FGI experiences in Multispectral ALS/MLS

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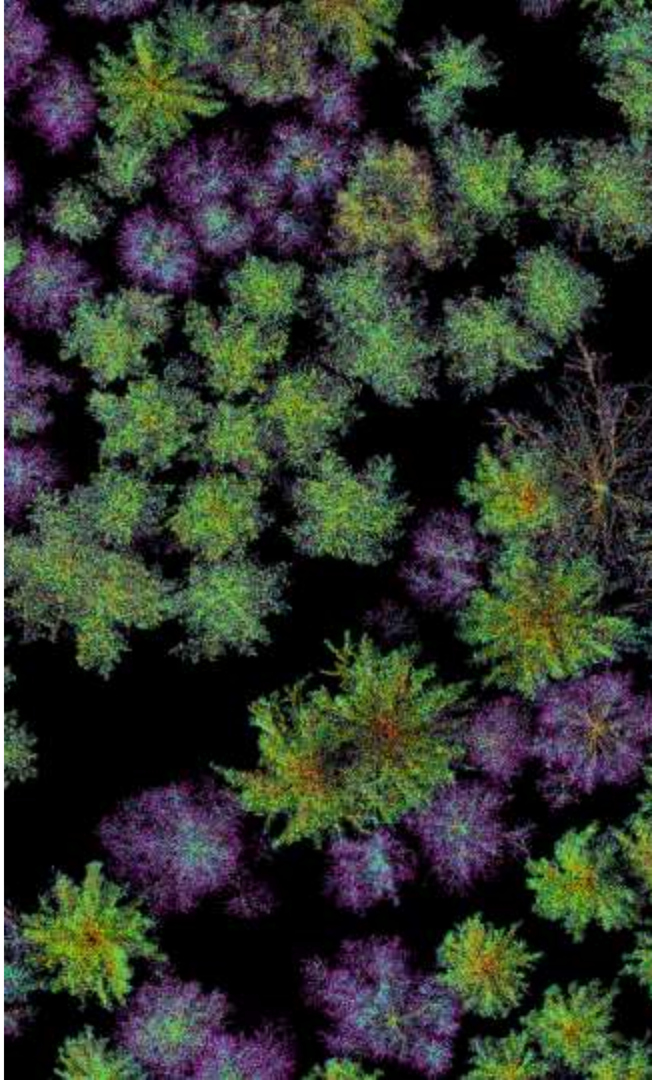
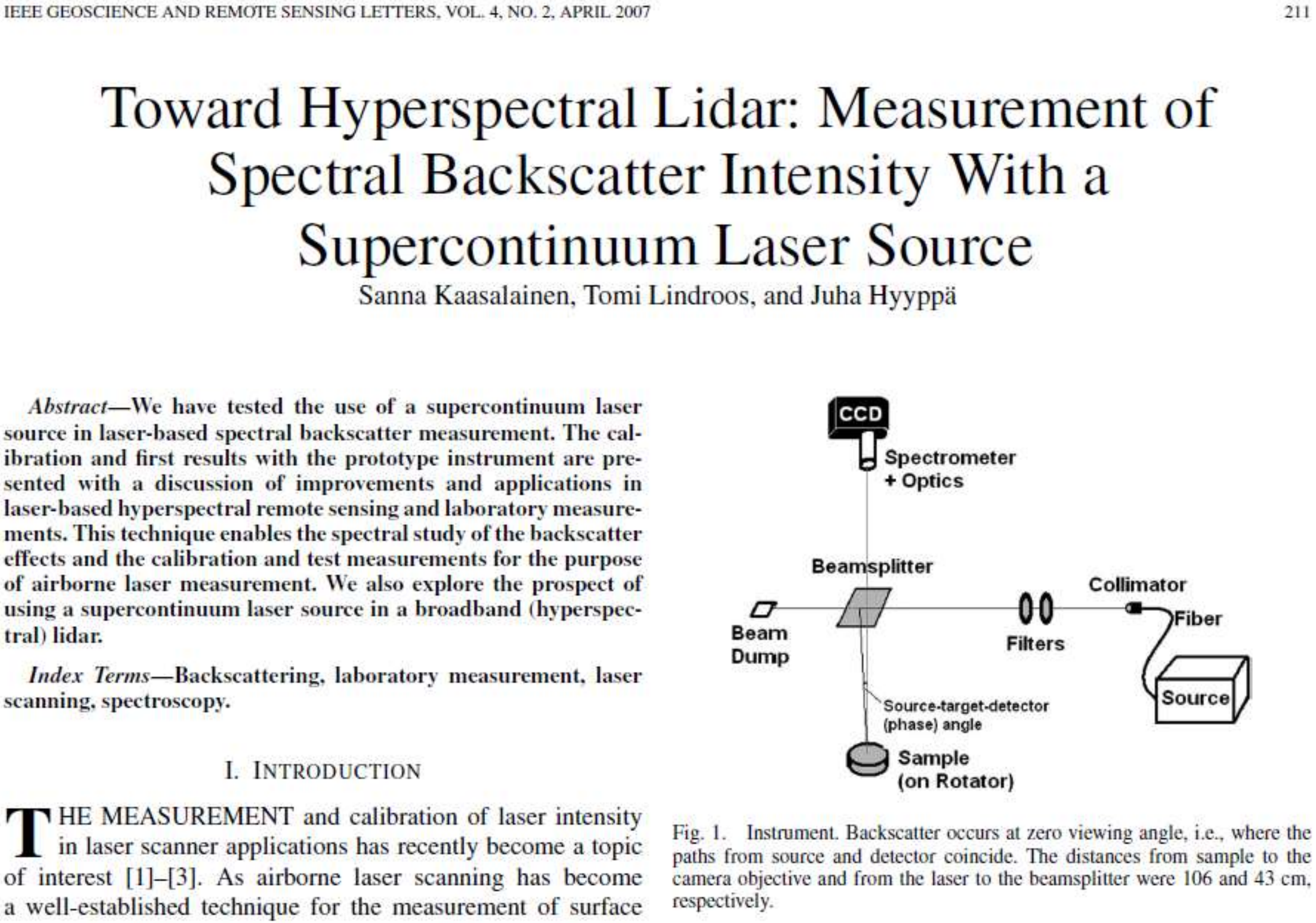


History

- ALS intensity calibration, 2003-2005, EuroSDR project (2008-2011)
- Original idea was to use multispectral point clouds for automatic point cloud classification (known today as semantic segmentation):
  - *"The multispectral or hyperspectral presentation of the target would provide a large number of spectral features for target classification allowing automatic classification of point clouds."(Kaasalainen, Lindroos, Hyyppä, 2007)*
- Some works towards absolute calibration using calibration targets
- First tests using multiple flights (each having different wavelength)
- Optech Titan 2014
- FGI HeliALS (3 wavelenth Riegl Laser scanners)
- Use of deep learning for semantic and instance segmentation



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Toward Hyperspectral Lidar: Measurement of Spectral Backscatter Intensity With a Supercontinuum Laser Source

Sanna Kaasalainen, Tomi Lindroos, and Juha Hyyppä

***Abstract*—We have tested the use of a supercontinuum laser source in laser-based spectral backscatter measurement. The calibration and first results with the prototype instrument are presented with a discussion of improvements and applications in laser-based hyperspectral remote sensing and laboratory measurements. This technique enables the spectral study of the backscatter effects and the calibration and test measurements for the purpose of airborne laser measurement. We also explore the prospect of using a supercontinuum laser source in a broadband (hyperspectral) lidar.**

***Index Terms*—Backscattering, laboratory measurement, laser scanning, spectroscopy.**

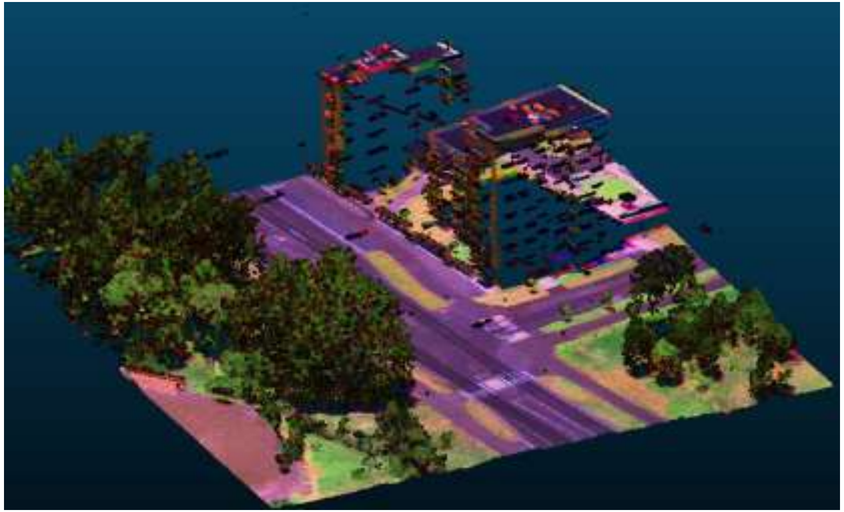
I. INTRODUCTION

THE MEASUREMENT and calibration of laser intensity in laser scanner applications has recently become a topic of interest [1]–[3]. As airborne laser scanning has become a well-established technique for the measurement of surface

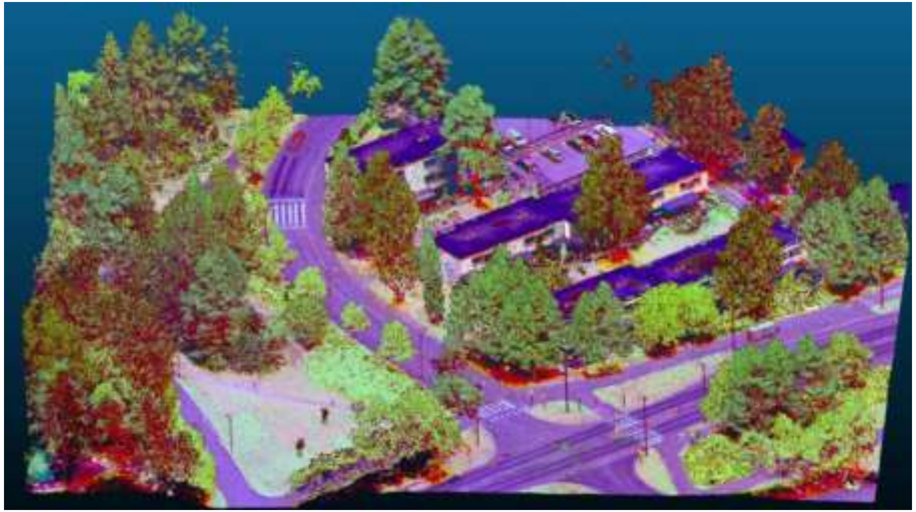
Fig. 1. Instrument. Backscatter occurs at zero viewing angle, i.e., where the paths from source and detector coincide. The distances from sample to the camera objective and from the laser to the beamsplitter were 106 and 43 cm, respectively.

