees, where the top of the crown was visible from the ground (subsubsection 2.4.1). ALS = Airborne laser scanning, ULS = UAV-borne laser scanning, TLS = Terrestrial laser scanning, FM = Field measurements. All height measurements refer to height above the ground level at the stem position. For each tree, there can be multiple values for one tree metric if they were derived from different sources.

	Metric	Unit	Description	Source(s)			
1	Tree height	m	Height of the tree	ALS	ULS leaf-on	(TLS)	(FM)
2	Diameter at breast height (DBH)	cm	Stem diameter, measured at $1.3\,\mathrm{m}$ above ground	-	-	TLS	FM
3	Crown base height (CBH)	m	Height of the lowest branch	ALS	ULS	-	FM
4	Crown base height (CBH) green	m	Height of the lowest green (living) branch	-	-	-	FM
5	Mean crown diameter (CD)	m	Mean of two orthogonal crown diameters	ALS	ULS	-	FM
6	Crown projection area (CPA)	m^2	Area of the tree crown	ALS	ULS	-	-

in dense forest stands where high tree tops are barely visible, tree height was only measured for about $10\,\%$ of the trees. These were mostly understory trees, where the crown was in direct view. As additional attributes, tree species and state (alive or dead) were recorded. For trees outside of the six field measurement plots, only species and state were determined. Field measurements and single tree point clouds were matched based on extracted tree positions, the distinct crown shape and branch architecture, and the local neighborhood of the trees. For this, additional field surveys were conducted, in which 3D views of the laser scanning point clouds were used to identify the corresponding trees in the field.

2.4.2 Tree metrics derived from point clouds

In addition to field measurements, tree metrics were estimated from the laser scanning point clouds. For the computation of the metrics, the height values of each tree point cloud were height-normalized by subtracting the z-coordinate of the tree position (representing the terrain height at the location of the stem) from all z-coordinates in the point cloud.

DBH was estimated only from TLS tree point clouds. Due to the terrestrial view point and close range, many returns are recorded from the stems, allowing accurate DBH estimation. A slice of the tree point cloud was extracted at a height between $1.28\,\mathrm{m}$ and $1.32\,\mathrm{m}$ above ground. In case the stem was partly occluded, a thicker slice was extracted or the vertical position of the slice was adapted to achieve better results. We projected the slice onto the x-y plane and fit a circle to the points using the

random sample consensus (RANSAC) algorithm to derive the diameter using 1000 random samples. For slanted trees, errors may arise from the projection of points to the x-y plane instead of a plane perpendicular to the stem. However, since most of our TLS trees were upright, this error is negligible. Some tree stems have a rather elliptical than circular stem shape. In these
225 cases (44 of 264 TLS point clouds), we fit an ellipse to the projected points of the stem slice using least squares[1]. The DBH was then determined as the arithmetic mean of the major and the minor axes of the ellipse. For all trees, the quality of the fit was controlled visually.

Tree height was derived as the height-normalized z-coordinate of the highest tree point.

CBH was determined by dividing the point cloud into height sections of $0.1\,\mathrm{m}$ and calculating the maximum x-y distance
230 between any two points in the section. Starting from the bottom, we iterate over the height sections. Once the maximum horizontal point distance exceeded a threshold of DBH + $1\,\mathrm{m}$ (if no DBH measurement was available, a default of $0.5\,\mathrm{m}$ was used), the center of the height section is defined as the CBH (Figure 6) and the iteration is terminated. Because of the fixed section height, CBH estimates have decimeter resolution.

The tree crown is defined by all points above the CBH. Crown projection area (CPA) was calculated in two different ways:

235 – as the area of the 2D (x-y) *convex hull* of all crown points using the Quickhull algorithm (Barber et al., 1996).

– as the area of the 2D (x-y) *concave hull* of all crown points using the k-nearest neighbors approach by Moreira and Yasmina Santos (2007) as implemented by Craig (2017).

Lastly, mean CD was computed as the mean of the largest diameter and the largest perpendicular diameter of the concave hull (Figure 6).

240 ## 3   Results

The data records are split into two parts:

– The full TLS and ULS point clouds and extracted ALS subsets covering the ULS, TLS and field measurement plots (see Figure 2)

– The extracted single tree point clouds and respective measured and point cloud-derived tree metrics

245 The folder structure is visualized in Figure 7.

3.1   LAS point format

All point clouds are stored in ASPRS LAS 1.4 format (ASPRS, 2013) or ASPRS LAS 1.2 (ASPRS, 2008), compressed (lossles) to LAZ. The field "Point source ID" holds the IDs of the flight lines or scan positions that the points originated from. All LAZ files contain the extra bytes amplitude [dB], reflectance [dB] and (pulse shape) deviation [] as exported by *RIEGL*

