Deep Learning Framework for Individual Tree Crown Detection and Delineation Using High-Resolution LiDAR and applications

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Introduction

- Three-dimensional (3D) individual tree crown (ITC) data is critical for quantifying key forest attributes such as aboveground biomass and carbon stocks, which are central to assessing climate change impacts on forest ecosystems.
- Overlapping canopies, varying tree shapes and sizes, and diverse species composition in mixed-wood forests challenge ITC detection and delineation, and the accuracy remains low.
- Advanced deep learning technique in computer vision combined with high-resolution LiDAR data provides promising solutions to enhance the accuracy and efficiency of ITC delineation.

Reviews

❑ Current issues

- CHM based methods face limitations in fully utilizing the 3D structural richness of LiDAR data
- Methods based on 3D LiDAR point clouds often suffer from high computational costs and a lack of high-quality 3D training datasets, particularly for mixed-wood forest environments.

❑ Motivations

- Need for a deep learning framework that can fully exploit 3D LiDAR data while improving the accuracy and efficiency of 3D ITC delineation

Objectives

Improve ITC detection and delineation in mixed-wood forests using deep learning and high-resolution LiDAR data

- Propose a two-stage framework combining Mask R-CNN treetop detection and 3D U-Net architecture to improve 3D ITC delineation
- Build a training dataset for high-resolution airborne LiDAR data in mixed-wood forests (5,000 trees) by integrating 2D CHM and LiDAR points
- Generate 2D and 3D ITC detection and delineation products for practical forestry applications

Study Area and Dataset

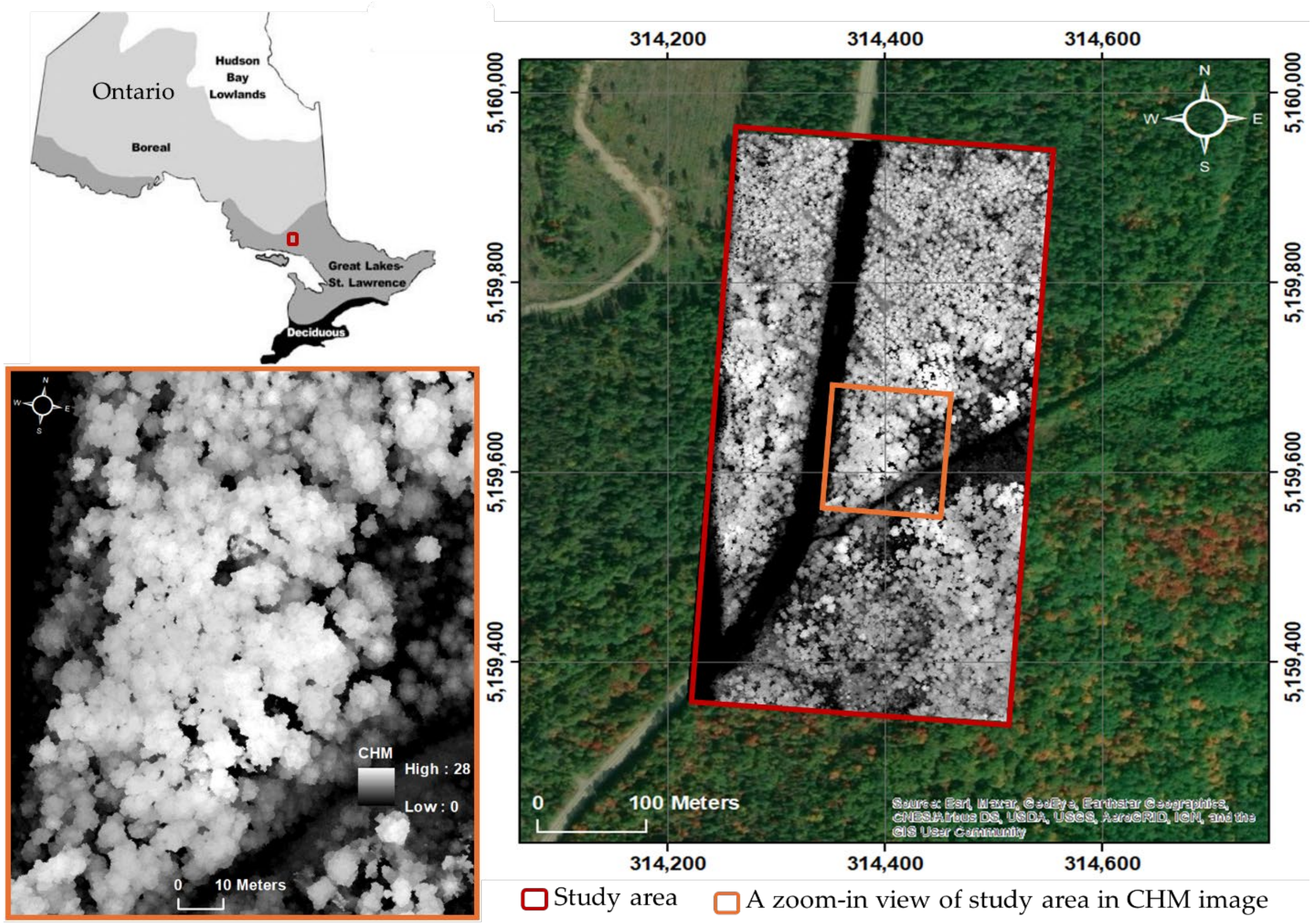
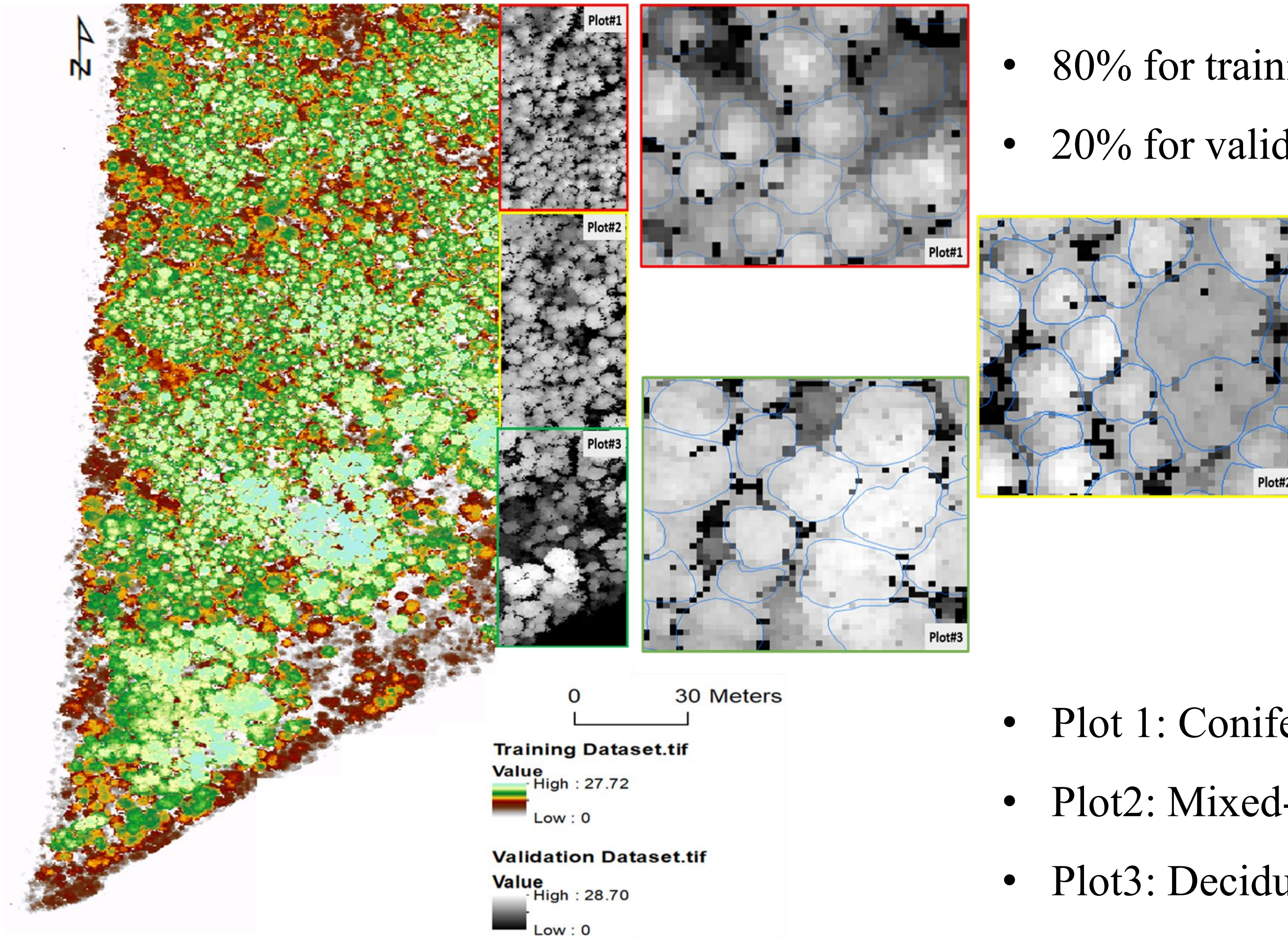