Applied systems by FGI

Optech Titan



FGI own system based on Riegl products



Multispectral laser scanner by FGI

Automation of forest field reference

https://singletree.eu/

Example data by FGI own systems

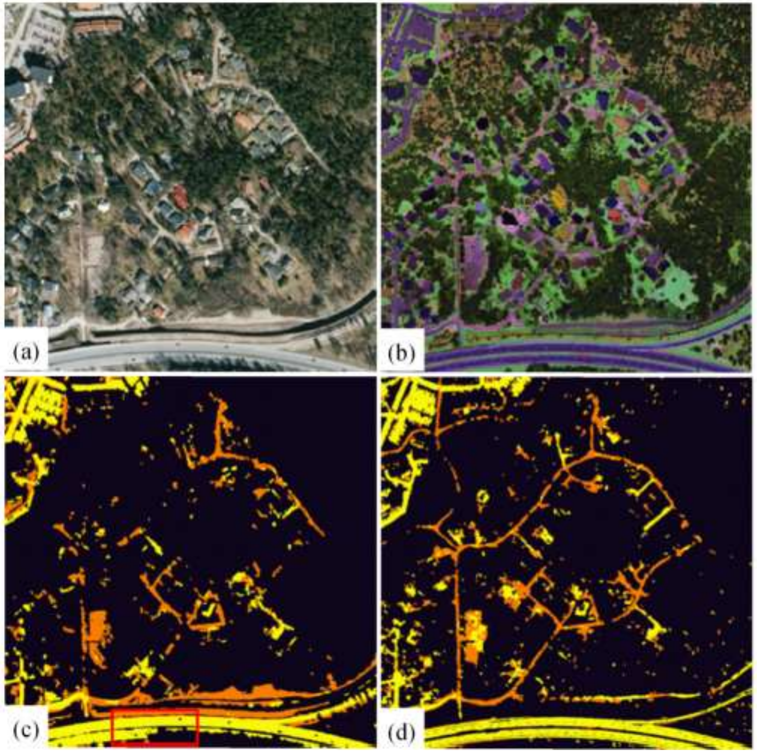
Example data by FGI own systems

Example data by FGI own systems

Example data by FGI own systems

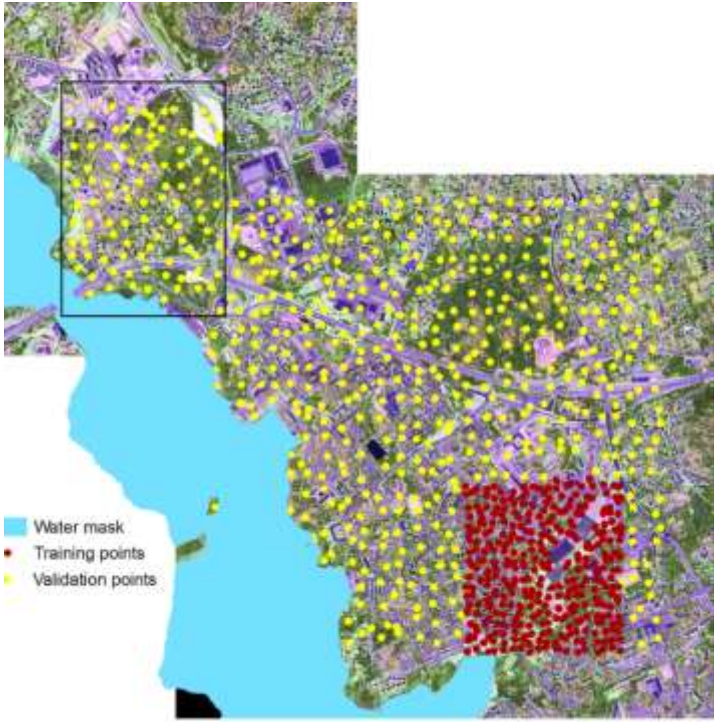
Road detection and classification

- Karila, K., Matikainen, L., Puttonen, E., & Hyyppä, J. (2017). Feasibility of multispectral airborne laser scanning data for road mapping. *IEEE Geoscience and Remote Sensing Letters*, *14*(3), 294-298.
- In a test using ALS data, 80.5% points representing roads were classified correctly. When aerial images were used, the percentage decreased to 71.6%. The overall accuracy for classification of gravel, paved, and other was 94.1% for the multispectral ALS, 91.3 % for the Aerial image, and for Aerial images + DSM 91.7 %



Land cover classification

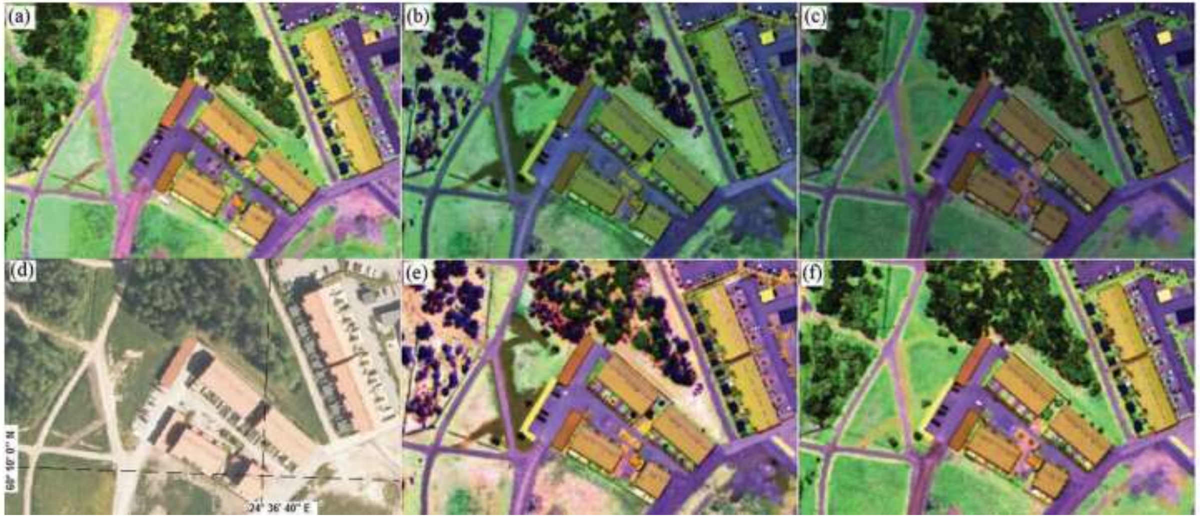
- Matikainen, L., Karila, K., Hyyppä, J., Litkey, P., Puttonen, E., & Ahokas, E. (2017). Object-based analysis of multispectral airborne laser scanner data for land cover classification and map updating. *ISPRS Journal of Photogrammetry and Remote Sensing*, *128*, 298-313.
- The overall accuracy of the land cover classification results with six classes was 96% compared with validation points. The classes under study included building, tree, asphalt, gravel, rocky area and low vegetation. Compared to classification of single-channel data, the main improvements were achieved for ground-level classes.



Seasonal changes in land cover classification

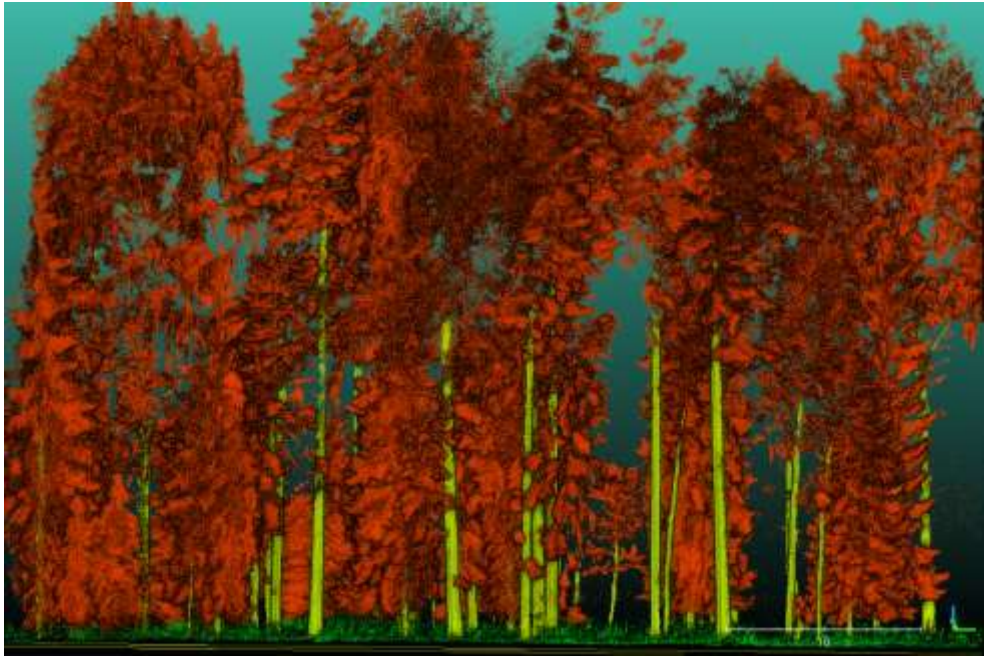
- Karila, K., Matikainen, L., Litkey, P., Hyyppä, J., & Puttonen, E. (2019). The effect of seasonal variation on automated land cover mapping from multispectral airborne laser scanning data. *International Journal of Remote Sensing*, *40*(9), 3289-3307.

- The overall accuracy of the land cover classification was 93.9% (May dataset), 96.4% (June) and 95.9% (August). The use of the May dataset acquired under leafless conditions resulted in more complete roads than the other datasets acquired when trees were in leaf. It was concluded that all datasets used in the study are applicable for suburban land cover mapping



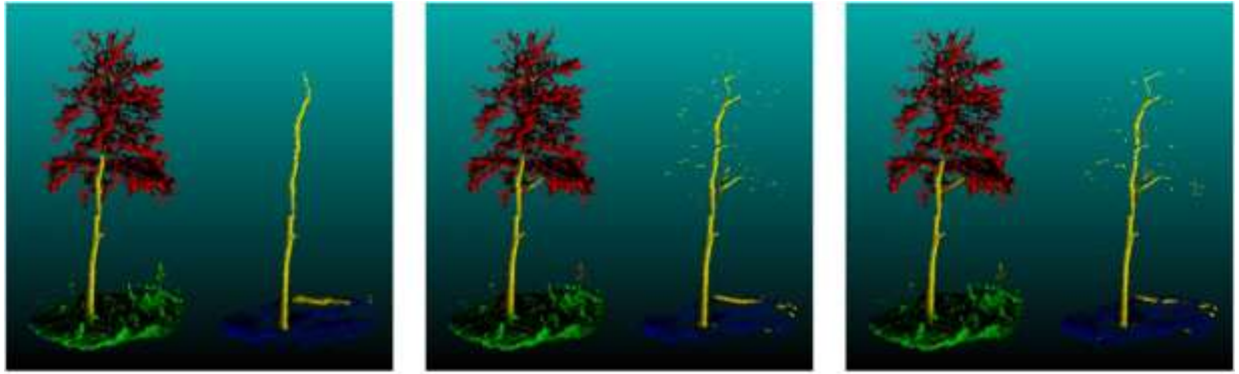
Semantic segmentation of forest point clouds

- Kaijaluoto, R., Kukko, A., El Issaoui, A., Hyyppä, J., & Kaartinen, H. (2022). Semantic segmentation of point cloud data using raw laser scanner measurements and deep neural networks. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, *3*, 100011.
- Semantic segmentation of trees with classes ground, understorey, tree trunk and foliage. Use of raw LS data instead of point clouds. Our best semantic segmentation network reached the mean Intersection-over-Union value of 80.1% and it is comparable to the 80.6% reached by the point cloud - based RandLA-Net.

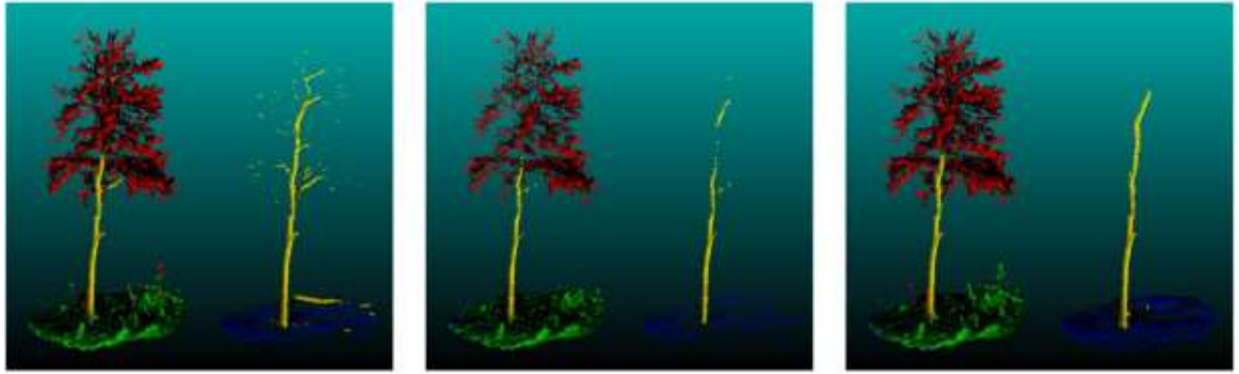


Echo data

Red:Only, Blue: First of many, Green: Intermediate, Yellow: Last of many



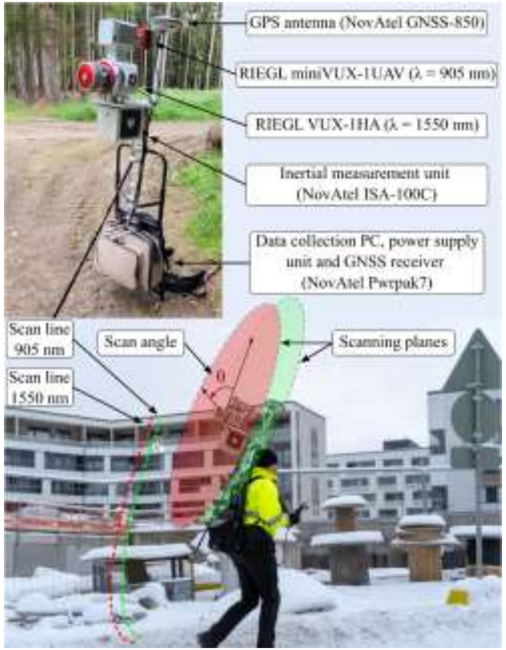
(a) Ground truth (b) LSSegNet1 (c) LSSegNet2

