Field Plot Measurements using Mobile Laser Scanning

Knowledge Transfer and Tools 4 — Final Project Report

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Scanning plot PRF193 with the Faro Orbis.

Executive Summary

This study assessed the potential of mobile laser scanning (MLS) for use in operational field data collection (DBH and height). MLS was tested in 8 stands ranging from relatively simple single canopy layer (single-tier) conditions (a young red pine plantation) to extremely challenging conditions with multiple canopy layers (two-tier) (35+m tall white pine with a significant midstory). Two tree extraction algorithms, 3DFIN and r-lidar, were evaluated.

The main questions addressed in this study were the following:

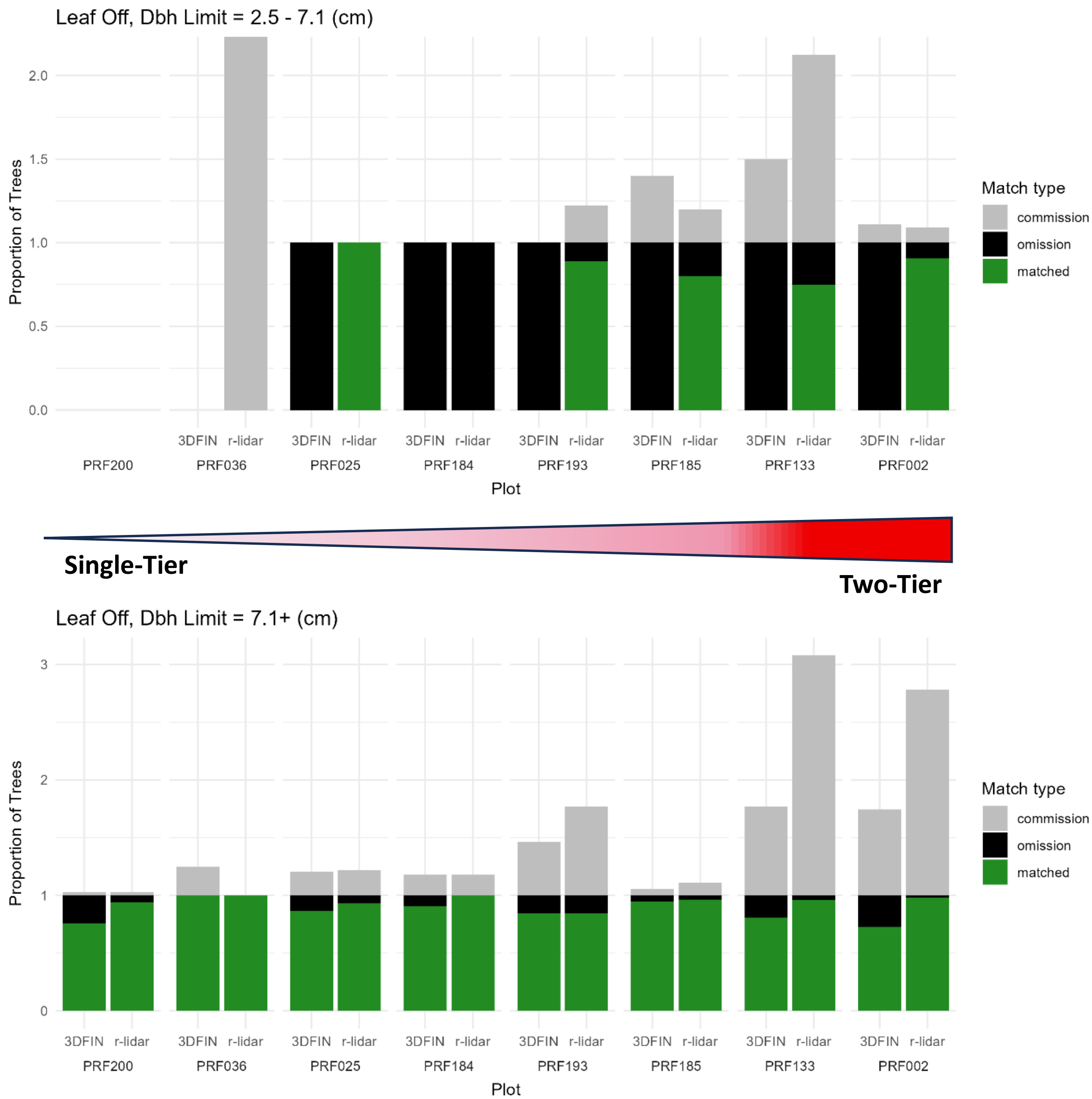
1. How well does MLS detect trees compared to a field inventory? Is tree size a factor?
2. How accurate are the extracted tree attributes?
3. What are the strengths and weaknesses of the two algorithms?
4. Are the results affected by leaf off/leaf on conditions?

1) How well does MLS detect trees compared to a field inventory? Is tree size a factor?

Tree detection and extraction is good for large trees. Detection of small trees is good but segmenting or isolating the main stem remains a challenge (specifically in clumped situations).

MLS detected most large trees (DBH ≥ 7.1 cm) and with a high level of matching (average recall or matching rate was 85%). For smaller trees (2.5 cm ≤ DBH < 7.1 cm), tree detection was also good, but the estimation of tree attributes had lower precision. For smaller trees, MLS beam divergence and stems/branches/foliage around 1.3m become limiting factors in extracting accurate estimates of DBH. **Theses small trees were detected but extracting a single stem from a cluster of saplings or from overlapping branches and foliage remains a challenge**. Frequently this led to overestimation of the DBH of small trees. This DBH overestimation for small trees led to relatively high rates of commission errors for plots with two-tiers (PRF133 and PRF002).

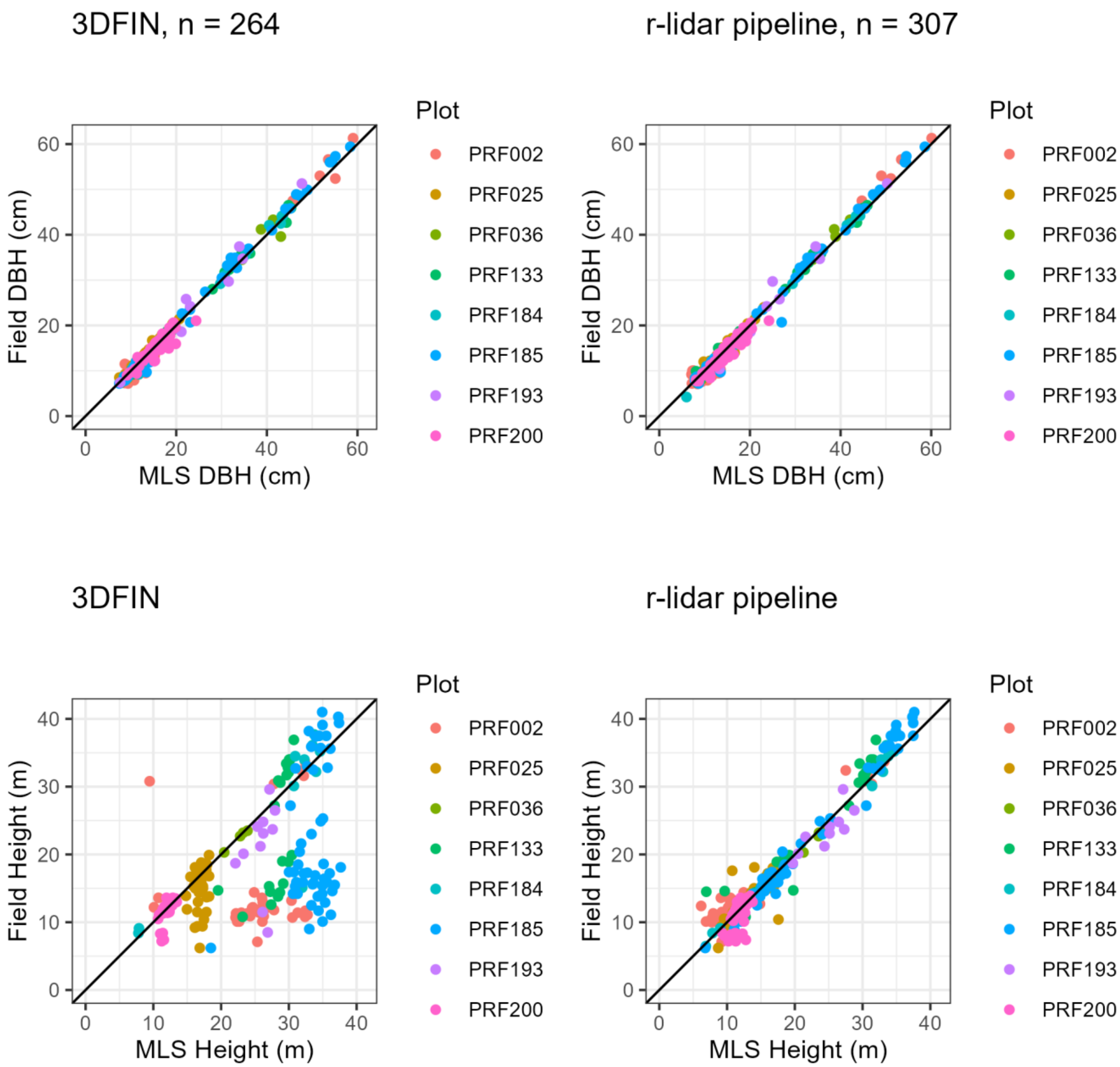
Forked trees were a challenge for MLS segmentation algorithms. For stems forked below breast height, generally only one “treeID” was extracted corresponding to both upper stems. For those cases, the DBH was extracted from the combined stems, leading to an overestimate of DBH, or for only one of the stems.



The matched, omission and commission rates are given by plot and algorithm for small trees (STP, 2.5 ≤ DBH < 7.1 cm) (upper graph) and large trees (LTP, DBH ≥ 7.1 cm) (lower graph). Matched is the proportion of field trees matched to MLS trees. Omission is the proportion of field trees not matched to MLS trees. Commission is the proportion of MLS trees not matched to field trees. Note the y-axis have different limits for small and large trees. The plots on the left (PRF200, PRF036, PRF025) are single-tiered. The middle plots (PRF184 and PRF193) have an understory. The plots on the right (PRF184, PRF133 and PRF002) have a midstory.

2) How accurate are the extracted tree attributes?

For matched trees, DBH estimates were within acceptable operational ranges for both algorithms. For height, 3DFIN consistently overestimated heights of understory and mid-canopy trees. The height estimates from r-lidar were within acceptable operational ranges and possibly superior to field estimates for tall trees.



For the matched trees, the field DBH and height are compared to the MLS extracted DBH and height. The DBH estimates from both algorithms were very good for the matched trees. The r-lidar heights were relatively accurate and precise while 3DFIN significantly overestimated the heights of understory trees.

3) What are the strengths and weaknesses of the two algorithms?

Both r-lidar and 3DFIN were good at extracting large trees (DBH $\geq$ 7.1 cm) with single main stems.

The main limitations for both algorithms were associated with small trees (DBH <7.1 cm). These trees were generally detected but individual stems were not always isolated/segmented correctly, especially in dense understories with trees in clumps, with branches and foliage near breast height. These conditions and current sensor limitations made it difficult to extract individual stems and estimate DBH. This would often lead to an overestimate of DBH and a commission error.

The main differences between the algorithms are the following:

- The height estimation in r-lidar works well in single and two-tier conditions. The height estimation algorithm in 3DFIN is limited to single story or very open conditions.
- 3DFIN is poor at isolating individual tree crowns. R-lidar does well at extracting individual tree stems through to its crown.
- R-lidar's Quantitative Structural Model (QSM) extraction shows great promise in extracting complete stems (for taper assessment) as well as segmenting branch and foliage components.

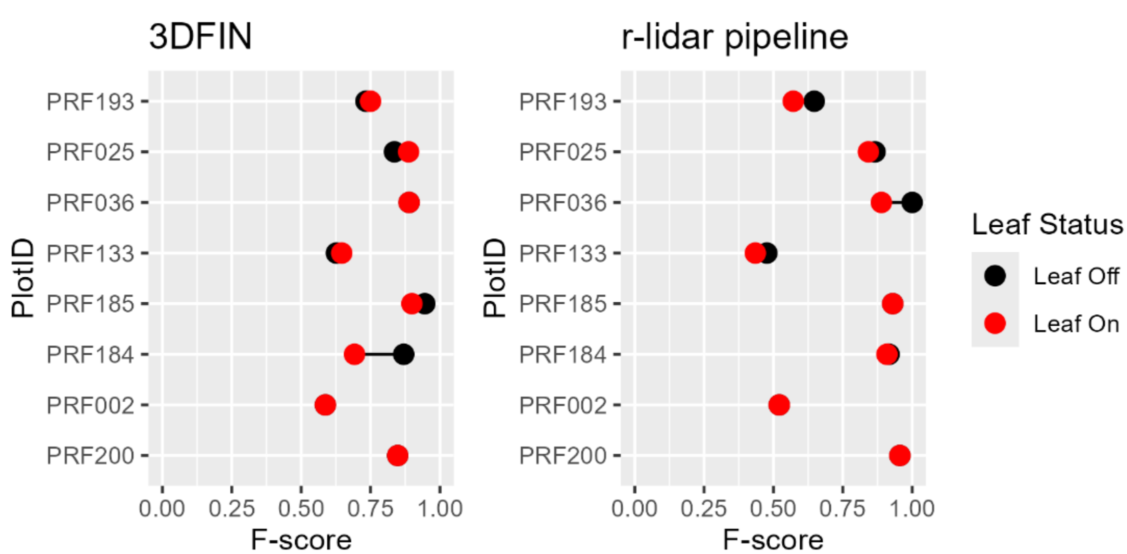
Development is ongoing for both algorithms. R-lidar is not yet publicly available but will likely be released as open source in the coming year.

Attribute	3DFIN	R-lidar pipeline
Tree detection and segmentation Large trees (DBH ≥ 7.1 cm)	• Excellent detection • Segmentation issues with forked trees	• Excellent detection • Segmentation issues with forked trees
Tree detection and segmentation Small trees (2.5 ≤ DBH < 7.1 cm	• Moderate detection • Less successful segmentation/isolation of main stem (leading to overestimation of DBH, commission error) with clumped trees • Poor segmentation/isolation of individual tree crowns associated with lower tree base.	• Good detection • Less successful segmentation/isolation of main stem (leading to overestimation of DBH, commission error) with clumped trees. • Good isolation of individual tree crowns associated with lower tree base
Assessing DBH Large trees (DBH ≥ 7.1 cm)	• Excellent	• Excellent
Assessing DBH Small trees (2.5 ≤ DBH < 7.1 cm	• Poor • Overestimation of DBH in tree clumps, overlapping branches	• Poor to good for single small tree stems • Overestimation of DBH in tree clumps, overlapping branches
Height	• Good in single-tier conditions • Poor for understory in two-tier conditions	• Good in all conditions, possibly better than field crews for tall trees

Attribute	3DFIN	R-lidar pipeline
Stem mapping	• Good for large trees. • Issues with single stem extraction for small trees in clumped conditions	• Good for large trees. • Issues with single stem extraction for small trees in clumped conditions
Additional outputs	• Easily provides diameters for user-specified intervals up the tree stem	• Partitions point cloud into wood/foliage • Extracts main stem, branches and foliage. • High potential for taper and biomass estimates through Quantitative Structure Models
User-required modeling Inputs	• Default parameters provided in GUI • Large list of parameters provided for local adjustment	• Runs in R • Robust default parameters provided • Possible to adjust a suggested set of parameters for local conditions
Active development	• Ongoing development	• Rapid development including use of PRF plots as well as an extensive hardwood dataset from Quebec.
Availability	• Open source	• Beta-release • Open source likely within a year

4) Are the results affected by leaf off/leaf on conditions?

Leaf-on versus leaf-off conditions had a limited impact in this dataset.



The effect of leaves on the F-scores was relatively minor. The plots are ordered from higher hardwood content at the top to pure conifer on the bottom (PRF200 and PRF002).

Summary

The results and continued rapid evolution of MLS technology and supporting tree attribute extraction software algorithms are highly promising. MLS can map, extract and "measure" large trees (≥ 7.1 cm) for DBH and height more quickly and efficiently than traditional field measurement. Stem mapping and heights are likely more accurate than traditional field measurements. In addition, MLS offers the capability to derive detailed structural attributes, including stem taper and estimates of branch volume. The main current limitations are small trees, species identification and tree numbering/identification. The extraction of small trees is limited by both current sensor beam divergence and software. Both continue to be an area of active research and improvement. Species identification continues to be a challenge. At least for the short term, trained field crews will be required to identify species. However, using artificial intelligence for species identification is an area of intense research. Identifying tree numbering was not a main focus of this project but the results show promise for a solution in the short term.

Project team and partners at Petawawa Research Forest.

1 Abstract

A study was initiated to better understand the role that a state-of-the-art mobile laser scanner (MLS) may have in enabling more efficient forest plot data collection and attribute extraction using open-source software. The study, conducted in the Great Lakes–St. Lawrence Forest region at the Petawawa Research Forest, scanned eight plots representing a range of forest types and varying overstory and understory conditions in leaf on and leaf off conditions. The project benefited greatly from the active participation of its partners.

The number of open-source software packages for processing both mobile and terrestrial lidar data continues to grow rapidly. This project focused on two software packages: 3DFIN and a developing r-lidar pipeline (beta, planned to be released as open-source). Both packages enabled rapid processing of dense point clouds. The developing r-lidar pipeline also incorporated several novel processing enhancements and produced additional outputs.

When field plot measurements were compared with MLS-derived plot summaries, both software packages showed strong DBH correlations for trees that were spatially matched. For height comparisons, 3DFIN consistently overestimated smaller tree heights in multi-tiered stand structures. In single-tier stands, both software systems performed well for the spatially matched trees. Large trees (i.e., ≥ 7.1 cm DBH) were generally well matched, whereas small trees (i.e., 2.5 cm ≤ DBH < 7.1 cm), due to sensor limitations and current algorithmic approaches, were not always segmented reliably. For some stand conditions, small MLS trees were incorrectly segmented as clustered groups and extracted as a single tree with a large DBH leading to high commission errors for large trees (e.g., PRF002). Generally, omission rates were low for large trees. Matching rates for small trees were generally poor.

MLS-based species assignment and tree number identification remain active areas of study. This project did identify an opportunity to use the return intensity to help interpret large spray-painted numbers on certain tree species and sizes. Very recent work in Europe and Finland has also reported promising results using deep learning approaches for species prediction from MLS-scanned tree data.

The use of MLS technology for field plot assessment is nearing operational use. Consistent extraction of large tree stem position, DBH and heights can be achieved in the stand structures studied. Small trees remain a challenge and although their contribution to total plot biomass is low, the accounting of their presence and diameter and height are important for field plot assessments.

2 Acknowledgements

The project co-leads gratefully acknowledge the contribution of the partners involved in this study. Thank you to Dr Bastien Vandendaele (formerly with the Northern Hardwoods Research Institute and now with the Canadian Forest Service) for his commitment, knowledge, experience and enthusiasm in advancing this project with its co-leads. Thanks to Jean-Romain Rousell (R-Lidar.com) for his ingenuity in developing software processing tools for projects such as this. Thanks to Dr Richard Fournier and his students, Amélie Juckler (PhD candidate) and Nicolas Paquet from the Université de Sherbrooke, for their input, guidance and contribution to scanning of the field plots. Thank you to Brian Lake from Point Cloud Solutions who provided the use of the Faro Orbis sensor and his processing expertise for all our acquisitions. Thank you to Ben Gwilliam and John Pineau from the Ontario Woodlot Association for their contribution of acquiring and processing drone imagery for the study plots. Thanks also to the Ontario Ministry of Natural Resources and Forestry Growth and Yield program for field measurement suggestions and interest in the project. Thank you to Peter Arbor and co-op students from Algonquin College, Tanner Dwyer and Maggie Nowicka for their contribution in scanning plots. Special thanks are warranted for the staff of the Petawawa Research Forest (Jeff Fera, Jessalyn Morin and summer staff) for their ongoing willingness to assist in research studies such as these. Finally, we would like to acknowledge the financial support of the Forestry Futures Trust in this project.

3 Introduction

The forest sector, both industry and government, is having difficulty finding and retaining trained, competent field staff for field plot measurement due, in part, to the seasonal and remote nature of this work. The high rate of worker turnover results in new and inexperienced staff gathering data each season, lower quality of the collected data and a slow pace of work. Even with experienced crews, the manual collection of this type of forest inventory data is time-consuming and therefore very expensive. Remeasurement of the provincial growth and yield permanent field plots (PSP – permanent sample plot, PGP – permanent growth plot) is well below targets, and field sampling (VSN – vegetation sampling network) for the T2 round of inventories struggled due to the cost and unavailability of field crews. There is a need to find alternative solutions to increase the capacity to measure forest plots and still meet data-quality requirements within budgets.

The recent development of mobile Lidar scanning (MLS) technology, a hand-held alternative to the more familiar airborne Lidar, has created an opportunity for the forestry community to address these challenges. This project was initiated to test MLS under a variety of forest conditions and compare the results to traditional field surveys.

4 Materials

4.1 Study site

The Petawawa Research Forest (PRF), covering approximately 10,000 hectares, is located in Ontario, Canada, about two hours (180 km) northwest of Ottawa (Figure 1). It lies within the mixedwood zone of the Great Lakes–St. Lawrence (GLSL) Forest region, where commonly found species include white pine (*Pinus strobus* L.), trembling aspen (*Populus tremuloides* Michx.), red oak (*Quercus rubra* L.), red pine (*Pinus resinosa* Ait.), white birch (*Betula papyrifera*), red maple (Acer rubrum), sugar maple, (*Acer saccharum*.), and white spruce (*Picea glauca*), among others (Wetzel et al. 2011). The GLSL serves as an ecological transition zone between the conifer-dominated boreal forests to the north and the deciduous-rich forests to the south. The PRF's tree species diversity, along with a long-standing history of silvicultural interventions, contributes to its structural complexity. The forest is actively managed by the Canadian Forest Service.

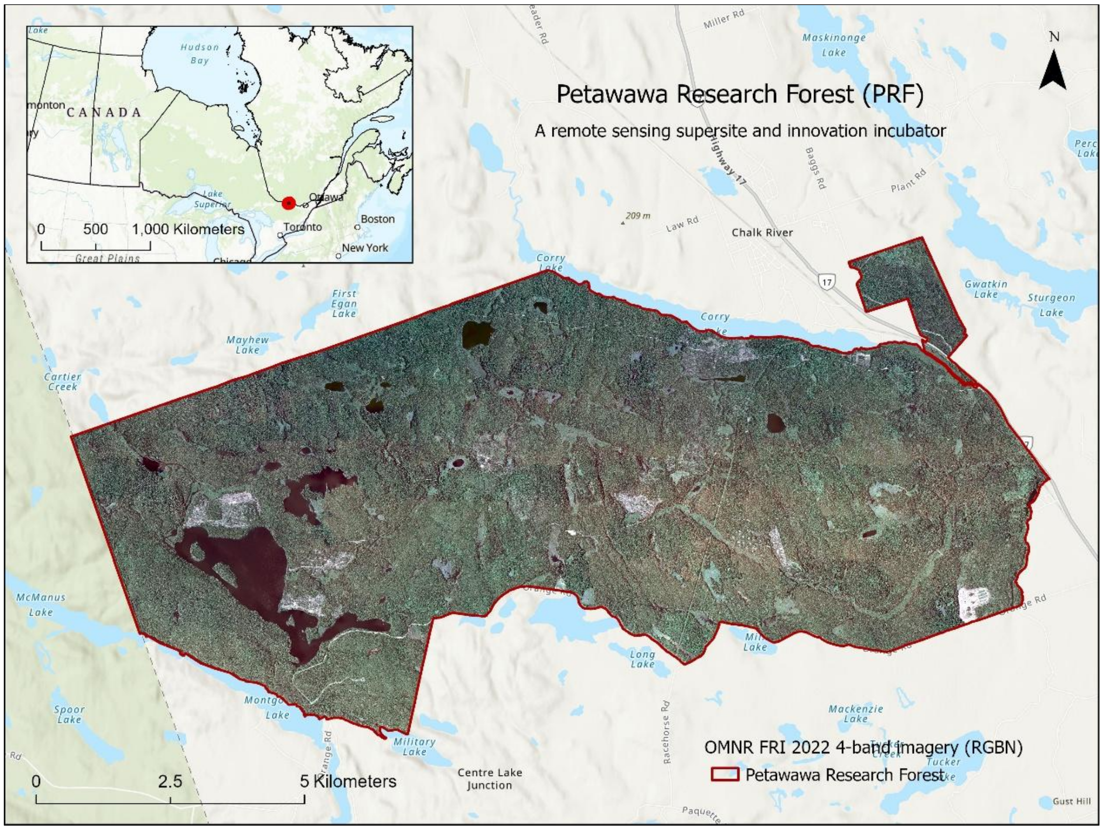


Figure 1 Location of Petawawa Research Forest in Ontario, Canada (© NFIS).

4.2 Field Inventory

A range of forest types and overstory and understory structural conditions were targeted for MLS to provide an understanding of how these varied conditions may potentially impact the acquired point cloud data and results of tree and plot level attribute (DBH, height, stem location, etc.) extraction. Eight plots were selected from an existing Airborne Lidar Scanning (ALS) calibration plots ($625m^2$) network and an inner $400m^2$ plot was measured and scanned for this study. Table 1 presents the sampling frame, and the associated plot numbers. The silvicultural history[1] of the plots as well as current images of their state are presented in Table 2. Their locations within the PRF are presented in Figure 2.

Table 1. Sampling framework with assigned field plot numbers.

	Overstory			
Forest Type	**Dense**	**Open**		
Natural Conifer	PRF185	PRF184	**Sparse**	**Understory**
		PRF002	**Dense**	
Planted Conifer	PRF200		**Sparse**	
		PRF133	**Dense**	
Natural Hardwood	PRF025	PRF036	**Sparse**	
		PRF193	**Dense**	

[1] Based on available records

Table 2. Current plot images and their silvicultural history.

Plot	Silvicultural Treatment History	Image
PRF200	• planted red pine (2002)	
PRF036	• uniform shelterwood – seeding cut (2016)	
PRF025	• clear cut / fire (1974)	
PRF184	• uniform shelterwood – seeding cut (2015) • mechanical site preparation (2016) • chemical tending (2023)	
PRF193	• uniform shelterwood – first removal (2019)	
PRF185	• natural stand	
PRF133	• planted red pine at 1.5m x 1.5m (1935) • thinned “Heavily” (~40%) (1941) • partial (30%) harvest (1993) • thinned (1999) • thinned (2011)	
PRF002	• uniform shelterwood – seeding cut (1994)	

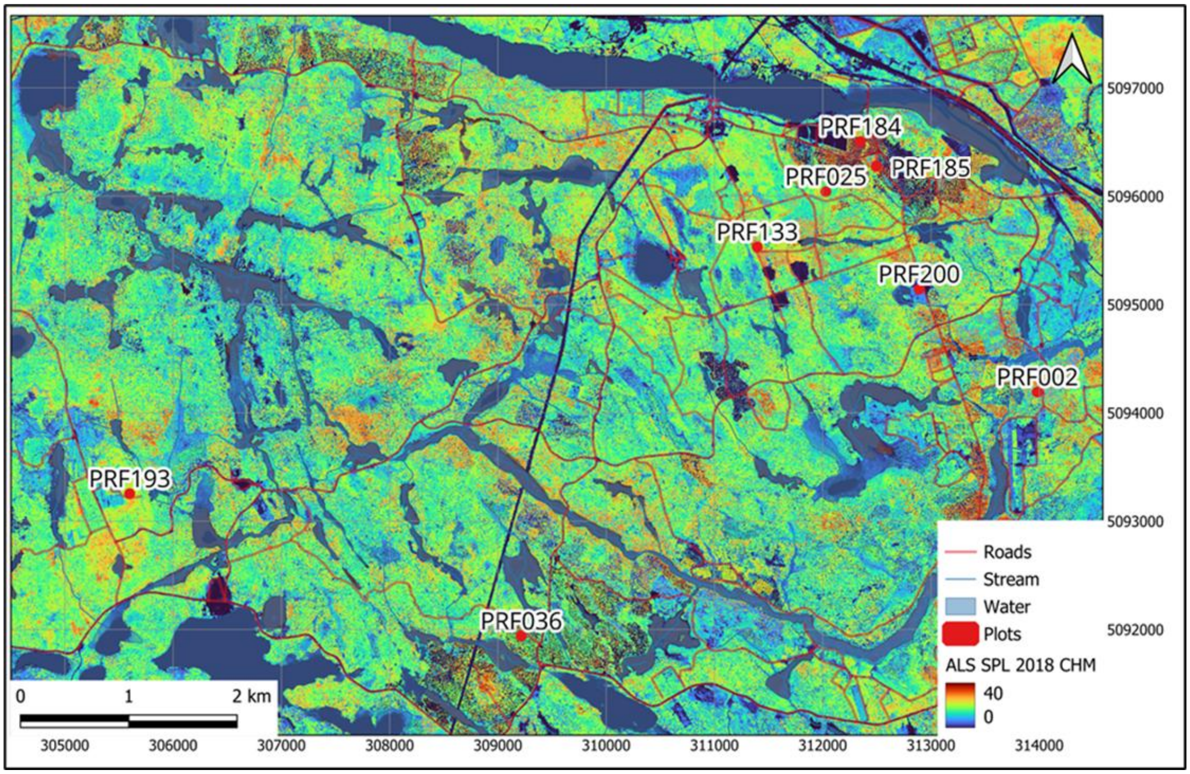


Figure 2. Location of the study area with the 8 sample plots (11.28 m radius). Figure was created using QGIS version 3.34.3. Background raster is of the 2022 airborne lidar canopy height model (CHM) in metres.

4.3 Plot Design

A nested plot design was used for field measurement efficiency (Figure 3). The large tree plot (LTP) (radius of 11.28 m – 400 m^2) was used to measure trees with DBH (diameter at breast height) $\geq$ 7.1 cm. A small tree plot (STP) (radius of 3.99 m – 50 m^2) was used to measure trees 2.5 cm $\leq$ DBH < 7.1 cm. The centre plot post had been GPS-located with a TOPCON GNSS system[2] and later post processed to sub-metre accuracy.

Field plots were measured between May 6 – 9, 2024. Deciduous leaves had just started to emerge. Within each LTP, all live and dead trees $\geq$ 7.1 cm were assessed for: species, status (dead or alive), DBH (cm), and total height (m). A calibrated TruePulse 360 Rangefinder[3] equipped with a vegetation filter was used to determine both distance and azimuth to each tree within the 11.28m radius plot.

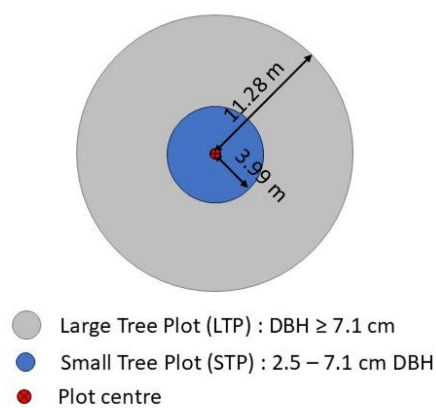


Figure 3. Plot design

[2] GPS and GNSS receivers, bases and rovers for positioning applications
[3] TruePulse® 360i Laser Rangefinder | Laser Tech

A wooden dowel rod cut to 1.3m was used to ensure the DBH measurement was taken at the appropriate height (ground measured from highest point of the ground around the tree stem). Diameter measurement height was adjusted upwards (and recorded) for situations where 1.3m occurred on a stem whorl or other stem deformity. Adjustments to the diameter measurements were made during compilation steps using a taper model to account for any diameters being measured above 1.3m. A Haglöf Vertex IV[4] was used for measuring the total height for each live tree. In the STP, all live trees 2.5 cm ≤ DBH < 7.1 cm were assessed for species, DBH and total height.

Tree data was summarized for "All Trees" (≥ 2.5 cm) and "Large Trees" (≥7.1 cm) (Table 3). Attributes summarized include stems/ha, mean DBH (cm), mean height (m), basal area (BA) (m^2 ha^{-1}). Additional information for each field plot is given in fact sheet format in Appendix A.

Table 3. Compiled plot statistics.