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[1] as implemented by Nicky van Foreest: https://github.com/ndvanforeest/fit_ellipse
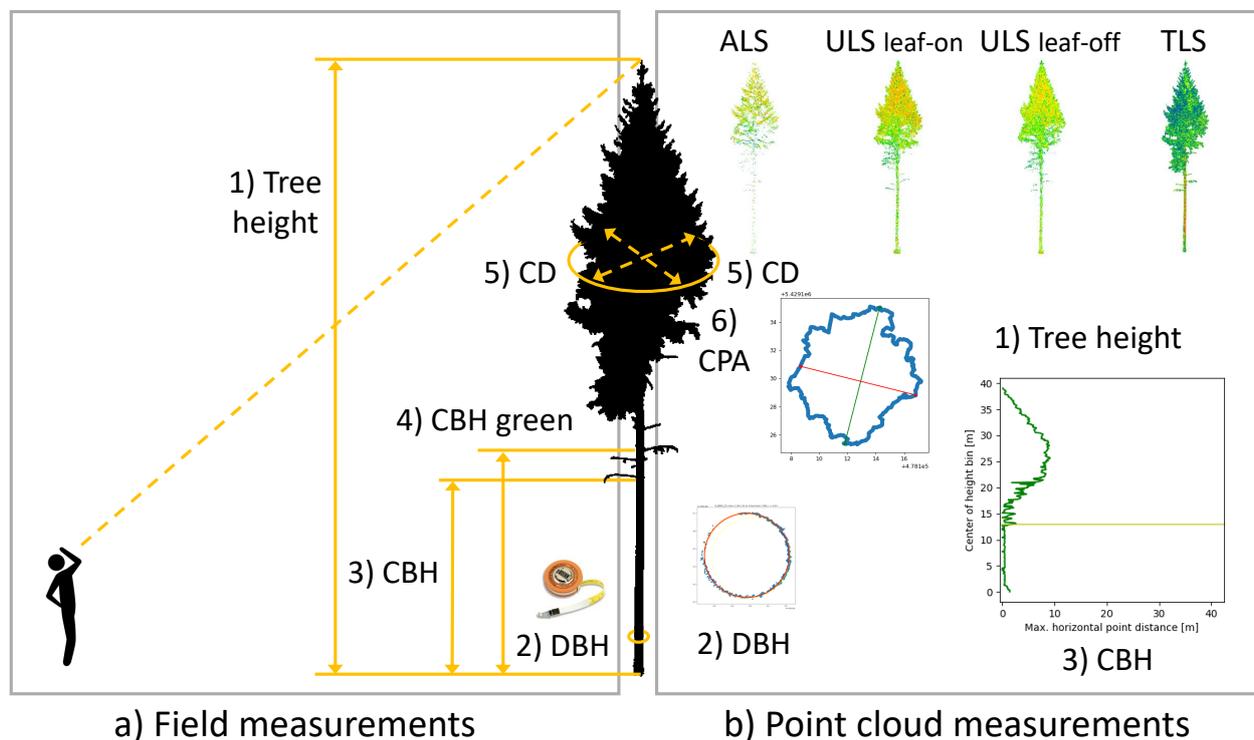
Figure 6. Overview of single tree measurements a) recorded in the field and b) derived from the point clouds. Numbers are corresponding to Table 4. Icon on the left ("man looking up") by DonBLC, https://thenounproject.com/. Picture of diameter tape from https://www.forestry-suppliers.com/.

250   systems. The amplitude is calibrated as the ratio of the optical power of the reflected light to the detection threshold of the instrument and depends on the distance of the target to the scanner (Pfennigbauer and Ullrich, 2010). The reflectance, however, is distance independent and determined by the properties of the target that was hit by the ray. Reflectance is given as the ratio of the amplitude of the hit target to the amplitude of the target the instrument was calibrated with, i.e., a diffuse white target (Pfennigbauer and Ullrich, 2010). The pulse shape deviation indicates the degree to which the shape of the received pulse

255   deviates from a device-specific reference pulse shape.

3.2   Full forest plot or acquisition records

In order to also capture the neighborhood context of the single trees, understory and terrain information, we provide the larger-area georeferenced point clouds of each platform. These include 31 LAZ files of the TLS acquisitions together with tab-separated txt-files containing the locations of scan positions in the same coordinate reference system (ETRS89/UTM zone 32N;

260   EPSG:25832; ellipsoidal height, GRS80). 20 LAZ-files are available containing the ULS point clouds acquired under leaf-on and leaf-off conditions as summarized in Table 3. Note that the ULS leaf-on data for plots BR03 and BR08 is included in one
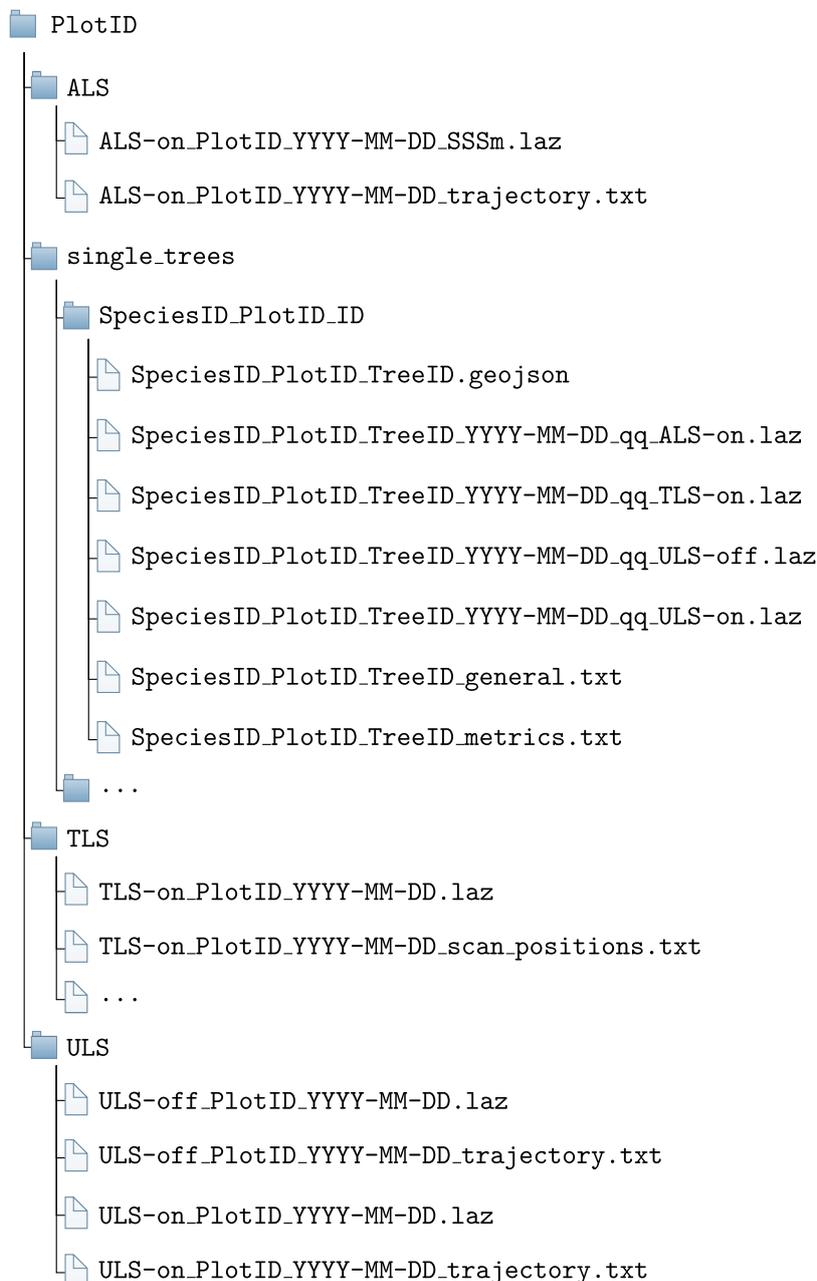
Figure 7. Folder structure for a single forest plot. PlotID = ID of the forest plot, e.g., BR01; SpeciesID = ID of the tree species, e.g., AcePse, see Table 5; TreeID = unique (in combination with PlotID and SpeciesID) identifier for the tree; YYYY-MM-DD = day of acquisition; qq = quality indicator, e.g., q2; on/off = canopy condition; SSSm = side length of the ALS forest plot in m, e.g. 300m. The ALS folder contains only one point cloud per plot. Multiple point clouds may be within the ULS folder due to different acquisition times and in the TLS folder due to different acquisition times and locations (in case of several acquisitions in the same plot on the same day, a suffix is added to distinguish the acquisitions, i.e., "_A", "_B", etc.). The single_trees folder always contains several subfolders, one for each tree.