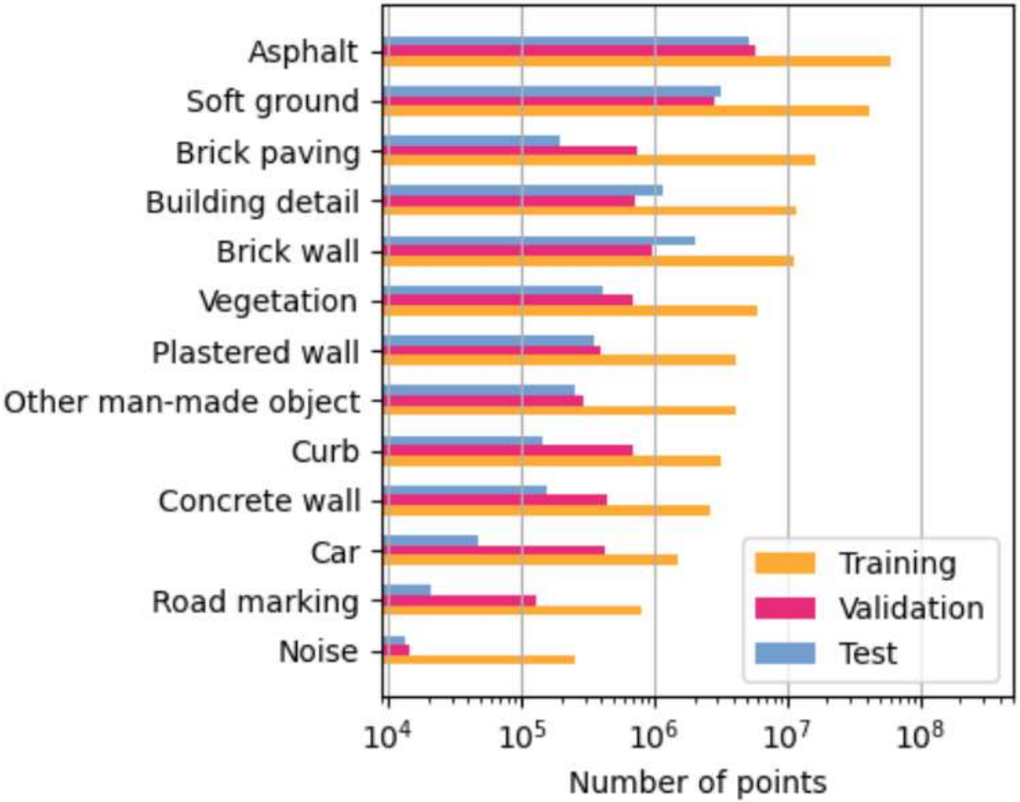


(d) LSSegNet3 (e) LSSegNet3_67% (f) RandLA-Net

Urban semantic point cloud segmentation

- Reichler, M., Taher, J., Manninen, P., Kaartinen, H., Hyyppä, J., & Kukko, A. (2024). Semantic segmentation of raw multispectral laser scanning data from urban environments with deep neural networks. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, *12*, 100061.
- The data was divided into 13 classes that represent various targets in urban environments. In the multispectral point cloud experiments we achieved a 71 % and 28 % relative increase in the segmentation mIoU (43.5 mIoU) as compared to the purely single-wavelength reference experiments, in which we achieved 25.4 mIoU (905 nm) and 34.1 mIoU (1550 nm).




Asphalt
Soft ground
Brick paving
Building detail
Brick wall
Vegetation
Plastered wall
Other man-made object
Curb
Concrete wall
Car
Road marking
Noise
10^4
10^5
10^6
10^7
10^8
Number of points
Training
Validation
Test

Unsupervised PC semantic segmentation

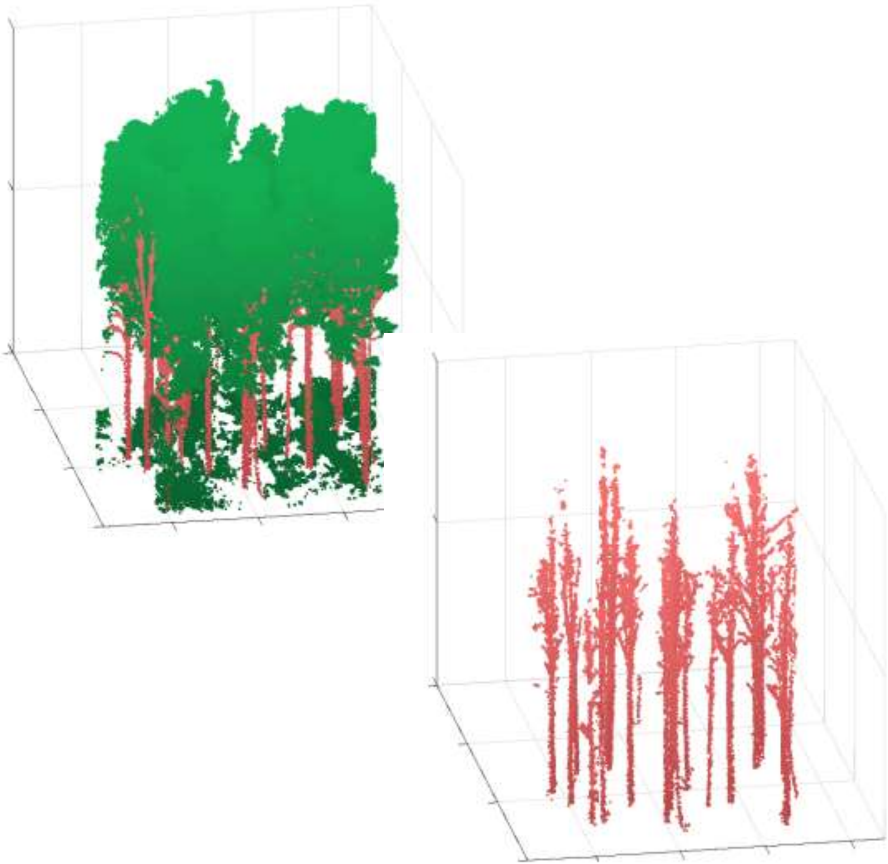
- Oinonen, O., Ruoppa, L., Taher, J., Lehtomäki, M., Matikainen, L., Karila, K., ... & Hyyppä, J. (2024). Unsupervised semantic segmentation of urban high-density multispectral point clouds. *arXiv preprint arXiv:2410.18520*.

- Unuspervised semenatic point cloud segmentation was cleated. It was also shown, that the GroupSP can semantically segment seven urban classes (building, high vegetation, low vegetation, asphalt, rock, football field, and gravel) with oAcc of 95% and mIoU of 75% using only 0.004% of the available annotated points in the mapping assignment.

Unsupervised forest point cloud semantic segmentation

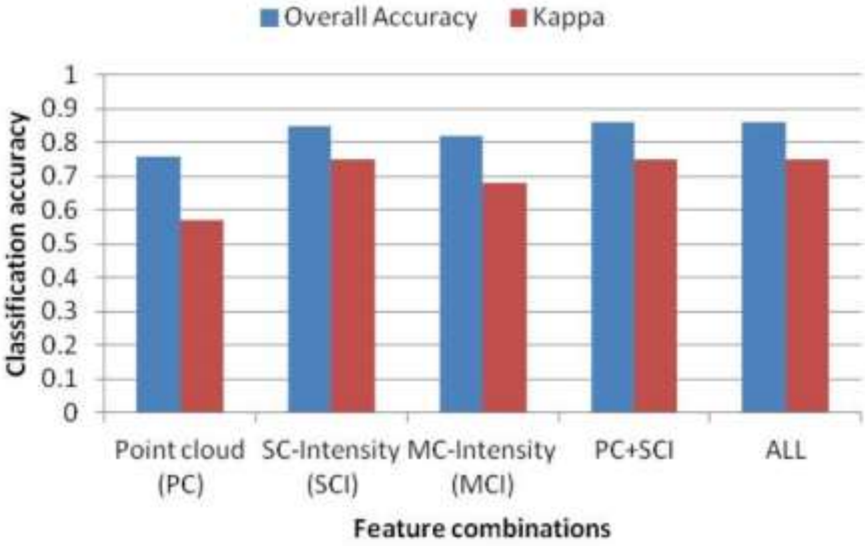
- Ruoppa, L., Oinonen, O., Taher, J., Lehtomäki, M., Takhtkeshha, N., Kukko, A., ... & Hyyppä, J. (2025). Unsupervised deep learning for semantic segmentation of multispectral LiDAR forest point clouds. *arXiv preprint arXiv:2502.06227*.

- Our method outperformed the previous unsupervised reference methods by a significant margin. When compared to supervised deep learning methods, our model performed similarly to the slightly older PointNet architecture. Our proposal increased the test set mIoU of GrowSP-ForMS by 29.4 percentage points (pp) in comparison to the original GrowSP model and that utilizing MS data improved the mIoU by 5.6 pp from the monospectral case.



Tree species classification

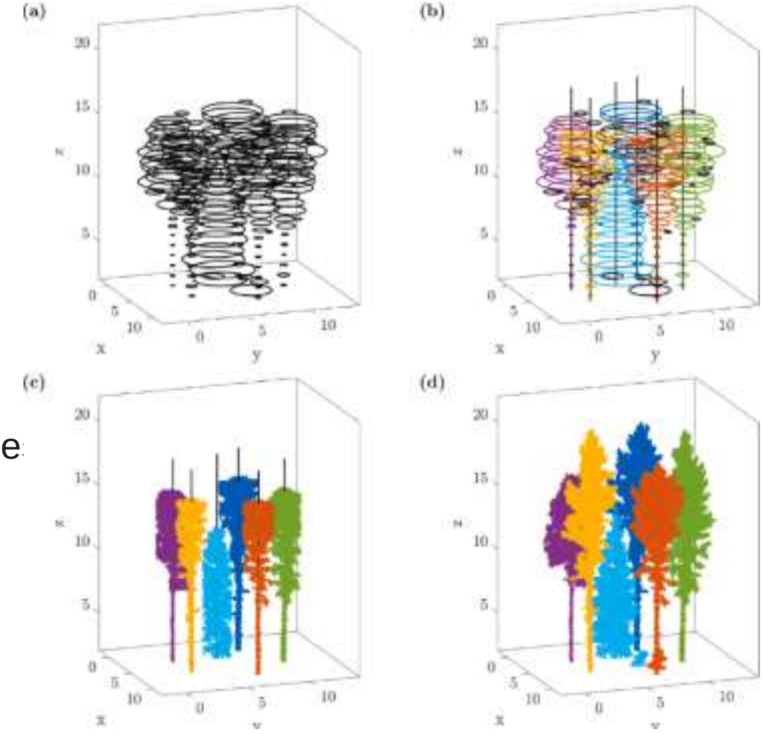
- Yu, X., Hyyppä, J., Litkey, P., Kaartinen, H., Vastaranta, M., & Holopainen, M. (2017). Single-sensor solution to tree species classification using multispectral airborne laser scanning. *Remote Sensing*, *9*(2), 108**.**
- Modest improvement to species classification. Intensity improves tree species classification by 10 % unit. The results suggest that Channel 2 (1064 nm) contains more information for separating pine, spruce, and birch, followed by channel 1 (1550 nm) and channel 3 (532 nm) with an overall accuracy of 81.9%, 78.3%, and 69.1%, respectively.



Tree Species 2

- Hakula, A., Ruoppa, L., Lehtomäki, M., Yu, X., Kukko, A., Kaartinen, H., ... & Hyyppä, J. (2023). Individual tree segmentation and species classification using high-density close-range multispectral laser scanning data. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, *9*, 100039.

- Results: The overall accuracy of the tree species classification was 73.1% when using geometric feature from the 1550 nm scanner data and 86.6% when combining the geometric features with reflectance information of the 1550 nm data. The use of multispectral reflectance and geometric features improved the overall classification accuracy up to 90.8%.