Plot	Forest Type	Stems (plot)	Mean DBH (cm)	Mean Height (m)	Basal Area (m^2 ha^{-1})	Stems (plot)	Mean DBH (cm)	Mean Height (m)	Basal Area (m^2 ha^{-1})
		"All Trees" - Trees 2.5 cm and larger				"Large Trees" - Trees 7.1 cm and larger			
PRF002	Pw/Pr	105	8.6	9.6	52.1	51	13.4	13.4	36.3
PRF025	Or	62	12.8	14.8	22.3	59	13.2	15.3	21.8
PRF036	Or	4	39.7	22.4	12.4	4	39.7	22.4	12.4
PRF133	Pr Plant	34	18.0	18.4	36.7	26	22.2	21.7	34.2
PRF184	Pw/Pr	18	18.9	18.0	23.4	11	28.5	25.6	21.8
PRF185	Pw/Pr	60	21.4	21.1	86.1	55	22.9	22.4	84.1
PRF193	Tol Hwd	22	15.0	13.9	19.1	13	23.1	20.2	17.4
PRF200	Pr Plant	103	14.9	12.0	47.0	103	14.9	12.0	47.0
Forest Type: Pw/Pr = White & Red Pine, Or = Red Oak, Pr Plant = Red Pine Plantation, Tol Hwd = Tolerant Harwood									

4.4 Mobile Laser Scanning (MLS)

The MLS data were collected during leaf-off condition from May 13 – 17, 2024 and leaf-on condition from July 8 – 10, 2024 using the FARO Orbis (FARO Technologies, Inc., Lake Mary, Florida, USA), which is a handheld device that includes a HESAI XT32 lidar sensor (Hesai Technology Co., Ltd., Shanghai, China), a data logger and an inertial measurement unit (IMU). The lidar has 32 channels and can capture up to 640,000 points s^{-1}, with a maximum range of 120 m and beam divergence of 3.14 mradians (0.18°). This results in a laser beam footprint of 3.14 cm in diameter at a distance of 10 m. The system records distances with a continuous wavelength of 905 nm and a lidar accuracy of 5 mm in mobile mode. The FARO Orbis uses Simultaneous Localization And Mapping (SLAM) technology to generate a 3D point cloud without requiring artificial reference targets or tripods. It uses lidar and IMU data for real-time mapping and generates a coherent map of its surroundings. Loop closure, or using the same point for start and finish, is recommended to update real-time mapping and reduce potential drifts that are associated with the SLAM algorithm.

[4] Vertex IV 1 0 eng rev3

Leaf-off and leaf-on scanning were conducted to better understand the potential limitations that foliage may have on range and tree attribute extraction. Most inventory field work is carried out in summer months when leaves have fully emerged. In this study, the leaves had started to emerge during the May leaf-off scan.

MLS data were acquired following a standardized protocol developed by the University of Liège (Figure 4). The scanning was performed by two operators: one guiding the trajectory, the other managing the device. The acquisition followed a three-part trajectory:

- Inner loop: a short central loop with four Stop-and-Go positions at cardinal ground control points (8 m radius).
- Petal pattern: a four-lobed scanning path covering the outer plot area up to 15 m from the center.
- Perimeter loop: a continuous 15 m circular path, ending at the center for scanner deactivation.

This pattern ensures consistent coverage and reduces occlusion for plot-level forest inventory.

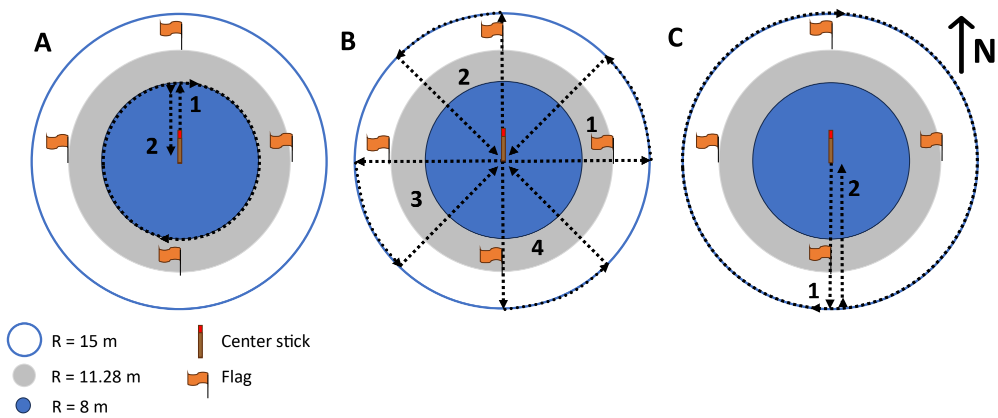


Figure 4. MLS acquisition walking pattern at the plot level starting with the inner loop (A), then the petal pattern (B) and ending with the perimeter loop (C).

5 Partnerships

5.1 Additional MLS and Terrestrial Lidar Scanning (TLS)

In conjunction with the Université de Sherbrooke, additional MLS scanning was conducted with the GeoSLAM ZEB-Horizon scanner (GeoSLAM ZEB Horizon RT Mobile Scanner | Hardware | FARO) and the FARO Focus TLS system (FARO Focus Laser Scanning Solution | Hardware | FARO) in support of student PhD programs. The MLS scanning with the Horizon followed the same acquisition walking pattern as the Faro ORBIS. The FARO Focus TLS system used a traditional stationary scan system from a minimum of 5 positions to reduce occlusion in the final scan product.

The data from the GeoSLAM ZEB-Horizon and the Faro Focus were not used here but will be used by students of Université de Sherbrooke for related and other potential future products. They will also have access to the field data collected as part of this project.

5.2 Airborne Laser Scanning (ALS) Data

The Ontario Ministry of Natural Resources and Forestry has deployed single photon lidar (SPL) technology for their provincial enhanced forest inventory (> 30 pts/m²). ALS data for PRF is available in open source here: https://opendata.nfis.org/mapserver/PRF.html . The Leica SPL100 sensor was flown aboard a Piper-PA-31-350 at an average altitude of 3760 m. Table 4 provides additional information regarding the acquisition parameters. The 2022 ALS point cloud data were later utilized in the alignment and georeferencing of the MLS datasets.

Table 4. 2022 ALS acquisition specifications for PRF.

Parameter	
Acquisition date	Summer 2022
Sensor	Leica SPL100
Laser wavelength (mm)	532
Laser beam divergence (mrad)	0.008
Average flying altitude (m AGL)	3760
Average flying speed (knots)	<180
Pulse repetition frequency (kHz)	60
Scan angle (degrees)	± 15
Swath width (m)	2000
Aggregate Nominal Pulse density (pulses/m^2)	32.4

5.3 Unmanned Aerial Vehicle (UAV) Data

The Ontario Woodlot Association (OWA), a project partner, provided UAV imagery and image point cloud data for each of the eight plots. A DJI Mavic 3E drone was used to acquire nadir and off-nadir (45°) imagery at an altitude of 100m AGL for each plot. An RTK module attached to the drone gave enhanced GNSS capabilities for precise positioning and all data were Post Processed Kinematic (PPK) in Emlid Studio[5] with data recorded from a stationary base station over a known point. The imagery was acquired May 16th, 2024, and subsequently processed in Agisoft Metashape Professional 2.1.1 [6] and ArcGIS Pro 3.3.0[7]. All point cloud and orthophotography data are projected in NAD 1983 CSRS UTM Zone 18N (EPSG: 2959) with a vertical CRS CGVD2013 height (EPSG: 6647). Photogrammetric point clouds were used as a visual reference to assess the ability of the MLS system to capture the canopy top.

6 Methods

6.1 Georeferencing MLS Point clouds

For each plot, a 40 m radius subset of the 2022 ALS point cloud was first clipped around the GNSS-derived plot center and used as a spatial reference. The corresponding raw MLS scan (for both the leaf-off and leaf-on datasets), which lacked precise georeferencing due to GNSS limitations under canopy, was co-

[5] Emlid Studio Land Survey Data Collection Software | Emlid

[6] https://www.agisoft.com/

[7] Desktop GIS Software | Mapping Analytics | ArcGIS Pro

registered directly and automatically to this ALS subset. Both datasets were first centered by translating their centroids to the origin to establish a common local coordinate system. A structured multi-step alignment pipeline was then applied using the *lidRalignment*[8] R package: (1) subsampling and clipping to reduce noise and focus on the core plot area; (2) generation of DTMs and canopy height models (CHMs) for both datasets; (3) coarse alignment via brute-force search over 2D translation and rotation parameters, optimizing a similarity metric based on CHM or DTM features; and (4) fine alignment using trimmed Iterative Closest Point (ICP), which iteratively minimized point-to-point distances between surfaces. A final vertical shift was applied to match ground elevation levels (refer to Figure 5). All transformation matrices were recorded per plot, allowing consistent downstream integration of MLS and ALS data in a unified spatial reference.

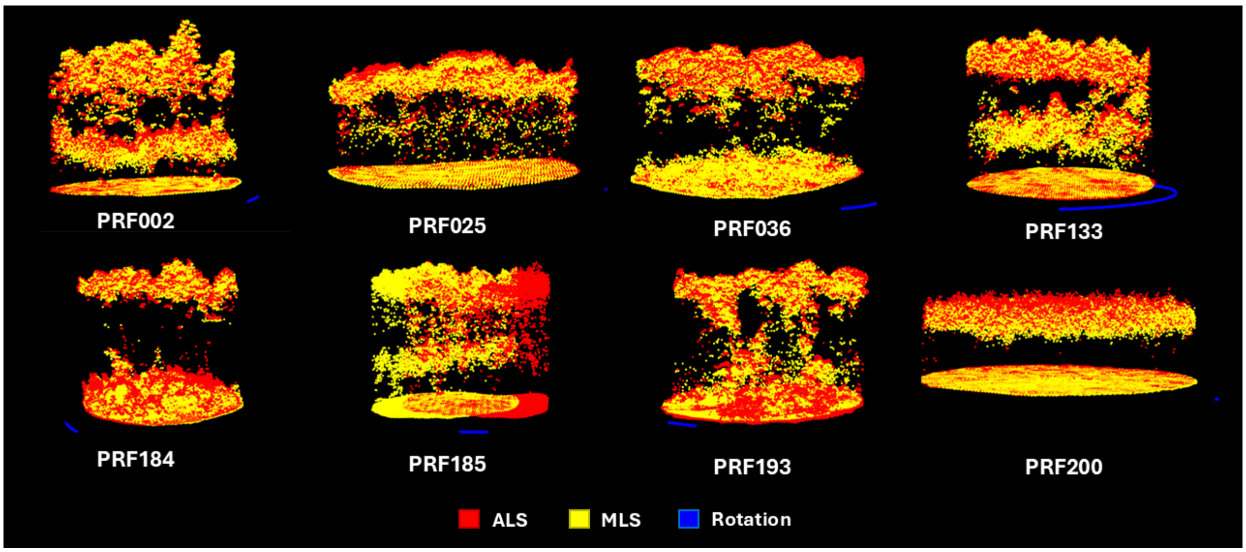


Figure 5. Illustration of the automatic georeferencing and co-registration of MLS data on ALS data (red: ALS; yellow: MLS; blue: rotation applied to the MLS data during the matching process).

6.2 Processing (Open-Source Software)

A key focus of this project was to evaluate open-source software currently easily available to extract tree level information (heights and diameters). While there exists a growing list of software packages (Murtiyoso et al. 2024), two rose to the top following some initial testing based on speed of processing the large point cloud datasets and flexibility in parameter adjustment (if necessary). The two packages evaluated were a beta R package, "**r-lidar**" (version 0.8.1.9), currently under development from r-lidar consulting[9] and **3DFIN**[10] (implemented within CloudCompare[11]).

6.2.1 r-lidar (beta)

r-lidar is a beta R package currently under development for processing forest TLS and MLS point clouds. At the time of writing, the package is not yet publicly available, but the full codebase is already

[8] r-lidar/lidRalignment: ALS MLS and TLS forest plot alignment
[9] r-lidar | consulting & development
[10] GitHub - 3DFin/3DFin: 3D Forest INventory
[11] CloudCompare - Open Source project

implemented on GitHub and maintained in a private repository. The pipeline is extensively documented, including a tutorial-style online manual with ready-to-use, copy-paste R code, similar in spirit to the lidR package. A public release is expected within the coming year. This project provided data in support of this effort and was a “super-tester” of the developed algorithms.

The r-lidar package allows “pipelines” of functions to be linked to process plot MLS point clouds from raw datasets through to individual segmented tree LAS point clouds, and tabular tree by tree summary attributes. Although it is possible to edit the r-lidar software parameters, the default parameters generally provide acceptable outputs. This lack of needing to test and adjust parameters for the multiple processing steps of r-lidar is an operational adoption advantage for the forestry community. In fact, in this report, all plots were processed using the same parameter set.

The r-lidar processing workflow is summarized below and illustrated in Figure 6.

1. Clip the raw geo-referenced point cloud to a 15m radius
2. Decimate the point cloud to a 25% retention level using a custom r-lidar pipeline hybrid-homogenization of points to maintain a more consistent distribution of returns from top to bottom of the tree. This approach applies a Barycentric Voxel Decimation (BVD) that retains the point closest to the barycenter of the points within each voxel. For each voxel, the point where the local density is highest is retained, thereby reducing noise in the point cloud. The result is a more homogenized point cloud. The final step is to re-inject a random subset of points (10%) previously discarded by the BVD to restore some potential local density lost.
3. Classify the point cloud into ground and vegetation returns
4. Generate a ground digital terrain model and compute the height above ground (HAG) for each point
5. Segment wood from foliage point cloud returns
6. Identify stem location seeds from woody points
7. Segment individual trees
8. Calculate individual tree spatial location
9. Calculate DBHs from an extracted 10cm slice of woody returns centred around 1.3m. First, 200 iterations of circle fits were conducted to subsets of the sliced point cloud data using a RANSAC (Random Sample Consensus) modeling approach. If a well-defined circle was not extracted, a diameter for breast height was extracted for the tree using a QSM (Quantitative Structure Model) approach.
10. Calculate heights as the maximum HAG for the segmented tree. DBH and heights.

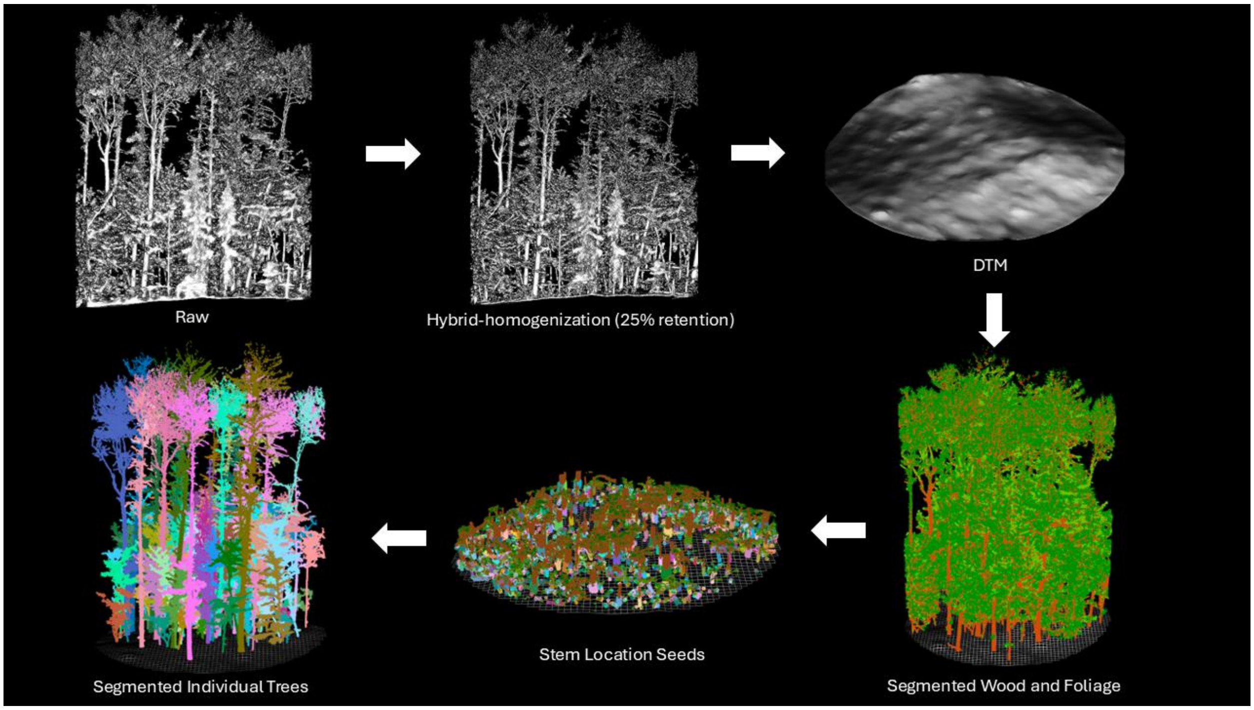


Figure 6. Generalization of processing steps for r-lidar pipeline processing

6.2.2 3DFIN

3DFIN is a user-friendly and open-source software designed for automatic 3D forest inventory using ground-based point clouds. The workflow follows a tree-centric, stem-driven approach focused on trunk detection and modelling (DBH and taper in the lower stem), with tree height derived from the detected structure rather than from fine-scale point-level canopy segmentation (Laino et al., 2024). The program is cross-platform and available as a plugin in CloudCompare and QGIS as well as a standalone software in Windows. In this report, the Python version (v0.6.0) was used within CloudCompare to facilitate visualization of inputs and outputs.

Similar to r-lidar, 3DFIN includes reasonable default parameter settings. For our analysis, we made two minor adjustments: the minimum diameter threshold was set to 0.25 m, and the DTM was generated using a 0.1 m raster resolution to match the settings used in r-lidar. To provide further consistency, the hybrid-homogenized point cloud to a 25% retention level used in r-lidar (step 2 of r-lidar processing) was also used for 3DFIN. The point cloud also had HAG calculated for each return.

The 3DFin processing workflow is summarized below and illustrated in Figure 7.

1. Clip the raw geo-referenced point cloud to a 15 m radius
2. Decimate the point cloud to a 25% retention level using a custom r-lidar pipeline hybrid-homogenization function
3. Calculate tree location “Stripes”
4. Segment individual trees
5. Calculate Section diameters
6. Calculate individual tree spatial location, DBH and heights.

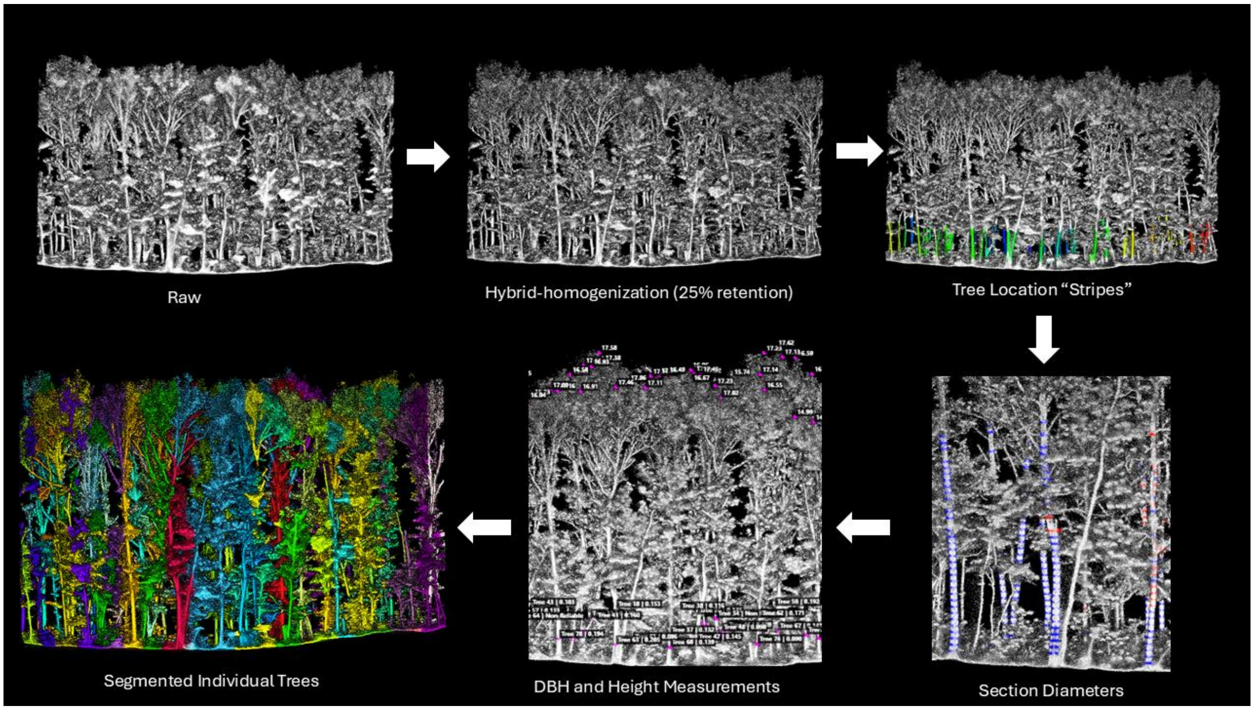


Figure 7. Generalized 3DFIN processing flow.

6.3 Tree matching

Field trees were matched to MLS-detected trees using the *TreeMatching*[12] R package (Figure 8), based on spatial proximity and similarity in tree attributes. Matching relies on minimizing a combined cost function that accounts for horizontal distance between stems (x,y) and differences in a reference attribute (z), where z corresponds to DBH for large trees and height for small trees.

Trees from the Large Tree Plot (LTP) and Small Tree Plot (STP) were matched separately to reflect their different DBH ranges and plot extents. On the LTP, both field and MLS trees were filtered to retain only trees with DBH ≥ 7.1 cm and height ≥ 6.0 m. The field plot radius was 11.28 m, while a slightly larger radius (11.58 m) was used for MLS to account for potential errors in field stem mapping, which may result in additional MLS detections.

For the LTP, the maximum allowed horizontal distance between matched trees (dxymax) was set to 2 m. The maximum allowed relative difference in z (dzmax) was set to 40% of the reference attribute (DBH for LTP). Horizontal distance and z differences were given equal weight (zrel = 50%) in the matching cost function, and the cost of leaving a tree unmatched was automatically determined by the algorithm.

The same matching strategy and parameters were applied to the STP, except that z was defined as tree height rather than DBH. Trees were included if 2.5 cm ≤ DBH < 7.1 cm and a minimum height of 2.0 m.

[12] Matching of Individual Trees in Forest Plot Inventories • TreeMatching

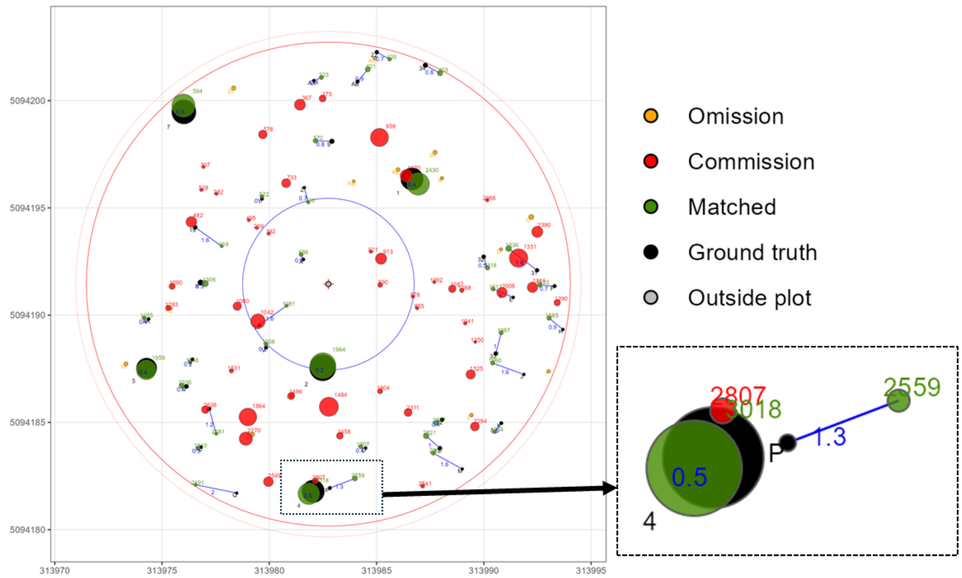


Figure 8. Field tree 4 (black) was matched to MLS tree 3018 (green) because they were close physically and in terms of DBH. Field tree P (black) is close to MLS tree 2807 (red) physically but the DBH difference was greater than 40% so they were not considered a match and it was matched with 2559 (green). The blue text represents the cost function score.

6.4 MLS assessment

The MLS-detected trees were evaluated in terms of tree detection and estimation of tree attributes.

6.4.1 Tree detection

Tree detection was evaluated in terms of how well field trees were matched to MLS trees. True positives (TP) are field trees matched with MLS trees. True negatives (TN) or omission trees are field trees with no MLS tree match. False positives (FP) or commission trees are MLS detected trees with no field tree match. False negatives (FN) are trees not measured in the field and not detected by MLS – effectively always zero.

The recall (also called matching rate), precision and F-score (Chen et al 2020), are

$$recall = \frac{TP}{TP + TN}$$

$$precision = \frac{TP}{TP + FP}$$

$$\text{F-score} = 2 \text{ x } \frac{precision \text{ x } recall}{precision + recall}$$

The omission rate is

$$\frac{TN}{TP + TN} = 1 - recall$$

The commission rate is

$$\frac{FP}{TP + FP} = 1 - precision$$

6.4.2 Tree attributes

For the matched trees, the accuracy of the MLS-estimated tree attributes was assessed by calculating the coefficient of determination (R^2) (Eq. 1), root-mean-square error (RMSE) (Eq. 2), the relative RMSE (%) (Eq. 3), the bias (Eq. 4) and the relative bias (%) (Eq. 5):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}{\sum_{i=1}^{n}\left(\bar{y}_i - y_i\right)^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{2}$$

$$RMSE\ (\%) = \frac{RMSE}{\bar{y}} \times 100 \tag{3}$$

$$bias = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i) \tag{4}$$

$$bias\ (\%) = \frac{bias}{\bar{y}} \times 100 \tag{5}$$

where n is the number of matched trees, y_i is the reference field inventory attribute (DBH or Ht) for the i^{th} tree, $\hat{y}_i$ is the MLS-estimated attribute for the i^{th} tree, and $\bar{y}$ is the mean of the field inventory reference attribute.

7 Results

7.1 Tree extraction

The results for each plot by algorithm are provided in the modeling fact sheets in Appendix B.

All standing live and dead trees were included in the comparison. The results presented here use a 25% retention rate from with a custom r-lidar pipeline hybrid-homogenization of points.

The effect of retention rate was investigated using 3DFIN (not reported here). The effect of retention rate was relatively minor and a retention rate of 25% gave good results and provided for quicker processing.

Results are first presented at the plot level (tree matching and stand level attributes). Then, for the matched trees, tree level results (DBH and height) are given.

The results of the tree segmentation for leaf-off conditions are illustrated in Figure 9 and Figure 10.

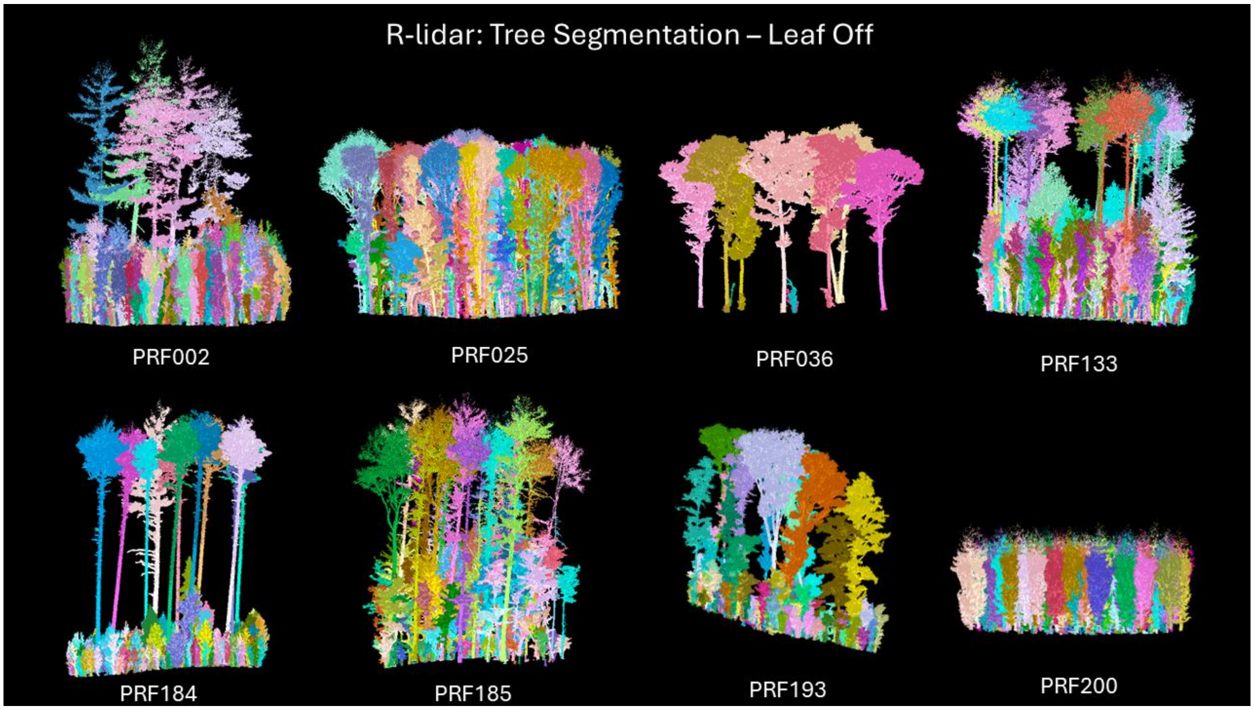


Figure 9. The results of tree segmentation using r-lidar pipeline are given. The extracted plot has a 11.58 m radius. For tall plots with a heavy understory (PRF002 and PRF133), the returns from the tops of the tallest trees are somewhat sparse

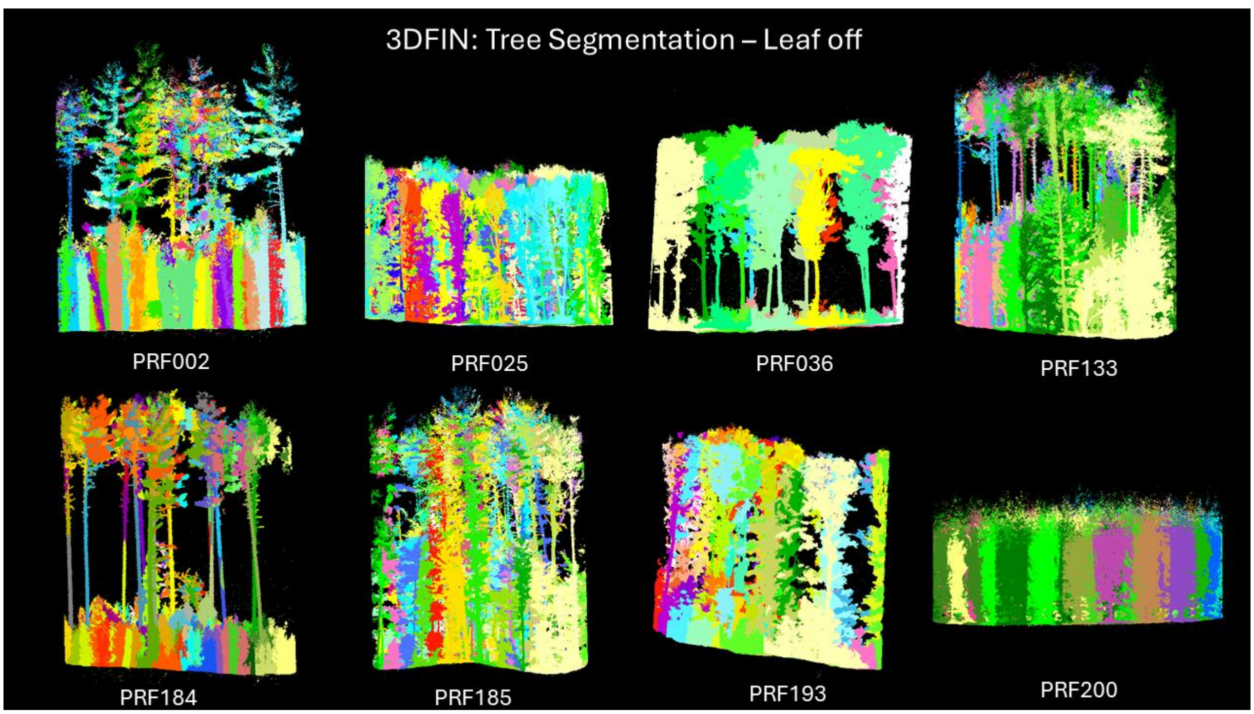


Figure 10. The results of tree segmentation using 3DFIN are given. The extracted plot has a 15 m radius. For tall plots with a heavy understory (PRF002 and PRF133), the returns from the tops of the tallest trees are somewhat sparse. Tree segmentation exhibits significantly more inaccuracies than the r-lidar pipeline (e.g. PRF184, PRF193) for small trees and crowns.

7.2 Plot-level assessment

The MLS results were assessed at the plot level by computing the tree matching, omission and commission rates by algorithm (3DFIN vs. r-lidar pipeline), DBH limit (2.5 – 7.1, 7.1+ cm) and season (leaf off vs. leaf on). The plot level results were also assessed by summarizing plot basal area and stems/ha.

7.2.1 Tree matching

An example of the results of the tree matching algorithm is given in Figure 11.