single LAZ file and no ULS data is available for plot BR04. For each acquisition, the trajectory is provided as a tab-separated txt-file, containing continuous records of the location and orientation of the sensor in the air. The "Time [s]" in the trajectory files corresponds with the "GPSTime" in the respective LAZ point cloud files and represents seconds since beginning of the

265   respective GPS week (ASPRS, 2013). Finally, we provide 12 LAZ files with extracted ALS point clouds, one for each plot (Figure 2). ALS point clouds of plots BR01, BR03, BR05, KA09, KA10 and KA11 are $300\,\text{m} \times 300\,\text{m}$ in size and encompass the $100\,\text{m} \times 100\,\text{m}$ plots in which field measurements were recorded. ALS point clouds of plots BR02 and BR06 are $200\,\text{m} \times 200\,\text{m}$ and ALS point clouds of BR04, BR07, BR08 and SP02 are $140\,\text{m} \times 140\,\text{m}$ in size. For these six plots (BR02, BR04, BR06, BR07, BR08 and SP92), no field measurements are available. We provide the trajectory points for the respective parts

270   of the flight strips covering the area in tab-separated txt-files. All ALS point clouds spatially overlap with the TLS and ULS acquisitions conducted in the respective plots.

3.3   Single tree point clouds and metrics

Point clouds and point cloud-derived metrics are provided for 1491 individual trees of in total 22 different species. An overview of tree species and the respective number of trees is given in Table 5. Field measured metrics are available for 1060 of the trees.

275   Tree point clouds acquired from all three platforms, i.e., ALS, TLS, and ULS (leaf-on), are provided for 249 trees. 1168 tree point clouds were extracted both from ULS leaf-on and ULS leaf-off data. A summary of all available data types per tree is given in Figure 8.

There are multiple reasons for the different available data types per tree:

-   TLS acquisitions did not cover the entire ALS/ULS acquisitions but only selected locations, so only 246 TLS point
280   clouds of trees are available.

-   No ULS acquisition was performed in plot BR04.

-   ALS point clouds of understory trees with very few points were discarded.

-   Some trees were only extracted manually from ALS point clouds and these were not used for automatic extraction due to the lower resolution compared to ULS and TLS point clouds, which would cause information loss (e.g., missing parts
285   of the stem).

Tree properties are provided in two tab-separated txt-files:

-   General tree characteristics such as the species and the tree position in geographic coordinates and in UTM coordinates are listed in a tab-separated txt-file with suffix "_general".

-   Tree metrics are provided in a tab-separated txt-file with suffix "_metrics". There is one row for each measurement source
290   (e.g., field inventory measurement (FI), ALS, etc.) and one column for each tree metric.

Table 5. Number of trees of each species in the dataset.

Species	SpeciesID	Number of trees
Abies alba Mill.	AbiAlb	25
Acer campestre L.	AceCam	7
Acer pseudoplatanus L.	AcePse	39
Betula pendula Roth	BetPen	6
Carpinus betulus L.	CarBet	94
Fagus sylvatica L.	FagSyl	398
Fraxinus excelsior L.	FraExc	11
Juglans regia L.	JugReg	19
Larix decidua Mill.	LarDec	30
Picea abies (L.) H. Karst.	PicAbi	205
Pinus sylvestris L.	PinSyl	158
Prunus avium (L.) L.	PruAvi	19
Prunus serotina Ehrh., nom. cons.	PruSer	7
Pseudotsuga menziesii (Mirb.) Franco	PseMen	191
Quercus petraea (Matt.) Liebl.	QuePet	156
Quercus robur L.	QueRob	7
Quercus rubra L.	QueRub	111
Robinia pseudoacacia L.	RobPse	1
Salix caprea L.	SalCap	1
Sorbus torminalis (L.) Crantz	SorTor	1
Tilia spec. L.	TilSpec	4
Tsuga heterophylla (Raf.) Sarg.	TsuHet	1
		1491

We furthermore provide all tree metadata in GeoJSON files, including geometry (position), properties (field measurements and point cloud metrics) and data (point cloud data filenames and metadata). These files can be loaded into common GIS software to visualize the tree positions and access the data.