Tree species 3

Multispectral airborne laser scanning for tree species classification: a benchmark of machine learning and deep learning algorithms

Preprint

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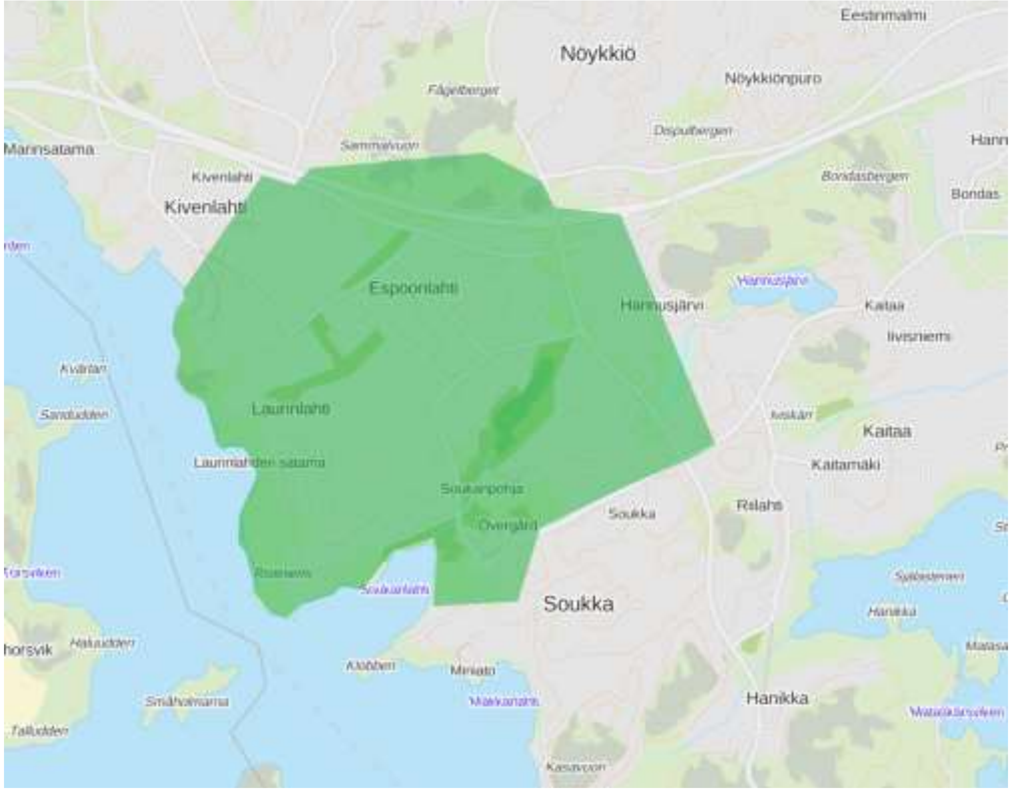
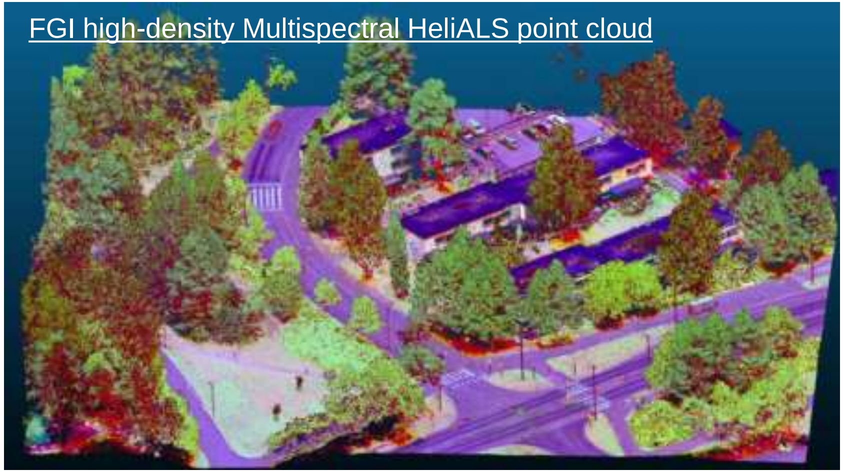
Test Site – Espoonlahti

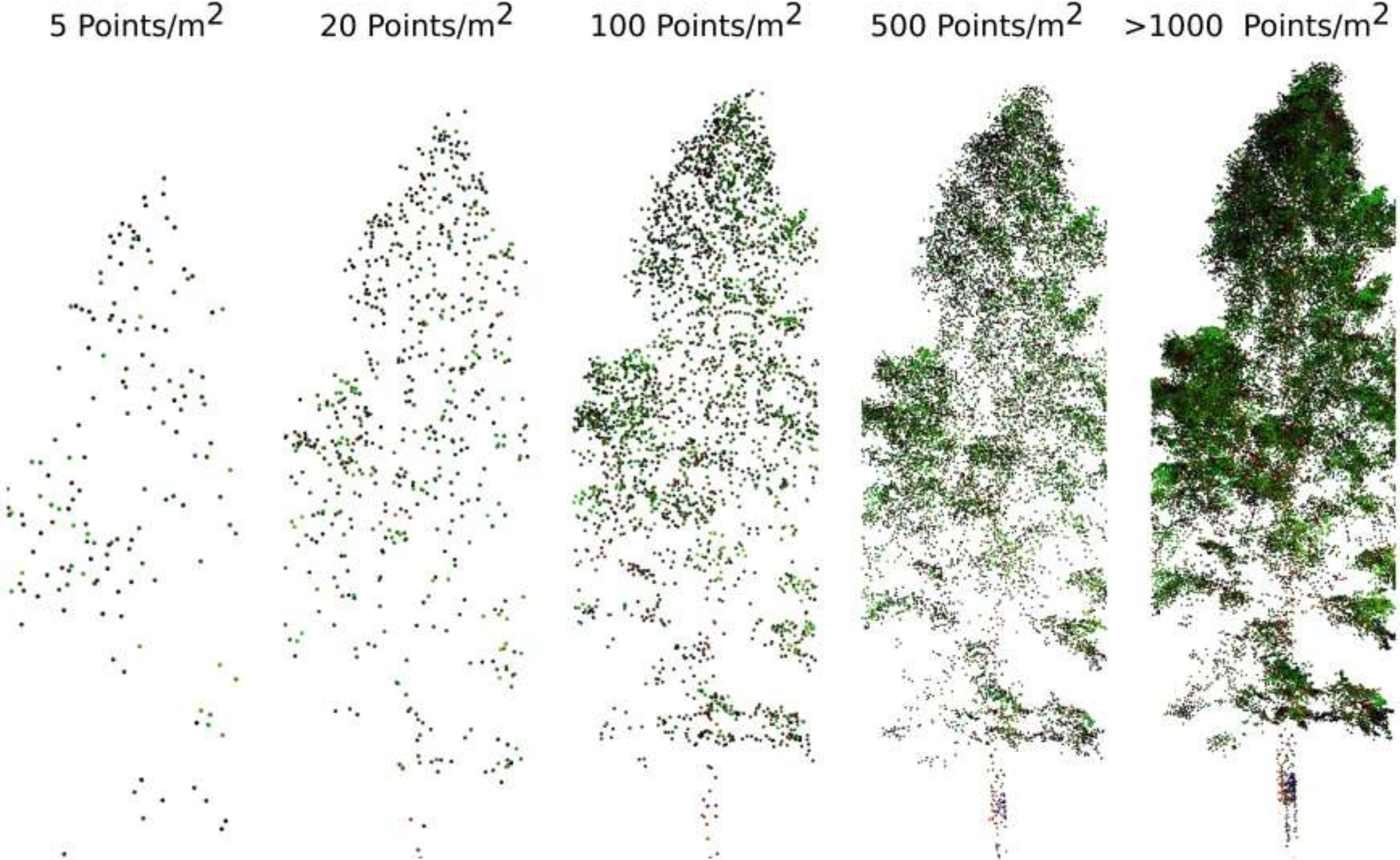


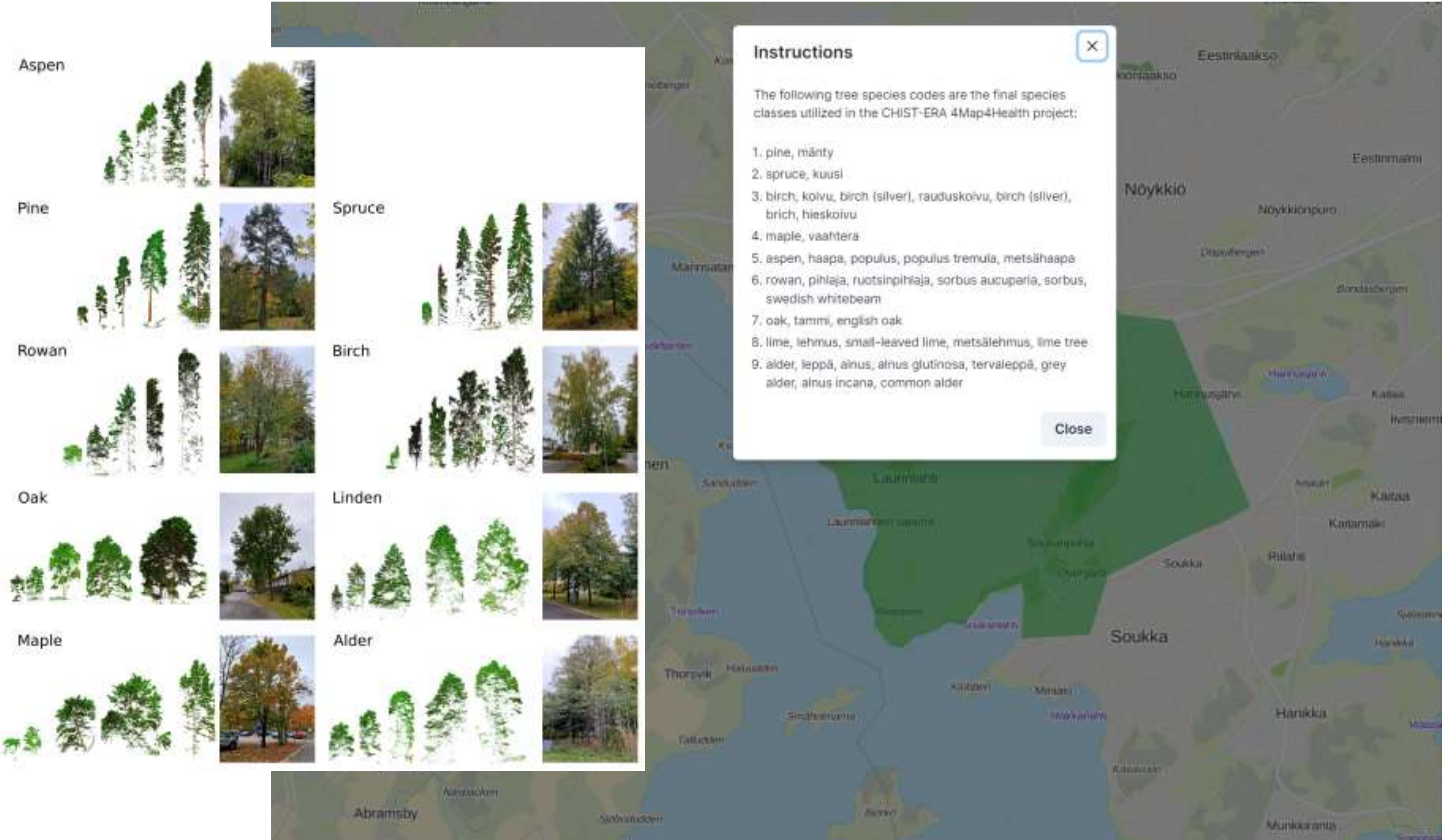
Tree species classification benchmarking