Figure 1. Location and characteristics of the study area. The forest regions of Ontario, depicted in the top left, are adapted from OMNR (2002a).

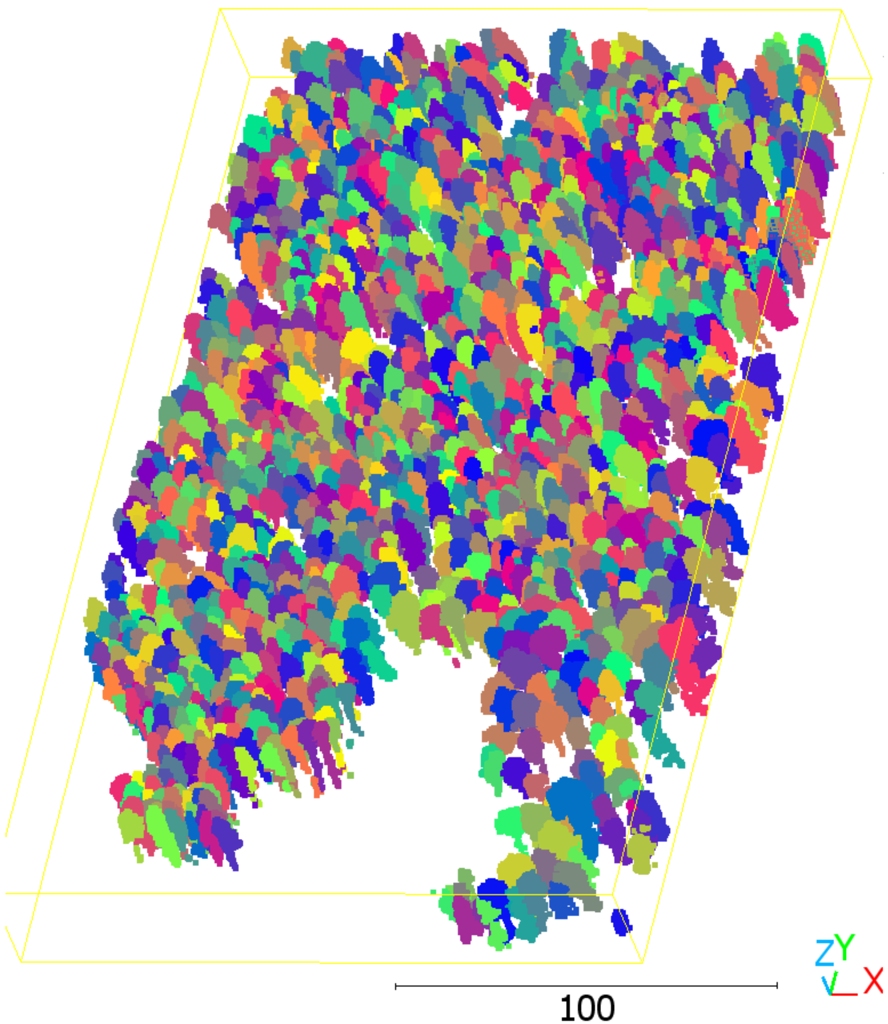
2D Training Dataset

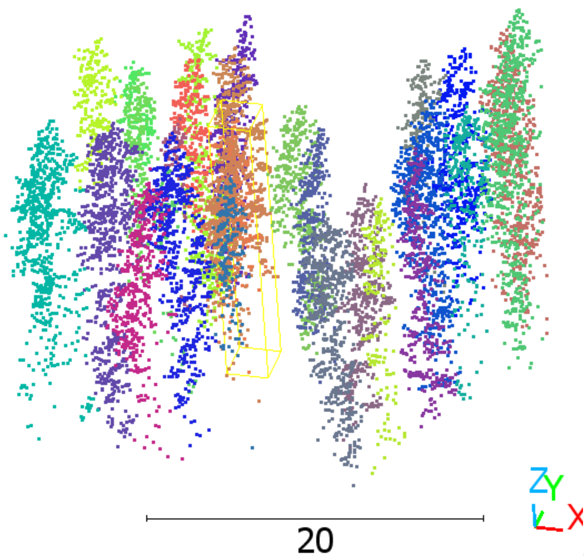


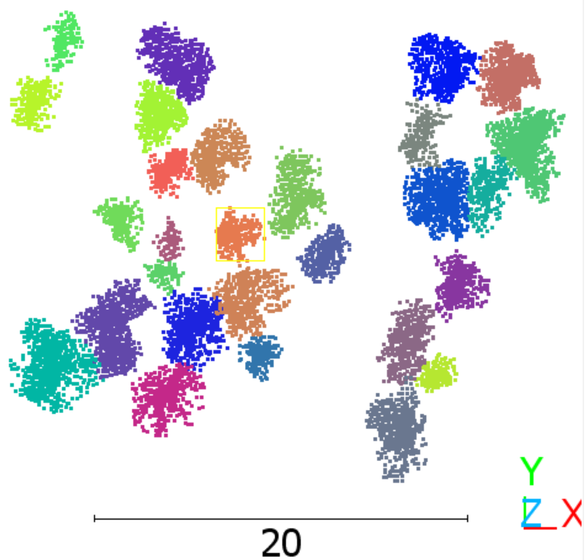
- 80% for training
- 20% for validation

- Plot 1: Coniferous
- Plot2: Mixed-wood
- Plot3: Deciduous

3D Training Dataset







Methodology

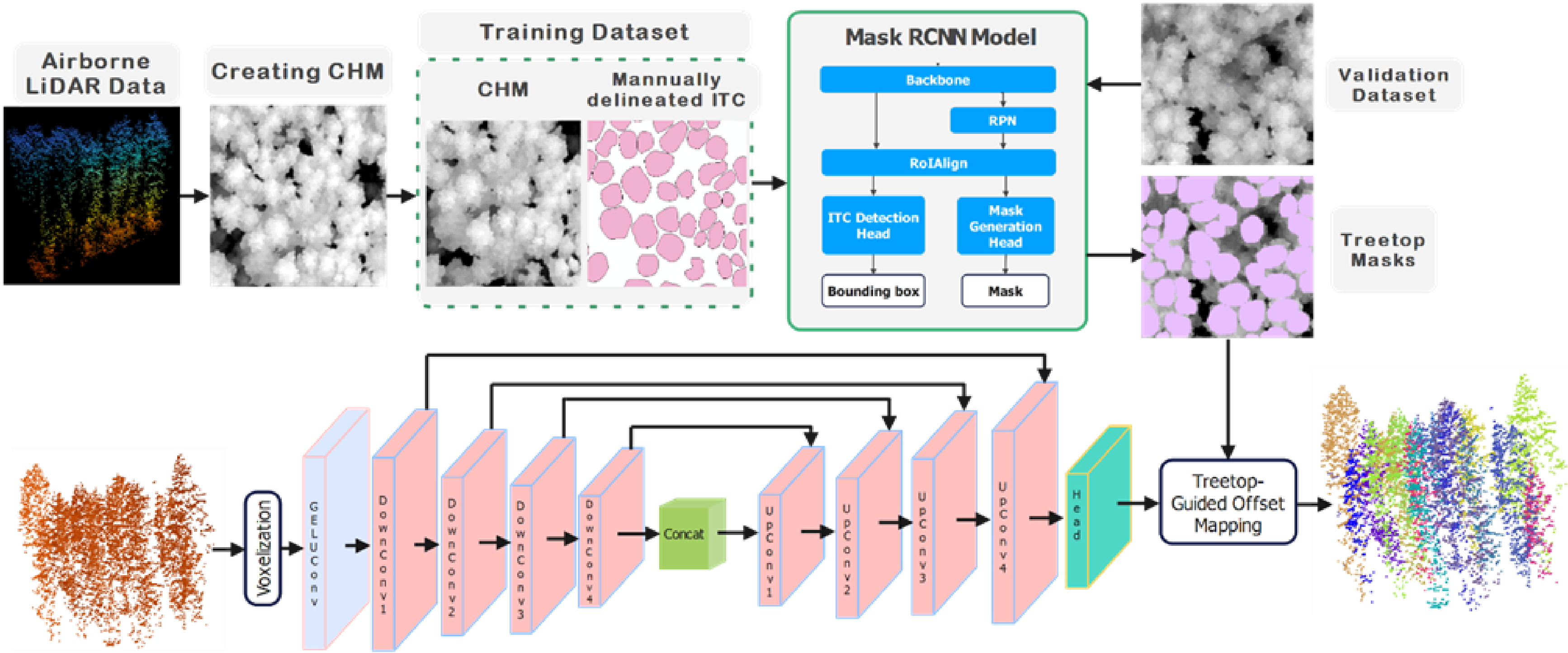


Figure 4. Workflow for the two-stage deep learning network combining Mask R-CNN and 3D U-Net.