4 Quality assessment

295 In the following, we describe how we assessed different aspects of data quality for our dataset. Table 6 summarizes all quality indicators related to point cloud alignment and georeferencing.
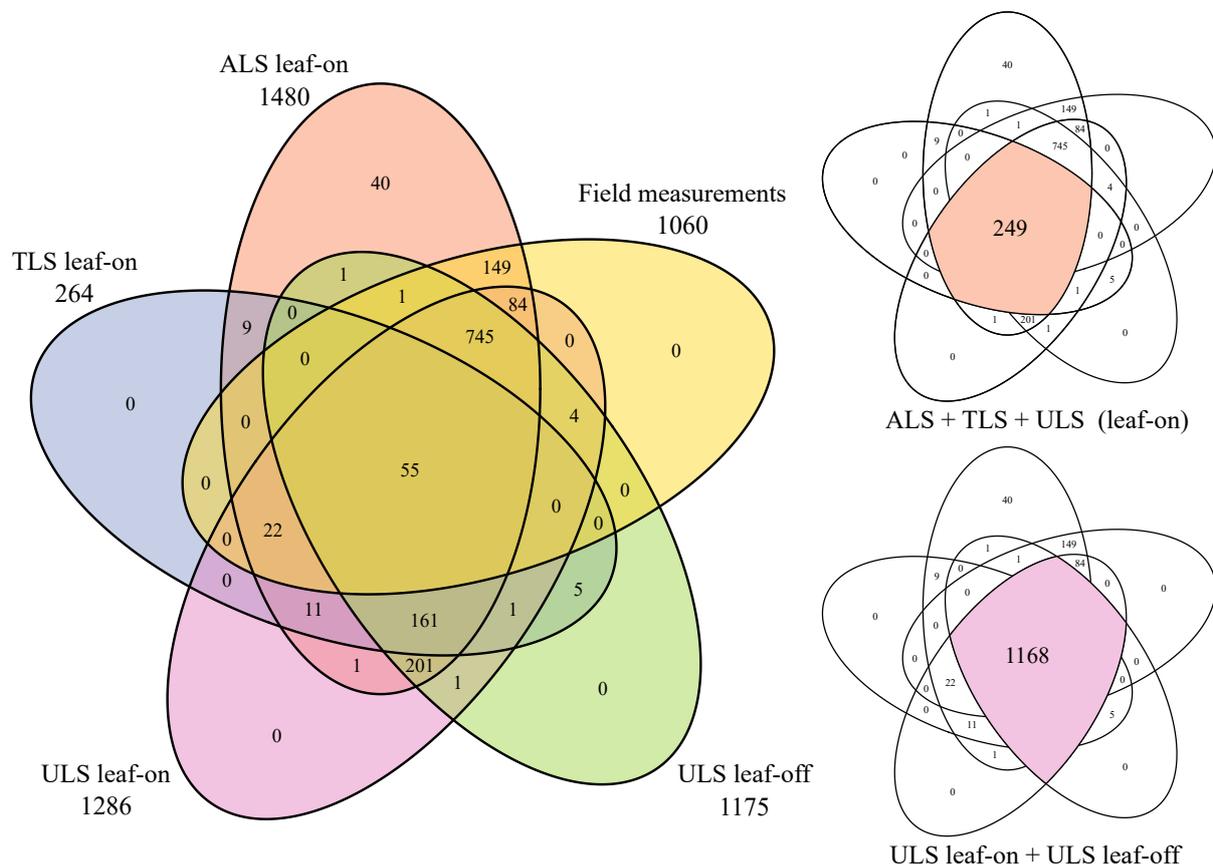
Figure 8. Venn diagrams showing the number of trees covered by the different acquisitions.

4.1 Airborne and UAV-borne laser scanning (ALS and ULS)

4.1.1 Positional accuracy

Positional accuracy of the ULS data was determined using roof-shaped wooden targets of $1\,\mathrm{m}$ length and $0.6\,\mathrm{m}$ width (for one
side of the roof). The two planes of the roofs were recorded with four points each using a Leica Viva GS10/GS15 RTK GNSS
unit tied into the SAPOS correction network (https://www.sapos-bw.de). A visual inspection of the the wooden target point
clouds and the GNSS reference measurements showed good alignment, with differences in the range that was expected due to
the limited scanner and RTK accuracies (Figure 9).

Absolute altitude accuracy of ALS data was determined by MILAN Geoservices GmbH using reference tiles recorded
with ULS by the 3DGeo Research Group of Heidelberg University. The height of selected reference points was compared to
the median of ALS points within a radius of $0.2\,\mathrm{m}$ (Bretten) and $0.3\,\mathrm{m}$(Karlsruhe). The mean altitude differences (standard
deviations) were $-0.003\,\mathrm{m}\,(\pm0.023\,\mathrm{m})$, $0.006\,\mathrm{m}\,(\pm0.016\,\mathrm{m})$, $-0.016\,\mathrm{m}\,(\pm0.026\,\mathrm{m})$, $-0.028\,\mathrm{m}$ and $(\pm0.029\,\mathrm{m})$ for the four

(a)   (b)
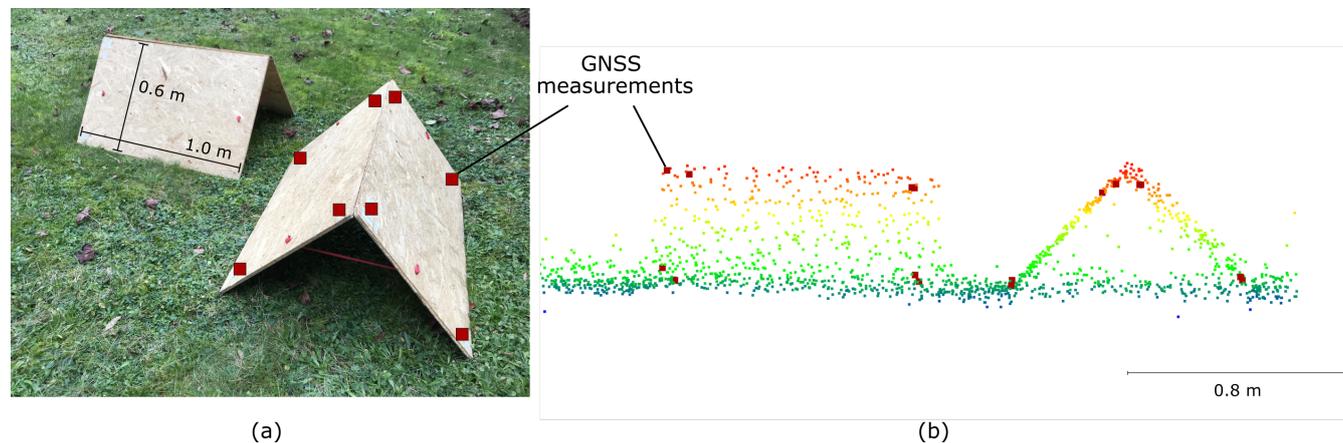
Figure 9. Roof-shaped wooden targets used for assessing the positional accuracy of the ULS point cloud. (a) Set-up in the field. The two planes of each roof are $1\,\mathrm{m}$ by $0.6\,\mathrm{m}$ in size. The red squares in both images mark the points, where GNSS measurements are taken. (b) View in a point cloud viewer. The ULS point cloud is colored by z-coordinate, the GNSS measurements are shown as large red squares. The georeferencing quality is considered good if the ULS points on the roofs agree closely with the GNSS reference measurements, as shown in this example.