Optech Titan Multispectral ALS point cloud



FGI high-density Multispectral HeliALS point cloud


5 Points/m^2 20 Points/m^2 100 Points/m^2 500 Points/m^2 >1000 Points/m^2



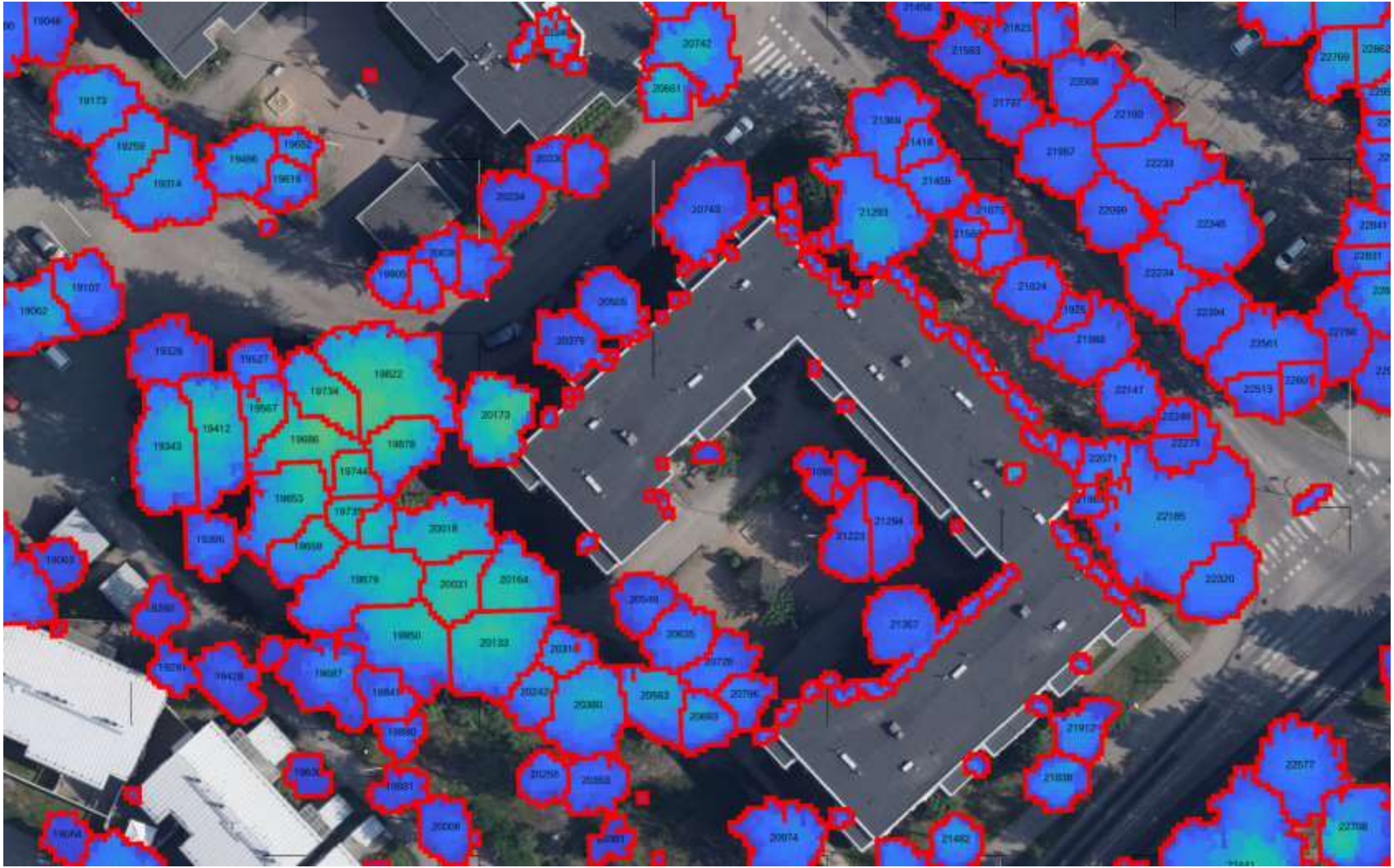
Instructions

The following tree species codes are the final species classes utilized in the CHIST-ERA 4Map4Health project:

1. pine, mänty
2. spruce, kuusi
3. birch, koivu, birch (silver), rauduskoivu, birch (sliver), brich, hieskoivu
4. maple, vaahtera
5. aspen, haapa, populus, populus tremula, metsähaapa
6. rowan, pihlaja, ruotsinpihlaja, sorbus aucuparia, sorbus, swedish whitebeam
7. oak, tammi, english oak
8. lime, lehmus, small-leaved lime, metsälehmus, lime tree
9. alder, leppä, alnus, alnus glutinosa, tervaleppä, grey alder, alnus incana, common alder

Reference Data Collection Process

- Segmentation using Optech Titan
- Web App development (segments, base maps, aerial images, CHM, crowdsourcing software)
- Crowdsourcing – training data selected
- Crowdsourcing – testing data selected
- Additing potential trees with aerial images
- Crowdsourcing – field checking for all segments
- Classification 1: single tree, single tree with undergrowth, many trees of same species, many trees of various species, sparse segment, tree section)
- Classification 2: dominant, co-dominant, suppressed, road side tree,


19046
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19686
19678
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19653
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19003
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20164
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19428
19597
19841
20242
20380
20562
20689
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20726
20605
20546
20258
20006
20974
21492
21838
21912
22577
22798
21367
21223
21294
22185
22320
22071
22279
22147
22513
22561
22394
22234
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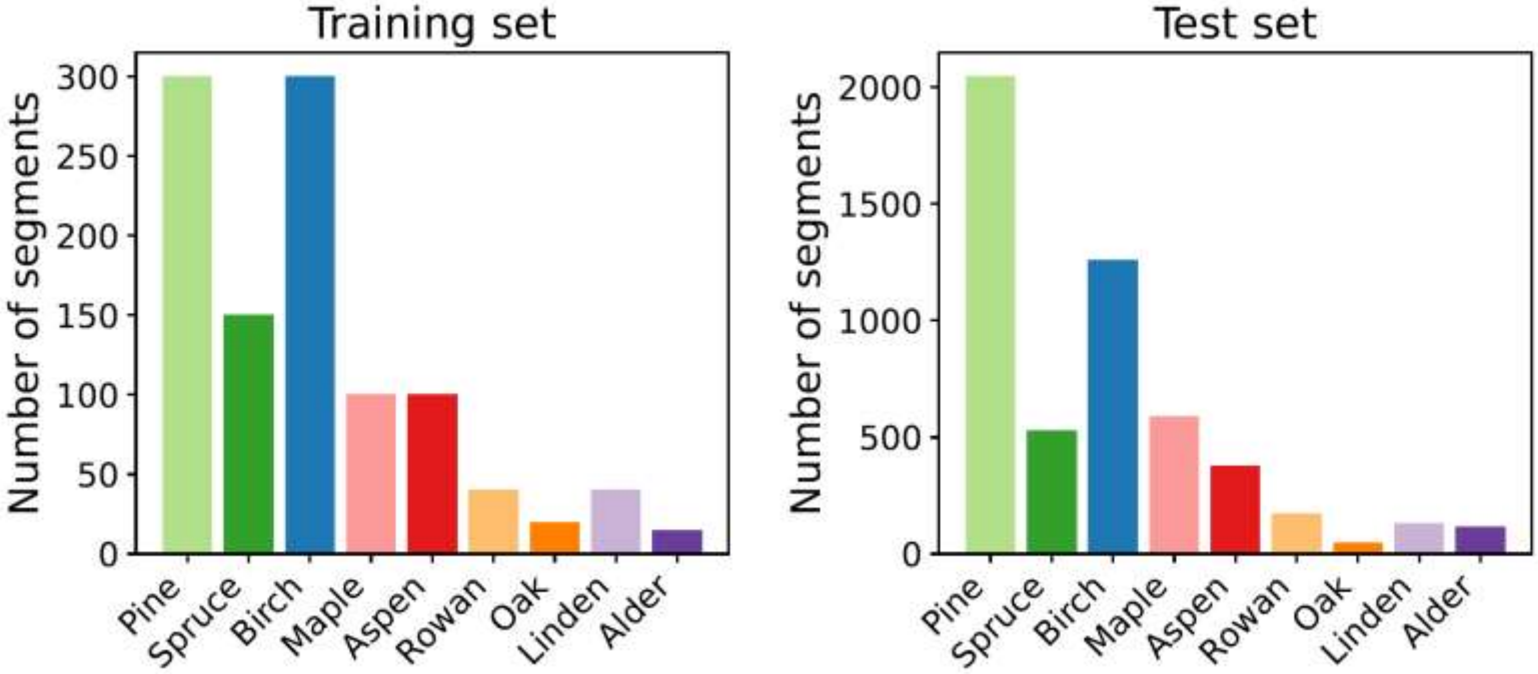
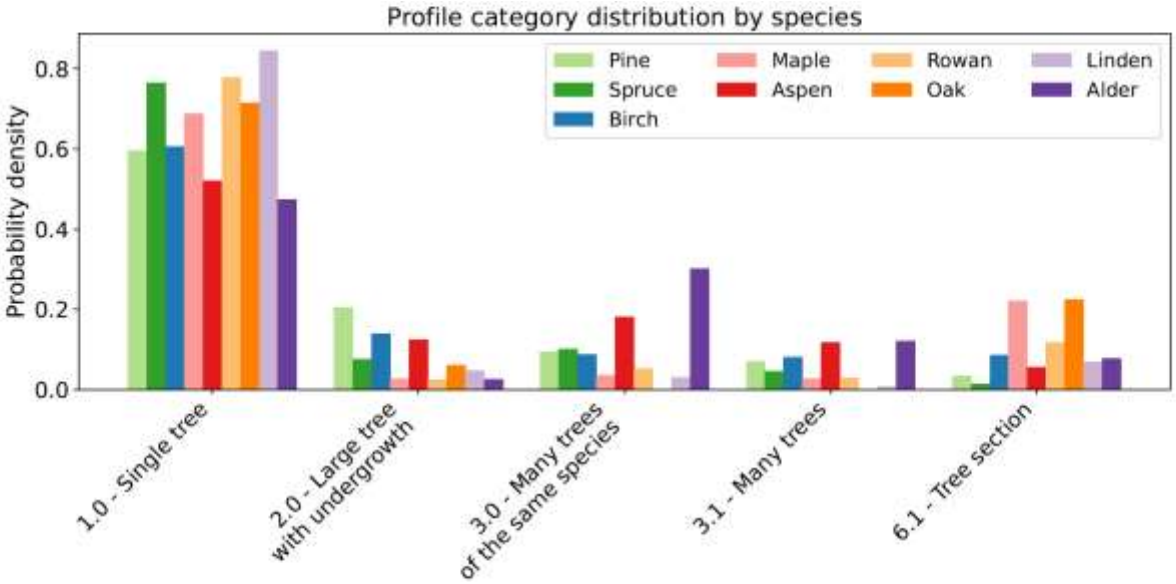
22233
21967
22108
22008
21737
21583
21823
22769
22862
21369
21418
21459
21293
20743
20742
20661
20234
20505
20379
20173
19805
21924
21988
22841

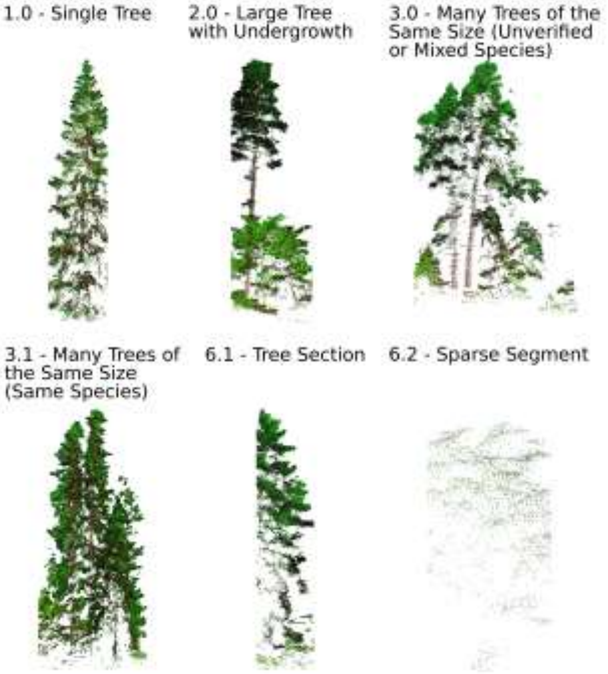
Area code	75_90
Label	18598
Tree height	21.58 m
Species	-
Notes	-
Verified	no ✗

Training (1000+) versus Testing (5000+)