Results: 3D Results and Visualization

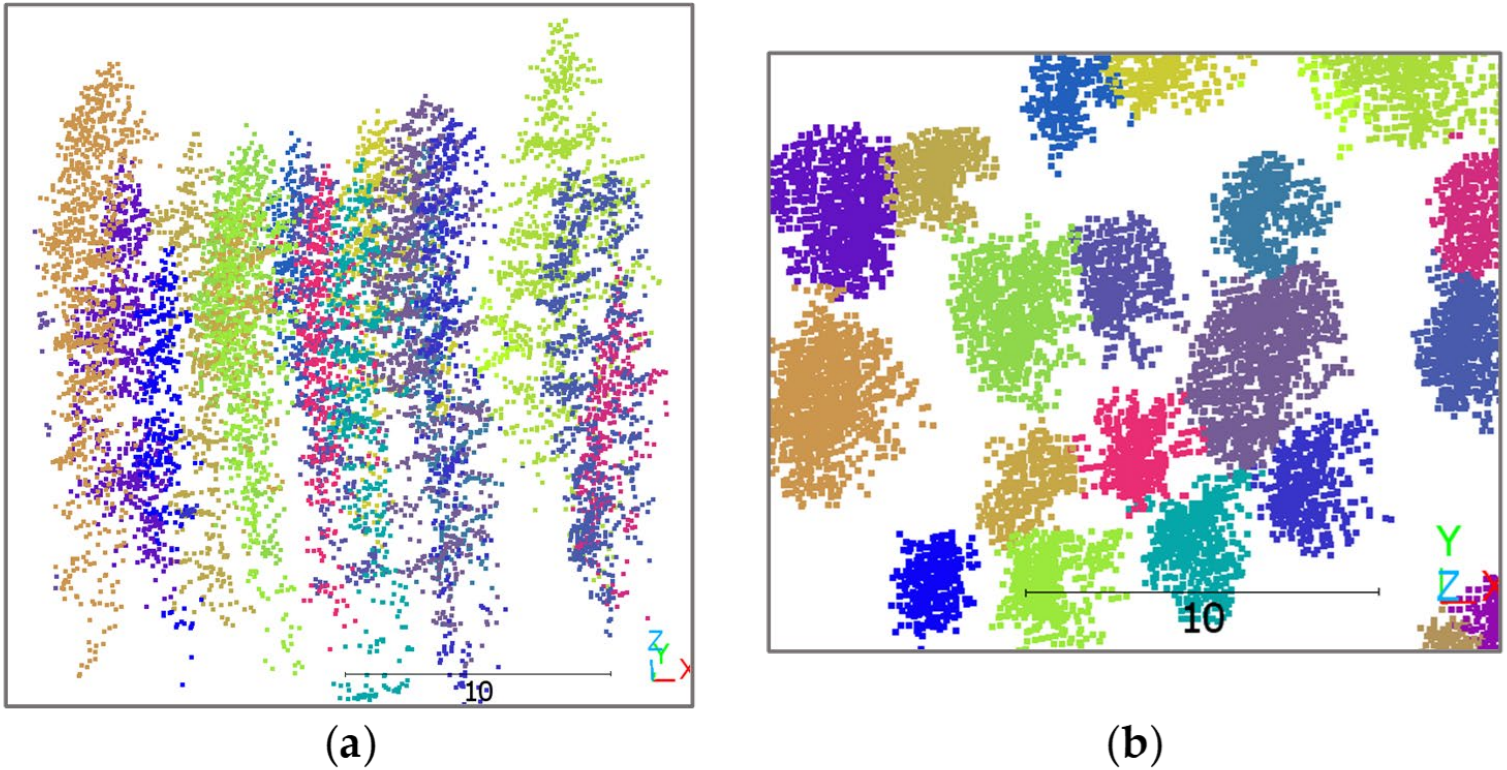


Figure 5. Example results from the two-stage deep learning network. ITCs are displayed in random colors, with corresponding ITCs in the same color in (a,b). (a) shows the 3D view of the delineated ITCs, while (b) provides the 2D view.

Results: Accuracy Assessment

Plots	Metrics	Two-Stage Method	MASK R-CNN	itcSegment
Plot-1	mIoU	0.82	0.78	0.76
	Delineation accuracy (%)	91.48	90.03	85.58
	Precision	0.92	0.91	0.72
	Recall	0.89	0.85	0.85
	F1 score	0.88	0.87	0.82
Plot-2	mIoU	0.81	0.76	0.73
	Delineation accuracy (%)	84.18	80.04	76.15
	Precision	0.86	0.75	0.70
	Recall	0.83	0.80	0.79
	F1 score	0.84	0.81	0.76
Plot-3	mIoU	0.79	0.72	0.74
	Delineation accuracy (%)	82.38	79.49	78.95
	Precision	0.84	0.78	0.71
	Recall	0.83	0.84	0.81
	F1 score	0.82	0.83	0.80