Leaf off versus Leaf on

The F-scores were relatively insensitive to season (leaf off/on, Figure 12). The effect of leaves on tree extraction and matching for r-lidar pipeline was minor with the exception of small trees for PRF133 and PRF193. Complete results are provided in Appendix C

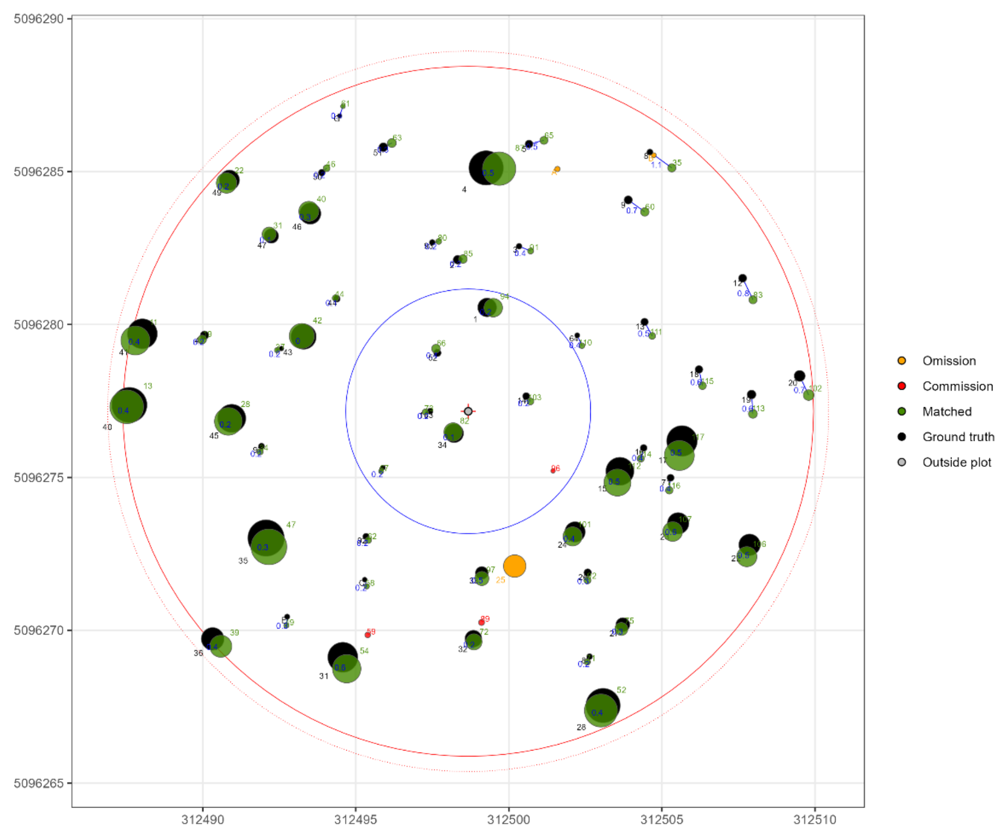


Figure 11. The results of tree matching for PRF185, leaf off, r-lidar pipeline. The solid red circle is the large tree plot (radius 11.28 m). The inner blue circle is the small tree plot (radius 3.99 m). The outer dotted red circle is the search radius for the tree matching algorithm (radius 11.58 m). The black and orange circles are the field measured trees. The green and red circles are the MLS trees. The grey trees are trees identified from the scanning that are outside the plot boundary (between 11.28 and 11.58 m). Circle diameters are proportional to DBH.

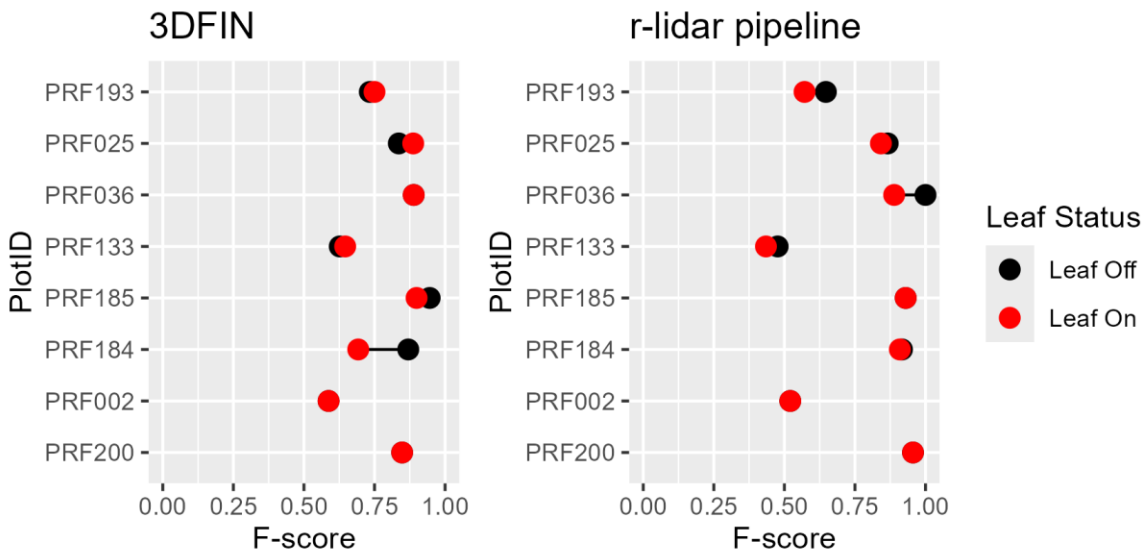


Figure 12. F-scores by algorithm and leaf status. The plots are presented with decreasing amounts of hardwood composition

Algorithm comparison

In general, r-lidar pipeline had a slightly higher matching rate than 3DFIN for large trees (Figure 13). In general, the commission rates tended to be higher than the omission rate. The matching rate for 3DFIN on the STP was very poor and slightly better for r-lidar pipeline. The omission rates were relatively high for both algorithms for the STP.

In terms of the F-score, the results were better using r-lidar pipeline than 3DFIN for the STP and single-tier conditions for the LTP (Figure 14). Full results are given in Appendix C.

7.2.2 Stand level BA and density

Results of extracting MLS basal area and stems are compared to field measurements in Figure 15 and Figure 16.

For the large trees, the basal area from both algorithms was close to the field estimates except when there was a significant midstory (PRF133 ad PRF002) and the algorithms overestimated basal area and stems/ha. For the STP, 3DFIN consistently underestimated the basal area and stems/ha of small trees. The STP results for r-lidar were more variable.

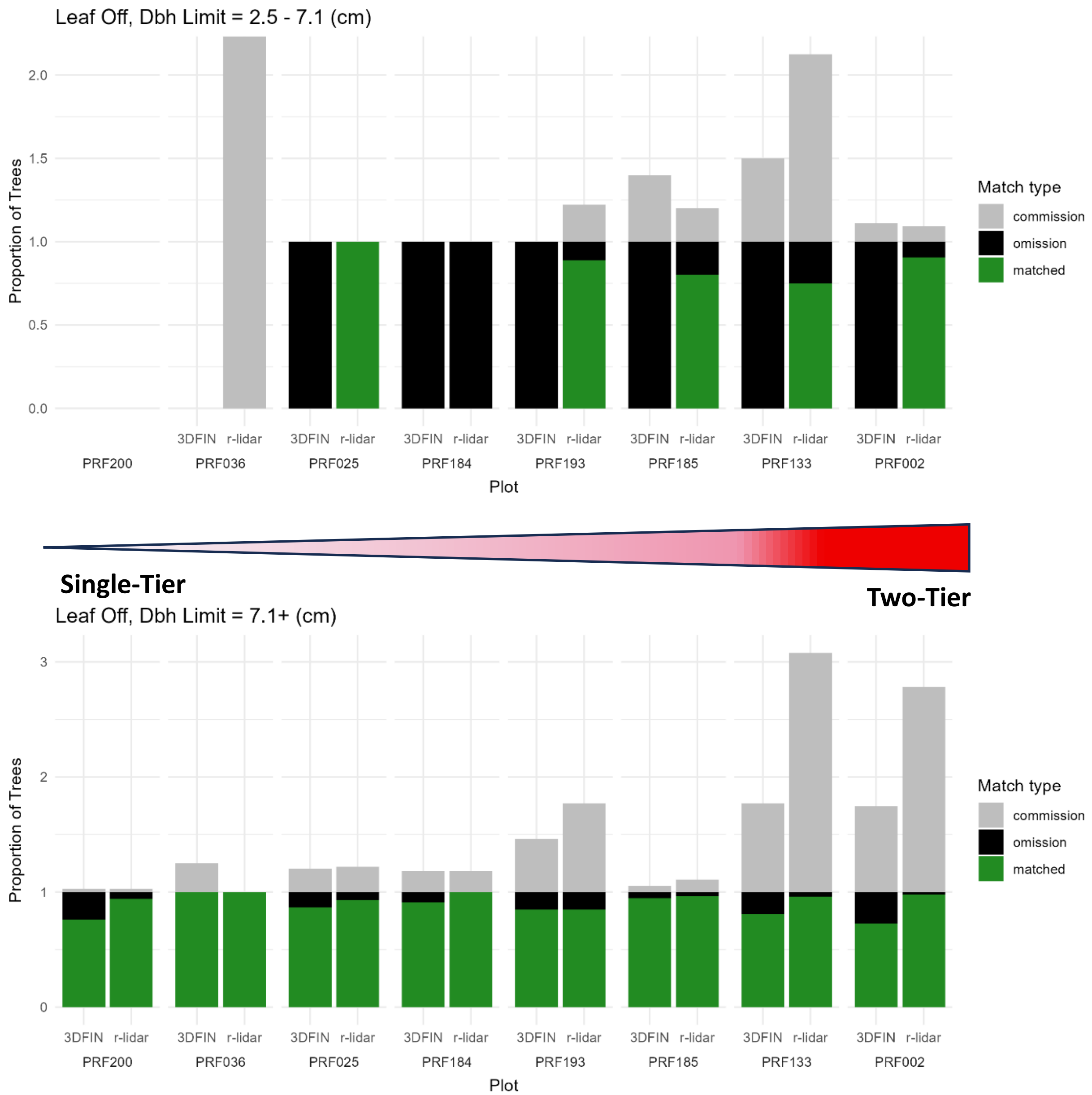


Figure 13. The matched, omission and commission rates are given by plot and algorithm for small trees (STP, 2.5 ≤ DBH < 7.1 cm) (upper graph) and large trees (LTP, DBH ≥ 7.1 cm) (lower graph). Matched or recall rate is the proportion of field trees matched to MLS trees. Omission (1 – recall) is the proportion of field trees not matched to MLS trees. Commission is the proportion of MLS trees not matched to field trees (1 – precision). Note the y-axis have different limits for small and large trees. The plots on the left (PRF200, PRF036, PRF025) are single-tiered. The middle plots (PRF184 and PRF193) have an understory. The plots on the right (PRF184, PRF133 and PRF002) have a midstory.

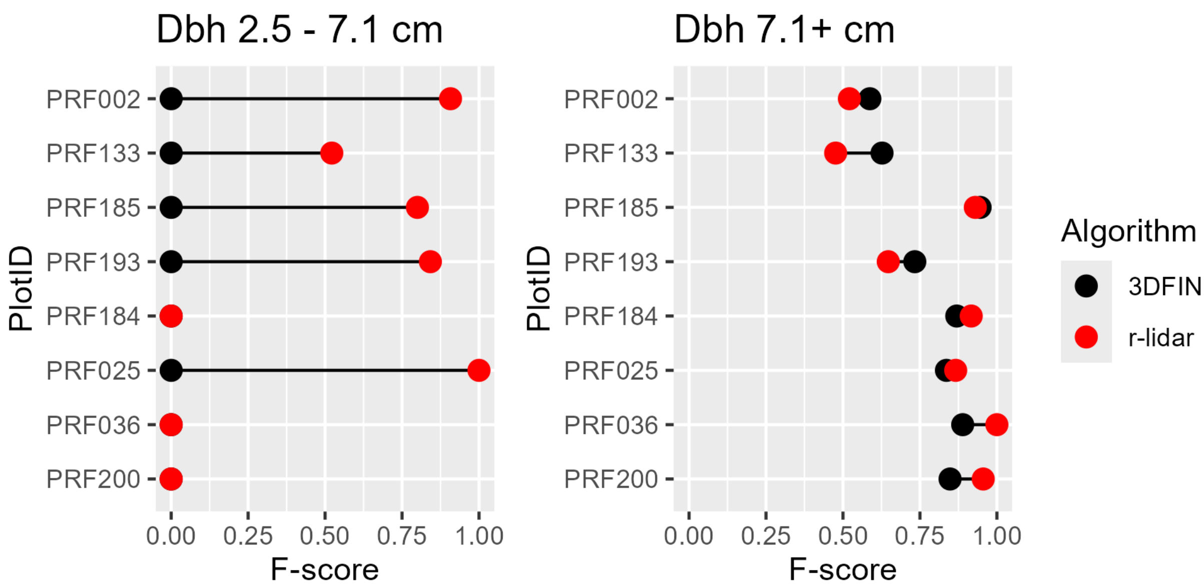


Figure 14. F-scores by size-classes by algorithm. Plots are presented from two-tier to single-tier structures

7.3 Tree-level assessment

The DBH and heights of the extracted MLS trees were compared to the field measurements for the matched trees. For the matched trees, both algorithms gave good results for DBH (Figure 17). Note that field and MLS trees are matched by closeness of DBH (LTP) and height (STP) in addition to proximity. The number of matched trees varies with algorithm. R-lidar pipeline had slightly more matched trees, particularly small trees, so the r-lidar-pipeline results represent more trees. There is some evidence of underestimation of DBH for larger trees (DBH > 25 cm).

The height results, particularly for 3DFIN, show more variation. 3DFIN had poor results for shorter trees for PRF002, PRF133, and PRF185, all of which had a significant intermediate layer under a taller overstory. There are indications of underestimation of the heights of the tallest trees for both algorithms, likely the result of fewer returns from the canopy above 30 m. For single story conditions (PRF036 and PRF200), the 3DFIN and r-lidar pipeline results were similar for height.

The effect of leaves on DBH (Figure 18) and height (Figure 19) estimation was relatively minor. As mentioned earlier, the leaf-off conditions were not ideal, as leaves had started to emerge.

Basal Area – Leaf Off

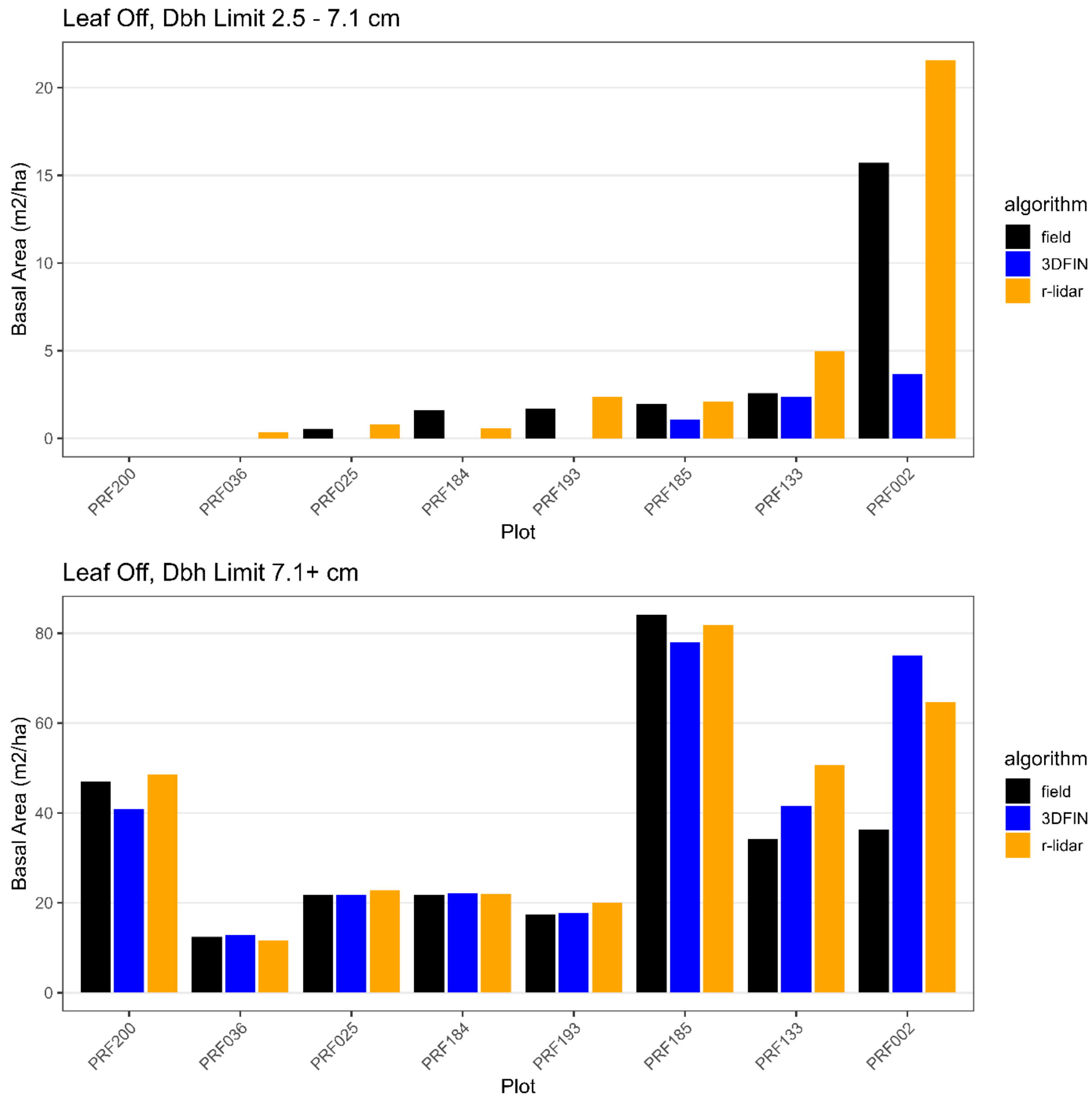


Figure 15. Comparison of algorithm estimates of basal area to field measurements for small and large trees.

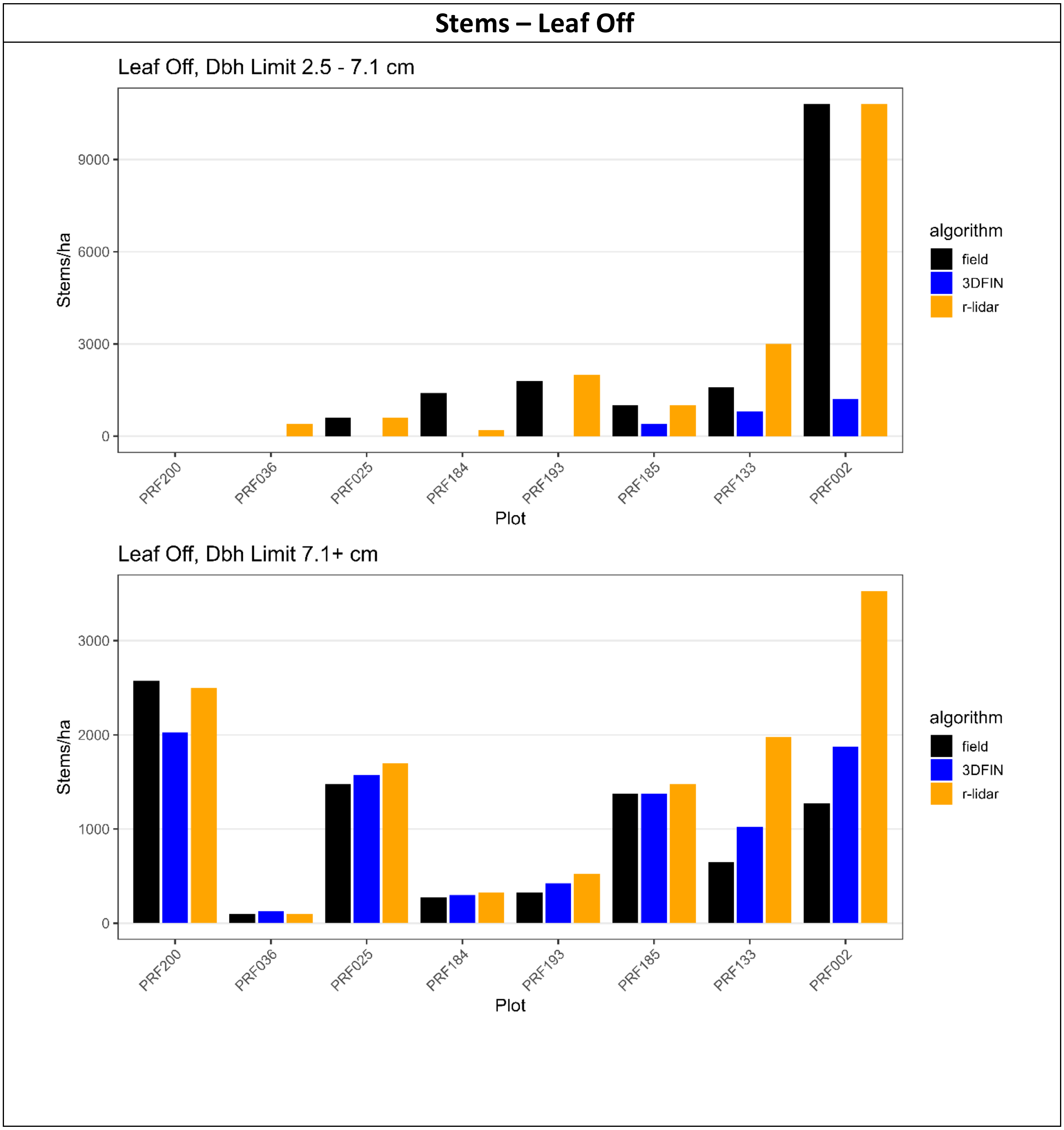


Figure 16. Comparison of algorithm estimates of stems to field measurements for small and large trees.

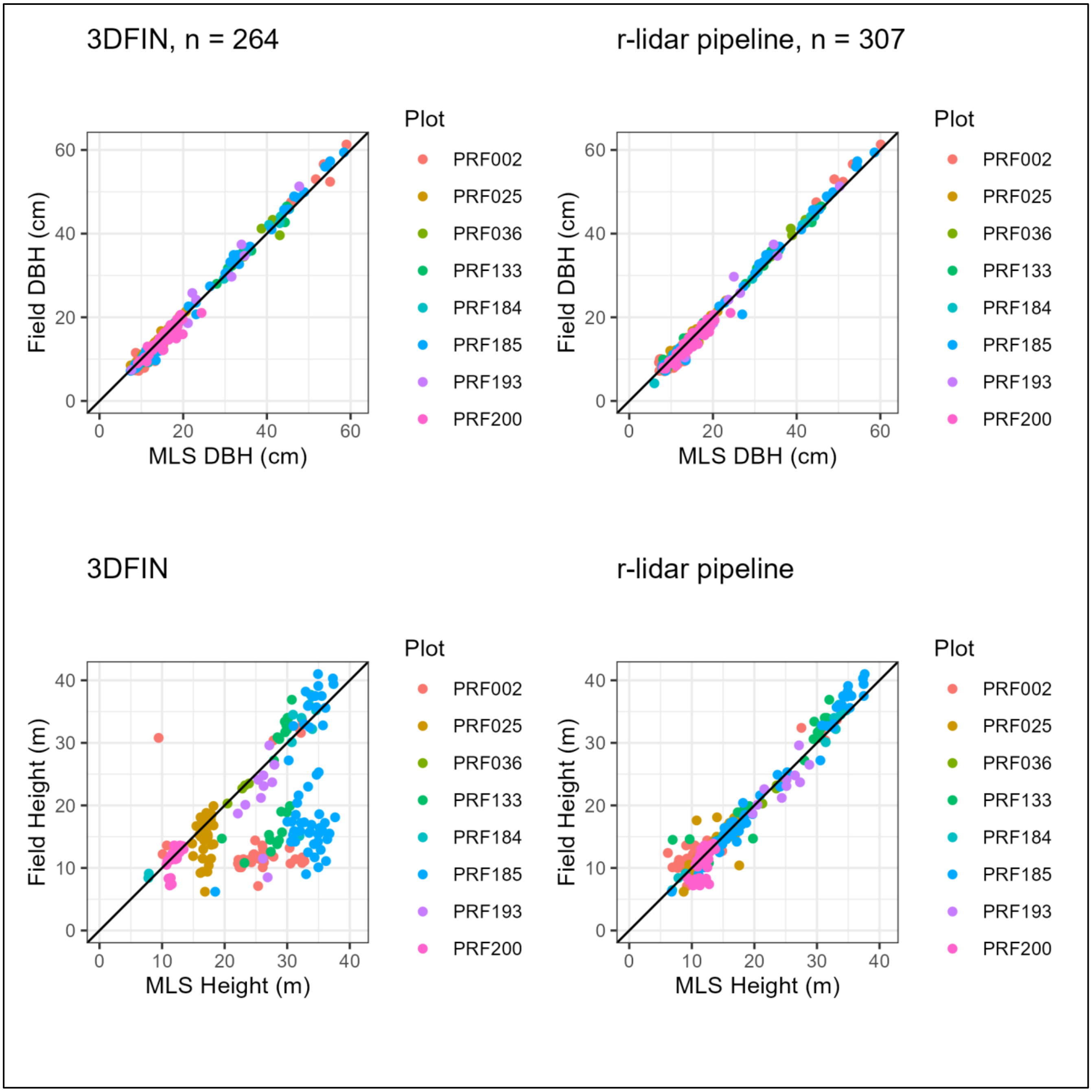


Figure 17. Comparison of algorithms for leaf off. There were slightly more matched trees for r-lidar pipeline compared to 3DFIN (particularly small trees), so the r-lidar pipeline graphs include more trees.

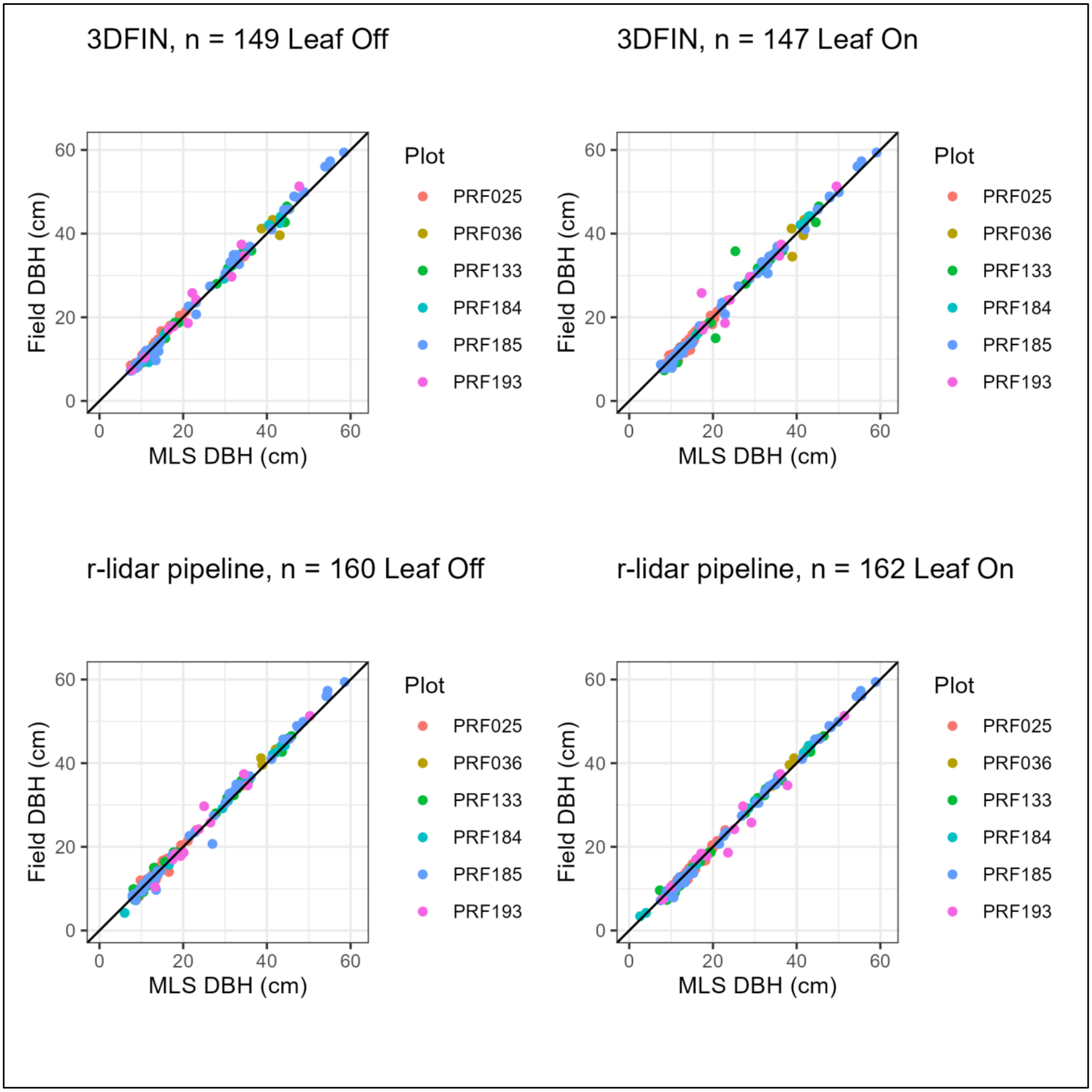


Figure 18. Comparison of leaf on versus leaf off for DBH (n = 6, PRF002 and PRF200 are excluded) by algorithm.

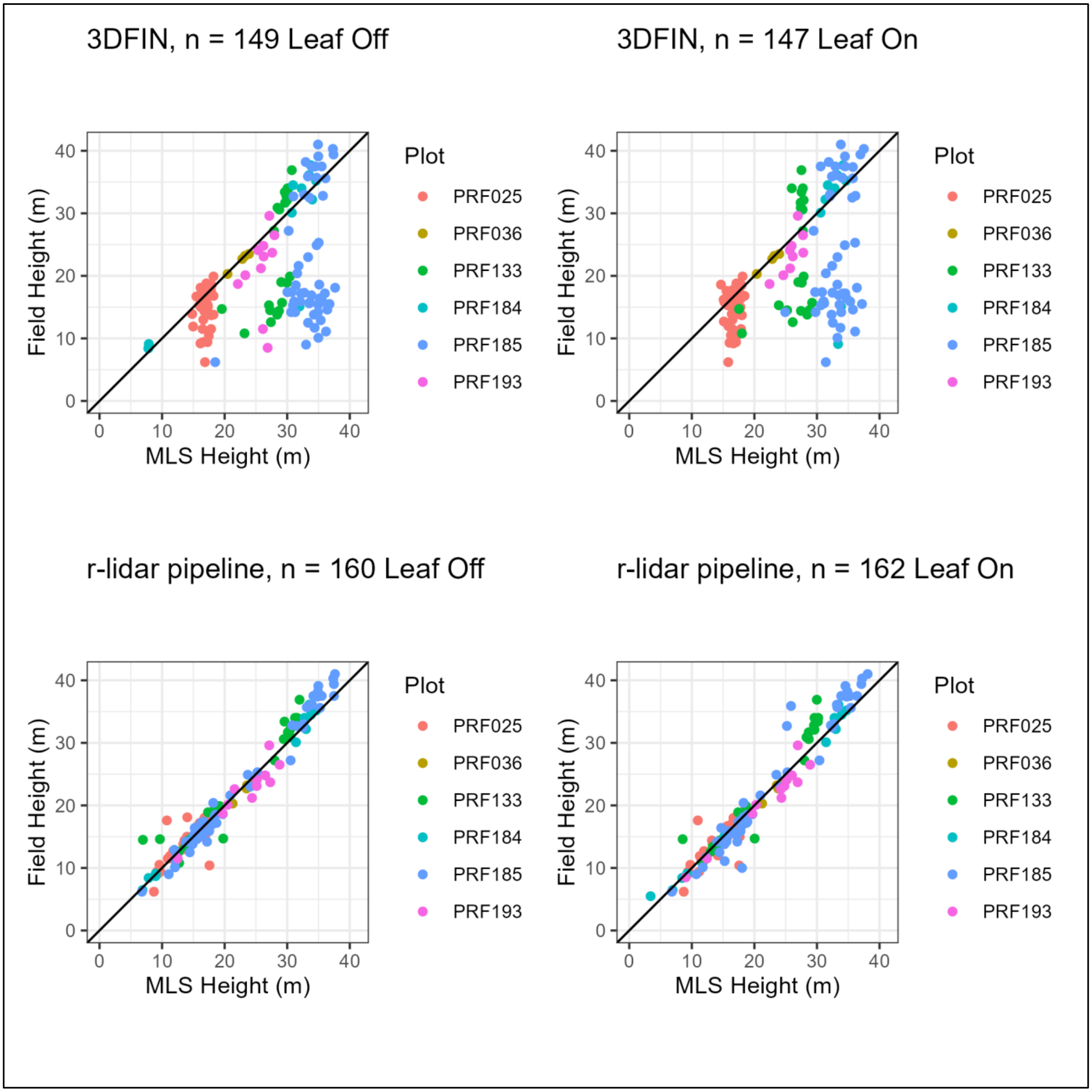


Figure 19. Comparison of leaf on versus leaf off for height (n = 6, PRF002 and PRF200 are excluded) by algorithm.

8 Operational and Monitoring Considerations

8.1 Scanning pattern and efficiency

The scanning pattern (illustrated in Figure 4) worked well for all stand conditions. Data collection was very efficient. Set up (flagging plot centre post, 8 m inner circle cardinal directions and outer 15 m boundary) took 30 – 60 minutes, depending on stand conditions. The actual scanning took approximately 15 minutes.