tiles in Bretten and $-0.016\,\mathrm{m}\,(\pm0.017\,\mathrm{m})$ for the tile in Karlsruhe. The quality of these reference tiles was, in turn, ensured by the same method as for the ULS data in general, see above.

310   Positional (horizontal) accuracy of the ALS data was controlled by MILAN Geoservice GmbH using building edges (i.e., stable surfaces). A building layout derived from TLS data, which was acquired by the 3DGeo Research Group and georefenced with RTK GNSS, was overlaid with the building layout derived by digitizing the classified ALS point cloud to control the positional accuracy.

    A further independent assessment of positional and altitude accuracy was conducted by the 3DGeo Research Group Heidel-
315 berg by comparing points sampled by ULS and ALS on roofs and other stable surfaces in control areas. Figures of the visual assessment are included in Appendix B in the metadata document published along with the dataset on the data repository PANGAEA (https://download.pangaea.de/reference/109167/attachments/SYSSIFOSS_2019-2020-metadata.pdf, Weiser et al. 2021a). To obtain quantitative measures, we computed cloud-to-cloud distances between these ALS and ULS point clouds of the stable areas (six in Karlsruhe, three in Bretten). Resulting mean distances were between $0.03\,\mathrm{m}$ and $0.06\,\mathrm{m}$, which
320 confirmed the good alignment.

4.1.2 Strip alignment

The internal alignment of ALS and ULS flight strips was investigated by the 3DGeo Research Group by quantifying the height differences between the flight strips with OPALS (version 2.3.2). For ALS, strip differences were quantified for the extracted

plot point clouds (with the extents as shown in Figure 2). The ULS point clouds were cropped to the 1-ha plots to exclude
325   points at the flight line edges.

For both datasets, single strip point clouds were first filtered for last returns. Second, grids of the standard deviation of the
interpolated height (sigmaZ) and of the distances between grid points and the center of gravity of data points (excentricity)
were computed to derive a mask of areas suited for the quality check. For the quantification of strip differences, areas with
sigmaZ $\geq 0.1\,$m and excentricity $\geq 0.8\,$m were masked. This concerns most areas with high vegetation, where strip differences
330   cannot be quantified reliably.

For the ALS point clouds, median absolute strip differences were below $5\,$mm for 10 of 12 plots. The maximum was $11\,$mm.
For ULS leaf-on point clouds, median absolute differences were up to $14\,$mm (mean: up to $55\,$mm). For ULS leaf-off point
clouds, median absolute strip differences were only up to $2\,$mm (mean: below $20\,$mm for 10 acquisitions, $51\,$mm and $62\,$mm
for the remaining two acquisitions), suggesting that the large values in the leaf-on differences are remaining influence from
335   vegetation. Histograms and maps of strip differences for ALS and ULS data are included in Appendix A in the metadata
document published along with the dataset on the data repository PANGAEA (Weiser et al., 2021a).

4.2   Terrestrial laser scanning (TLS)

4.2.1   Positional accuracy and alignment to ULS point clouds

TLS point clouds were georeferenced by coarsely registering them to the ULS data via stem matching, followed by a fine
340   alignment with the ICP-algorithm. Before running the ICP, we created downsampled TLS point clouds with the octree filter in
RiSCAN Pro with voxel sizes of $0.05\,$m. For each voxel of the octree, a new point is created by taking the center of gravity
for all the points within each voxel. We performed an ICP adjustment with 5 iterations, keeping the ULS point cloud fixed
while transforming the TLS point cloud. With these settings, we achieved mean point-to-plane distances of less than $2\,$mm
with standard deviations between $120\,$mm and $140\,$mm.

345   For 13 of the 31 point clouds, we still observed significant shifts in a visual assessment and repeated the ICP with revised
settings: We used the ULS point cloud as moving, preferably the one acquired under leaf-off canopy condition (if available)
due to the better representation of the stems, and the TLS point clouds as fix point clouds. This means, that the subset of points,
for which correspondences are established and to which planes are fitted to subsequently minimize point-to-plane distances
are selected from the TLS point cloud. This is likely to achieve better results, because the TLS point cloud has higher point
350   density (allowing for better plane fit) and higher accuracy. We used the full resolution TLS point clouds and in some cases
filtered for points below $15\,$m or $10\,$m to exclude crown points. For the tree crowns, the coverage of TLS and ULS point
clouds is very different and there are many moving objects (branches and leaves). We furthermore increased the number of
iterations to up to 10. We then applied the inverse output transformation matrix to the TLS point cloud to ensure that the
final georeference is derived from the ULS data. This resulted in mean point-to-plane distances of below $4\,$mm with standard
355   deviations of $50\,$mm–$100\,$mm. More importantly, the visual alignment improved considerably.

Because of the lack of bigger planar areas in the scene, the influence of moving branches and leaves, the different viewing geometries and resulting occlusions of the ULS and TLS point clouds, and the sensor accuracy limits, it is expected that no sub-millimeter point-to-plane distances were achieved and the standard deviation is comparably high. The final alignment is sufficient for our main intention, i.e., the extraction of trees from ULS and ALS point clouds using template TLS point clouds.

360 A visual impression of the quality of the alignment between the datasets acquired from the different platforms is given in Figure 4. The visual assessment and the low mean distances suggest no remaining systematic shifts.