Results: Comparison

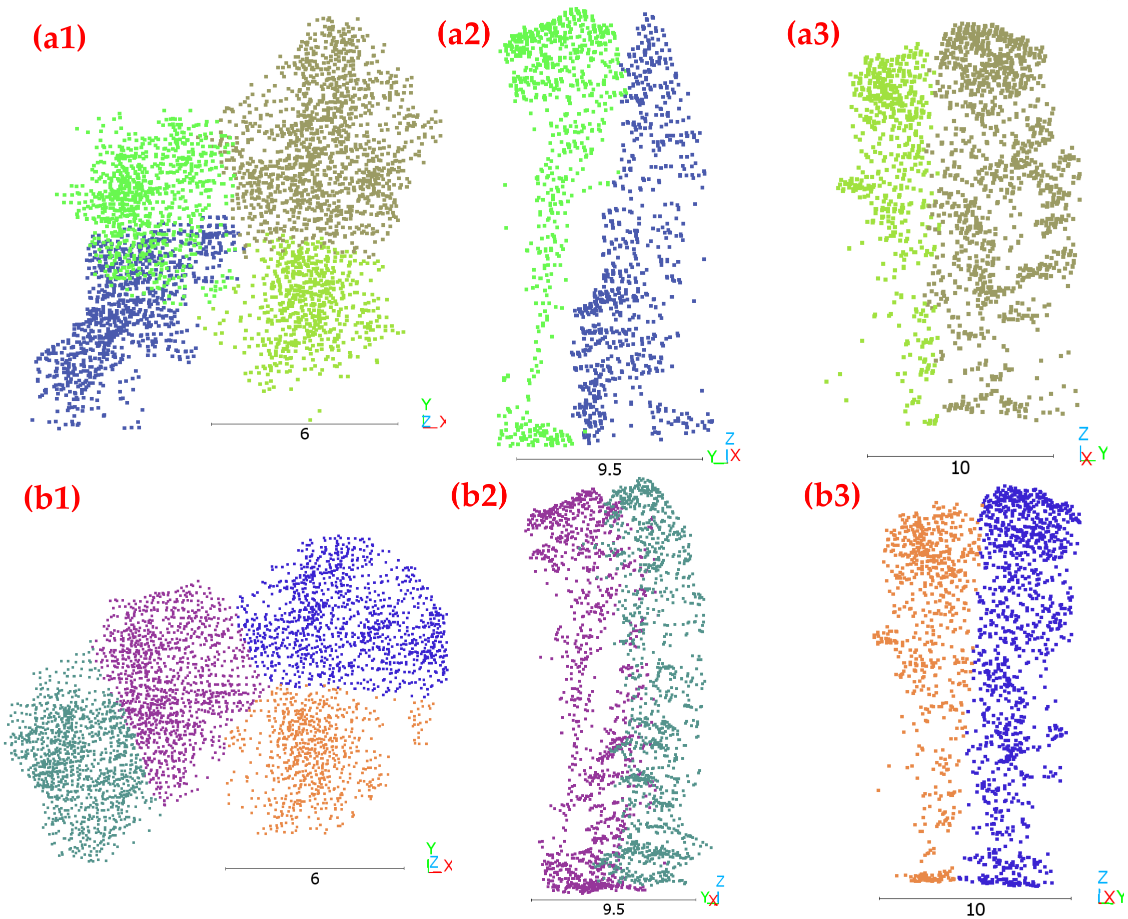


Figure 6. Examples of 3D ITC delineation comparison of the proposed method with the itcSegment algorithm in lidR.