8.2 Comparison of UAV and MLS point clouds for tree heights

The Faro ORBIS's ability to scan the tops of the tall (often >35 m) forests commonly found in the PRF was investigated. A Structure from Motion (SFM) point cloud was generated from the UAV data collected over the plots using Agisoft Metashape Professional 2.1.1. The UAV data were overlaid onto the MLS point cloud (5-8 m profile) to determine whether a similar total-height assessment was possible from the scanned MLS point cloud. From this test we observed that an unfiltered MLS point cloud, collected using an appropriate ground-scanning pattern, can yield high-quality tree-height estimates. It should be noted that the SFM and MLS data compared here were collected in early spring, when deciduous leaf break had just begun. It remains unclear whether the same results are achievable in dense stands that are primarily hardwoods.

An example of PRF002, PRF025 and PRF036 comparisons are provided below (Figure 20). The complete plot UAV and MLS comparison images can be found in Appendix D.

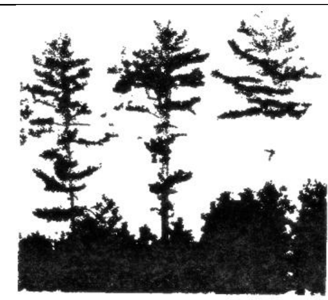
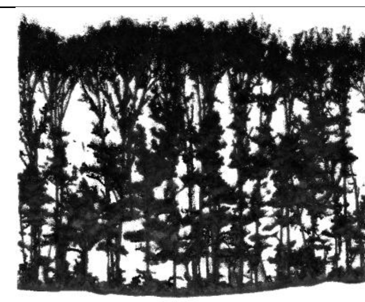
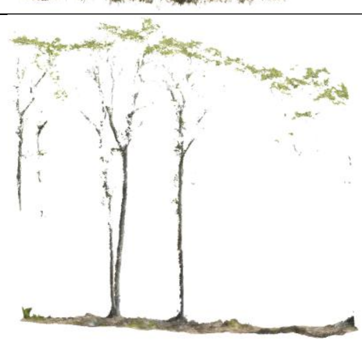
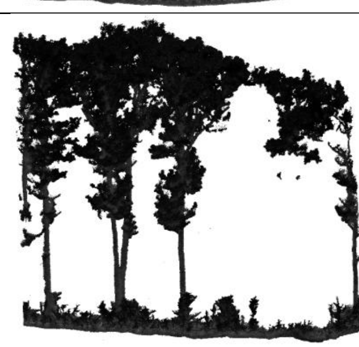
Plot	SFM	MLS	SFM & MLS
PRF002 Pine			
PRF025 Oak			
PRF036 Oak			

Figure 20. Comparison of UAV Structure from Motion (SFM) point clouds (colored) and MLS point clouds (black) for selected plots. The dominant height of PRF002-32.1 m, PRF025-19.0 m, PRF036-22.4 m. The complete examples or UAV SFM heights and MLS point clouds for all plots are provided in Appendix D.

8.3 Monitoring Plot Considerations - Tree numbering

Another option for tree matching is to somehow uniquely identify the trees in the MLS scans. 3M reflective tape wrapped around the tree stems was highly visible in the MLS intensity field. Tree paint was also visible. Freshly painted black or blue painted numbers on red pine proved to be visible in the intensity field (Figure 21) in some conditions.

Figure 21. 3M reflective tape showed up well in the intensity field of tree scans. Fresh black or blue painted tree numbers showed up reasonably well in some conditions but depended on tree size, bark condition and age of paint.

The Faro Orbis scanner also captures RGB imagery during the scanning. It was hoped this could be used to identify tree numbers. This was evaluated for a few of the scanned plots. Unfortunately, it proved very difficult to interpret tree numbers from the lidar encoded RGB values (Figure 22).

8.4 Tree species

The automation of identifying tree species from MLS point clouds remains a challenge and is a focus of many national and international agencies. MLS/TLS systems can provide highly detailed information about individual trees (Figure 23). The human brain can interpret these 2D (and 3D) images and assign species labels based on visual cues, knowledge, and experience. Until recently, automated species identification was poor in conditions with high species diversity. With the emergence of Artificial Intelligence (AI) tools and an expanding library of MLS/TLS-scanned tree species examples, this challenge may soon be overcome or at least reduced.

Korkeala et al. (2025) used MLS tree data from Finland and trained a deep learning model with an image classification network for seven species. Their testing on MLS data achieved an accuracy of over 94% for species determination. Other studies, such as Straker et al. (2025), working with TLS data from seven

European species and using deep learning approaches, achieved cross-validation mean accuracies exceeding 95%. It is conceivable that the challenges of species prediction based on these dense point clouds may become more common in the near future.

Figure 22. Example of an RGB encoded lidar point cloud for assessment of tree numbers. Number interpretation proved difficult.

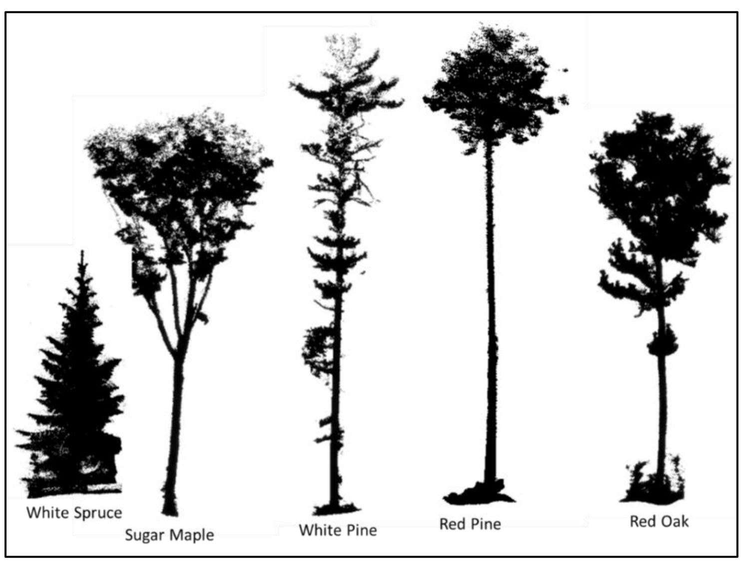


Figure 23. MLS scanned examples of extracted trees for a range of species.

9 Discussion

The stand conditions examined here cover a broad range of forest conditions from relatively simple conditions (PRF036, PRF200) to extremely complex conditions with very tall trees (PRF002, PRF133, > 35m), clumped small stems, dense midstory, and forked stems. Two software tools were used to evaluate the operational readiness of MLS technology for field-plot measurements. Both tools have strengths as well as opportunities for improvement (Table 5). The rapid pace of software development and sensor innovation supports the expectation that the limitations observed today (and discussed below) will be resolved in the near future.

Table 5. Comparison of 3DFIN and r-lidar pipeline strengths and weaknesses.

Attribute	3DFIN	R-lidar pipeline
Tree detection and segmentation Large trees (DBH ≥ 7.1 cm)	• Excellent detection • Segmentation issues with forked trees	• Excellent detection • Segmentation issues with forked trees
Tree detection and segmentation Small trees (2.5 ≤ DBH < 7.1 cm	• Moderate detection • Less successful segmentation/isolation of main stem (leading to overestimation of DBH, commission error) with clumped trees • Poor segmentation/isolation of individual tree crowns associated with lower tree base	• Good detection • Less successful segmentation/ isolation of main stem (leading to overestimation of DBH, commission error) with clumped trees. • Good isolation of individual tree crowns associated with lower tree base
DBH extraction Large trees (DBH ≥ 7.1 cm)	• Excellent	• Excellent
DBH extraction Small trees (2.5 ≤ DBH < 7.1 cm	• Poor • Overestimation of DBH in tree clumps, overlapping branches	• Poor to good for single small tree stems • Overestimation of DBH in tree clumps, overlapping branches
Height extraction	• Good in single-tier conditions • Poor for understory in two-tier conditions	• Good in all conditions, possibly better than field crews for tall trees
Stem mapping	• Good for large trees. • Issues with single stem extraction for small trees in clumped conditions	• Good for large trees. • Issues with single stem extraction for small trees in clumped conditions
Additional outputs	• Provides diameters for user-specified intervals up the tree stem	• Partitions point cloud into wood/foliage. • Extracts main stem, branches and foliage. • High potential for taper and biomass estimates through Quantitative Structure Models

Attribute	3DFIN	R-lidar pipeline
User-required modeling Inputs	• Default parameters provided in GUI • Large list of parameters provided for local adjustment	• Runs in R • Robust default parameters provided • Possible to adjust a suggested set of parameters for local conditions
Active development	• Ongoing development	• Rapid development including use of PRF plots as well as an extensive hardwood dataset from Quebec.
Availability	• Open source	• Beta-release • Open source likely within a year

9.1 Tree segmentation

In general, both algorithms were very good at segmenting the bottom portion of large trees (DBH $\geq$ 7.1 cm). R-lidar was consistently better at segmenting the entire bole and crown of large trees, while 3DFIN performed poorly, frequently partitioning the crown of one tree with the lower bole of another tree.

Forked Trees

Challenges exist with both algorithms when trying to segment forked trees for both small and large trees. In the field, trees forked below breast height are tallied as separate trees. However, in r-lidar, currently these trees are segmented as a single tree, and a DBH is only fit to one stem (Figure 24). While the solution to this situation is not simple, it is believed that this shortcoming can be overcome in time.

Figure 24. Example of an r-lidar pipeline segmented tree (DBHs of both stems >35 cm) that is forked below breast height. This tree should be segmented into two separate trees but is segmented as one, with only a single DBH fit to one stem.

In 3DFIN, for trees forked below breast height and segmented as a single tree, DBH is assessed 1.3m above the base of the tree. For the tree in Figure 25, DBH was assessed between the 2 stems and resulted in a meaningless estimate. 3DFIN provides the option to measure diameters up the stem at a user specified interval. Figure 25 illustrated how the algorithm is attempting to isolate a single stem and is alternating measurements from one stem to the other moving up the tree.

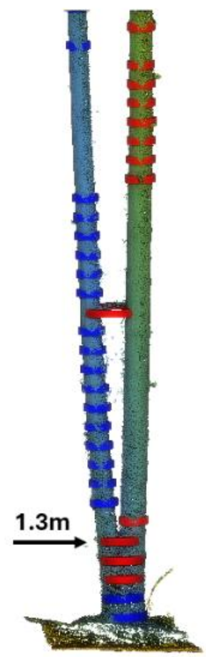


Figure 25. Example of a tree forked below breast height tree with 3DFIN-extracted diameters up the tree bole. Note that DBH is assessed as a measurement including both stems.

Tree Clumps

Tree segmentation issues often occur in clumps of smaller diameter trees (<7.1 cm in this study) due to their spatial proximity to one another and the sensor beam divergence limitations not permitting adequate point cloud resolution of small diameters. In our study, many small diameter trees were detected. The challenge arose during the segmentation process when groups of neighbouring small stems were segmented as one tree. The resulting DBH fits were poor and didn't represent any of the trees within the clump. In addition, the tree location did not correspond to any individual stem. Situations like this lead to commission errors.

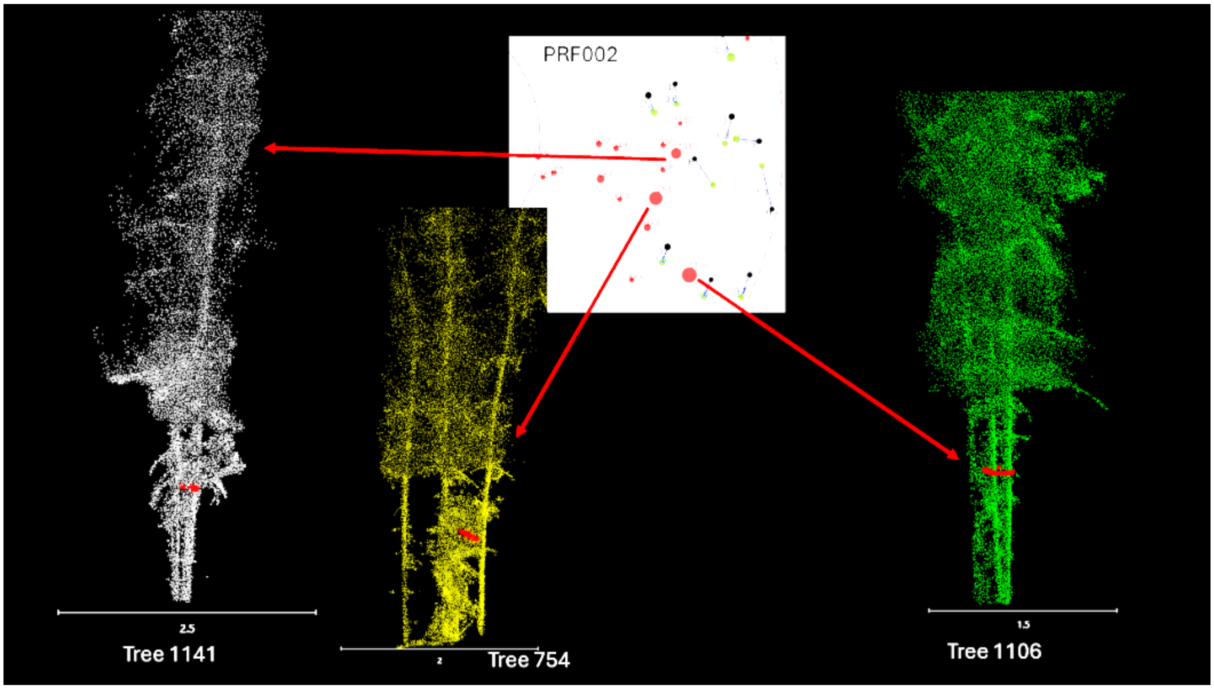


Figure 26. For PRF002, clumps of small white pine (DBH < 7.1 cm) were extracted in r-lidar pipeline as a single large tree with a DBH > 7.1 cm.

9.2 Tree matching and how it relates to Omission and Commission errors

Tree matching is not a trivial problem and has a significant impact on the results. Tree matching was more successful for larger trees because they tend to be well spaced with few low branches. Tree matching for smaller trees is more difficult due to tree clumps and branches. These trees also have higher positional and DBH error, both of which are used in tree matching. Often these small trees are smaller than the DBH threshold (for this study $\geq$ 7.1 cm). Currently, both MLS algorithms struggle in these situations. Most often these trees are detected but, due to their proximity to one another, the clump is segmented as a single stem. As a result, the DBH is often overestimated either based on a slice of the point cloud at DBH or through a QSM approach (unique to r-lidar pipeline).

There are additional potential sources of error affecting tree matching. All the field measurements include error including the stem mapping. The distance measured to a tree includes error depending on how well the instrument was held over the plot centre. The manual interpretations of the coordinates of the plot centre post from the point cloud potentially includes some error.

<u>Omission and Commission errors</u>

The omission rate was very low for most conditions and generally involved smaller trees (for PRF002, the DBH range for r-lidar pipeline omission trees was 7.1 – 10.0 cm) or forked trees (PRF200 had 3 forked trees).

As noted earlier, the algorithms had more difficulty segmenting small trees, particularly clumps of small trees (Figure 26, Figure 27) or stems forked near the ground (Figure 28) often leading to an overestimate of DBH. This led to high commission rates for PRF002 and PRF133 where the overestimation of DBH resulted in the MLS trees being classified as large trees (DBH ≥ 7.1 cm). On the LTP, these trees were not recorded in the field (Field DBH < 7.1 cm) but are included in the MLS extraction and summary (MLS DBH ≥ 7.1 cm and Ht > 6 m). These are identified as commission trees (MLS tree with no field match) but **the real issue is overestimation of DBH due to the grouping and fitting of a DBH to multiple small stems identified as a single "treeID"**. The commission rates were higher than the omission rates, leading to overestimation of stand level attributes of basal area and stems/ha. The commission trees tended to be smaller so the impact on stems/ha was higher than basal area. It is expected that stem extraction of small trees will improve with sensor and algorithm development. Figure 29 illustrates successful small tree extraction.

Whorls at or near breast height can also impact DBH extraction (3DFIN example - Figure 30). In the case of r-lidar pipeline, it fits a circle to a 10 cm slice of points around 1.3 m. If the circle is considered a poor fit, the algorithm can extract a DBH from the QSM model of the tree stem. In matching trees, If the MLS DBH is more than 40% different from the Field DBH, the trees are not matched, and the field tree is an omission and the MLS tree is a commission.

DBH estimates are also influenced by small stems adjacent to the tree of interest (Figure 31). Again, both an omission and commission error were reported.

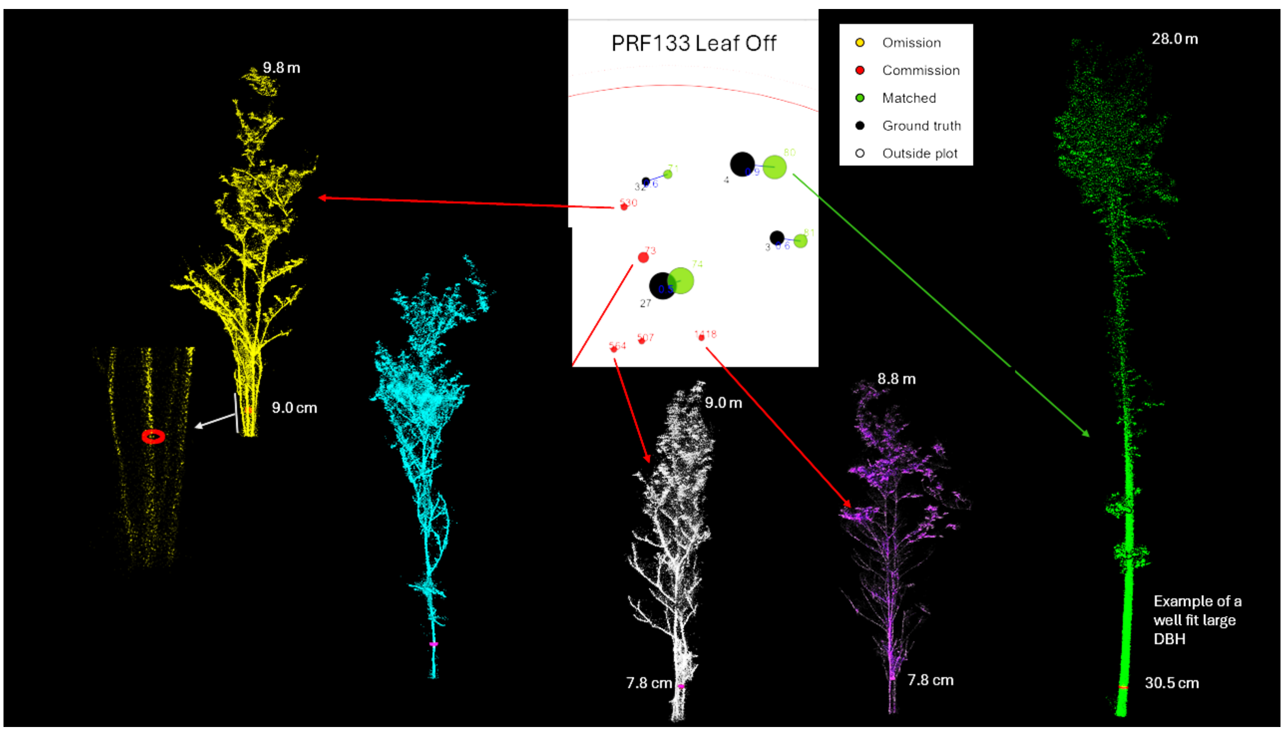


Figure 27. For PRF133, the DBH of small red maple trees (DBH < 7.1 cm) was overestimated for clumps and forked trees. They were segmented as a single large tree with a DBH > 7.1 cm in r-lidar pipeline.

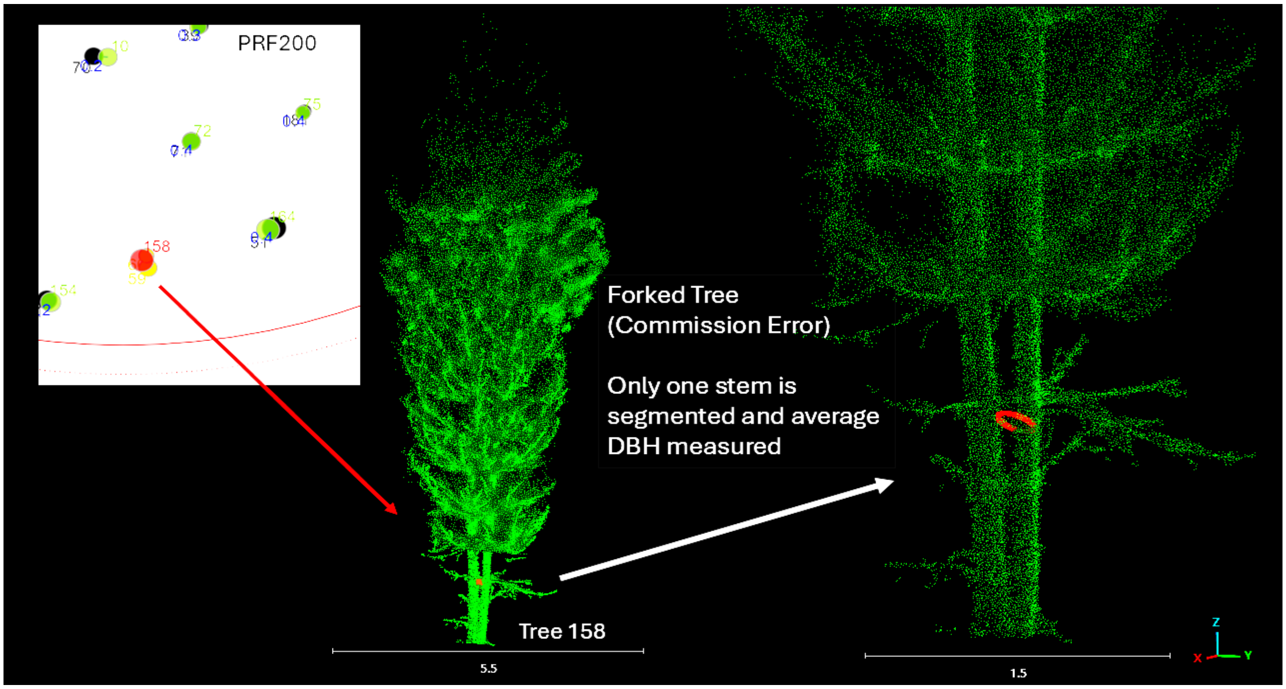


Figure 28. The tree extraction algorithms have difficulty with trees forked near the ground (< 1.3 m) where two trees would have been measured in the field. In this case, only one tree was segmented (leading to an overestimate of DBH – one commission error, and two omission errors) in r-lidar pipeline.

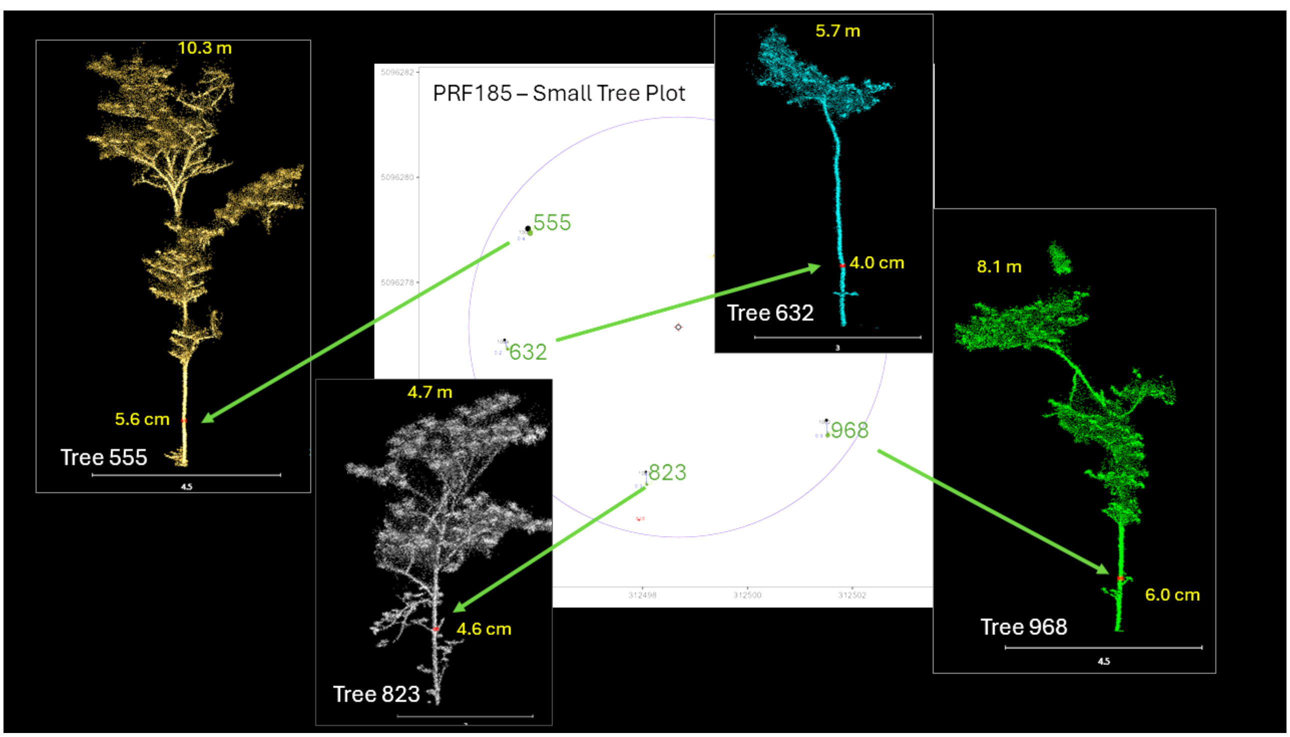


Figure 29. Examples are given of correctly extracted small trees from r-lidar pipeline.

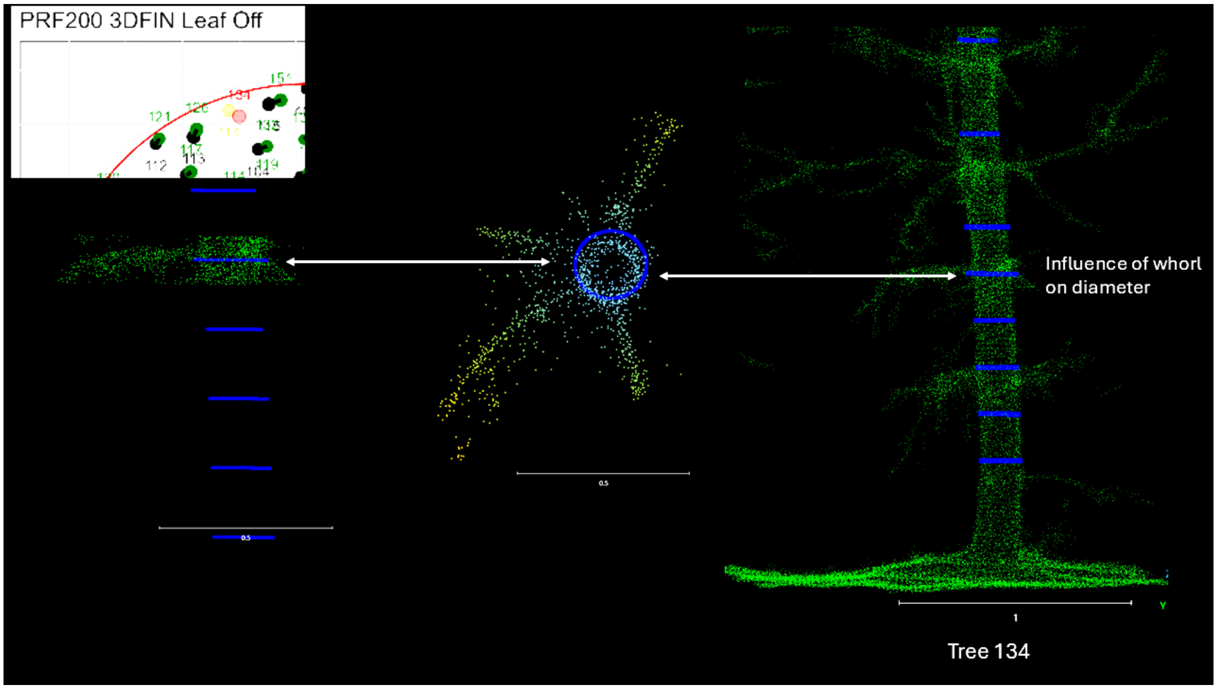


Figure 30. An example of the impact a conifer whorl may have when fitting DBH to an extracted point cloud section in 3DFIN.

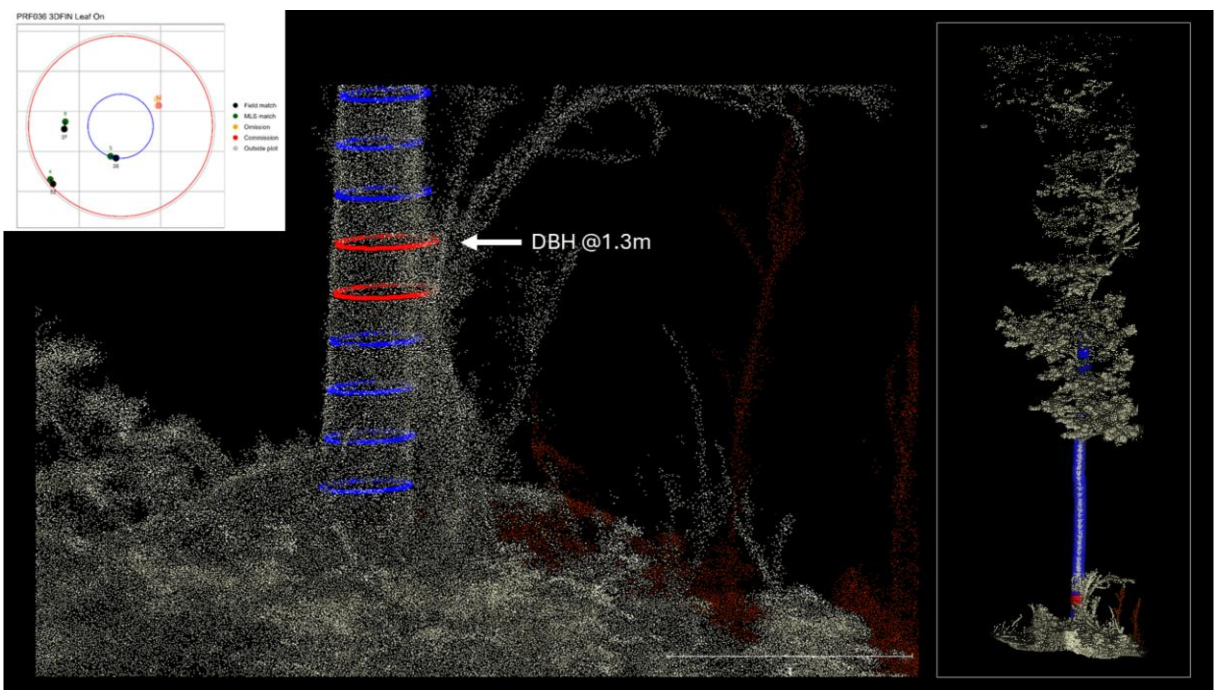


Figure 31. The adjacent regeneration in leaf-on conditions leads to overestimation of DBH and the MLS tree not being matched to the field tree in this 3DFIN example.

9.3 Tree-level assessment

Both algorithms did well estimating DBH for the matched trees. R-lidar pipeline was clearly superior to 3DFIN in estimating height, particularly for mid-canopy trees. There is some evidence of slight underestimation of height for the tallest trees (height > 30m), likely due to fewer MLS returns from the upper canopy. Field measurements of heights of tall trees, particularly in the presence of a mid canopy, is challenging and includes error. The small, consistent underestimation of DBH for larger trees (DBH > 25 cm) may be due to a number of issues, including thicker bark with larger fissures and departures from a circular cross section. The algorithms assume a circular stem. Measuring field DBH using diameter tape will slightly overestimate DBH for oval (vs. circular) stems.

In general, 3DFIN significantly overestimated the height of small trees (Figure 32). Rather than extracting the height of the small tree, 3DFIN extracts the highest point above the location of the small trees (Figure 33).