4.2.2 Internal co-registration of single scan positions

Co-registration quality of scan positions relative to the main stable position for each plot was assessed in two stages. In the first stage we investigated differences computed in the least squares algorithm of the Multi Station Adjustment performed

365 in RiSCAN Pro. The overall average of the standard deviation of registration error (RMSE) was $5\,\mathrm{mm}$ with a maximum of $8\,\mathrm{mm}$. In the second stage, a visual assessment was conducted by projecting a narrow section of the point cloud onto a plane and coloring the points by their scan position. We used stem slices for assessing horizontal registration errors and cylindrical reflective targets for assessing vertical registration errors. Horizontal stem slices were manually extracted for selected trees with an approximate section width of $0.2\,\mathrm{m}$. To minimize the influence of wind effects, stem slices were cut out from low

370 heights above ground where tree stems are very stable. This was especially relevant for younger trees where tree stems are smaller in diameter and therefore more prone to movement. No significant vertical registration errors were present in any of the plots. In most of the acquisitions (26 of 31), no or very small ($< 10\,\mathrm{mm}$) horizontal registration errors were observed. In five acquisitions the maximum horizontal registration error was estimated to be between $10\,\mathrm{mm}$ and $20\,\mathrm{mm}$. Appendix C in the metadata document published along with the data (https://doi.org/10.1594/PANGAEA.933426, Weiser et al. 2021b) shows

375 the assessment of horizontal and vertical TLS registration errors.

4.3 Quality of single tree point clouds

Tree point clouds were assigned a quality tag from highest (q1) to lowest (q6). Reasons for lower grades include

– segmentation errors, e.g., additional branches in the point cloud

– extraction errors, e.g., additional points from neighboring trees in the point cloud because of the fixed search radius used

380 for the automatic kNN-based extraction

– missing parts/occlusion of tree parts

– wind effects (in case of TLS)

– scan position or flight strip alignment errors

The quality tags were subjectively assigned by different operators. For most trees that were extracted automatically using

385 the kNN-algorithm, the quality was set to one lower than the source point cloud. The quality tag therefore provides a rough idea of the point cloud quality but is not guaranteed to be comparable across the entire dataset.

Table 6. Summary of the different indicators for georeferencing and alignment quality. SD = Standard deviation.

Quality aspect	Quality indicator	Quantitative results	Qualitative results
ULS georeferencing accuracy	Agreement of GNSS measurements on roof-shaped targets with ULS points (subsubsection 4.1.1)		Visual assessment showed no evident systematic errors
	Height difference between ALS and ULS point clouds in stable areas (subsubsection 4.1.1)	Mean (per area) = −0.028 m–0.006 m SD (per area) = 0.016 m–0.029 m	
ALS georeferencing accuracy	Cloud-to-cloud distances between ALS and ULS point clouds in (different) stable areas (subsubsection 4.1.1)	Mean (per area) = 0.03 m–0.06 m SD (per area) = 0.01 m–0.023 m	Visual assessment (Weiser et al. 2021a, Appendix B)
	Agreement of a TLS-derived building layout with the ALS point cloud		Visual assessment showed no evident systematic errors
ULS strip alignment	Flight strip differences per acquisition (subsubsection 4.1.2)	Leaf-on: Median ≤ 0.014 m Leaf-off: Median ≤ 0.002 m	Histograms and maps in Weiser et al. 2021a, Appendix A
ALS strip alignment	Flight strip differences per plot (subsubsection 4.1.2)	Median ≤ 0.005 m for 10 of 12 plots, Max. = 0.011 m	Histograms and maps in Weiser et al. 2021a, Appendix A
TLS scan position alignment	RMSE of the registration error (as quantified in RiSCAN)	Mean (over all acquisitions): 0.005 m Max. = 0.008 m	
TLS scan position alignment	Differences between point clouds from different scan positions, quantified on stem slices (subsubsection 4.2.2)	≤ 0.02 m	Visual assessment (Weiser et al. 2021a, Appendix C)
TLS georeferencing	Point-to-plane distances between the TLS and ULS point clouds after the ICP adjustment (subsubsection 4.2.1)	Mean ≤ 0.004 m SD = 0.05 m–0.14 m	Visual assessment showed no evident systematic errors

4.4 Quality of the tree metrics

The quality of the tree metrics computed from the tree point clouds depends on the accuracy of the tree point cloud segmentation and the point density of the tree point cloud. Error of commission in the segmentation may cause higher tree height, mean CD

390 and CPA values and lower CBH values, while error of omission or a low point density may cause the opposite. Especially ALS tree point clouds of understory trees have a low point density and thus the computed metrics might differ from the field measured metrics. As field measurements were conducted from the ground, field measured height, mean CD and CBH of high trees have higher uncertainty than those of smaller trees. It is difficult to consider either the field measurements or the point cloud derived metrics as true reference. By comparing field measured and point cloud derived metrics, we can nevertheless get

395 an idea of the error ranges and potential biases.

Tree metrics derived from different sources are highly correlated (except CBH). The Pearson correlation coefficient (ρ) of DBH measured in the field and DBH computed from the TLS tree point clouds is 0.98 and the root-mean-square error ($RMSE$) is only $3.5\,\mathrm{cm}$. The correlation of tree heights derived from different laser scanning point clouds is 1.00 and the RMSE is $0.3\,\mathrm{m}$–$0.4\,\mathrm{m}$. This is lower than the search radius of $0.5\,\mathrm{m}$ which was mostly used for the automatic tree extraction.