Classification 1





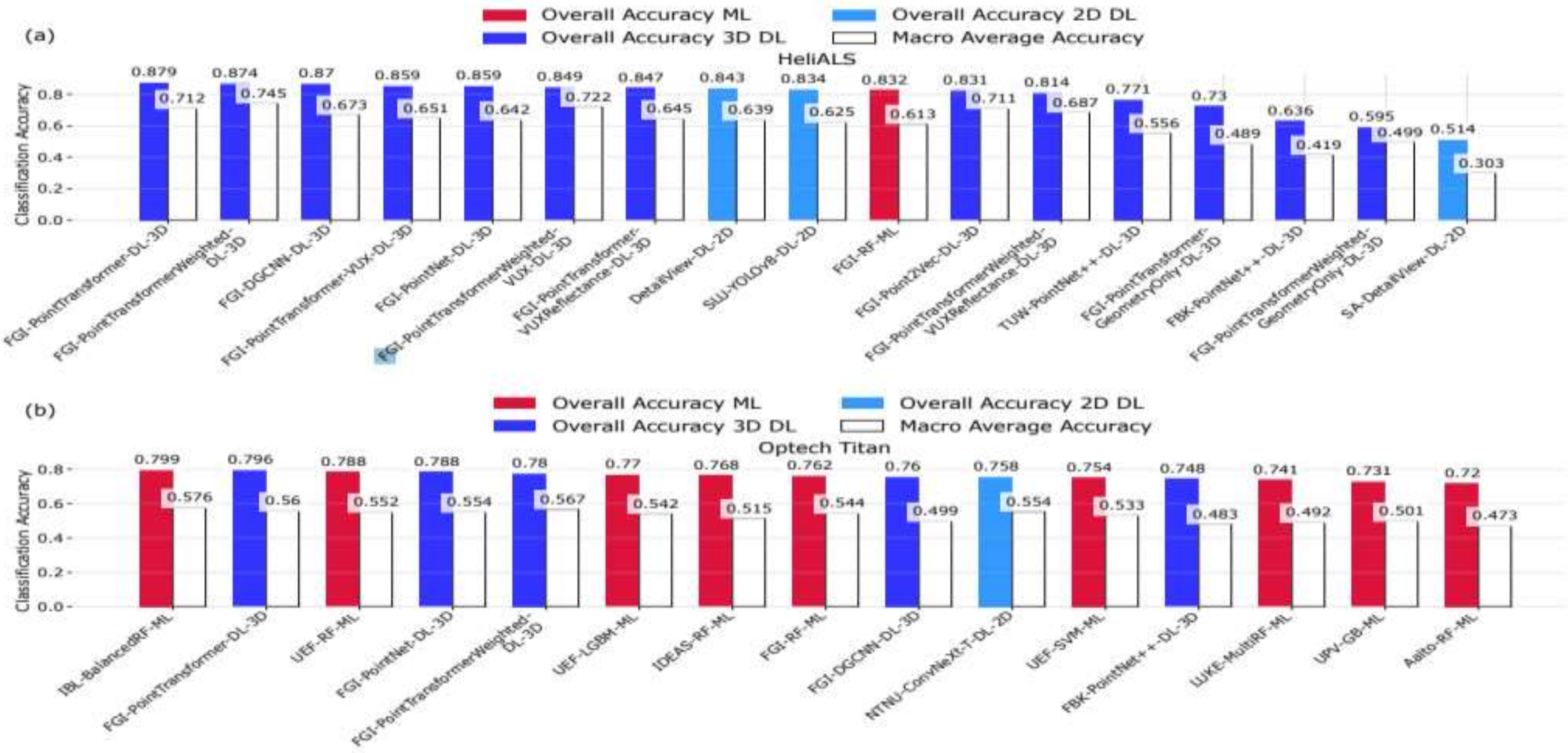
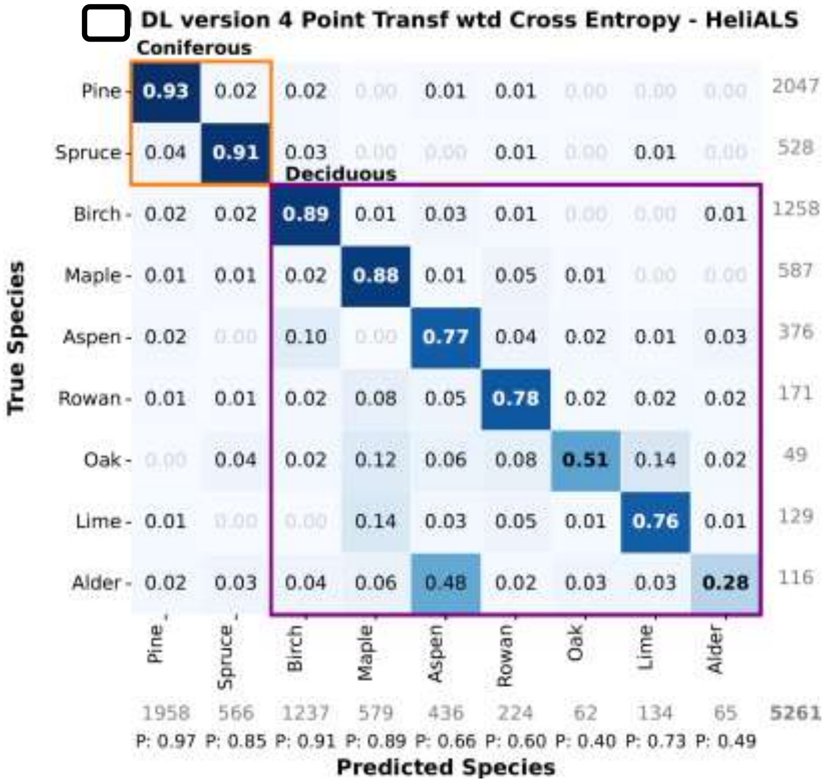


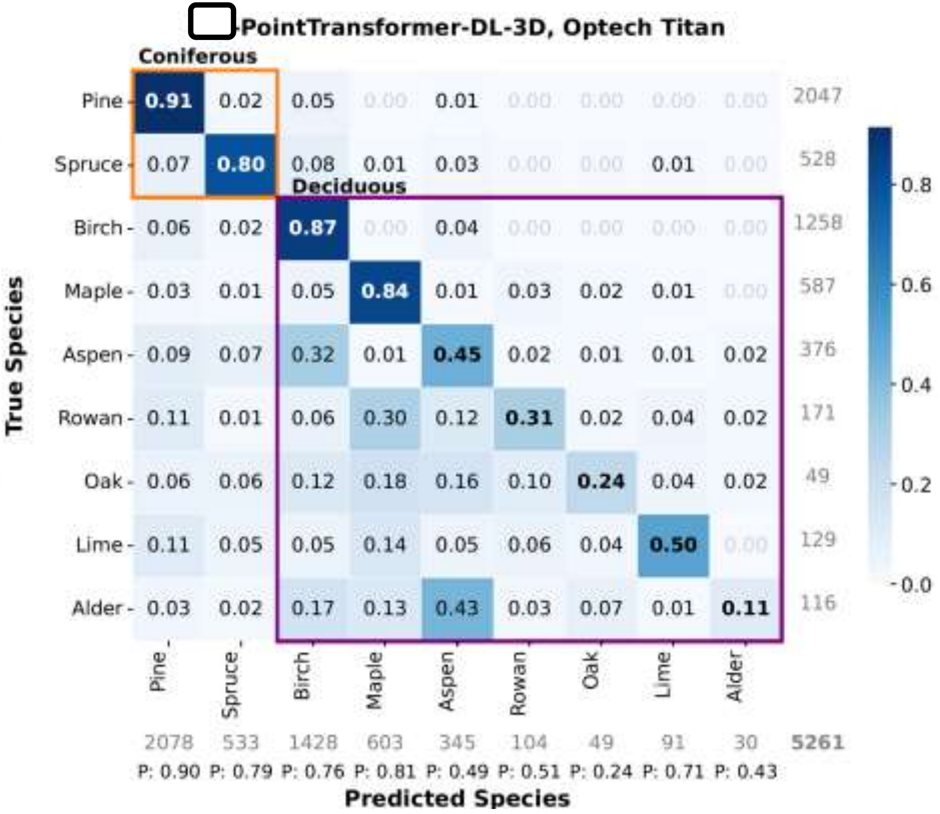
Figure 6: (a) Comparison of overall (filled bar) and macro-average (outline) accuracy for methods using HeliALS data, with point-based DL methods shown with dark blue color, image-based DL methods shown with light blue color, and machine learning methods shown with red color. SA-Detailview-DL-2D was not retrained on the training set of the current study, and the model parameters were directly transferred from Puliti et al. (2025). When neglecting aspens, rowans and alders not present in the FOR-species20K dataset (Puliti et al., 2025), SA-Detailview-DL-2D reached an overall accuracy of 58.8% and a macro-average accuracy of 45.4%. (b) Same as (a) but for the methods using the Optech Titan dataset.

Effect of point density



DL version 4 Point Transf wtd Cross Entropy - HeliALS

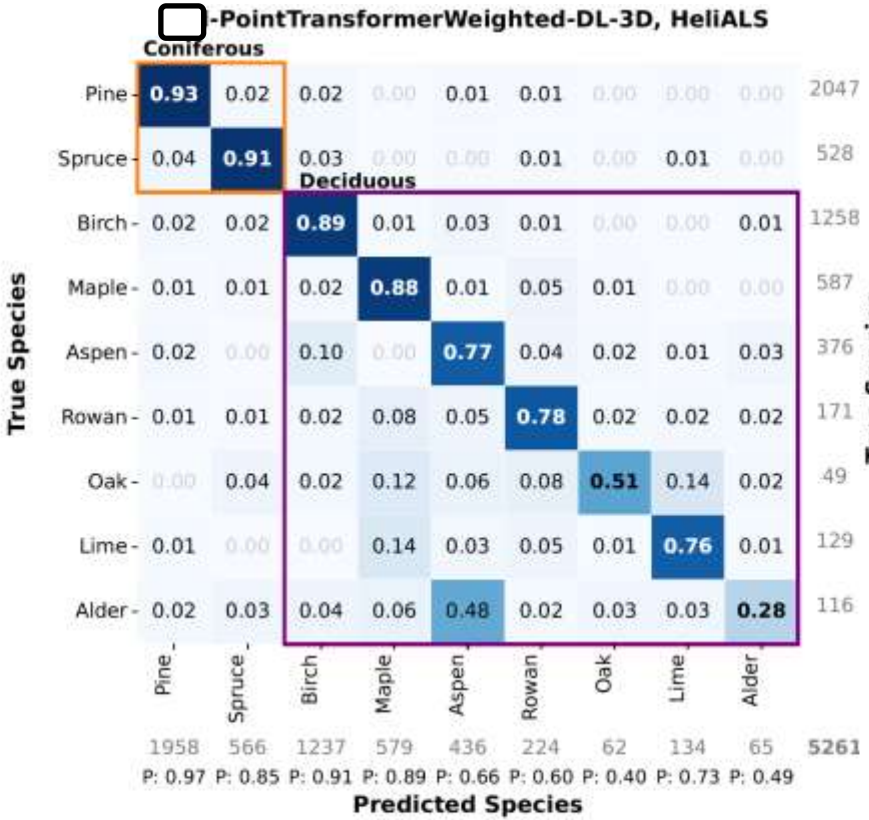
	Pine	Spruce	Birch	Maple	Aspen	Rowan	Oak	Lime	Alder	
Pine	0.93	0.02	0.02	0.00	0.01	0.01	0.00	0.00	0.00	2047
Spruce	0.04	0.91	0.03	0.00	0.00	0.01	0.00	0.01	0.00	528
Birch	0.02	0.02	0.89	0.01	0.03	0.01	0.00	0.00	0.01	1258
Maple	0.01	0.01	0.02	0.88	0.01	0.05	0.01	0.00	0.00	587
Aspen	0.02	0.00	0.10	0.00	0.77	0.04	0.02	0.01	0.03	376
Rowan	0.01	0.01	0.02	0.08	0.05	0.78	0.02	0.02	0.02	171
Oak	0.00	0.04	0.02	0.12	0.06	0.08	0.51	0.14	0.02	49
Lime	0.01	0.00	0.00	0.14	0.03	0.05	0.01	0.76	0.01	129
Alder	0.02	0.03	0.04	0.06	0.48	0.02	0.03	0.03	0.28	116
	1958	566	1237	579	436	224	62	134	65	5261
	P: 0.97	P: 0.85	P: 0.91	P: 0.89	P: 0.66	P: 0.60	P: 0.40	P: 0.73	P: 0.49	