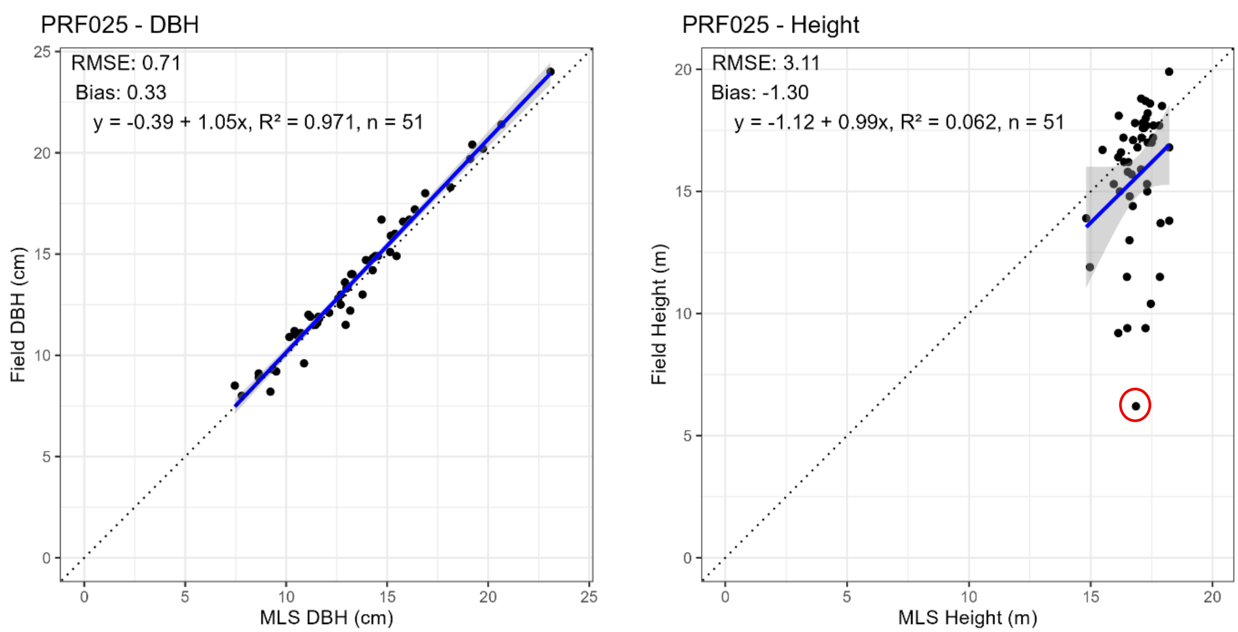


Figure 32. The results for PRF025, leaf off, using 3DFIN are given. The results are for matched trees only. The blue line is the least squares regression of field measurement (Y) on MLS extracted measurement (X). The equation associated with the regression line, the R2 and the associated 95% confidence interval (grey shading) are given. The 1:1 line is the dashed grey line. The root mean squared error (RMSE) and bias are given. Note, these are not the MSE and bias associated with the regression line. The circled observation is further examined in Figure 33.

9.4 Stand-level assessment

Comparing the diameter distributions of all field-measured trees on the LTP with the results extracted by 3DFIN and the r-lidar pipeline provides a stand-level view of where MLS-derived outputs perform well and where current limitations remain. The primary challenges, particularly the commission error of small trees, have been described earlier. Despite this, for many of the stand structures sampled, the large tree size classes (≥ 7.1 cm) are being extracted well and aligning closely with field measurements.

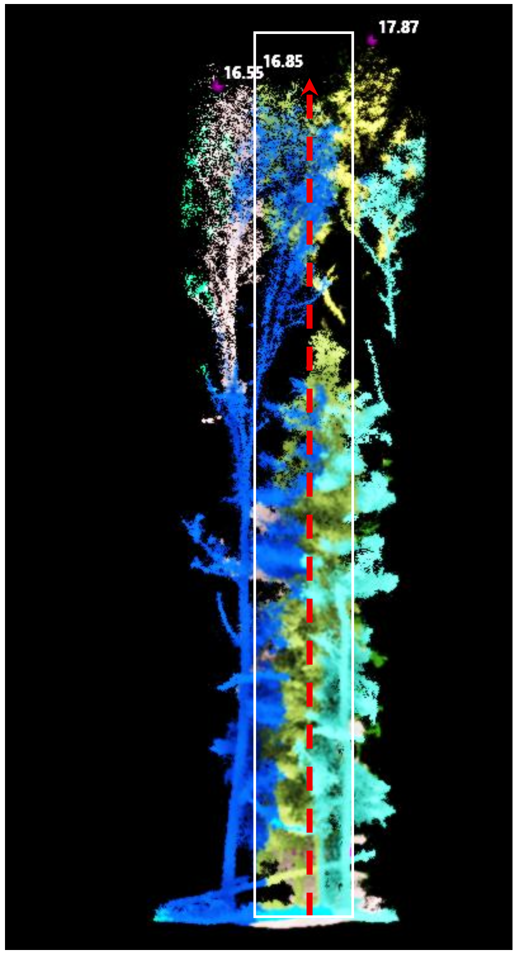


Figure 33. 3DFIN extracts the height of a tree as the highest return above the tree base for a segmented “treeID”. For midstory stems, this leads to overestimation. The dashed arrow refers to outlier circled in Figure 32 (greenish yellow in the point cloud) with an MLS height of 16.85 m and a DBH of 9.2 cm (Field measurement of 6.2 m and 8.2 cm).

In single-tier stands without understory, or in stands with a lightly developing understory, both modeling algorithms perform adequately to very well in capturing the field-observed size-class distributions (Figure 34). More complex two-tiered stands, especially those with well-defined mid canopies composed of small-diameter stems, have proven more difficult. The reasons for this have been discussed previously.

Figure 35 illustrates the stand-level impact of these small-diameter stems. Both algorithms over-predict the number of trees in the smaller diameter classes, with the r-lidar pipeline identifying more than 3DFIN. In these cases, both algorithms frequently detect and report small stems as > 7.1 cm, resulting in their inclusion in the LTP summary. These commission errors arise from the algorithms segmenting “clumps” of small trees and incorrectly generating instances of larger stems where large trees don’t exist.

However, even under these challenging stand conditions, both algorithms still provide a good estimate for the larger diameter classes, where tree segmentation is more robust.

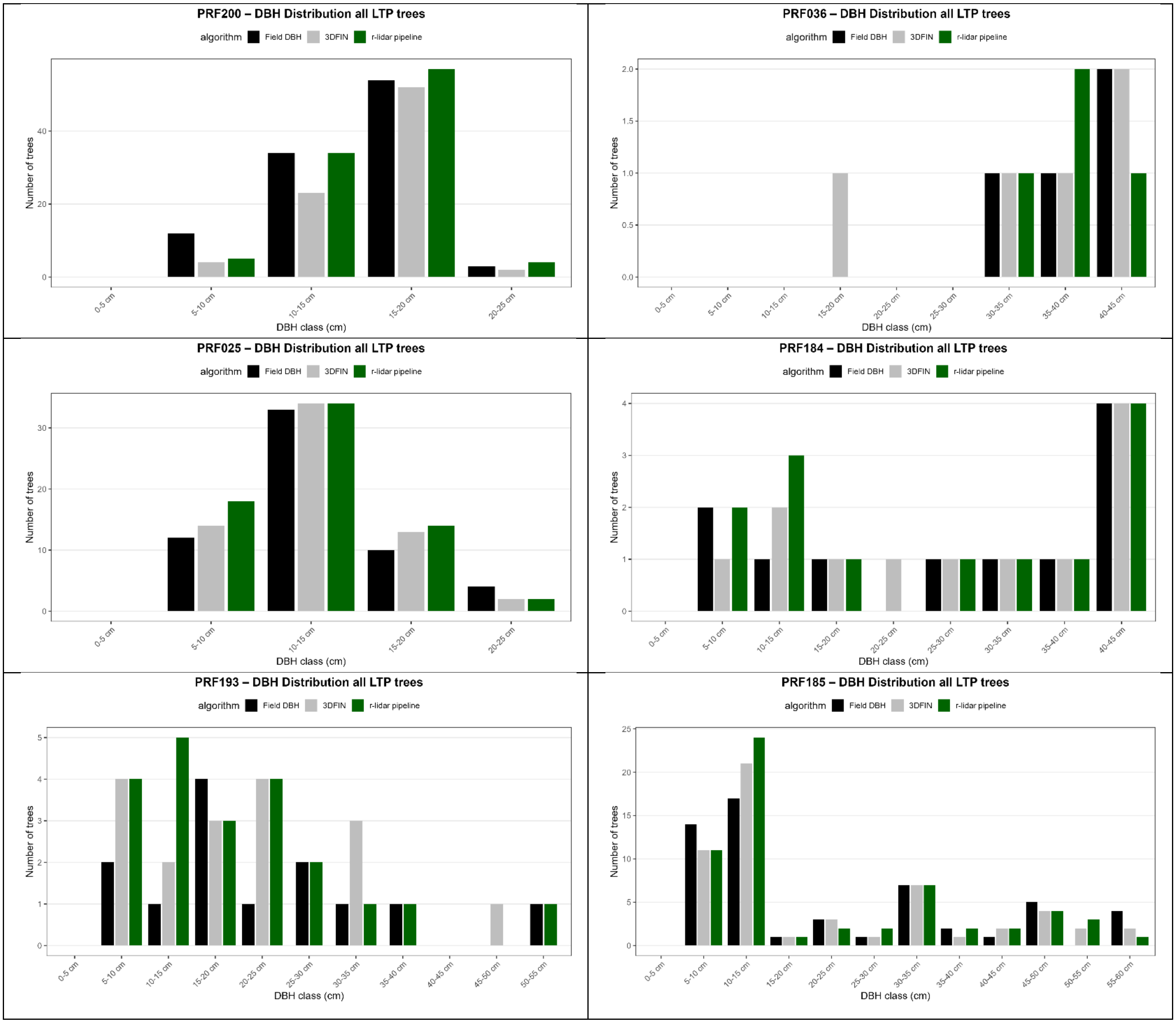


Figure 34. Large tree plot stand-level diameter class comparison of all trees measured on the single-tier field plots with no or little understory (PRF200, PRF036) to plots with developing understories (PRF025, PRF184, PRF193, PRF185), versus 3DFIN and r-lidar pipeline results for leaf-off conditions. All trees reported had a minimum DBH of 7.1 cm.

10 Conclusions

The operational use of MLS technology for forest plot or tree measurements is near. For something like operational cruising where the primary objective is measuring merchantable trees, this tool may meet the need. Existing MLS scanners and software tools are available now that can readily map tree location,

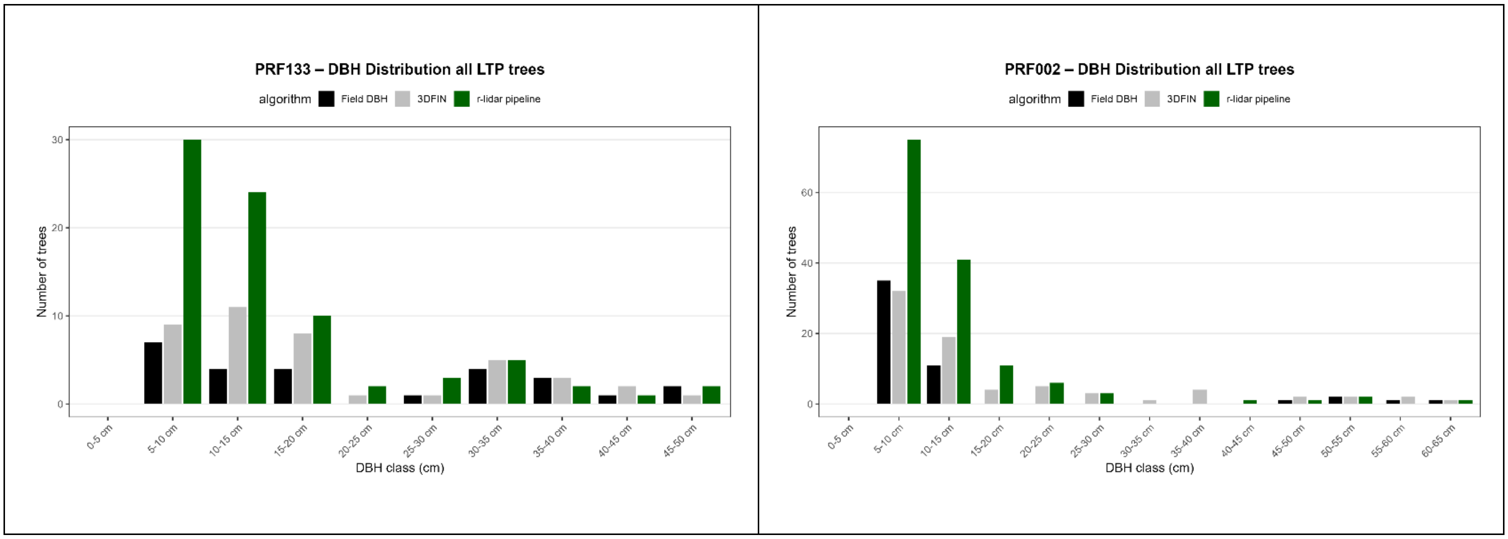


Figure 35. Large tree plot stand-level diameter class comparison of all trees measured on the two-tier field plots with a well established midstory (PRF133, PRF002), versus 3DFIN and r-lidar pipeline results for leaf-off conditions. All trees reported had a minimum DBH of 7.1 cm.

measure DBH (and other diameters along the visible stem) and total height. In addition, some software tools are creating quantitative structural models (QSMs) of trees that will allow for taper assessments and volume/biomass allocation by stem components (Figure 36).

While challenges remain in making this technology fully operational for all stand conditions, major strides forward were made in pre-processing MLS data and extracting tree attributes through the partnerships of this project.

MLS was tested under a wide range of conditions. Tree detection and extraction worked well for large trees. Detection of small trees is good but segmenting or isolating the small stems individually remains a challenge (specifically in clumped situations).

MLS detected most large trees (DBH ≥ 7.1 cm) and with a high level of matching (average recall or matching rate was 85%). For smaller trees (2.5 ≤ DBH < 7.1 cm), tree detection was also good, but the estimation of tree attributes had lower precision. For smaller trees, MLS beam divergence and stems/branches/foliage around 1.3 m become limiting factors in extracting accurate estimates of DBH. **These small trees were detected but extracting a single stem from a cluster of saplings or from overlapping branches and foliage remains a challenge**. Frequently this led to overestimation of the DBH of small trees. This DBH overestimation for small trees led to relatively high rates of commission errors for plots with two tiers (PRF133 and PRF002).

Forked trees were a challenge for MLS segmentation algorithms. For stems forked below breast height, generally only one "treeID" was extracted corresponding to both upper stems. For those cases, the DBH was extracted from the combined stems, leading to an overestimate of DBH, or for only one of the stems.

The effect of leaf status (leaf off or leaf on) was relatively minor.

Figure 36. Example of QSM stem output for PRF025. A zoomed in portion of 3 trees is also provided.

The main limitation of further operational adoption of this technology at this point is extraction of small, clumped trees, forked trees and trees with branches around breast height. For 3DFIN, heights of mid-canopy trees were consistently overestimated.

10.1 Project Team Accomplishments

MLS data acquisition was efficient, and the sensor range was more than adequate for the forest conditions including trees with height > 35 m. A 400 m^2 plot can be "measured" in approximately 15 minutes and processed from raw georeferenced data to tree attributes in approximately 15 to 30 minutes (depending on the software chosen and computer system). The initial data SLAM processing and georeferencing step plot alignment may require approximately 45 to 60 minutes to complete.

Data from this project contributed to the development of several software tools that improved the results and reduced the processing time. The R package *lidRalignment* quickly aligns the scans to existing ALS datasets, eliminating the need (and cost in term of time and money) to establish and GPS targets for plot geo-referencing. The *TreeMatching* R package matches field measured trees to MLS detected trees based on physical proximity and size. The package allows users to use the built-in matching/weighting parameters or enter their own.

The r-lidar beta package was tested on the data provided by this project[13]. This future planned open-source package will provide a very capable toolbox for processing and extracting tree attributes. To facilitate quicker processing times of MLS point clouds, a hybrid-homogenization filtering algorithm was developed and implemented with the r-lidar software suite of functions. This function permits decimation of the MLS/TLS point cloud while still maintaining similar point densities throughout the vertical profile to ensure retention of upper canopy returns for estimation of tree heights. In addition, r-lidar software separates foliage from woody MLS returns. This enhancement will allow for better biomass estimation as well as permit both leaf-off and leaf-on MLS point clouds to be processed, thereby extending the season for MLS

[13] r-lidar | consulting & development

collection. R-lidar's enhanced methods of QSM for 3D reconstruction of individual trees will greatly improve volume estimation.

10.2 Ongoing development

The use of MLS technology in forestry is forecasted to expand as scanners (reduced beam divergence) and software tools continue to evolve and results from studies like these and others (nationally and internationally) are more commonly known of.

Opportunities for improvement of sensors and processing software still exist. Small trees continue to be a challenge to both sensors and algorithms. Continued development to reduce sensor beam divergence will result in more useable returns on smaller diameter trees and help alleviate current issues (minimum that can reasonably be expected with the Faro Orbis is approximately 4 cm).

This study, with its partners, was able to test and contribute to the development of software for a range of species and stand conditions including:

- quick data acquisition and new automated georeferencing approach for MLS point clouds
- end-to-end processing of a plot in ~30 minutes, from raw georeferenced data to tree-level attributes, including a full tree map (XY location) with DBH, and height (QSM, stem volume, taper, crown dimensions — not reported on), as well as
- stand-level metrics such as basal area and diameter distributions.

Tree number tracking on plots requires more study. The Faro Orbis image quality in 2024 was not sufficient to easily interpret the tree numbers painted on the tree stems when the RGB was encoded to the lidar returns. However, painted tree numbers were visible in the lidar intensity field on large, smoother-barked tree stems. It was also demonstrated that 3M brand reflective tape offered high-contrast visibility in the intensity field. It may be possible to easily read tree numbers if some type of reflective paint was used.

Automated tree species identification continues to be a challenge. This is a major area of international study for both ALS and MLS data. Recent AI model development may provide an approach to extract this sought-after attribute. The field and scanner data from this project are available upon request and are being used in r-lidar development and by project partners.

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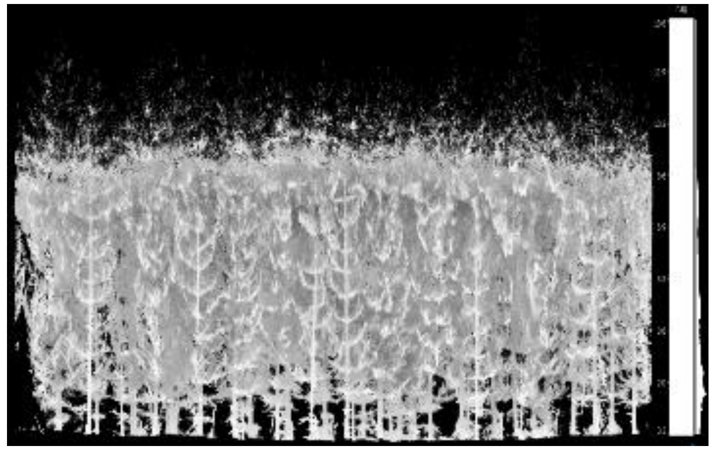
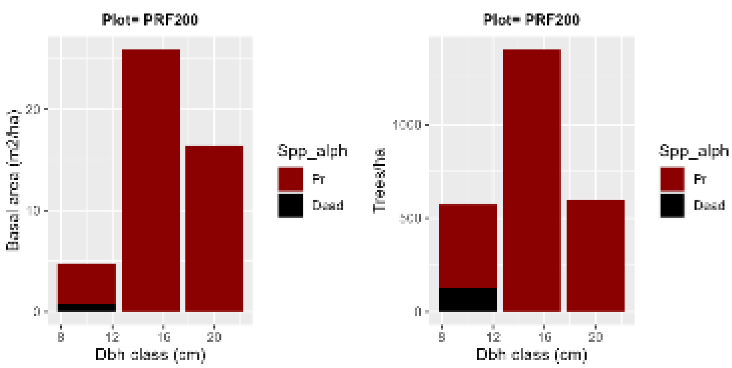
Scanning plot PRF002 with the Faro Orbis.

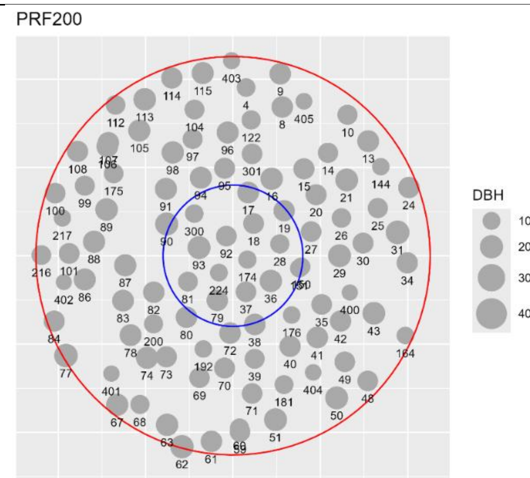
12 Appendix A – Field Plot Factsheets

The field plot factsheets are presented in order of stand vertical complexity; simple single-tier conditions to complex two-tier situations.

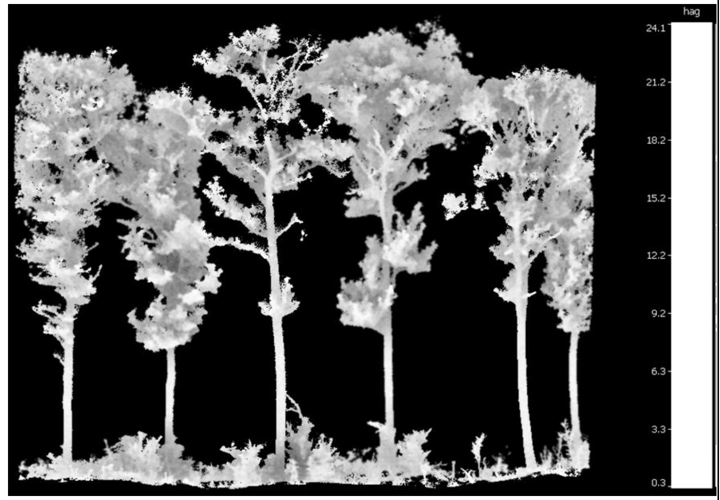
MLS Plot	Species Composition	Strata		
		Forest Type	Overstory	Understory
PRF200	Pr 100	Plant Con	Open	Sparse

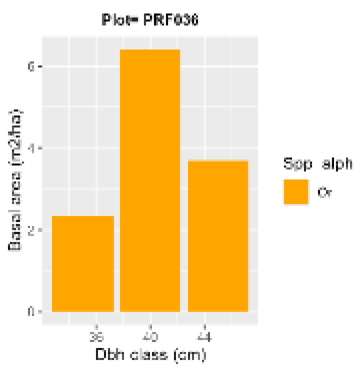


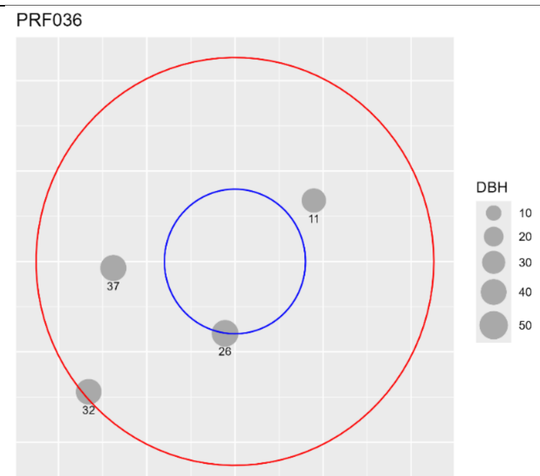




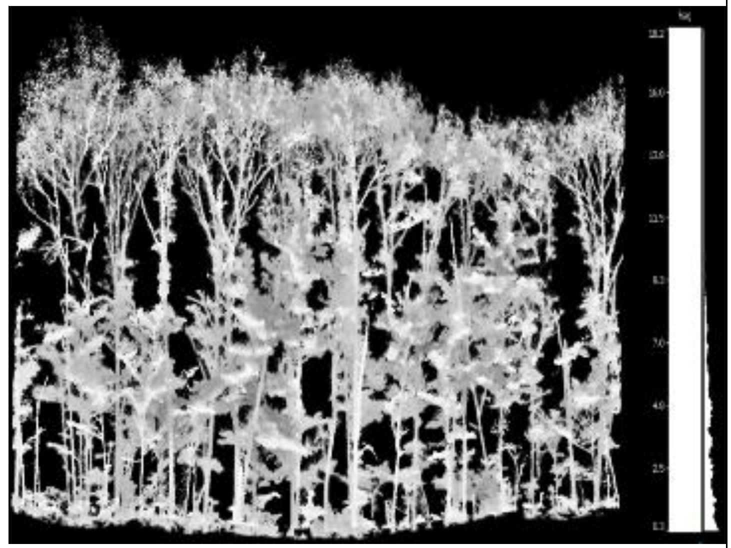
MLS Plot	Species Composition	Strata		
		Forest Type	Overstory	Understory
PRF036	Or 100	Nat Hwd	Open	Sparse

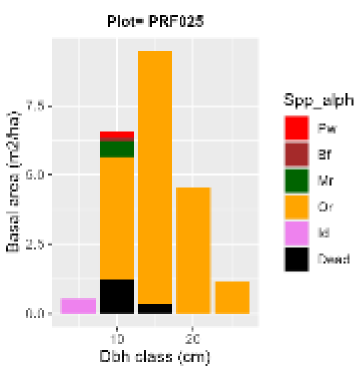


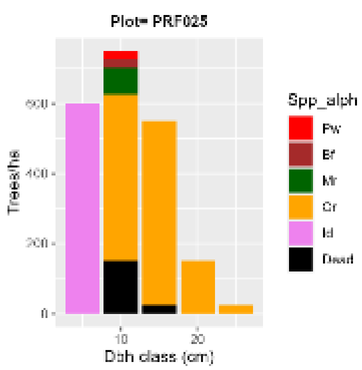


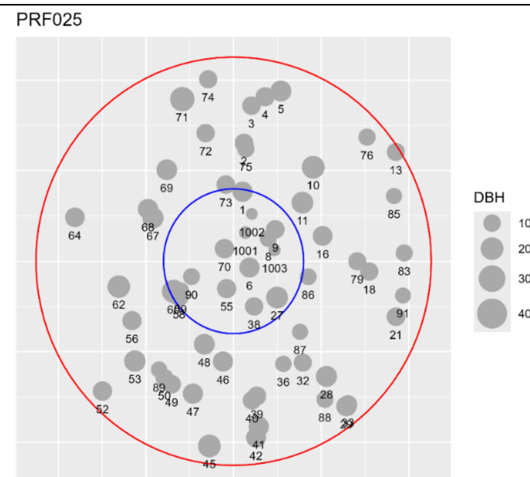


MLS Plot	Species Composition	Strata		
		Forest Type	Overstory	Understory
PRF025	Or $_{93}$ Mr $_{3}$ Id $_{3}$ Pw $_{1}$ Bf $_{1}$	Nat Hwd	Dense	Sparse

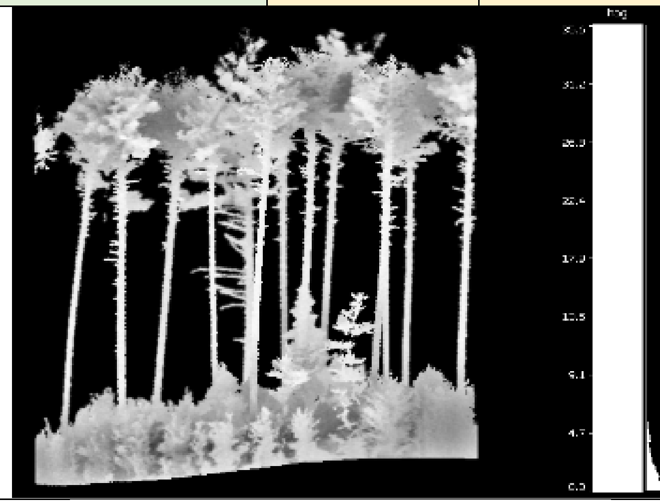


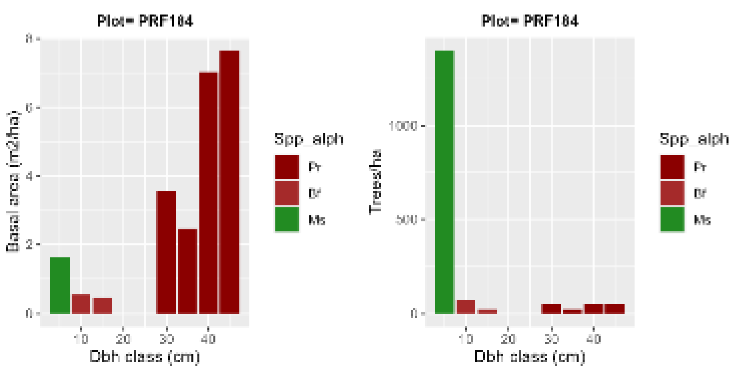




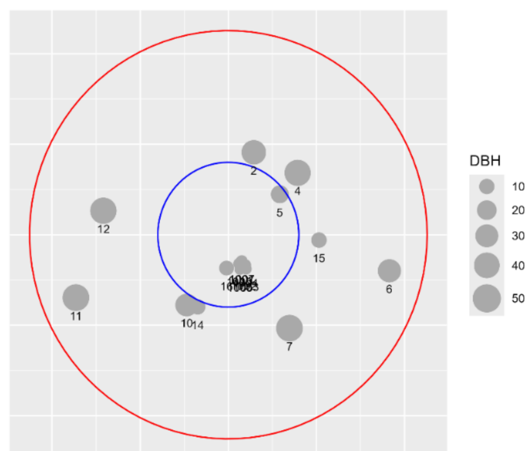


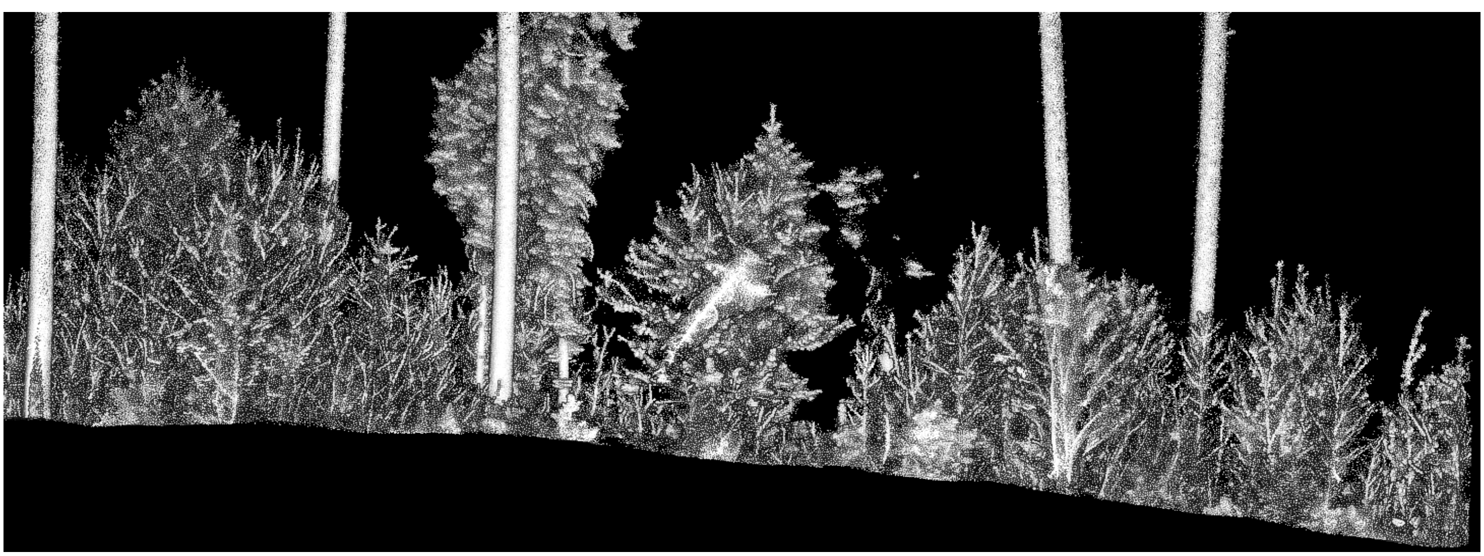
MLS Plot	Species Composition	Strata		
		Forest Type	Overstory	Understory
PRF184	Pr $_{89}$ Ms $_{7}$ Bf $_{5}$	Nat Conifer	Open	Sparse