400 The deviation of field measured tree height to point cloud tree height is higher (RMSE = $2.5\,\mathrm{m}$–$2.7\,\mathrm{m}$, $\rho = 0.96$). Field measured tree heights might be less accurate especially in case of high trees with flat crowns, where the tree top was not visible from the ground. The RMSE of mean CD is $0.7\,\mathrm{m}$–$1.2\,\mathrm{m}$ between different point cloud metrics ($\rho = 0.97$–0.98) and $1.5\,\mathrm{m}$–$1.6\,\mathrm{m}$ ($\rho = 0.88$–0.90) between field measurements and point cloud metrics. Absolute crown diameters are between $2\,\mathrm{m}$ and $22.1\,\mathrm{m}$ with a median value of $7.7\,\mathrm{m}$ (values based on field measurements). Higher deviations in CD between field measurements

405 and point cloud metrics occur for trees with an elongated horizontal crown extent where the direction of the two orthogonal diameter measurements is more important than for crowns with nearly circular circumference. The CD values computed from point clouds might be overestimated for slanted trees, because the part of the stem which is not covered by the crown may still be included in the crown extent if it is above the estimated CBH. Field measured diameters might be inaccurate for high tree crowns where the outer crown circumference was difficult to estimate. The definition and determination of CBH is difficult both

410 in the field and in the point cloud, resulting in high deviation of CBH values derived from different data sources. The RMSE of CBH computed from different laser scanning point clouds is $4.8\,\mathrm{m}$–$6.9\,\mathrm{m}$ ($\rho = 0.66$–0.76). On the one hand, the point-cloud derived CBH is sensitive to segmentation errors especially in case of the automatic tree extraction from template point clouds. If understory points are wrongly assigned to a tree point cloud, the CBH may be underestimated. On the other hand, the lowest branches may not be sampled well in ULS and especially ALS point clouds, hence the CBH may be overestimated. The field-

415 measured CBH accuracy is negatively affected by an over- or underestimation of branch lengths resulting in a wrong selection of the lowest branch defining the CBH. The RMSE between field measured and point cloud derived CBH is $4.0\,\mathrm{m}$–$5.1\,\mathrm{m}$ and ρ is 0.59–0.72 Figure 10 shows scatter plots of field measured compared to point cloud-derived DBH, tree height, mean CD and CBH.
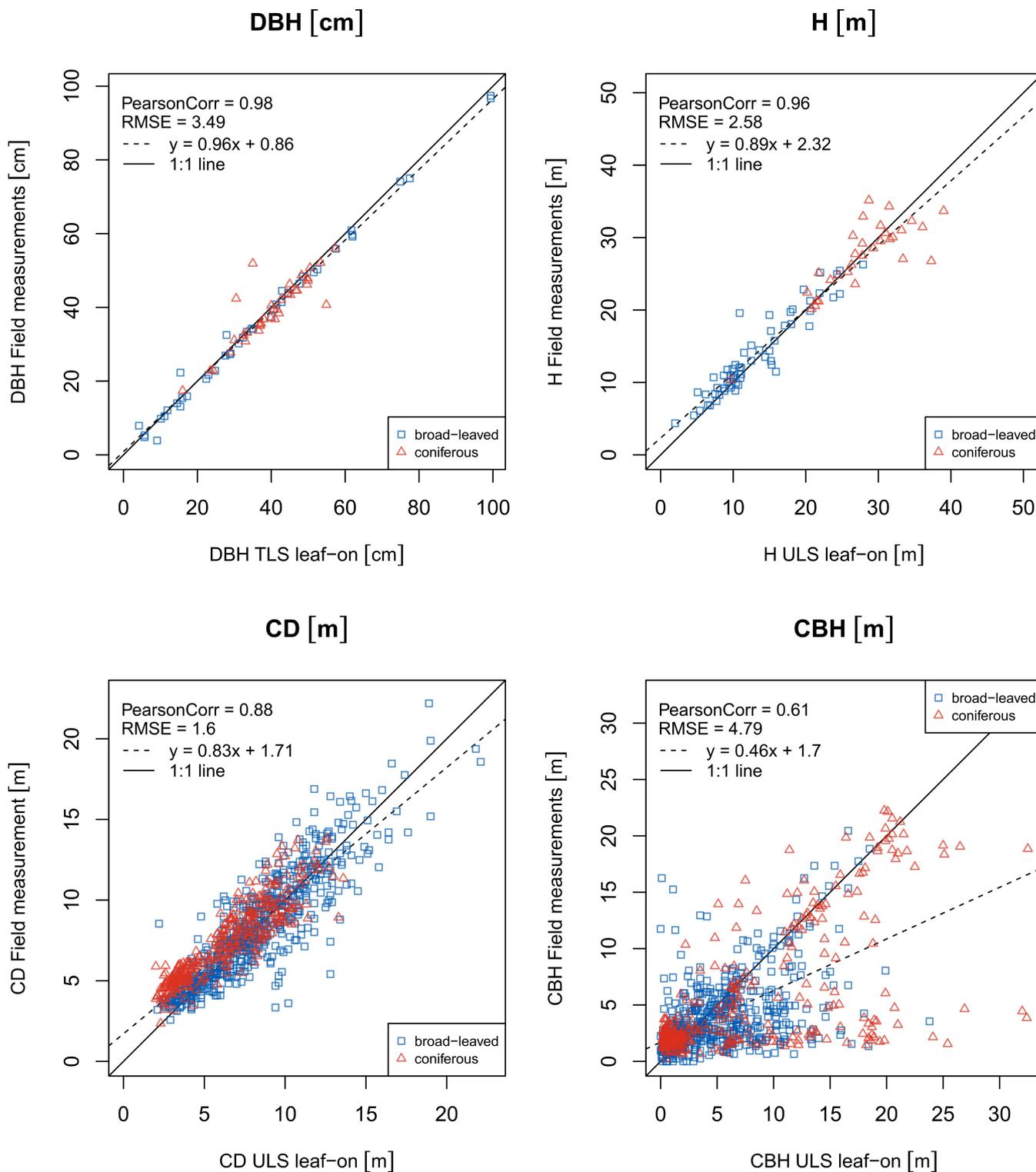
Figure 10. Scatter plots of metrics computed from tree point clouds and measured in the field. Pearson correlation, root-mean-square error and the equation of a linear model fit to the data are given. DBH = diameter at breast height, H = tree height, CD = crown diameter, CBH = crown base height.