Results: Tree Attributes

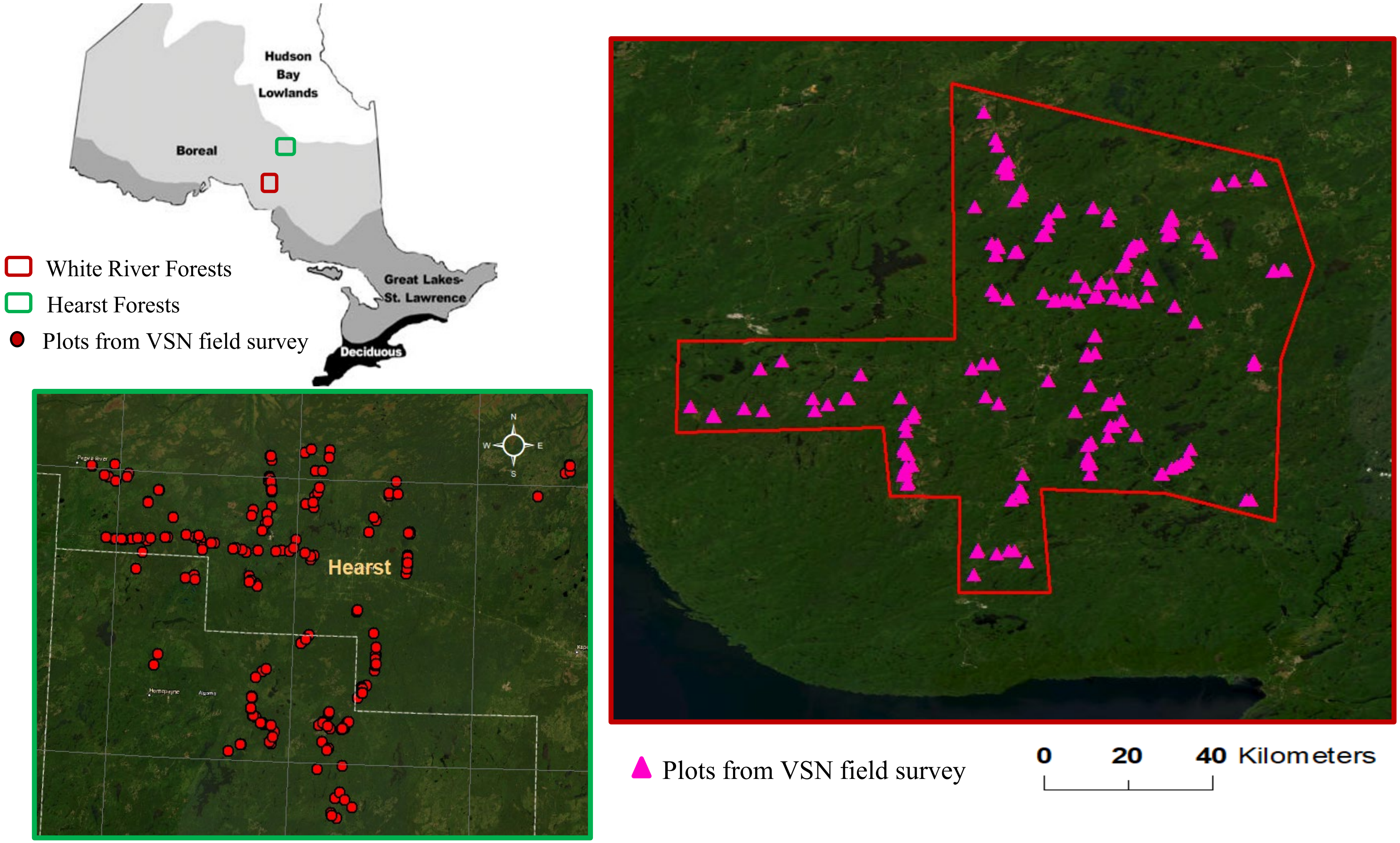
ITC_ID	x	y	z	Height	Crown_Area	Local_Peaks	IoU
1	774,203.14	5,163,280.91	314.87	7.26	0.07	0	0.005
2	774,212.023	5,163,285.82	323.28	20.61	58.73	9	0.751
3	774,215.229	5,163,267.141	325.34	22.31	18.20	3	0.939
4	774,229.105	5,163,295.991	322.14	19.53	29.34	3	0.854
5	774,232.105	5,163,275.46	323.49	20.70	8.51	4	0.399
6	774,222.139	5,163,299.257	323.80	21.00	36.42	5	0.784
7	774,216.146	5,163,280.994	325.87	22.45	25.81	3	0.492
8	774,230.796	5,163,279.74	327.54	24.00	32.18	5	0.862
9	774,222.343	5,163,293.852	321.90	20.01	24.64	4	0.706
10	774,249.046	5,163,273.842	328.27	25.50	22.74	2	0.693
11	774,251.172	5,163,269.53	326.04	23.27	16.31	1	0.673
12	774,248.529	5,163,289.822	324.53	23.54	30.47	4	0.876
13	774,224.019	5,163,273.397	325.80	22.51	17.84	3	0.660
14	774,211.021	5,163,272.464	325.47	22.62	23.55	5	0.790
15	774,217.062	5,163,295.945	323.51	20.83	23.51	2	0.780
16	774,234.042	5,163,265.536	326.28	23.96	39.35	6	0.718
17	774,249.729	5,163,294.858	319.66	17.53	14.66	2	0.920
18	774,246.805	5,163,264.895	325.16	23.53	40.53	6	0.879
19	774,211.265	5,163,298.707	322.85	19.58	24.45	2	0.792
20	774,221.886	5,163,308.862	324.16	21.54	68.65	8	0.478

- Tree attributes derived from ITCs generated from proposed model
- Tree location map (ITC_ID, x, y, z)
- Tree height, crown area, and local peaks of ITCs
- ITC point cloud data of ITC for analysis

Application of ITC delineation

Lichen Mapping with Single-Photon LiDAR and VSN Data in Ontario Boreal Mixed-Wood Forests