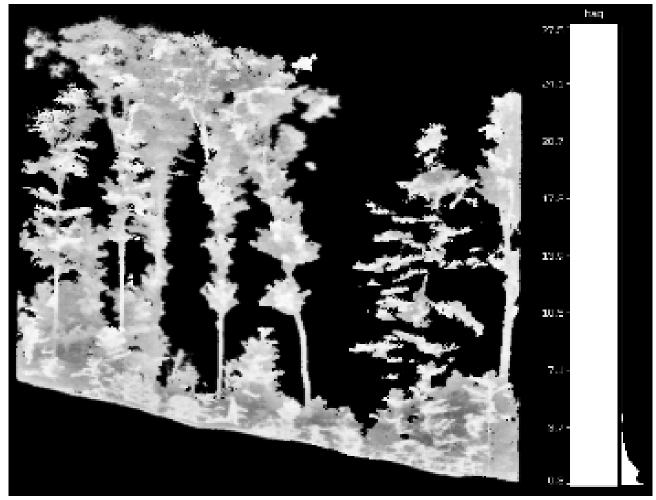


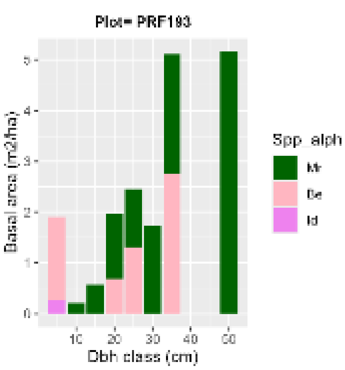
PRF184

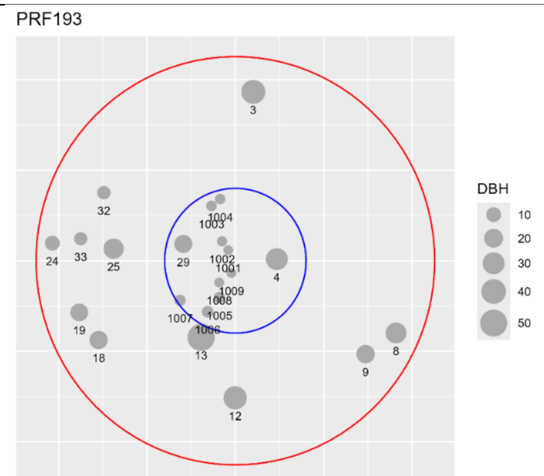


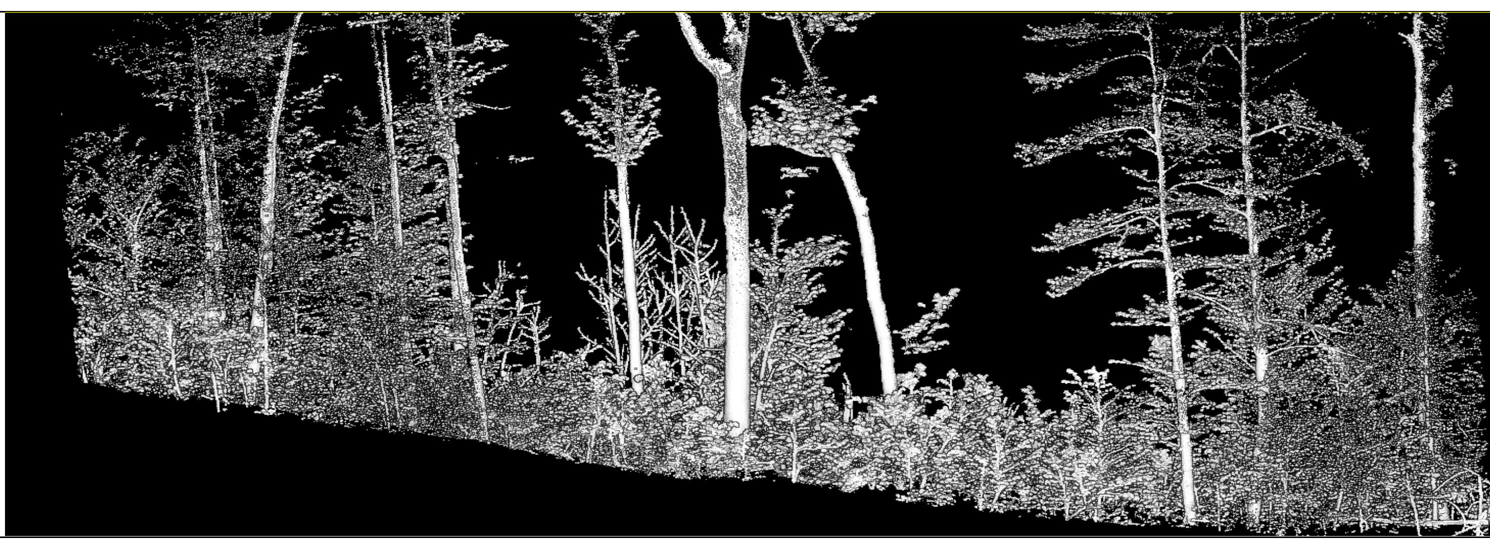


MLS Plot	Species Composition	Strata		
		Forest Type	Overstory	Understory
PRF193	Mr $_{65}$ Be $_{33}$ Id $_{1}$	Nat Hwd	Open	Dense

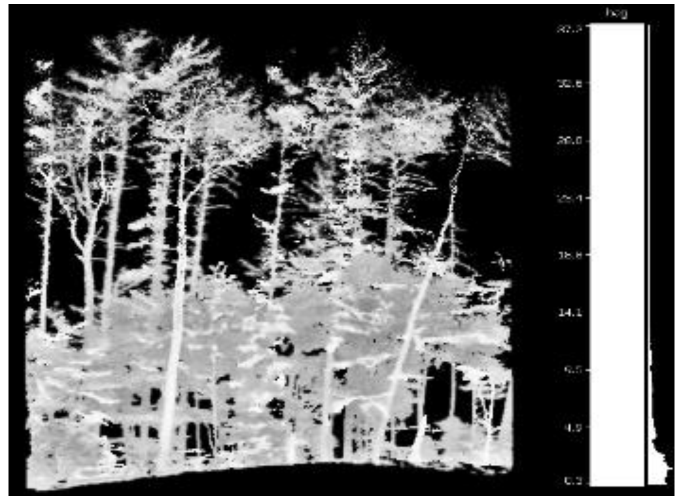


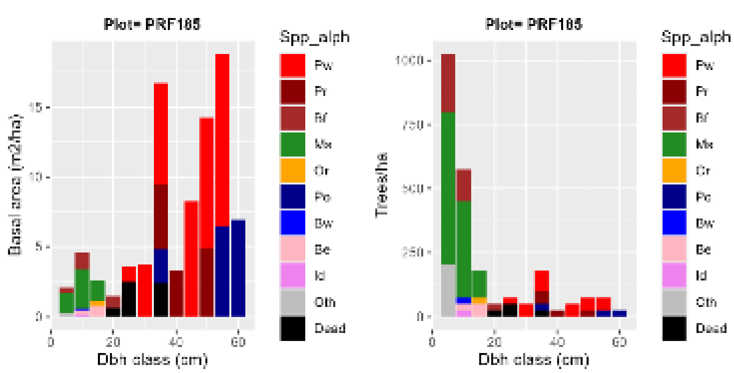


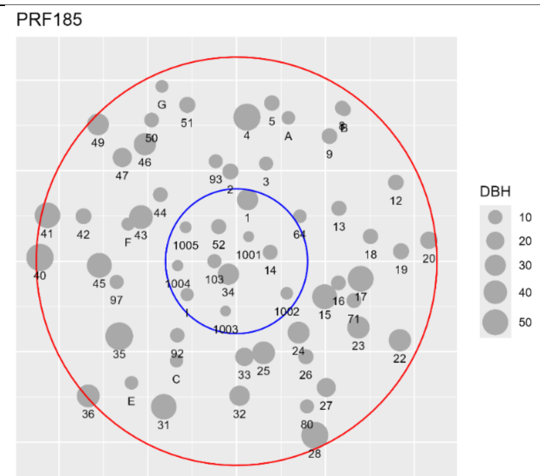




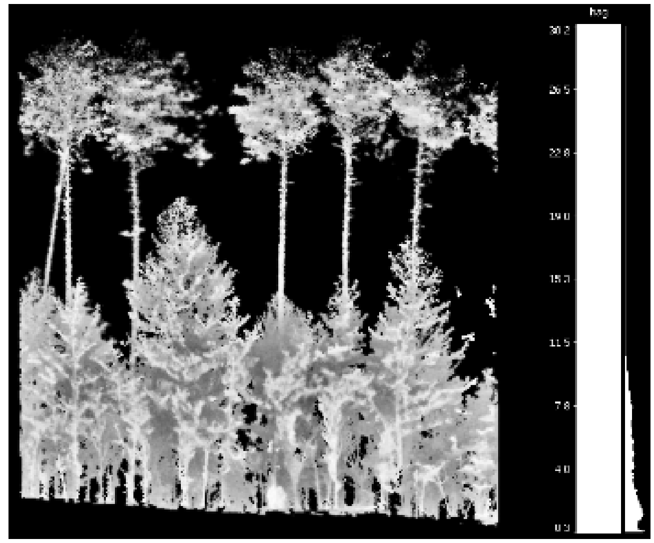
MLS Plot	Species Composition	Strata		
		Forest Type	Overstory	Understory
PRF185	$Pw_{52}\ Po_{20}\ Pr_{16}\ Ms_{7}\ Bf_{3}\ Be_{1}\ Oh_{1}$	Nat Conifer	Dense	Sparse

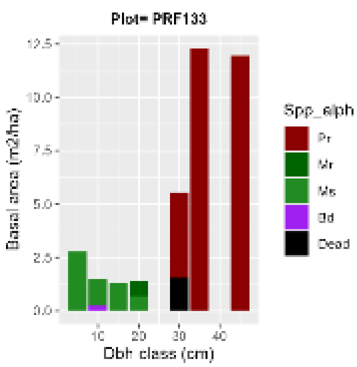


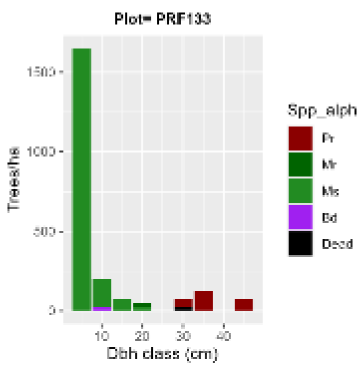


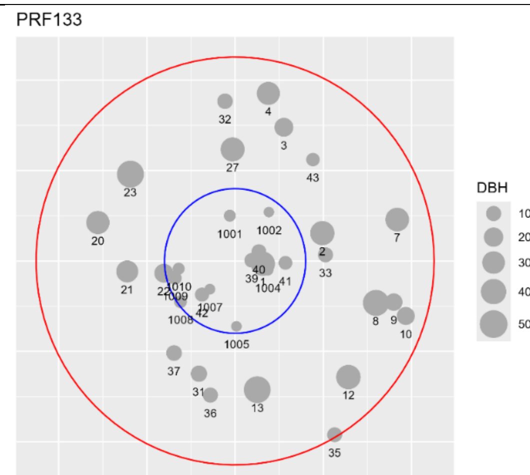


MLS Plot	Species Composition	Strata		
		Forest Type	Overstory	Understory
PRF133	Pr $_{80}$ Ms $_{17}$ Mr $_{2}$ Bd $_{1}$	Plant Con	Open	Midstory Dense hwd

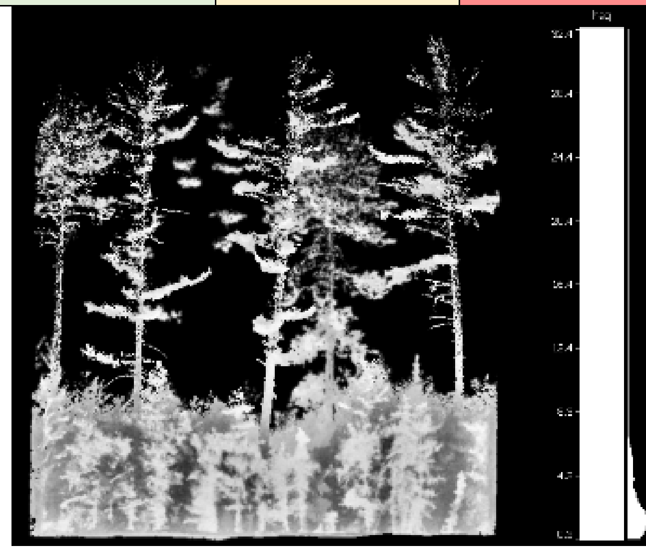


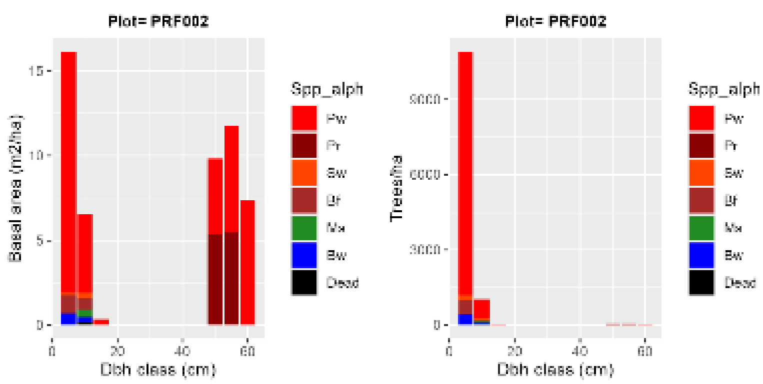


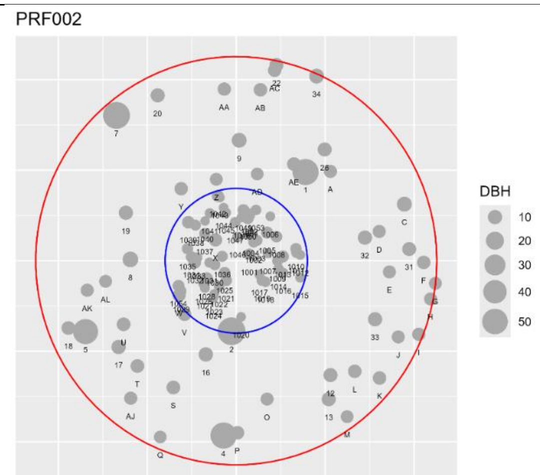


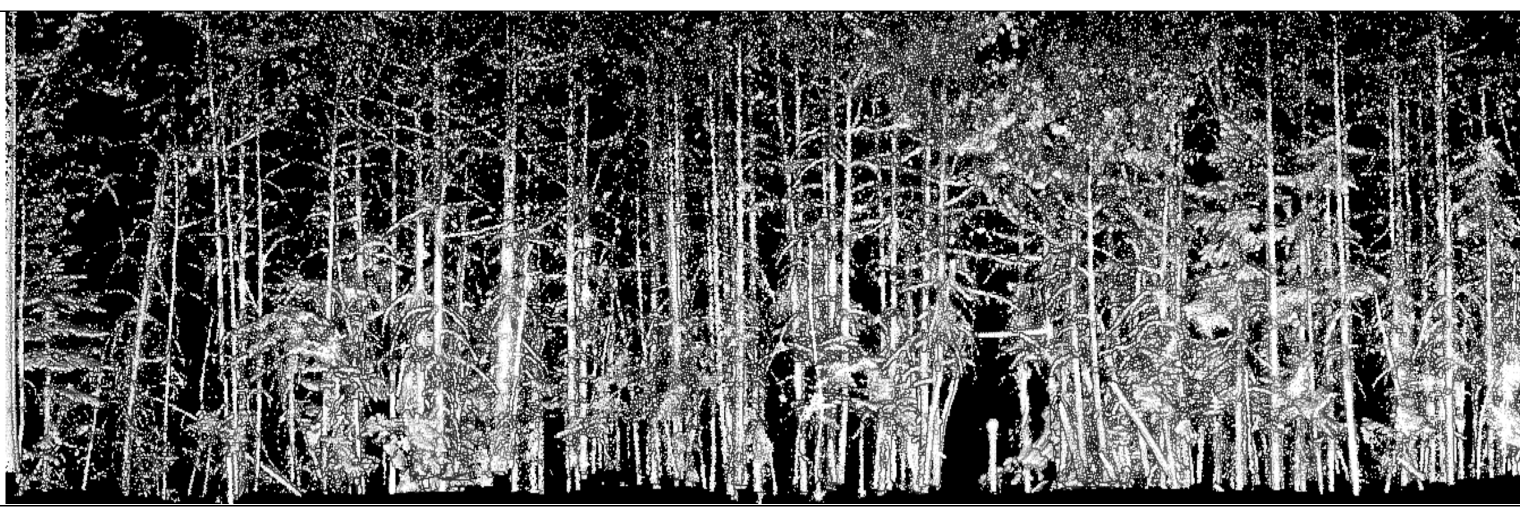


MLS Plot	Species Composition	Strata		
		Forest Type	Overstory	Understory
PRF002	Pw $_{72}$ Pr $_{21}$ Bf $_{3}$ Bw $_{2}$ Ms $_{1}$ Sw $_{1}$	Nat Conifer	Open	Dense Conifer









13 Appendix B – Modeling Fact Sheets

The modeling factsheets are presented in order of stand vertical complexity; simple single-tier conditions to complex two-tier situations.

Six of the eight plots have leaf-off and leaf-on results for the 2 algorithms presented (3DFIN and r-lidar pipeline). The plots that were scanned for both leaf-off and leaf-on conditions have 2 factsheets each; one for 3DFIN and one for r-lidar pipeline presenting the results by leaf status.

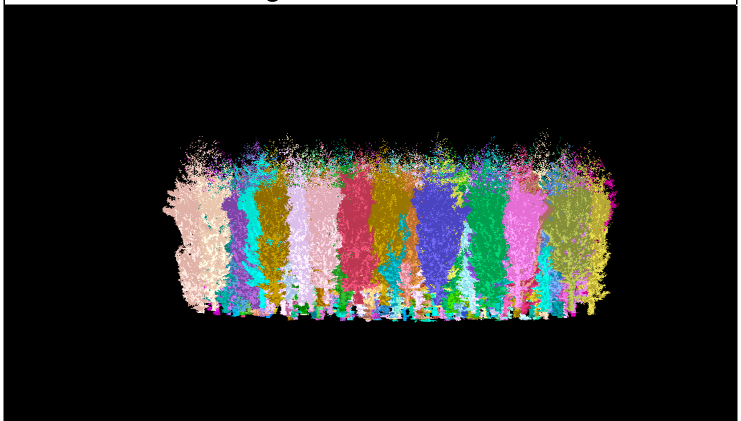
Plots that were just scanned for leaf off (PRF002 and PRF200) have one factsheet each that compares the results of the 2 algorithms. The following is the order the fact sheets are presented and the formats

Plot		Comparison by Algorithm	Results for r-lidar pipeline & Leaf Status	Results for 3DFIN & Leaf Status
PRF200				
PRF036				
PRF025				
PRF184				
PRF193				
PRF185				
PRF133				
PRF002				

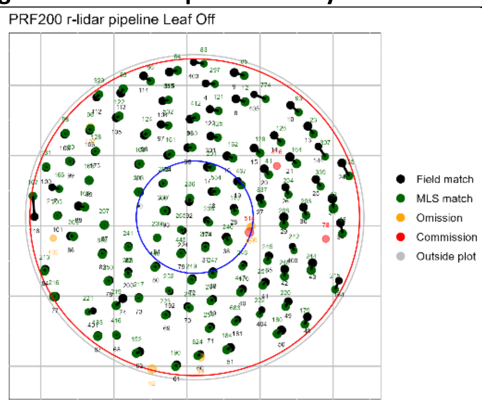
PRF200 – Pine – Leaf Off

r-lidar pipeline

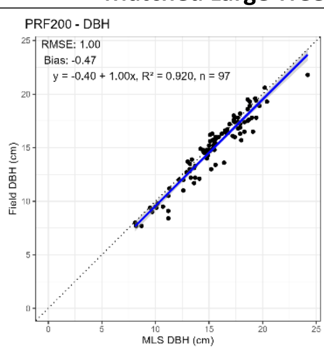
Segmentation - Leaf Off

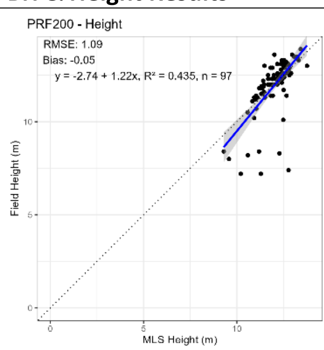


Large Tree Stem Map Matched by DBH & Location



Matched Large Tree DBH & Height Results

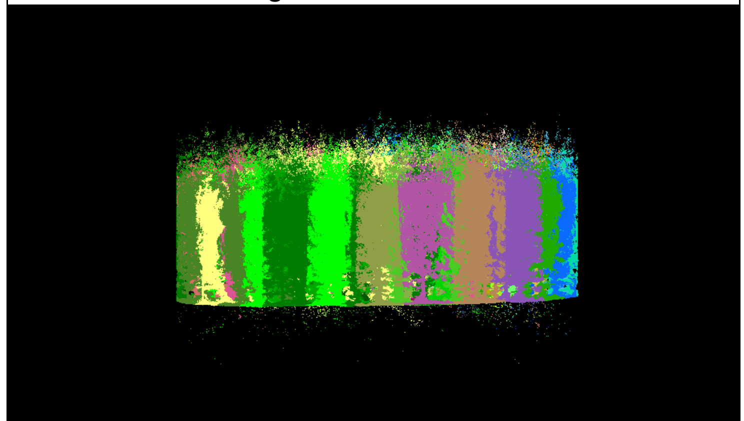




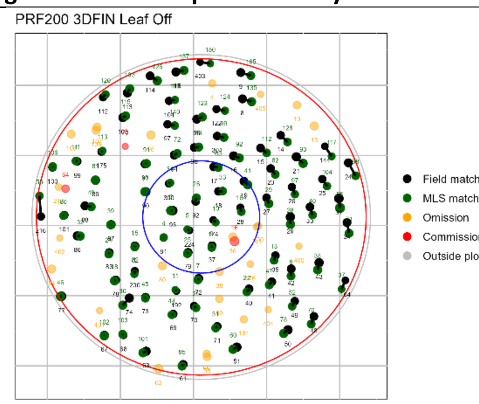
PRF200 – Pine – Leaf Off

3DFIN

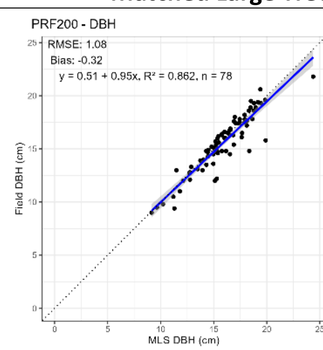
Segmentation - Leaf Off

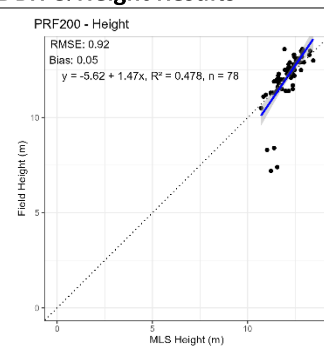


Large Tree Stem Map Matched by DBH & Location

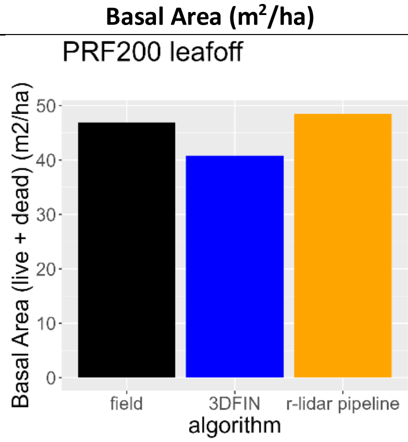


Matched Large Tree DBH & Height Results

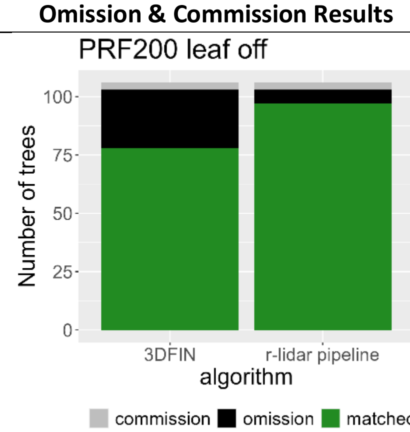




Basal Area (m^2/ha)



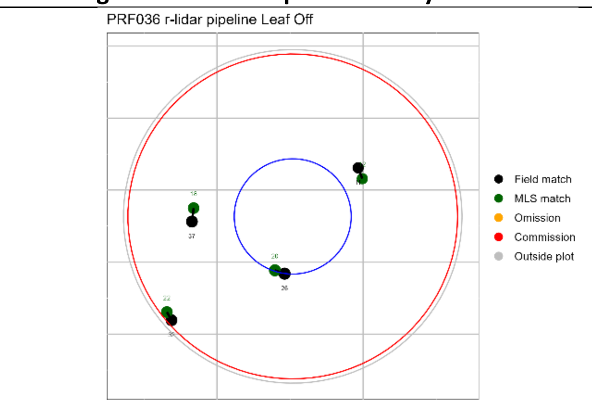
Omission & Commission Results

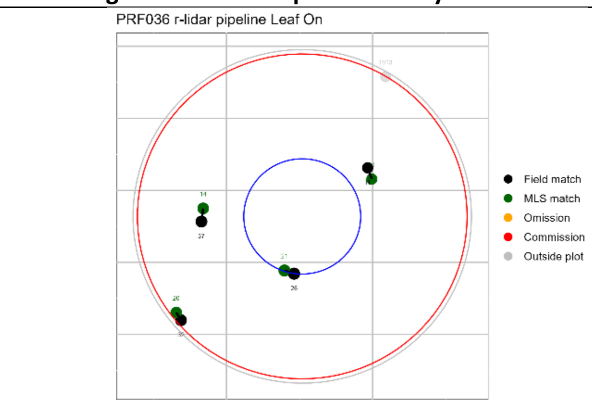


PRF036 – Hardwood	Algorithm: r-lidar pipeline

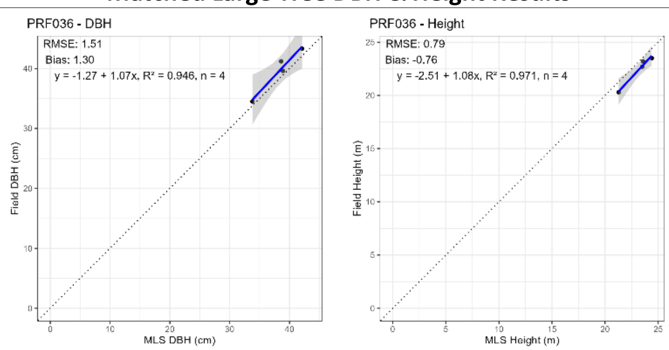
Segmentation - Leaf Off	Segmentation - Leaf On

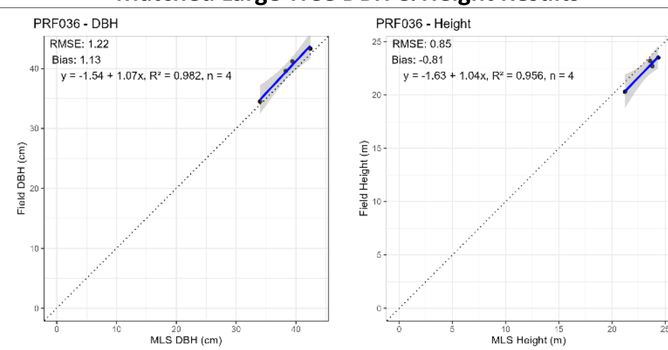
Large Tree Stem Map Matched by DBH & Location	Large Tree Stem Map Matched by DBH & Location



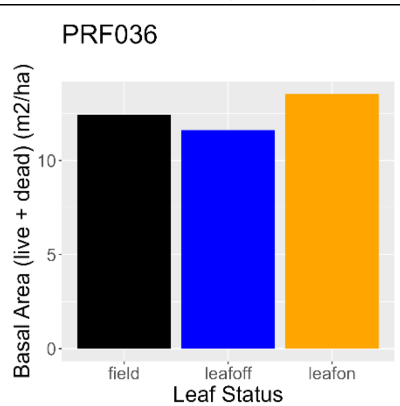


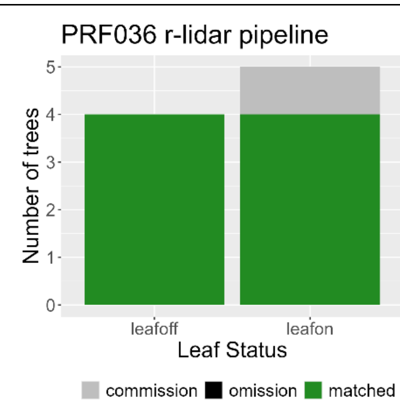
Matched Large Tree DBH & Height Results	Matched Large Tree DBH & Height Results





Basal Area (m²/ha)	Omission & Commission Results





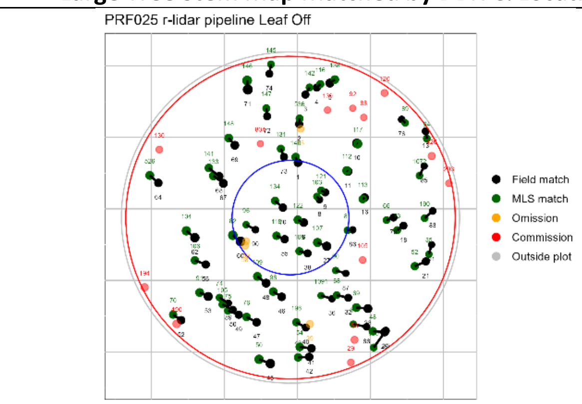
PRF025 – Hardwood

Algorithm: r-lidar pipeline

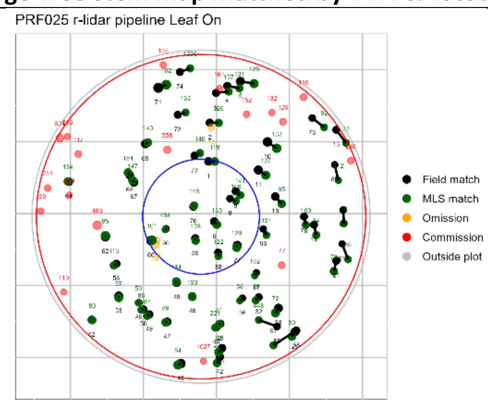
Segmentation - Leaf Off

Segmentation - Leaf On

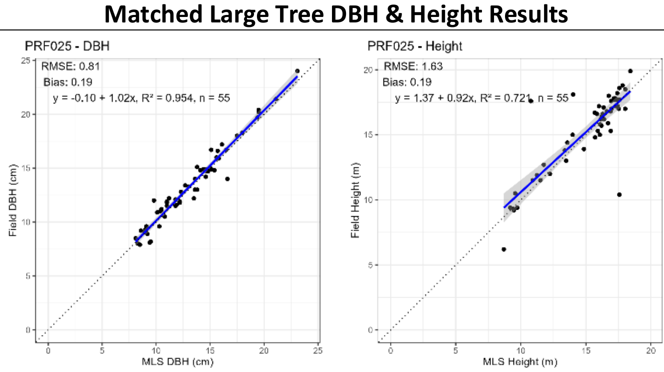
Large Tree Stem Map Matched by DBH & Location



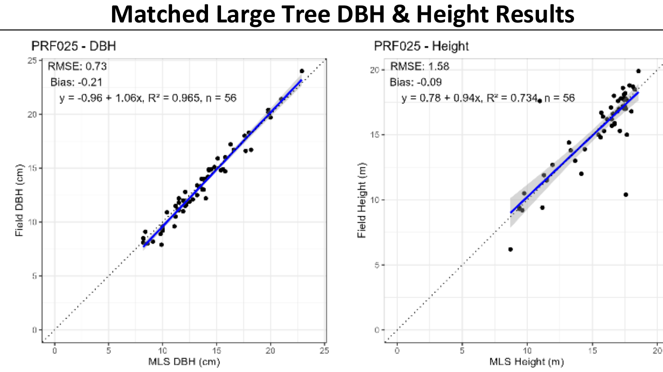
Large Tree Stem Map Matched by DBH & Location



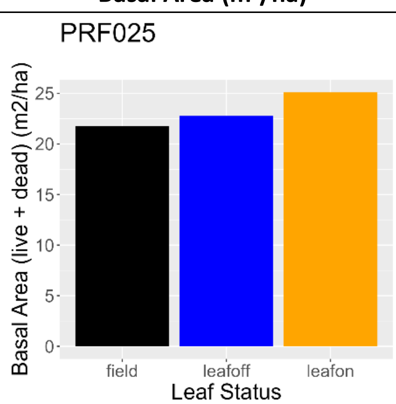
Matched Large Tree DBH & Height Results



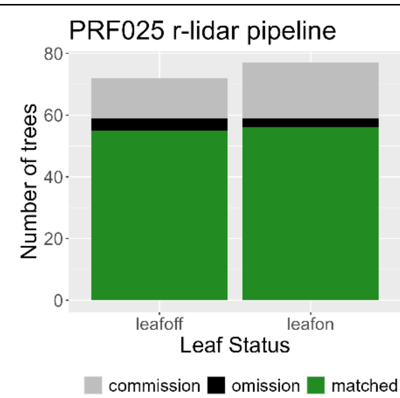
Matched Large Tree DBH & Height Results



Basal Area (m²/ha)