5 Usage notes

420 There are different methods to clean point clouds prior to further processing, e.g., applying the statistical outlier removal (SOR, Rusu et al. 2008) as implemented, e.g., in the Point Cloud Library (PCL, Rusu and Cousins 2011) or in CloudCompare. When working with the TLS data, we recommend to filter the point cloud by pulse shape deviation (as defined by *RIEGL*). This deviation can give an idea of the reliability of the range measurement, so excluding points with high deviation can improve the overall quality of the point cloud (Pfennigbauer and Ullrich, 2010). We found a value of 50 to be a suitable threshold.

425 Because we define the tree position as the position of the stem at ground level, this position (in ETRS89 / UTM 32N coordinates; EPSG:25832, ellipsoidal height, GRS80) can be used to normalize the height values of the point clouds to derive heights above ground.

Point clouds can be visualized and processed using the open-source software CloudCompare, other LiDAR software like OPALS (Pfeifer et al., 2014) or LAStools (Rapidlasso GmbH, 2020), or custom code.

430 Software for the generation of tree models from TLS tree point clouds include TreeQSM (Raumonen, 2020; Raumonen et al., 2013), SimpleForest (Hackenberg et al., 2015; Hackenberg, 2021), PlantScan3D (Boudon, 2021) and AdTree(Du et al., 2019; Nan et al., 2021). These tools reconstruct the woody structure of the trees and therefore require input point clouds without leaf points. Leaves may be removed from TLS point clouds using spectral and geometric features, as proposed in multiple studies (Krishna Moorthy et al., 2020; Vicari et al., 2019; Wang et al., 2020; Yun et al., 2016; Zhou et al., 2019) and implemented in 435 different software packages (TLSeparation, Vicari 2021; LeWoS, Wang 2020). Structural tree reconstruction algorithms may also perform well on some of the ULS leaf-off point clouds, for which no leaf removal is required. Trees may furthermore be reconstructed using voxel-based approaches (Weiser et al., 2021).

To perform simulation studies with the reconstructed 3D forest scenes, e.g., to conduct sensitivity analyses, radiative transfer models such as DART (Gastellu-Etchegorry et al., 2004), librat (Calders et al., 2013; Lewis and Muller, 1993; Philip Lewis, 440 1999) or Rayspread (Widlowski et al., 2006) may be used. DART also allows to simulate LiDAR. Furthermore, there are specialized LiDAR simulators such as HELIOS++ (Winiwarter et al., 2022, 2021). The point clouds presented here can be used as scene parts for HELIOS++ after converting LAZ files to ASCII files, e.g. using LAStools:

```
las2txt -i <pointcloud.laz> -o <pointcloud.xyz> -oparse xyz
```

and using the xyzloader of HELIOS++https://github.com/3dgeo-heidelberg/helios/wiki/Scene#xyz-point-cloud-loader). Alternatively, the trees can be loaded as DetailedVoxels (https://github.com/3dgeo-heidelberg/helios/wiki/Scene#detailedvoxels), 445 e.g., after deriving voxel-based plant area density estimates using the software AMAPVox (Vincent et al. 2017; Weiser et al. 2021, https://amap-dev.cirad.fr/projects/amapvox).

Our dataset can furthermore be used as a benchmark and testing dataset for tree segmentation and species classification algorithm. It may be used to explore the differences between the point cloud measurements from different acquisition platforms and the tree and forestry metrics that can be derived from them. Our dataset can be valuable for developing and testing 450 algorithms on the retrieval of forestry parameters on the single tree or the plot level. Furthermore, open forest datasets like this can serve as reference datasets for the calibration and validation of spaceborne data products like biomass maps from satellite

images or from spaceborne LiDAR data such as the NASA's Global Ecosystem Dynamics Investigation GEDI (Dubayah et al., 2020).

6 Conclusions

455 Our dataset encompasses terrestrial and airborne laser scanning point clouds acquired from three different platforms: a static tripod, an uncrewed aerial vehicle (UAV) and an aircraft. We thus obtain georeferenced different point cloud representations of the overlapping forest areas at different resolutions and from different viewpoints. UAV-borne laser scanning (ULS) point clouds were furthermore recorded in different season, under leaf-on and leaf-off canopy condition. From the full point clouds, which are also provided within this publication, we identified and extracted individual single trees, resulting in 4205 point clouds of

460 1491 individual trees of 22 different species. Most of these trees were captured by airborne and UAV-borne laser scanning, for 249 trees, high-resolution terrestrial laser scanning point clouds are additionally available. We furthermore recorded tree measurements in the field, which we compare to and complement with point cloud derived tree metrics. This results in single tree forest inventory data with 3D point cloud representations of each tree. The full aerial point clouds, the single tree point clouds and the measured and point-cloud derived tree metrics have high reuse value for numerous applications. We identi-

465 fied the following main areas for such applications: i) Development of allometric equations between 3D tree structures and forest inventory variables, ii) application as training data for machine learning applications like tree instance segmentation, tree species classification or tree metric computation, and iii) creation of detailed tree models for LiDAR simulations or for computer rendering.

7 Code and data availability

470 Our dataset is published with PANGAEA and available under the DOI: https://doi.org/10.1594/PANGAEA.933426 (Weiser et al., 2021b). For each forest plot, one zip folder is provided, containing the forest plot point clouds with trajectory or scan position information and the single tree point clouds and measurements. Point clouds of the full airborne laser scanning acquisitions (covering around $65\,\mathrm{km}^2$ in Karlsruhe and $32\,\mathrm{km}^2$ in Bretten) and associated full-waveform data are not part of the PANGAEA dataset, but are available from the authors on reasonable request.

475 Python code used for processing the dataset is openly available on GitHub (https://github.com/3dgeo-heidelberg/syssifoss). The code uses the libraries NumPy, pandas, laspy, pykdtree, SciPy, jsonschema and Matplotlib. The scripts for georeferencing use the Python bindings of OPALS (Pfeifer et al., 2014) modules and were tested with versions 2.3.1 and 2.3.2. Please contact the authors for guidance on using the code.

Author contributions. B.H. and F.F. conceived the study, L.W., J.S., N.K. and H.W. collected and analyzed the data, F.F., J.S. and H.W.

480 drafted the manuscript. All authors reviewed the manuscript.

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