Study area and VSN dataset

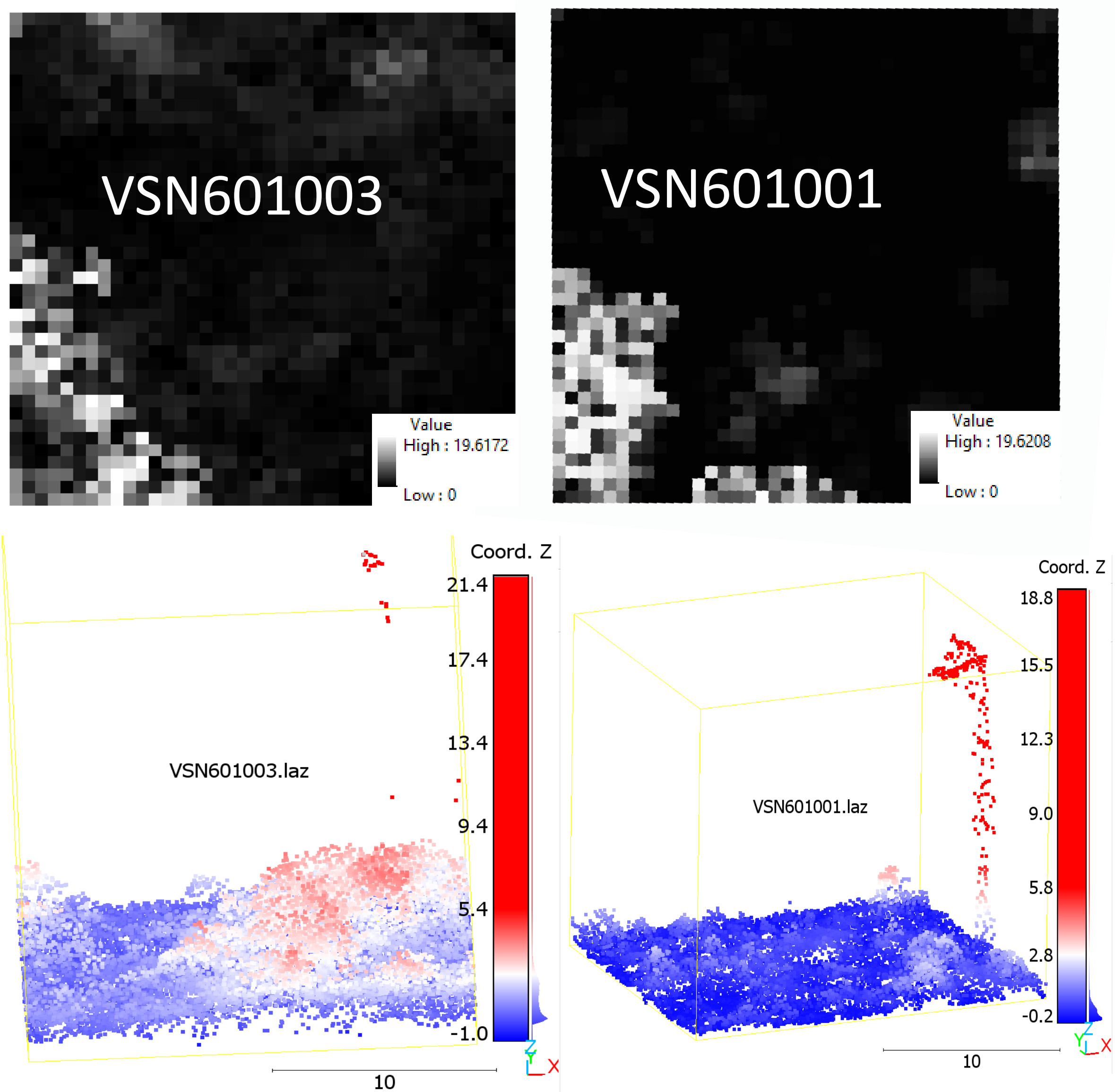


Spatial Analysis: Use GPS coordinates from field data to align with map for integrated spatial analysis. The forest regions of Ontario, depicted in the top right, are adapted from OMNR (2002a).

Study area and VSN dataset

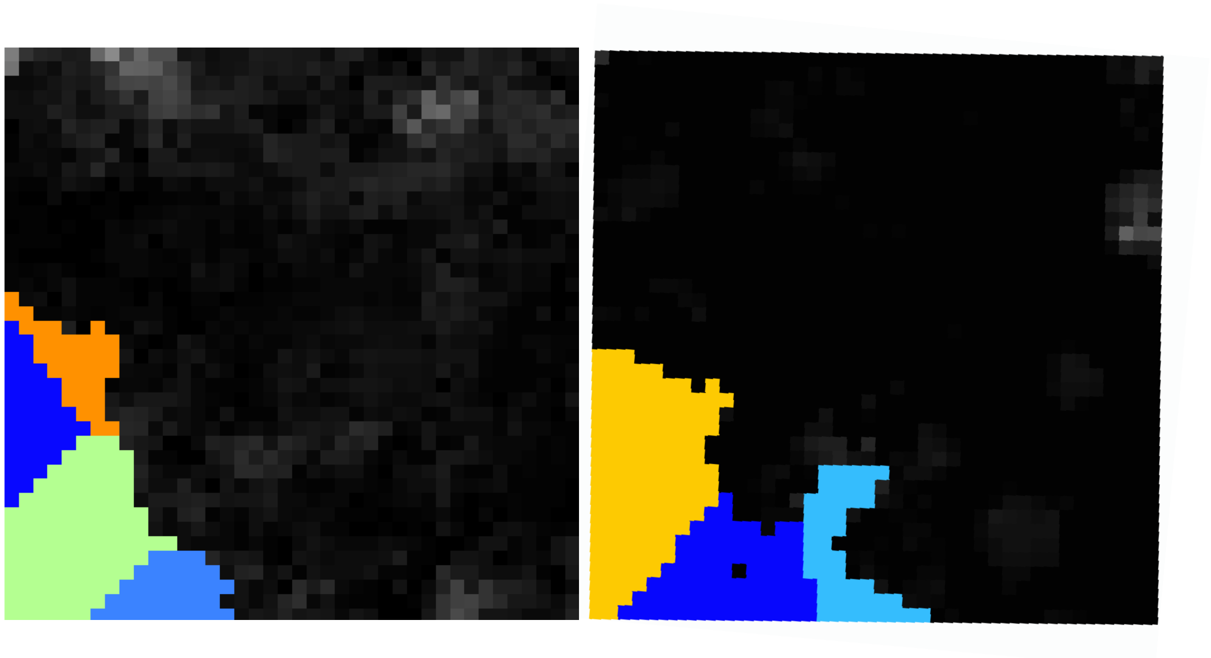
- Vegetation Sampling Network (VSN) established by the Ontario Ministry of Natural Resources and Forestry.
- 360° panoramic photographs captured at the center of each VSN plot.

Canopy Height Model(CHM) and LiDAR points



- Example of SPL-derived CHM and SPL point cloud subsets clipped to 20 × 20 m windows for two VSN plots

Individual Tree Crown (ITC) delineation



- Example of ITC delineation results (masks in yellow, blue, green colors) using the proposed method and CHM for two VSN plots named VSN 601001 and VSN 601003.

Lichen Prediction: Feature Extraction

Table 2. Summary of LiDAR-derived features used in lichen presence modeling from 20 × 20 m plots.