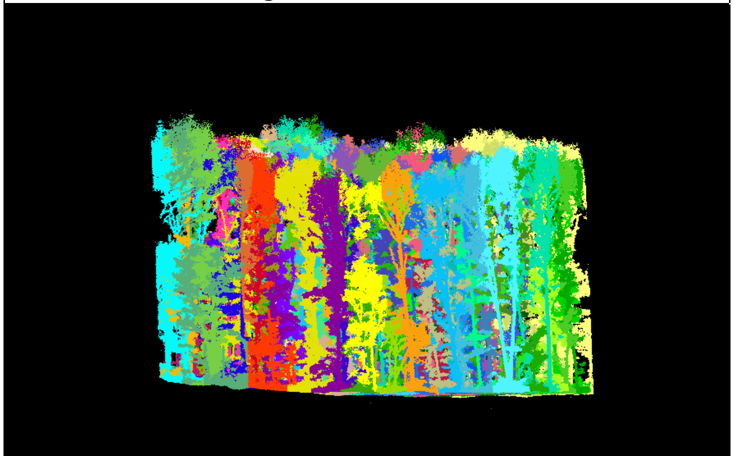
Omission & Commission Results



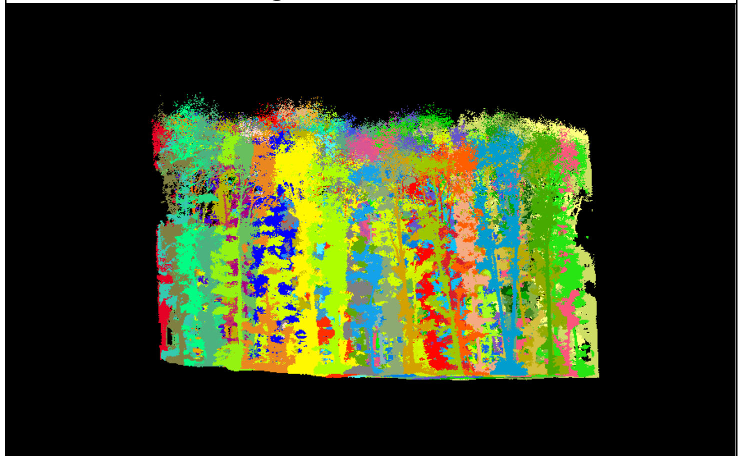
PRF025 – Hardwood

Algorithm: 3DFIN

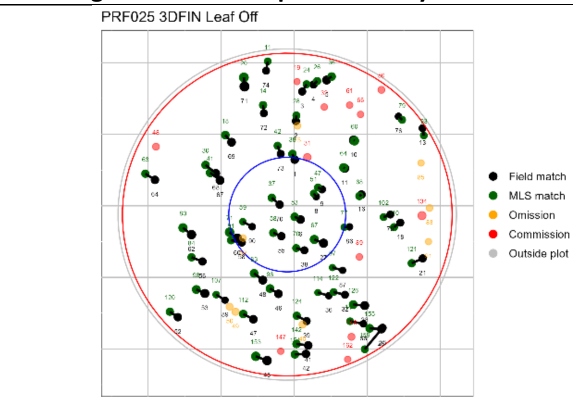
Segmentation - Leaf Off



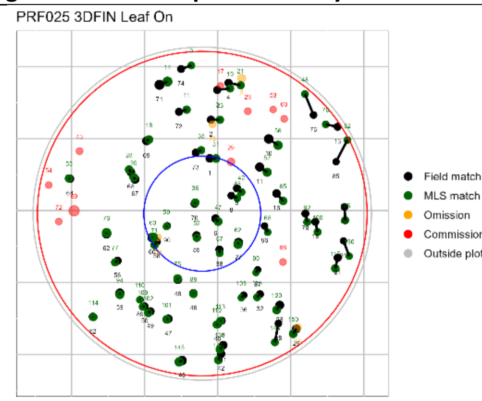
Segmentation - Leaf On



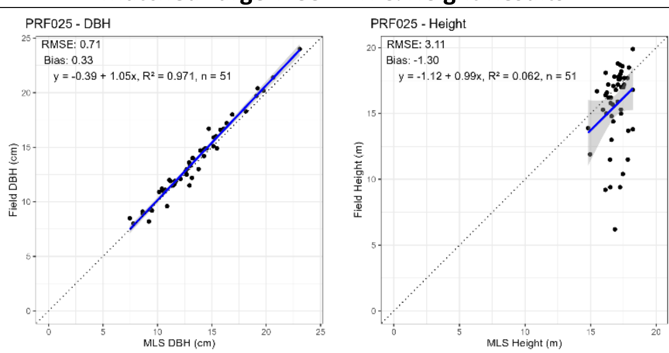
Large Tree Stem Map Matched by DBH & Location



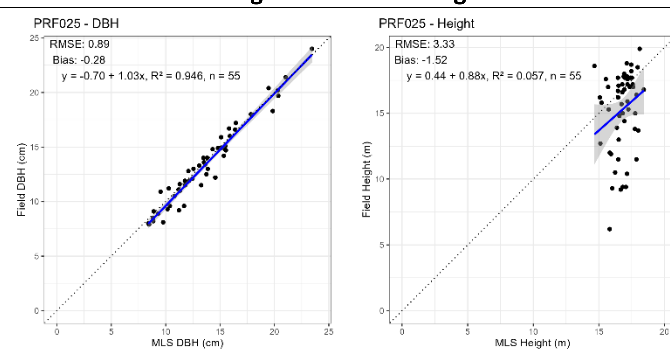
Large Tree Stem Map Matched by DBH & Location



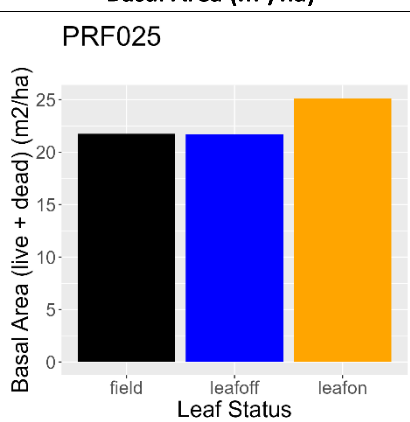
Matched Large Tree DBH & Height Results



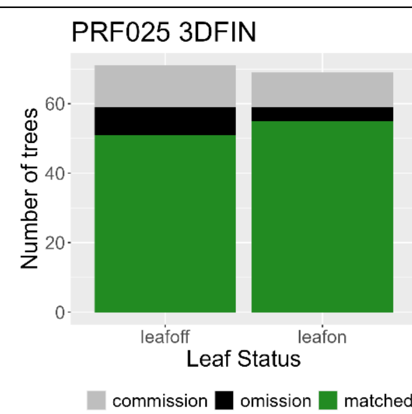
Matched Large Tree DBH & Height Results



Basal Area (m^2/ha)



Omission & Commission Results

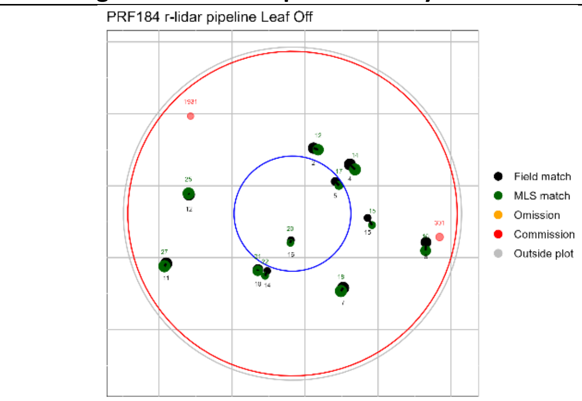


PRF184 – Conifer   Algorithm: r-lidar pipeline

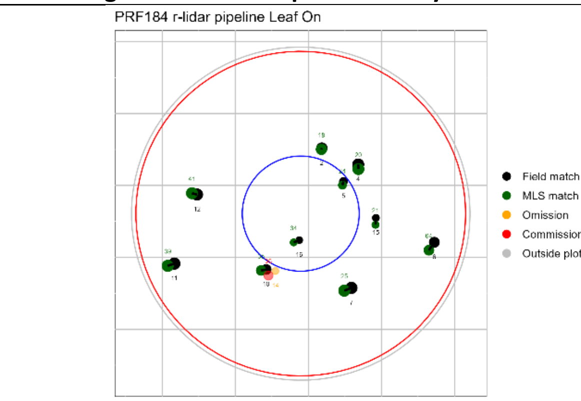
Segmentation - Leaf Off

Segmentation - Leaf On

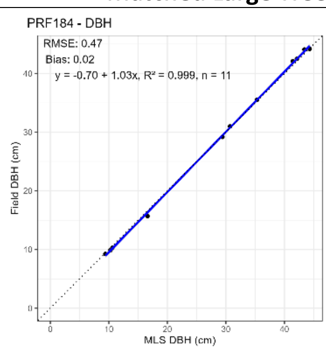
Large Tree Stem Map Matched by DBH & Location

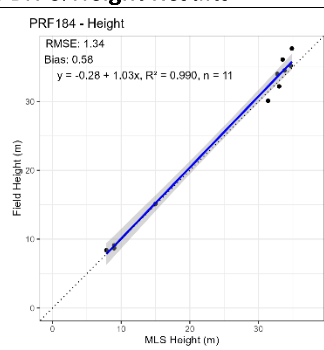


Large Tree Stem Map Matched by DBH & Location

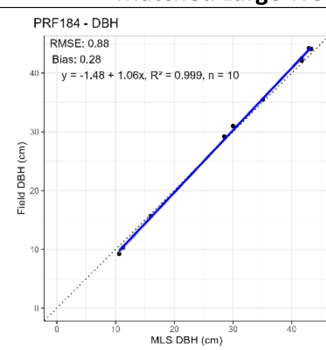


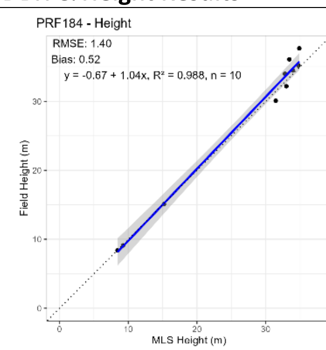
Matched Large Tree DBH & Height Results



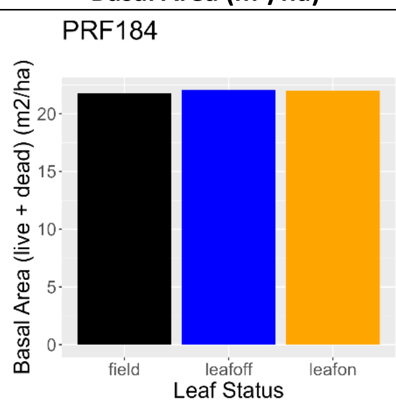


Matched Large Tree DBH & Height Results

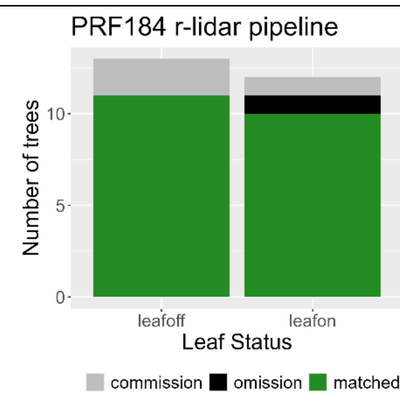




Basal Area (m²/ha)

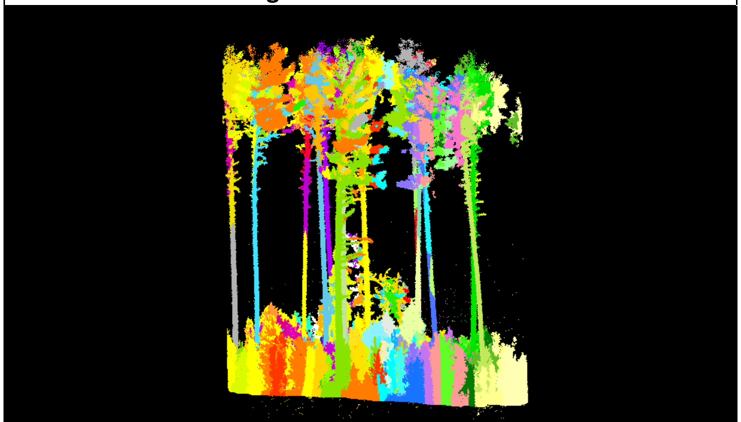


Omission & Commission Results

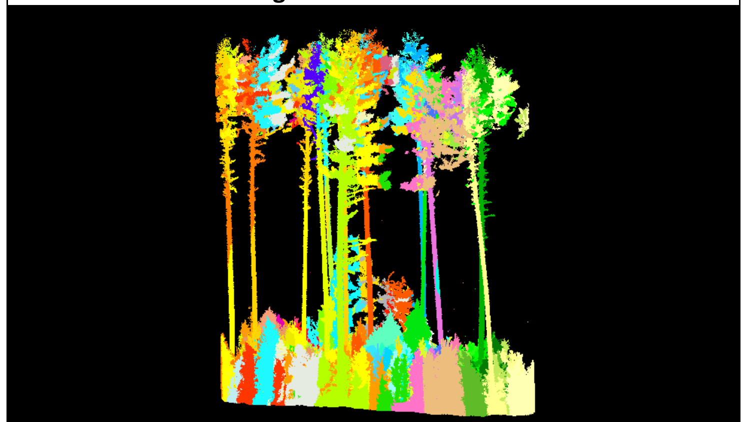


PRF184 – Conifer | Algorithm: 3DFIN

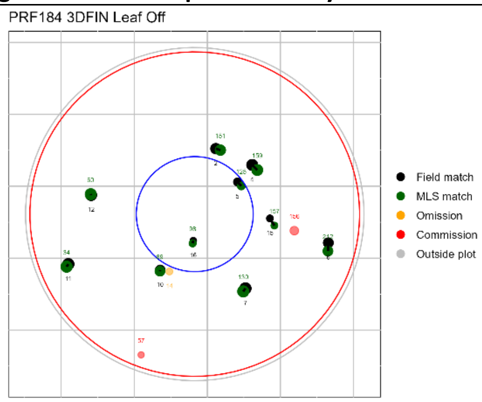
Segmentation - Leaf Off



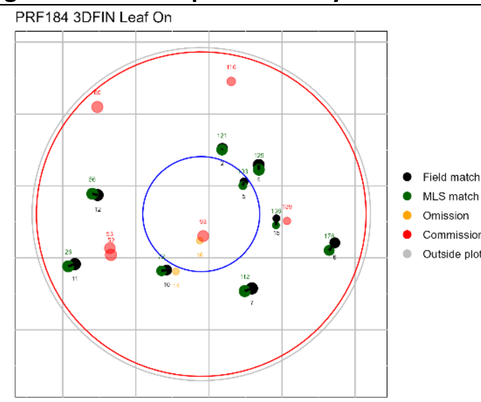
Segmentation - Leaf On



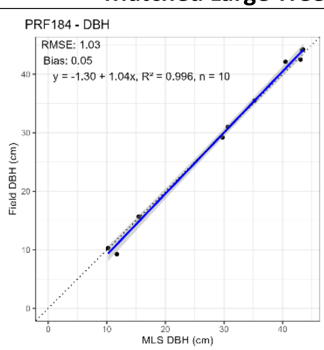
Large Tree Stem Map Matched by DBH & Location

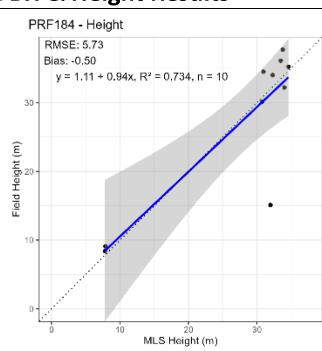


Large Tree Stem Map Matched by DBH & Location

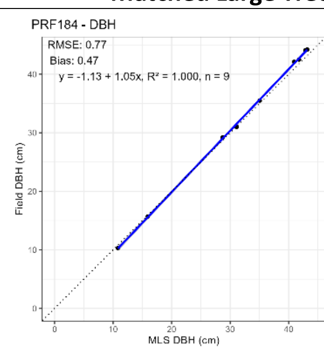


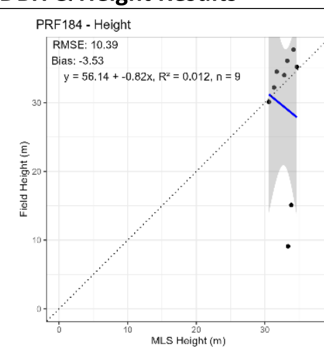
Matched Large Tree DBH & Height Results



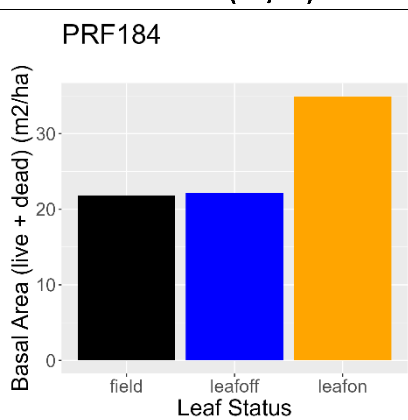


Matched Large Tree DBH & Height Results

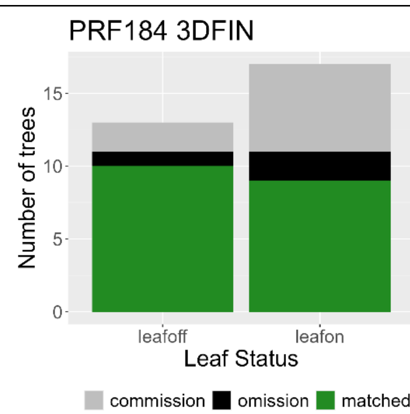




Basal Area (m^2/ha)

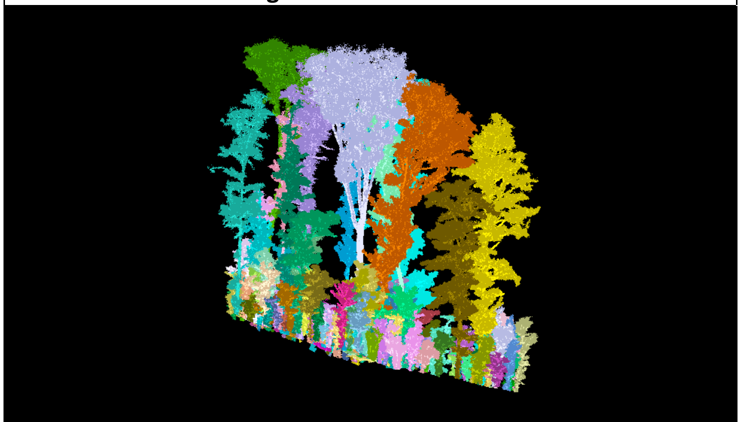


Omission & Commission Results

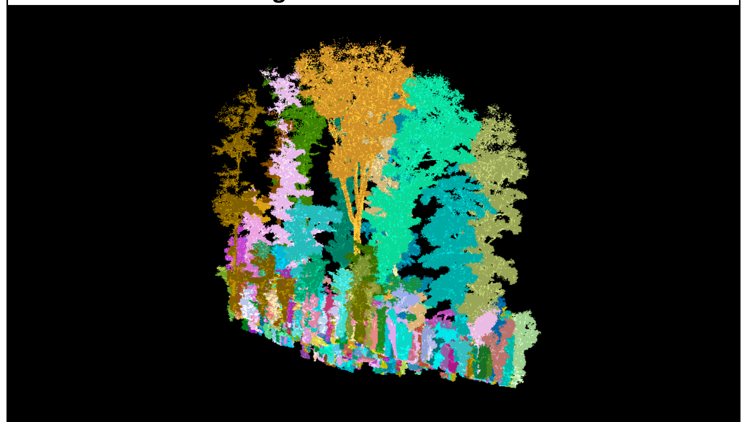


PRF193 – Hardwood　　Algorithm: r-lidar pipeline

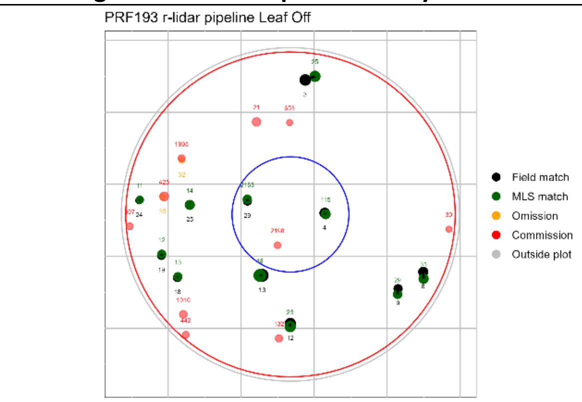
Segmentation - Leaf Off



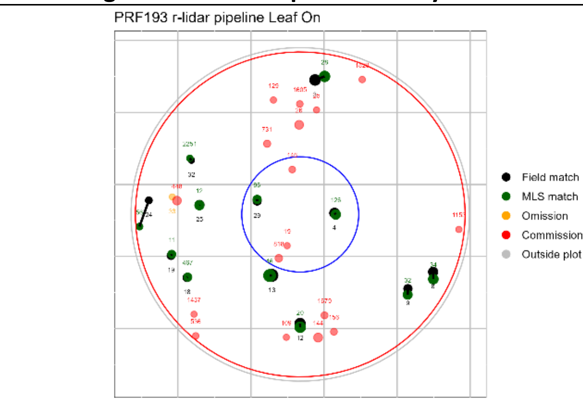
Segmentation - Leaf On



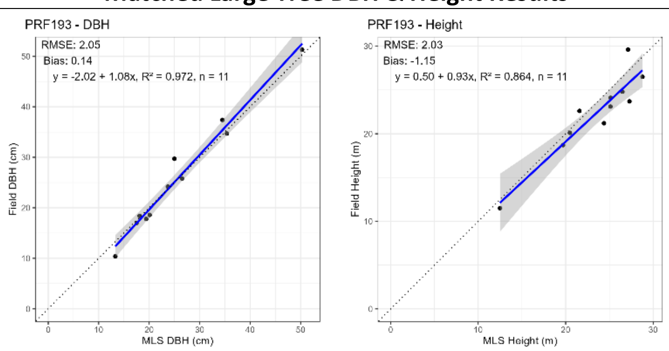
Large Tree Stem Map Matched by DBH & Location



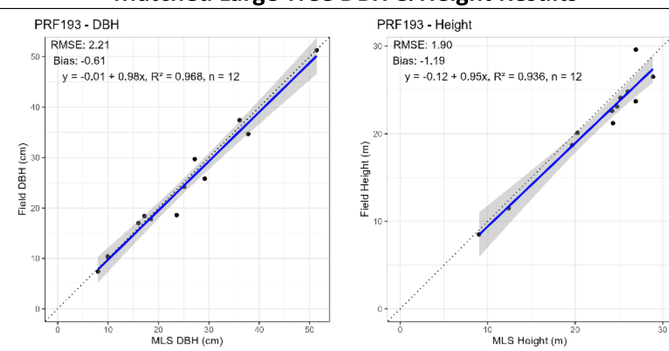
Large Tree Stem Map Matched by DBH & Location



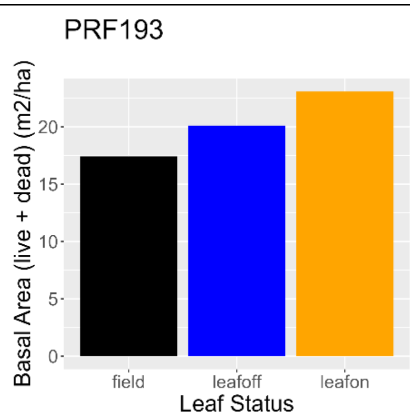
Matched Large Tree DBH & Height Results



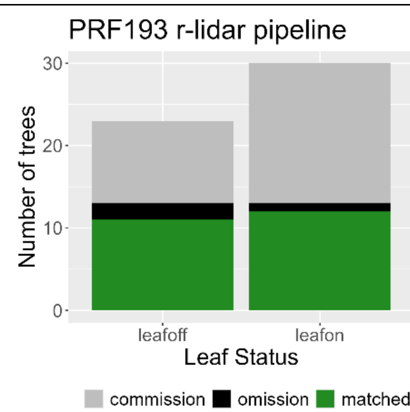
Matched Large Tree DBH & Height Results



Basal Area (m^2/ha)

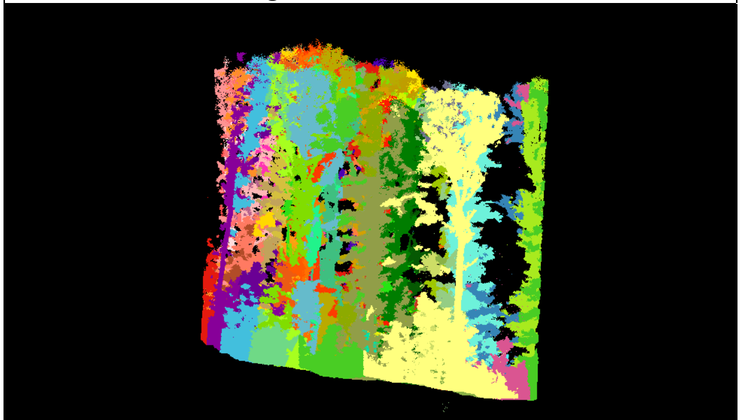


Omission & Commission Results

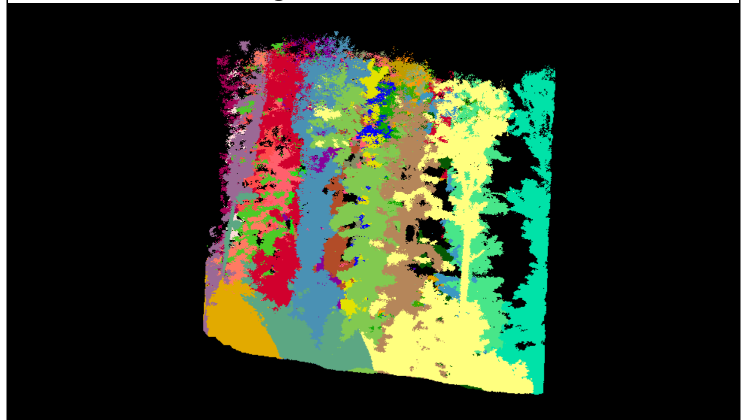


PRF193 – Hardwood Algorithm: 3DFIN

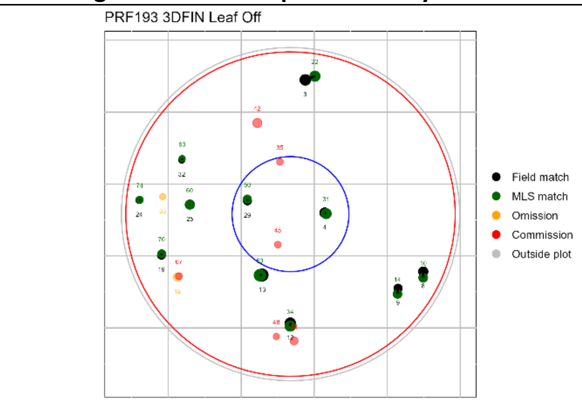
Segmentation - Leaf Off



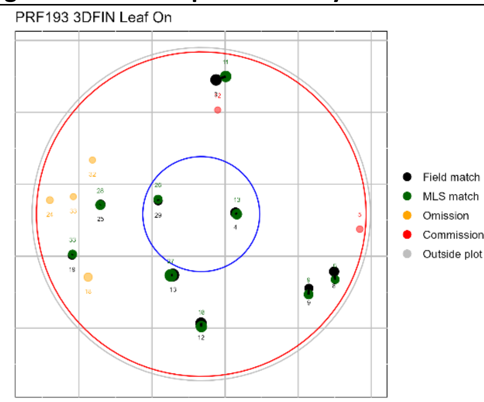
Segmentation - Leaf On



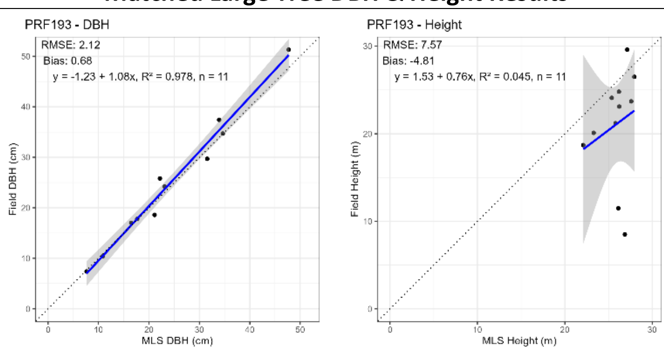
Large Tree Stem Map Matched by DBH & Location



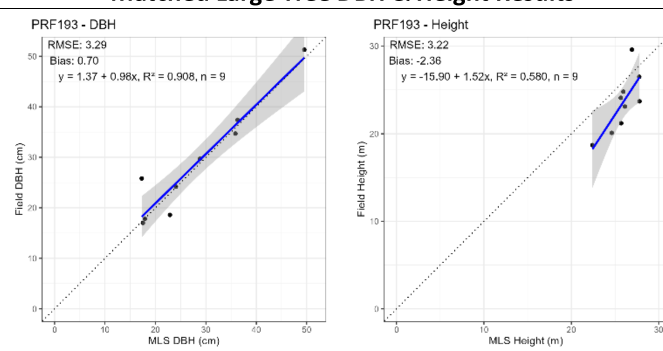
Large Tree Stem Map Matched by DBH & Location



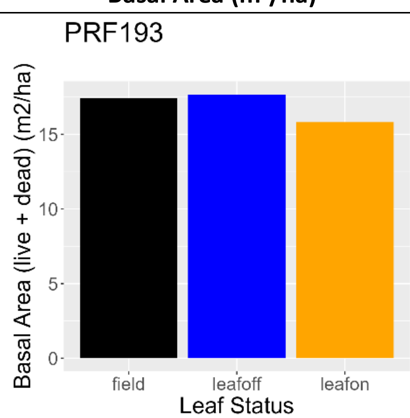
Matched Large Tree DBH & Height Results



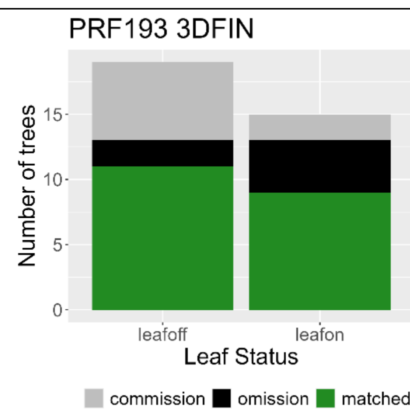
Matched Large Tree DBH & Height Results



Basal Area (m^2/ha)

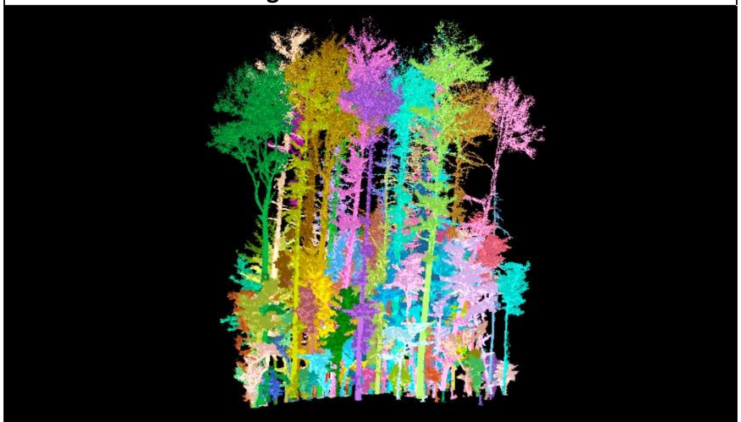


Omission & Commission Results



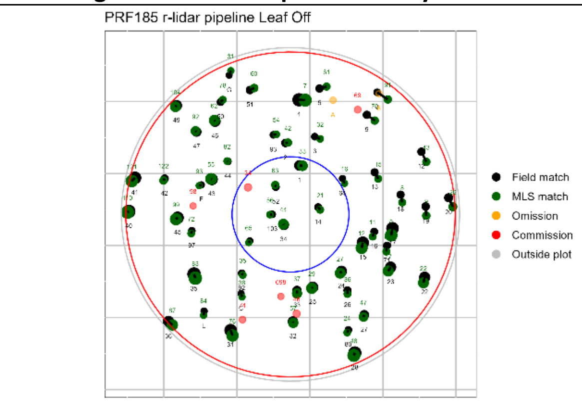
PRF185 – Conifer   Algorithm: r-lidar pipeline

Segmentation - Leaf Off

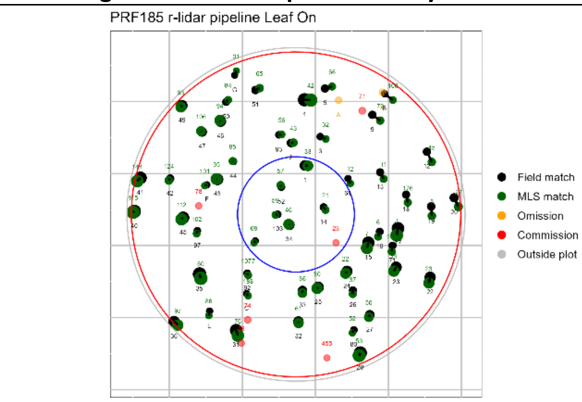


Segmentation - Leaf On

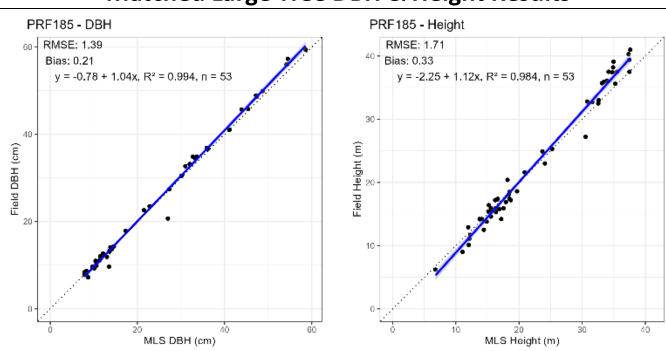
Large Tree Stem Map Matched by DBH & Location



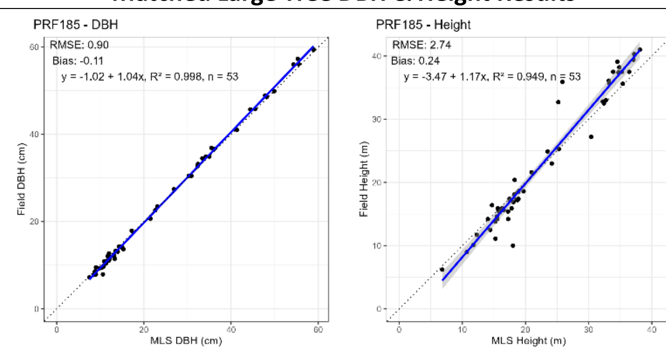
Large Tree Stem Map Matched by DBH & Location