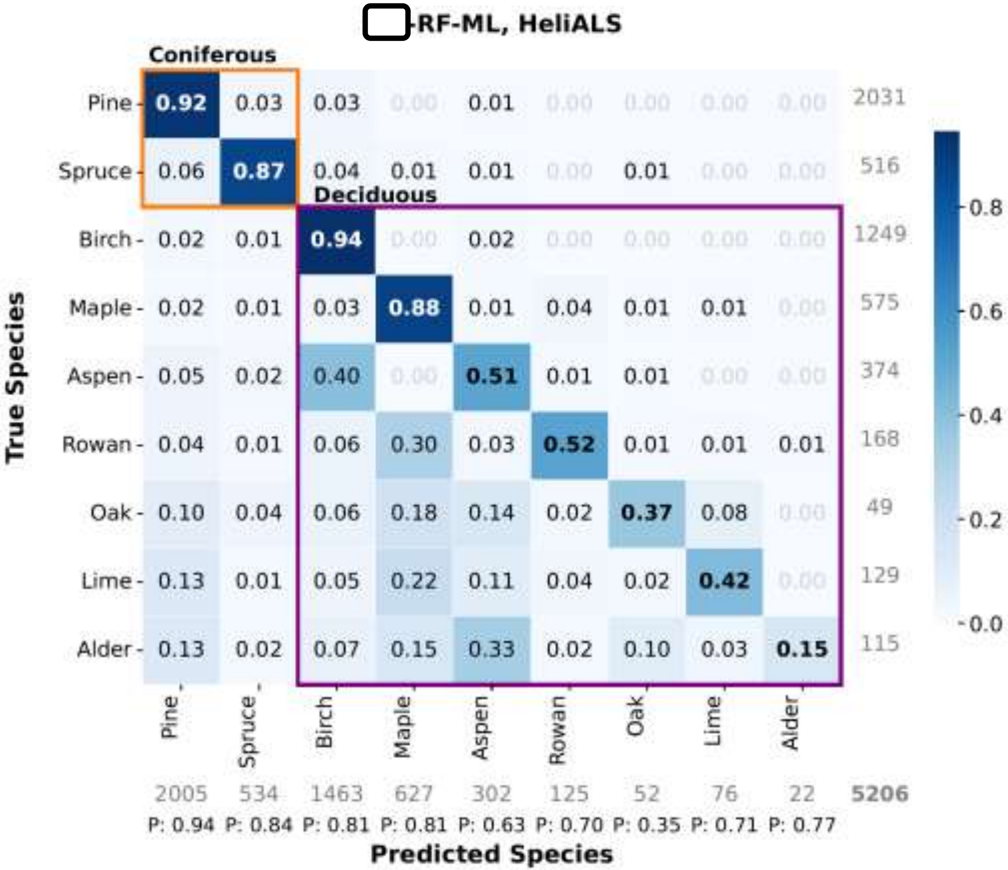
PointTransformer-DL-3D, Optech Titan

	Pine	Spruce	Birch	Maple	Aspen	Rowan	Oak	Lime	Alder	
Pine	0.91	0.02	0.05	0.00	0.01	0.00	0.00	0.00	0.00	2047
Spruce	0.07	0.80	0.08	0.01	0.03	0.00	0.00	0.01	0.00	528
Birch	0.06	0.02	0.87	0.00	0.04	0.00	0.00	0.00	0.00	1258
Maple	0.03	0.01	0.05	0.84	0.01	0.03	0.02	0.01	0.00	587
Aspen	0.09	0.07	0.32	0.01	0.45	0.02	0.01	0.01	0.02	376
Rowan	0.11	0.01	0.06	0.30	0.12	0.31	0.02	0.04	0.02	171
Oak	0.06	0.06	0.12	0.18	0.16	0.10	0.24	0.04	0.02	49
Lime	0.11	0.05	0.05	0.14	0.05	0.06	0.04	0.50	0.00	129
Alder	0.03	0.02	0.17	0.13	0.43	0.03	0.07	0.01	0.11	116
	2078	533	1428	603	345	104	49	91	30	5261
	P: 0.90	P: 0.79	P: 0.76	P: 0.81	P: 0.49	P: 0.51	P: 0.24	P: 0.71	P: 0.43	

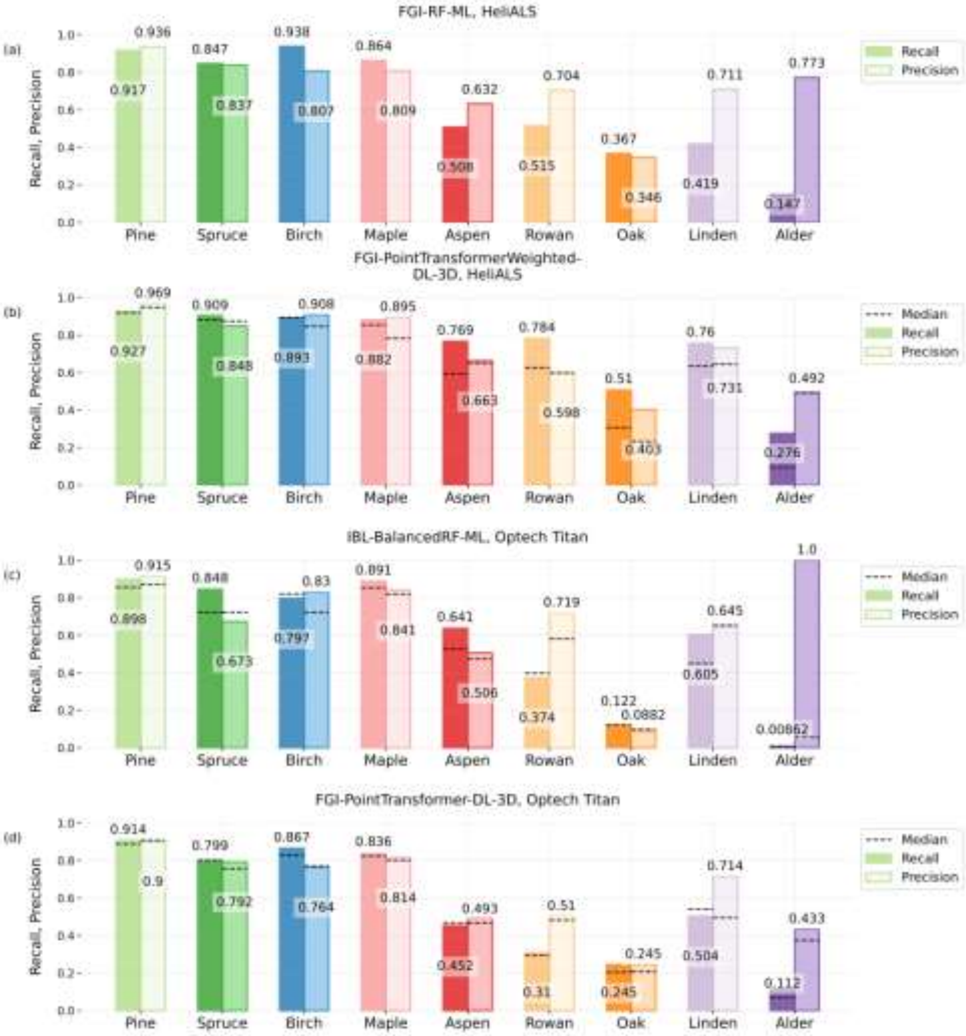
DL versus ML


-PointTransformerWeighted-DL-3D, HeliALS

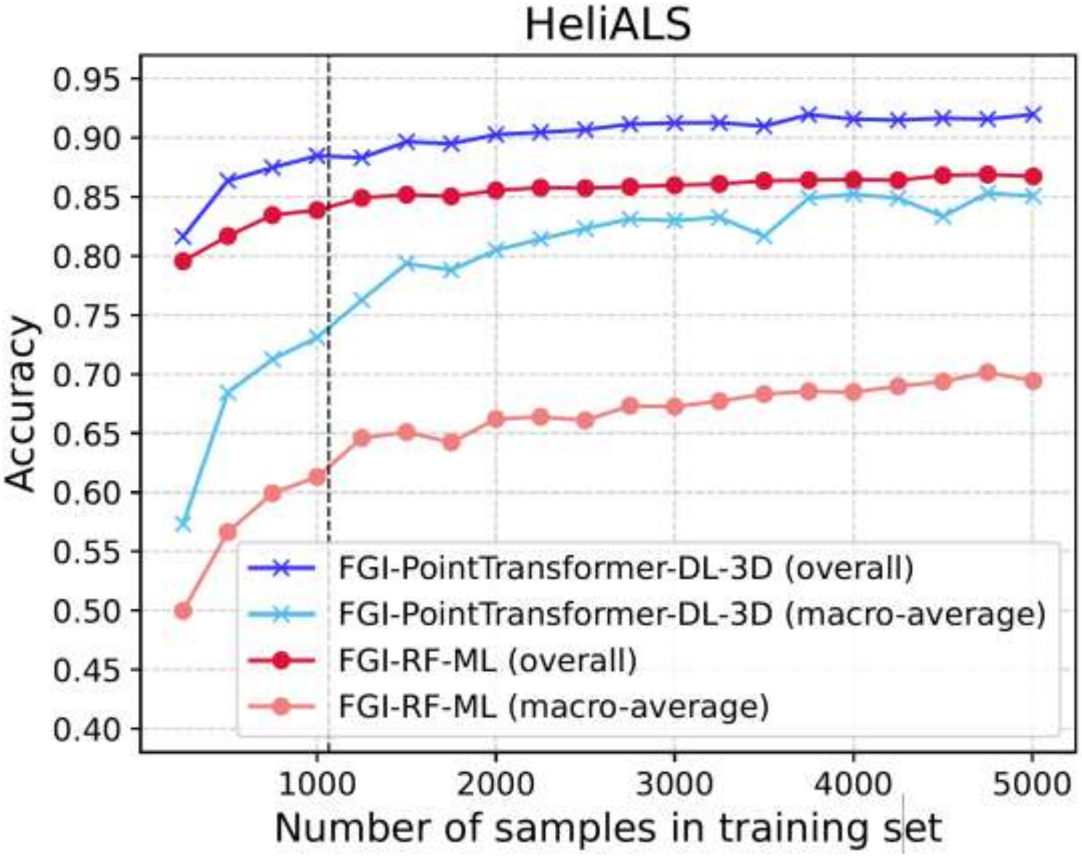
	Pine	Spruce	Birch	Maple	Aspen	Rowan	Oak	Lime	Alder	
Pine	**0.93**	0.02	0.02	0.00	0.01	0.01	0.00	0.00	0.00	2047
Spruce	0.04	**0.91**	0.03	0.00	0.00	0.01	0.00	0.01	0.00	528
Birch	0.02	0.02	**0.89**	0.01	0.03	0.01	0.00	0.00	0.01	1258
Maple	0.01	0.01	0.02	**0.88**	0.01	0.05	0.01	0.00	0.00	587
Aspen	0.02	0.00	0.10	0.00	**0.77**	0.04	0.02	0.01	0.03	376
Rowan	0.01	0.01	0.02	0.08	0.05	**0.78**	0.02	0.02	0.02	171
Oak	0.00	0.04	0.02	0.12	0.06	0.08	**0.51**	0.14	0.02	49
Lime	0.01	0.00	0.00	0.14	0.03	0.05	0.01	**0.76**	0.01	129
Alder	0.02	0.03	0.04	0.06	0.48	0.02	0.03	0.03	**0.28**	116
	1958	566	1237	579	436	224	62	134	65	**5261**
	P: 0.97	P: 0.85	P: 0.91	P: 0.89	P: 0.66	P: 0.60	P: 0.40	P: 0.73	P: 0.49	