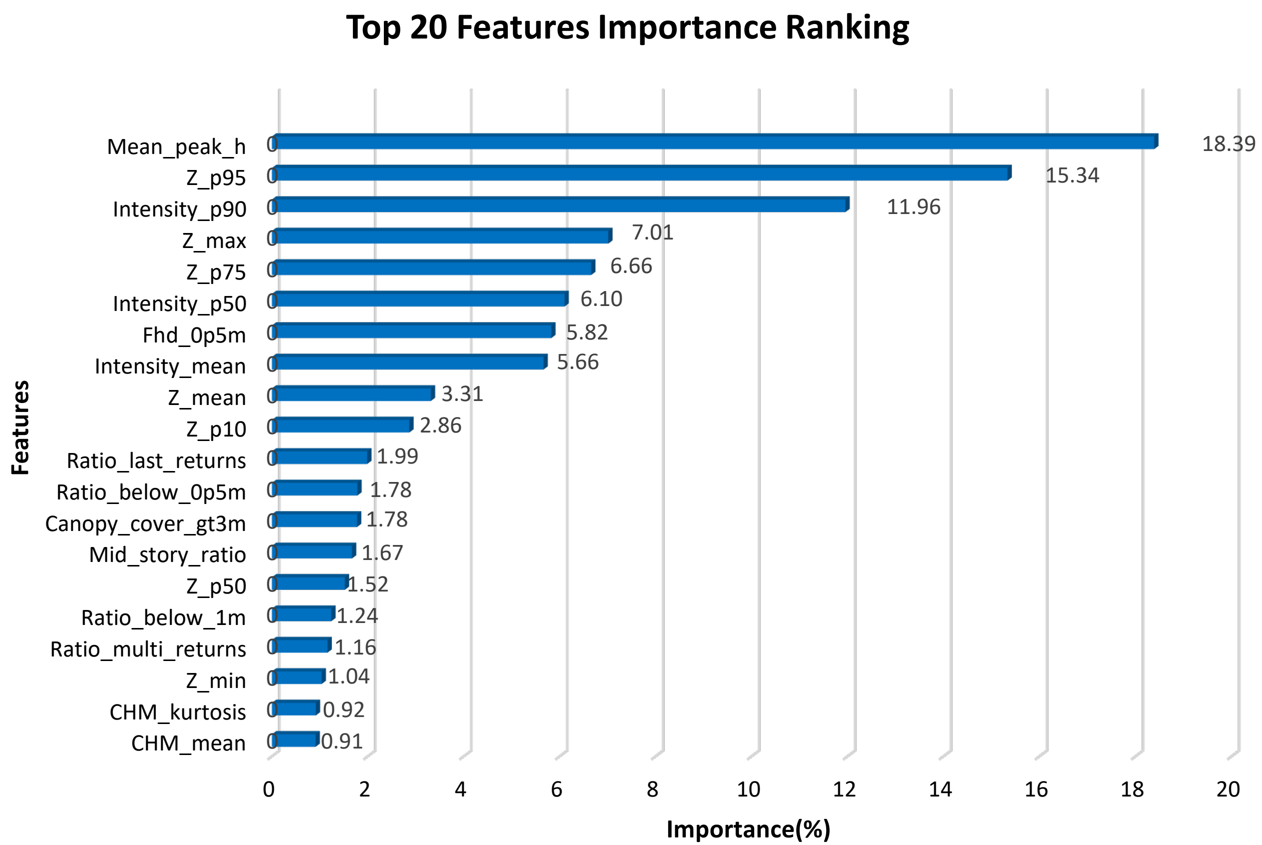
Category	Feature examples	What they capture
CHM-derived (plot)	Mean / std / max height, canopy cover >3m & >5m, gap fraction & largest gaps, CHM texture	Overall canopy height, openness, and gap structure
Point-cloud (plot)	Height percentiles (P10–P95), foliage height diversity, returns below 0.5–1 m & mid-story, first/last/multi-return ratios, intensity stats	Vertical structure, understory density, canopy penetration, and reflectance
Tree-crown (ITC)	Number of crowns, total crown area & cover ratio, mean crown radius & variability, edge trees, mean treetop height	Tree density, crown size and packing, edge effects, and overstory height

Lichen Prediction: Modeling

Table 3. The hyperparameters table used in RF, Logit-EN, and SVM-RBF models.

Model	Tuning protocol	Selected hyperparameters
RF	5-fold CV on train	n_estimators=600; max_depth=12; min_samples_leaf=2; max_features=√p; bootstrap
Logit-EN	5-fold CV on train	C=1.0; l1_ratio=0.5; solver=SAGA; class_weight=balanced
SVM-RBF	5-fold CV on train	C=1.0; γ=scale; probability=True; class_weight=balanced

Lichen Prediction: Results



The share-of-total importance ranking of top 20 features used in RF.

Lichen Prediction: Results

Table 4. Performance of the Random Forest classifier under two decision thresholds.

Threshold	Accuracy	Precision (Presence)	Recall (Presence)	F1 (Presence)	ROC-AUC	PR-AUC/AP	Brier Score
0.50 (fixed)	0.69	0.79	0.57	0.66	0.73	0.67	0.17
0.30 (CV-optimal, F1.5)	0.61	0.58	0.82	0.68	0.73	0.67	0.17

Table 5. Performance comparison of the three models at the conventional 0.50 threshold.

Model	Threshold	ROC AUC	PR AUC	Brier	Accuracy	F1
RF	0.50	0.63	0.63	0.32	0.69	0.66
Logit-EN	0.50	0.50	0.54	0.26	0.59	0.52
SVM-RBF	0.50	0.55	0.58	0.28	0.61	0.65

Lichen Prediction: Conclusion

- SPL features show canopy height, openness, gaps, and intensity as key drivers of lichen presence.
- RF model performs well (ROC-AUC 0.73, PR-AUC 0.67); 0.5 threshold favors precision, 0.3 threshold favors recall and habitat protection.
- SPL provides structural proxies that complement spectral data for lichen mapping under closed canopies.
- SPL + VSN plots give a scalable framework for lichen habitat mapping and caribou conservation across Ontario.

Lichen Prediction: Limitation and Future Work

- **Limitations**
  - Small, spatially limited plot sample (n = 201) may not capture full lichen habitat gradients or rare conditions.
  - Binary presence/absence labels simplify true lichen cover and ignore within-plot variability.
- **Future Work**
  - Expand and diversify labeled plots via additional field surveys and monitoring partnerships.
  - Integrate SPL with hyperspectral, UAV multispectral, and Sentinel-2 data to improve species-level discrimination and abundance estimation.

Acknowledgement

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