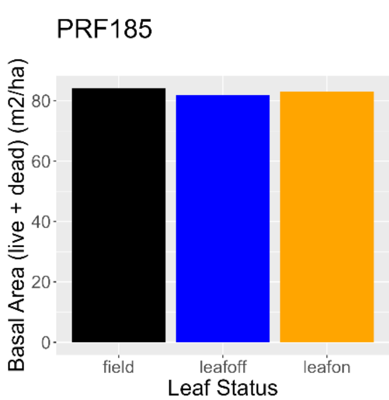
Matched Large Tree DBH & Height Results



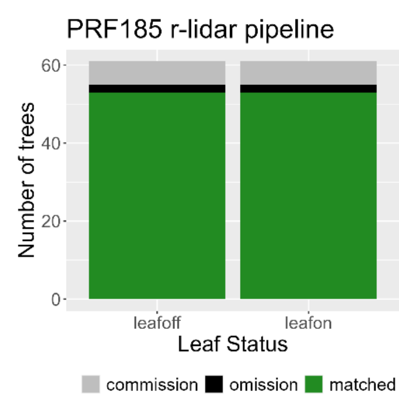
Matched Large Tree DBH & Height Results



Basal Area (m^2/ha)

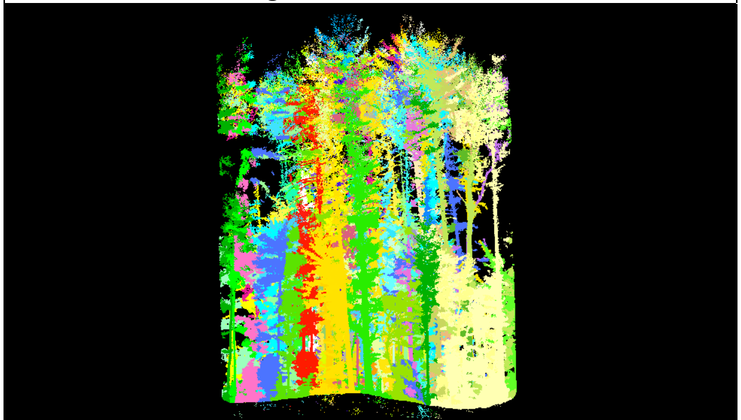


Omission & Commission Results

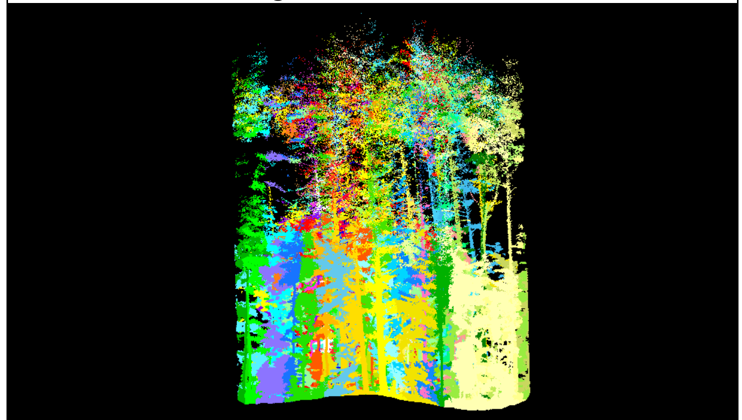


PRF185 – Conifer | Algorithm: 3DFIN

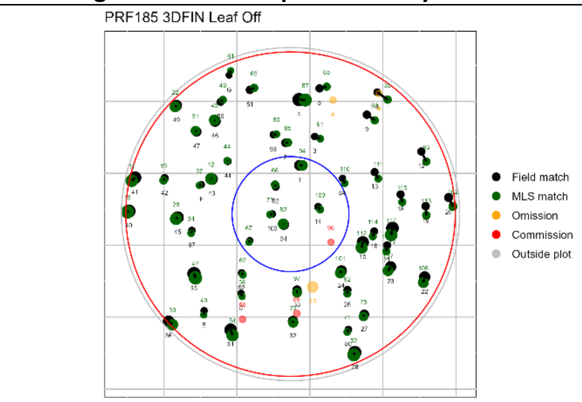
Segmentation - Leaf Off



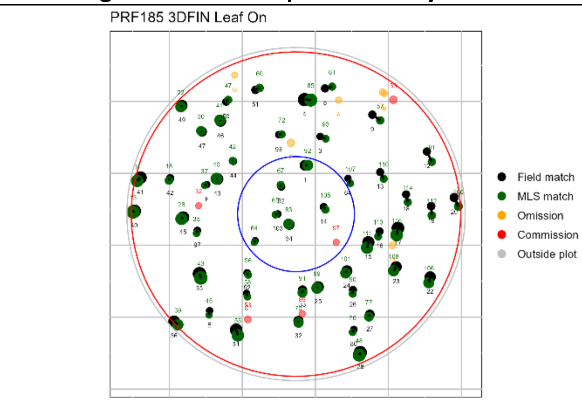
Segmentation - Leaf On



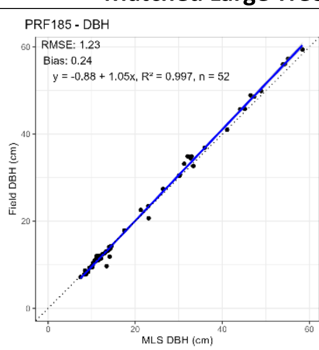
Large Tree Stem Map Matched by DBH & Location

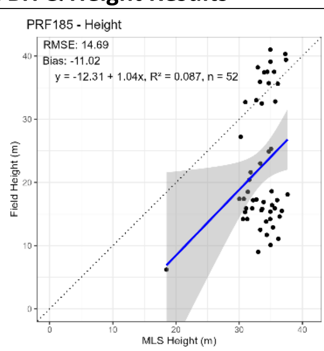


Large Tree Stem Map Matched by DBH & Location

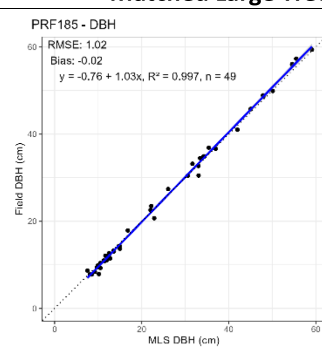


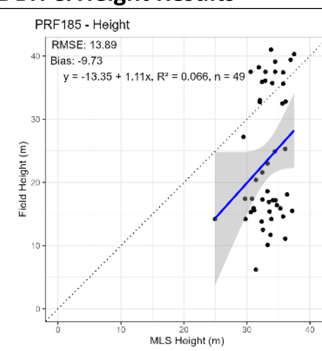
Matched Large Tree DBH & Height Results



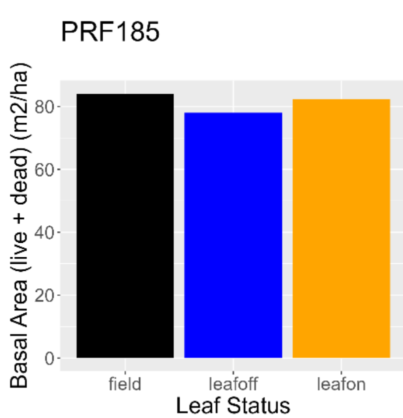


Matched Large Tree DBH & Height Results

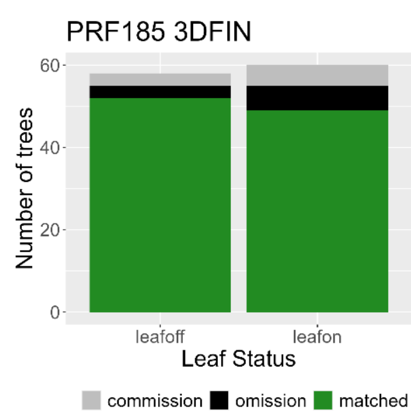




Basal Area (m^2/ha)

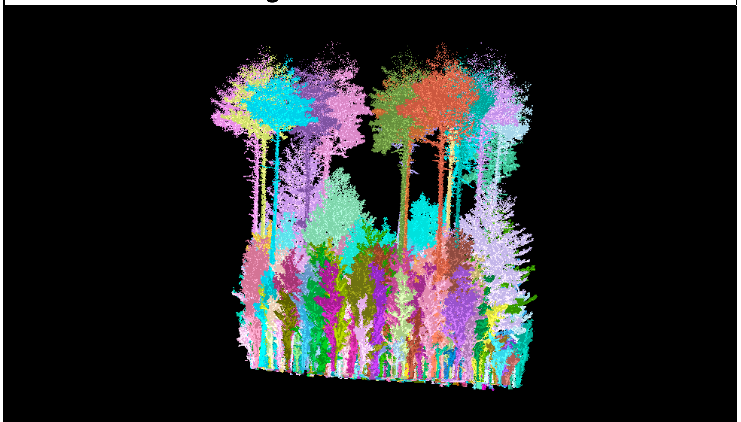


Omission & Commission Results

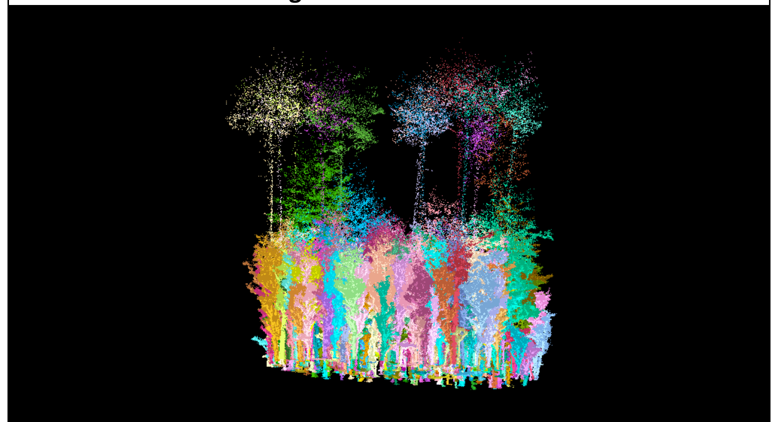


PRF133 – Plantation Conifer | Algorithm: r-lidar pipeline

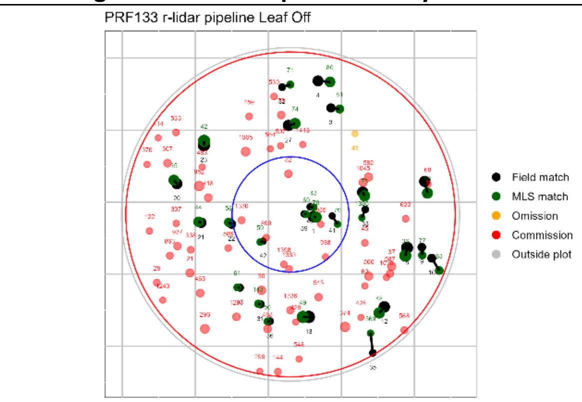
Segmentation - Leaf Off



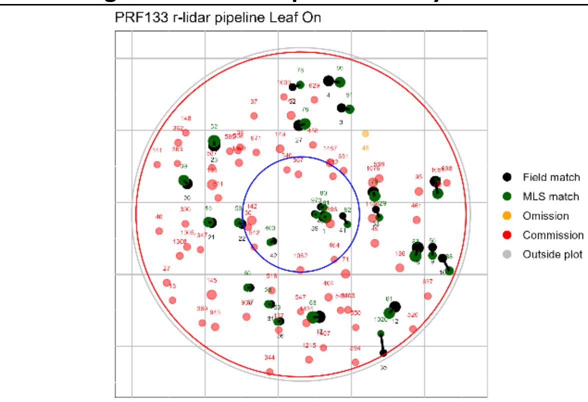
Segmentation - Leaf On



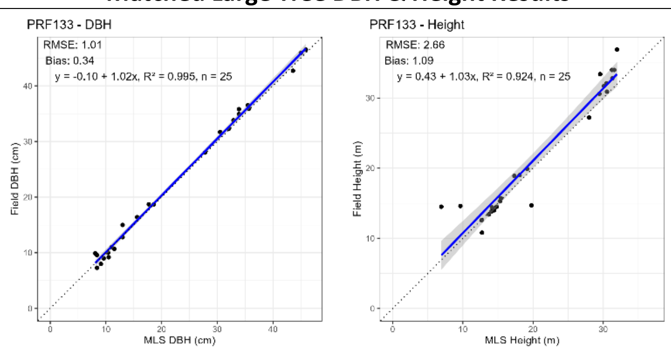
Large Tree Stem Map Matched by DBH & Location



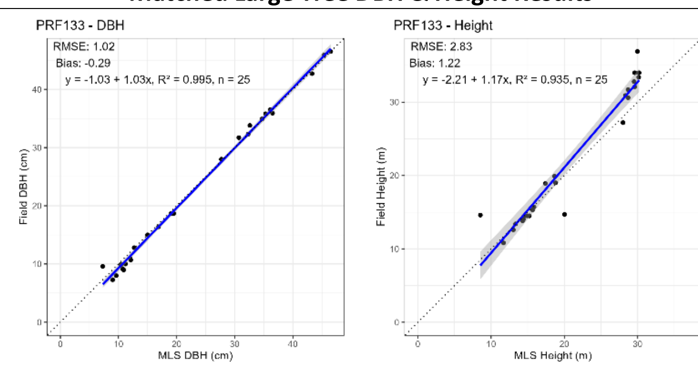
Large Tree Stem Map Matched by DBH & Location



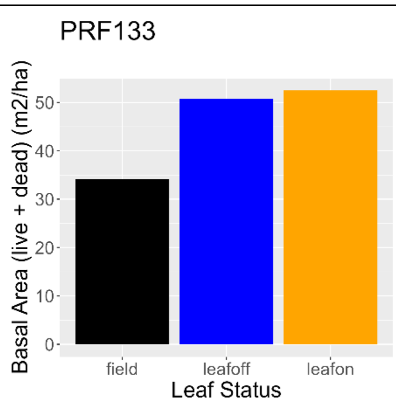
Matched Large Tree DBH & Height Results



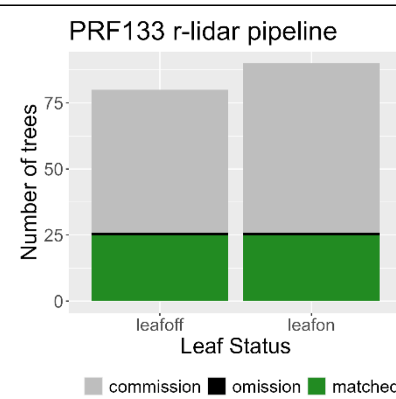
Matched Large Tree DBH & Height Results



Basal Area (m^2/ha)

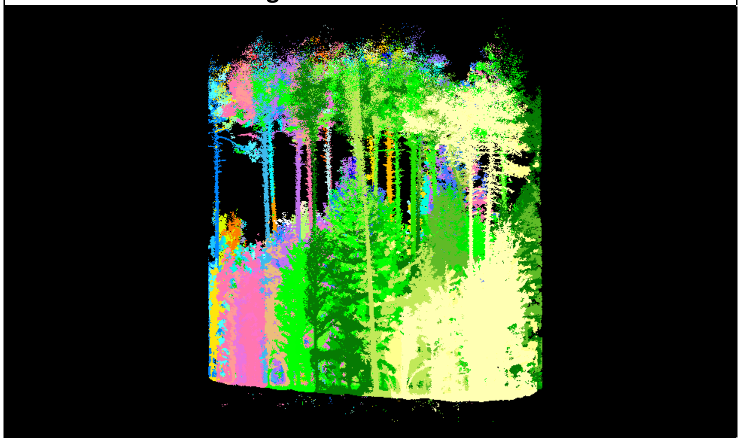


Omission & Commission Results

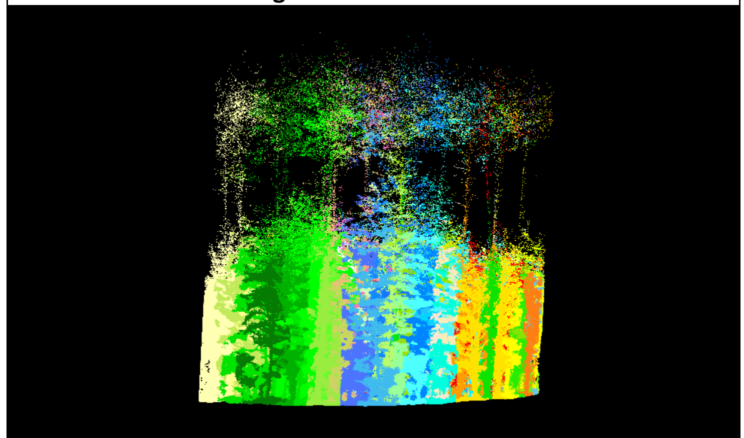


PRF133 – Plantation Conifer Algorithm: 3DFIN

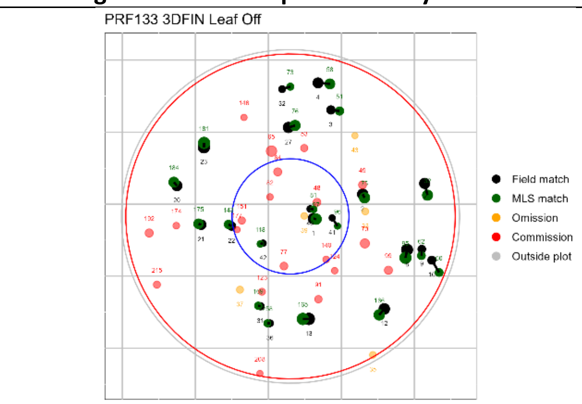
Segmentation - Leaf Off



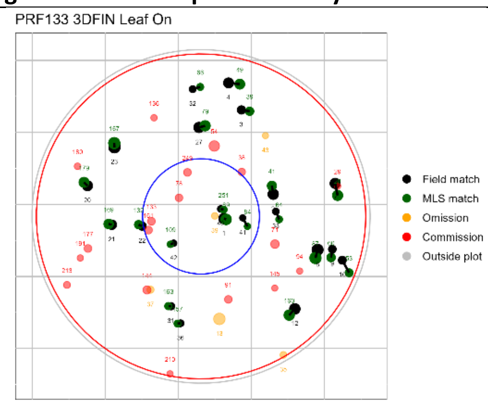
Segmentation - Leaf On



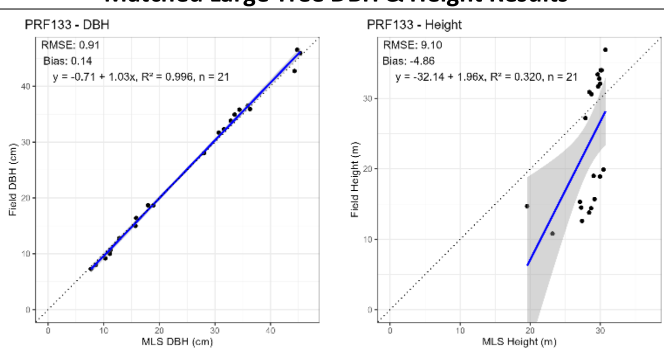
Large Tree Stem Map Matched by DBH & Location



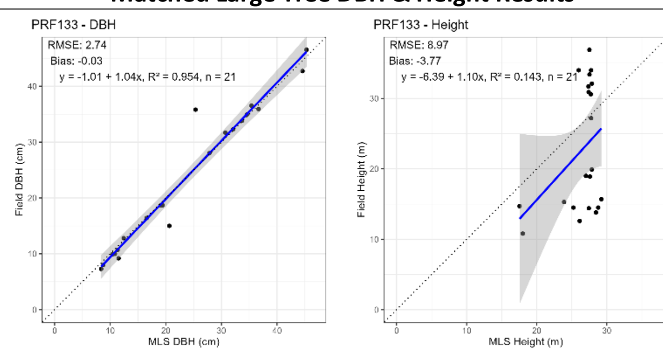
Large Tree Stem Map Matched by DBH & Location



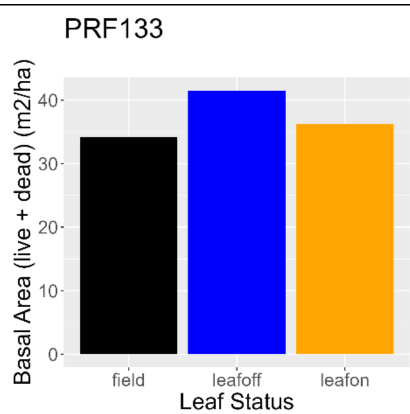
Matched Large Tree DBH & Height Results



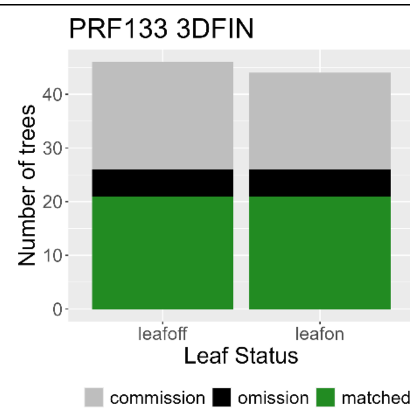
Matched Large Tree DBH & Height Results



Basal Area (m^2/ha)

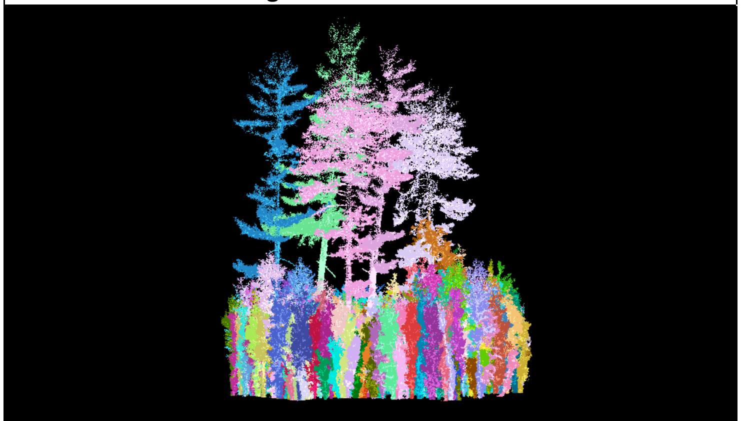


Omission & Commission Results

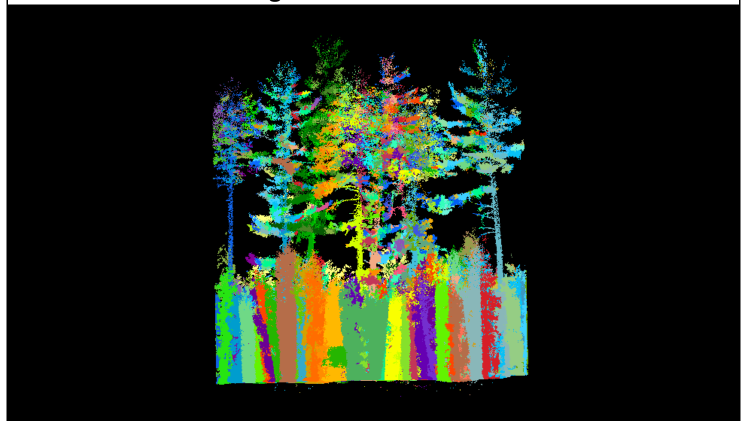


PRF002 – Pine – Leaf Off	PRF002 – Pine – Leaf Off
r-lidar pipeline	**3DFIN**

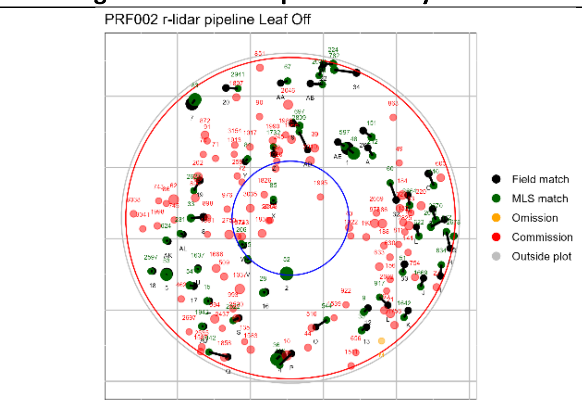
Segmentation - Leaf Off



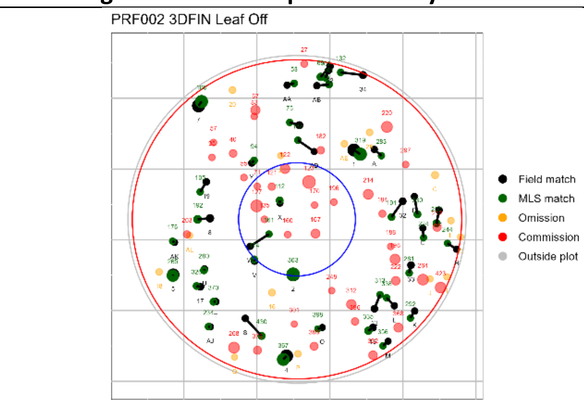
Segmentation - Leaf Off



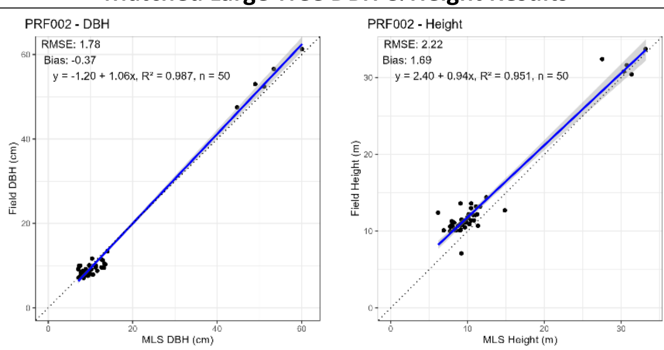
Large Tree Stem Map Matched by DBH & Location



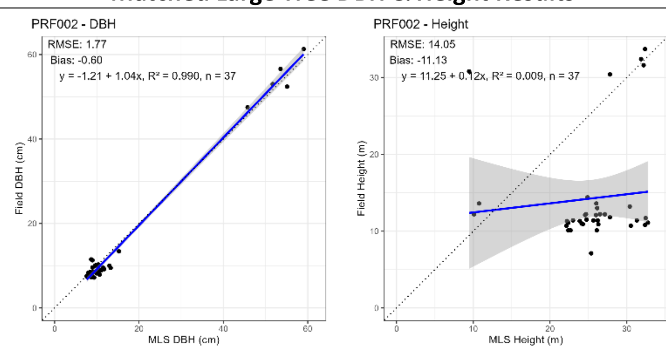
Large Tree Stem Map Matched by DBH & Location



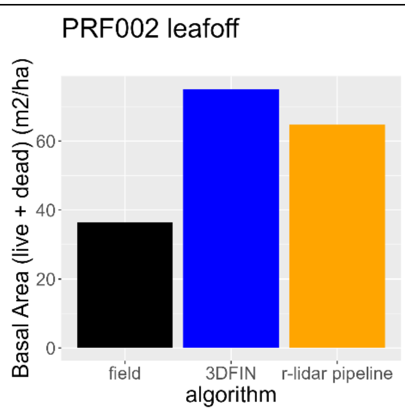
Matched Large Tree DBH & Height Results



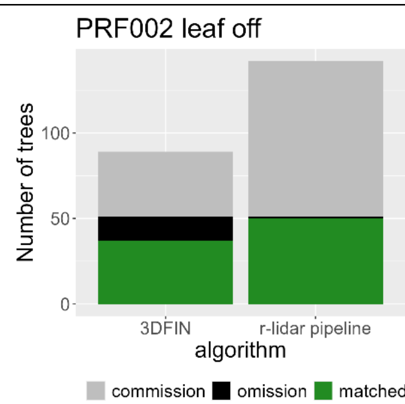
Matched Large Tree DBH & Height Results



Basal Area (m^2/ha)



Omission & Commission Results



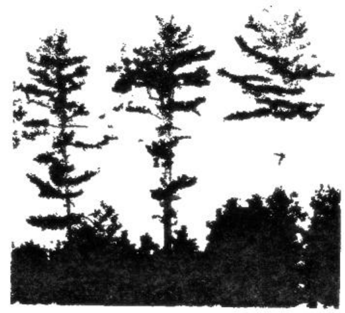
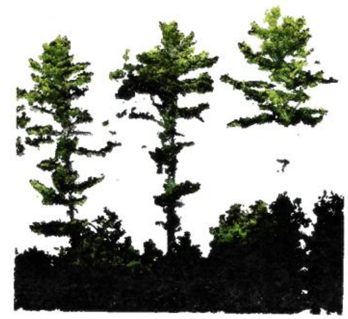
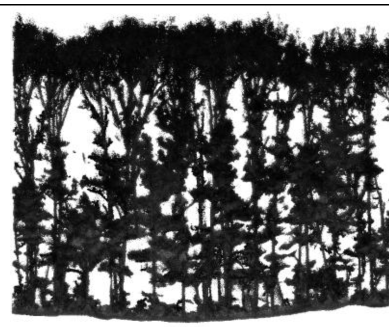
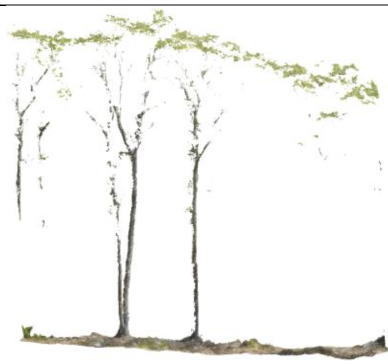
14 Appendix C – F-score, Precision and Recall values for plots by Algorithm and Leaf Status

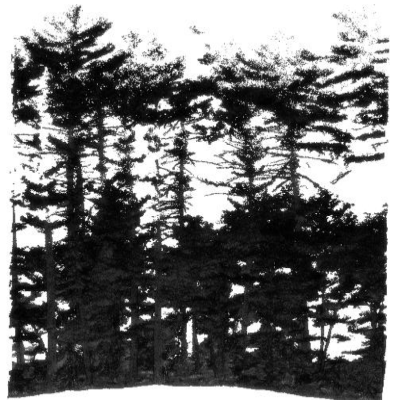
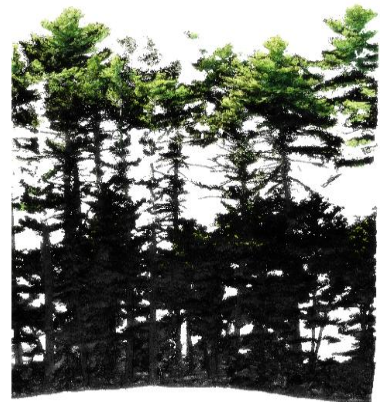
The precision (p = n_matched/n_MLS), retention (r = n_matched/n_field) and F-score (F = 2 x r x p/(r + p)) are given by plot, DBH limit, leaf on/leaf off and algorithm

Plot	DBH limit (cm)	r-lidar pipeline						3DFIN					
		F		r		p		F		r		p	
		Leaf Off	Leaf On	Leaf Off	Leaf On	Leaf Off	Leaf On	Leaf Off	Leaf On	Leaf Off	Leaf On	Leaf Off	Leaf On
PRF200	2.5												
PRF200	7.1	0.96		0.94		0.97		0.85		0.76		0.96	
PRF036	2.5					0	0						
PRF036	7.1	1	0.89	1	1	1	0.80	0.89	0.75	1	0.75	0.80	0.75
PRF025	2.5	1	1	1	1	1	1			0	0		0
PRF025	7.1	0.87	0.84	0.93	0.95	0.81	0.76	0.84	0.76	0.86	0.85	0.81	0.69
PRF184	2.5			0	0		0			0	0		
PRF184	7.1	0.92	0.91	1	0.91	0.85	0.91	0.87	0.45	0.91	0.82	0.83	0.31
PRF193	2.5	0.84	0.84	0.89	0.89	0.80	0.80			0	0		
PRF193	7.1	0.65	0.57	0.85	0.92	0.52	0.41	0.73	0.74	0.85	0.77	0.65	0.71
PRF185	2.5	0.80	0.80	0.80	0.80	0.80	0.80			0	0	0	0
PRF185	7.1	0.93	0.93	0.96	0.96	0.90	0.90	0.95	0.84	0.95	0.87	0.95	0.82
PRF133	2.5	0.52	0.43	0.75	0.63	0.4	0.33			0	0	0	0
PRF133	7.1	0.48	0.43	0.96	0.96	0.32	0.28	0.63	0.48	0.81	0.81	0.51	0.34
PRF002	2.5	0.91		0.91		0.91				0		0	
PRF002	7.1	0.52		0.98		0.35		0.59		0.73		0.49	

15 Appendix D – UAV Structure From Motion point clouds vs MLS point clouds for plots.

Comparison of UAV Structure from Motion (SFM) point clouds (colored) and MLS point clouds (black) for selected plots. The dominant height of PRF002-32.1 m, PRF025-19.0 m, PRF036-22.4 m, PRF133-34.6 m, PRF184-35.9 m, PRF185-40.0 m, PRF193-26.2 m, PRF200-13.6 m

Plot	SFM	MLS	SFM & MLS
PRF002 Pine			
PRF025 Oak			
PRF036 Oak			
PRF133 Red Pine			

PRF184 Pine			
PRF185 Pine			
PRF193 Tol Hwd			
PRF200 Red Pine