-RF-ML, HeliALS

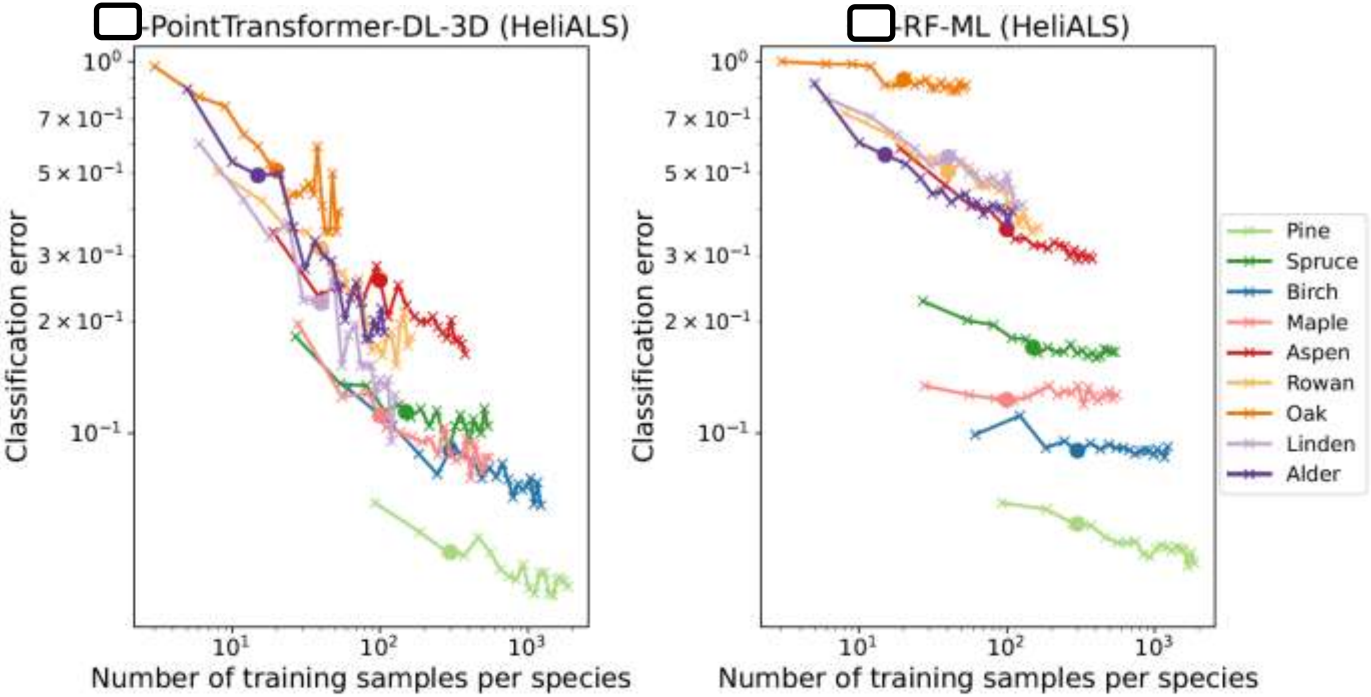
	Pine	Spruce	Birch	Maple	Aspen	Rowan	Oak	Lime	Alder	
Pine	**0.92**	0.03	0.03	0.00	0.01	0.00	0.00	0.00	0.00	2031
Spruce	0.06	**0.87**	0.04	0.01	0.01	0.00	0.01	0.00	0.00	516
Birch	0.02	0.01	**0.94**	0.00	0.02	0.00	0.00	0.00	0.00	1249
Maple	0.02	0.01	0.03	**0.88**	0.01	0.04	0.01	0.01	0.00	575
Aspen	0.05	0.02	0.40	0.00	**0.51**	0.01	0.01	0.00	0.00	374
Rowan	0.04	0.01	0.06	0.30	0.03	**0.52**	0.01	0.01	0.01	168
Oak	0.10	0.04	0.06	0.18	0.14	0.02	**0.37**	0.08	0.00	49
Lime	0.13	0.01	0.05	0.22	0.11	0.04	0.02	**0.42**	0.00	129
Alder	0.13	0.02	0.07	0.15	0.33	0.02	0.10	0.03	**0.15**	115
	2005	534	1463	627	302	125	52	76	22	**5206**
	P: 0.94	P: 0.84	P: 0.81	P: 0.81	P: 0.63	P: 0.70	P: 0.35	P: 0.71	P: 0.77	


FGI-RF-ML, HeliALS
(a)
Recall, Precision
1.0
0.8
0.6
0.4
0.2
0.0
0.917
0.936
0.847
0.837
0.938
0.807
0.864
0.809
0.508
0.632
0.515
0.704
0.367
0.346
0.419
0.711
0.147
0.773
Pine
Spruce
Birch
Maple
Aspen
Rowan
Oak
Linden
Alder
Recall
Precision
FGI-PointTransformerWeighted-DL-3D, HeliALS
(b)
Recall, Precision
1.0
0.8
0.6
0.4
0.2
0.0
0.927
0.969
0.909
0.848
0.893
0.908
0.882
0.895
0.769
0.663
0.784
0.598
0.51
0.403
0.76
0.731
0.276
0.492
Pine
Spruce
Birch
Maple
Aspen
Rowan
Oak
Linden
Alder
Median
Recall
Precision
IBL-BalancedRF-ML, Optech Titan
(c)
Recall, Precision
1.0
0.8
0.6
0.4
0.2
0.0
0.898
0.915
0.848
0.673
0.797
0.83
0.891
0.841
0.641
0.506
0.374
0.719
0.122
0.0882
0.605
0.645
0.00862
1.0
Pine
Spruce
Birch
Maple
Aspen
Rowan
Oak
Linden
Alder
Median
Recall
Precision
FGI-PointTransformer-DL-3D, Optech Titan
(d)
Recall, Precision
1.0
0.8
0.6
0.4
0.2
0.0
0.914
0.9
0.799
0.792
0.867
0.764
0.836
0.814
0.452
0.493
0.31
0.51
0.245
0.245
0.504
0.714
0.112
0.433
Pine
Spruce
Birch
Maple
Aspen
Rowan
Oak
Linden
Alder
Median
Recall
Precision

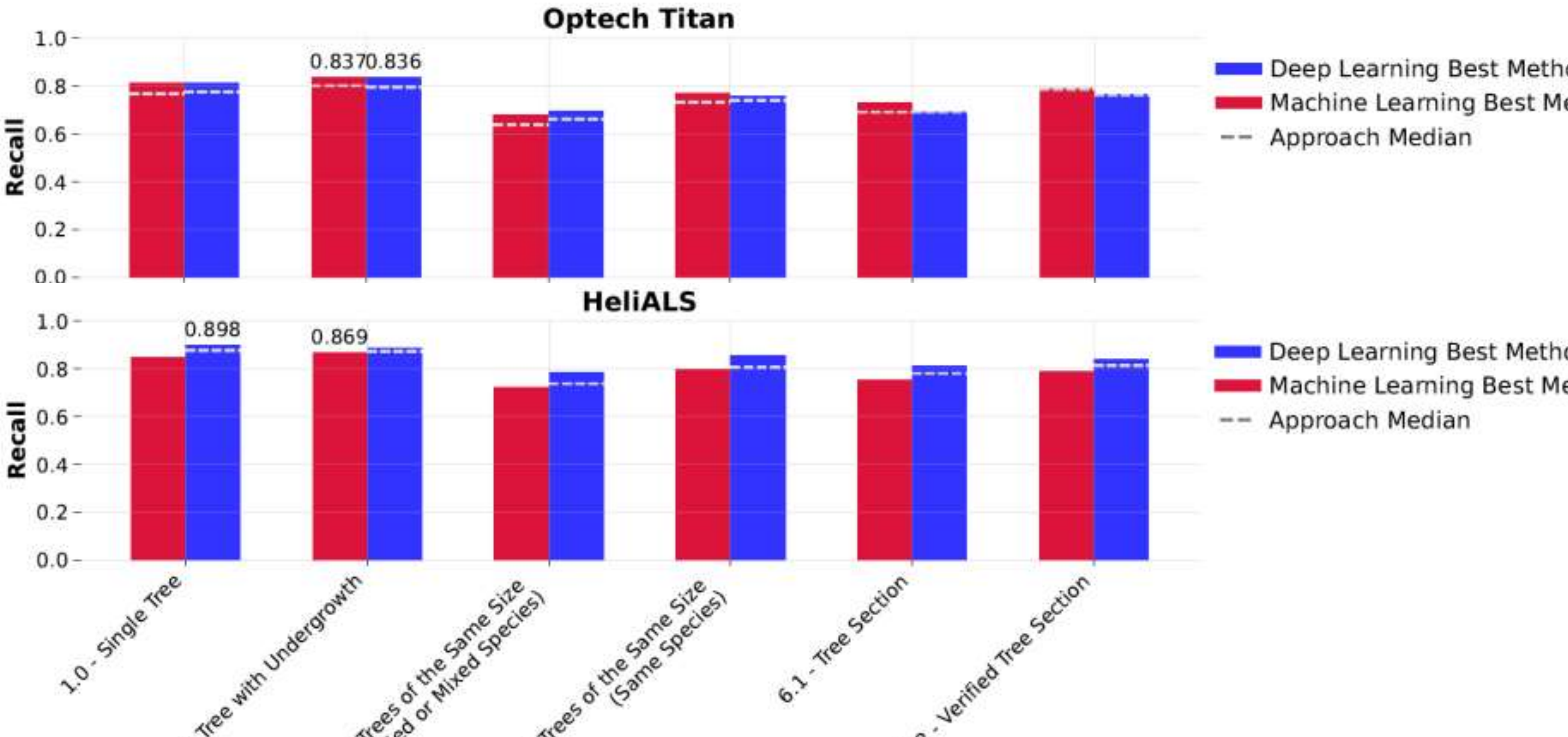
Effect of training data size 1

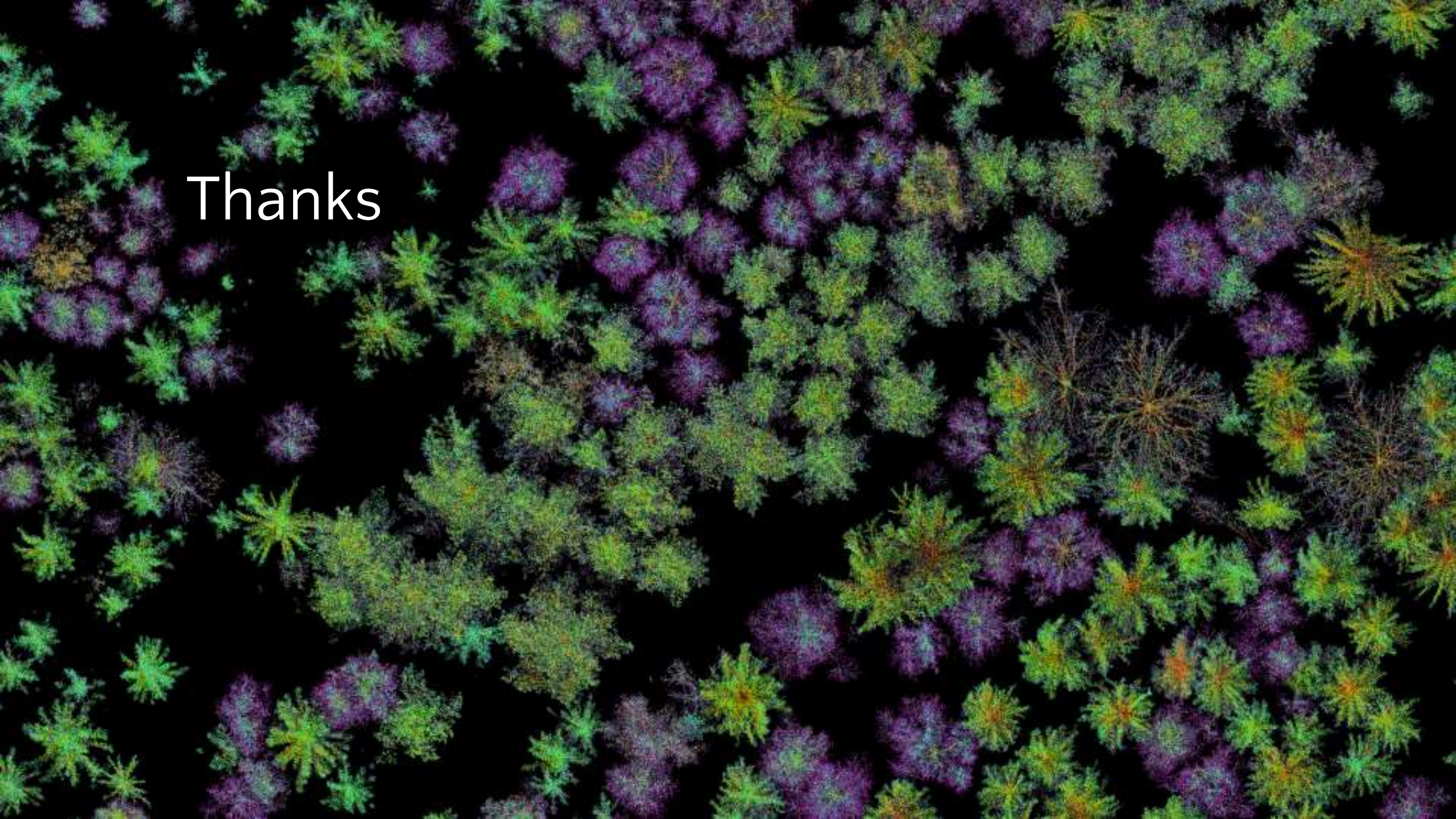


Effect of training data size 2



Effect of segmentation





Thanks