



*An enhanced* Private Land Inventory in the  
United Counties of Prescott and Russell

**November 30<sup>th</sup>, 2023**

**Forestry Futures Trust | KTTD Round 3**

**John Pineau (Executive Director) and Ben Gwilliam (Private Lands Inventory Analyst)**

Ontario Woodlot Association

# Presentation Overview

- 1. The Ontario Woodlot Association**
- 2. Private Land Inventory Project Impetus**
- 3. Private Land Inventory Project Overview**
- 4. Methodology**
- 5. Private Land Inventory Validation Results**
- 6. Analysis of Economic Potential in UCPR**
- 7. Project Takeaways**
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# The Ontario Woodlot Association

## VISION

Ensuring the sustainability of Ontario's privately owned forests now and in the future.

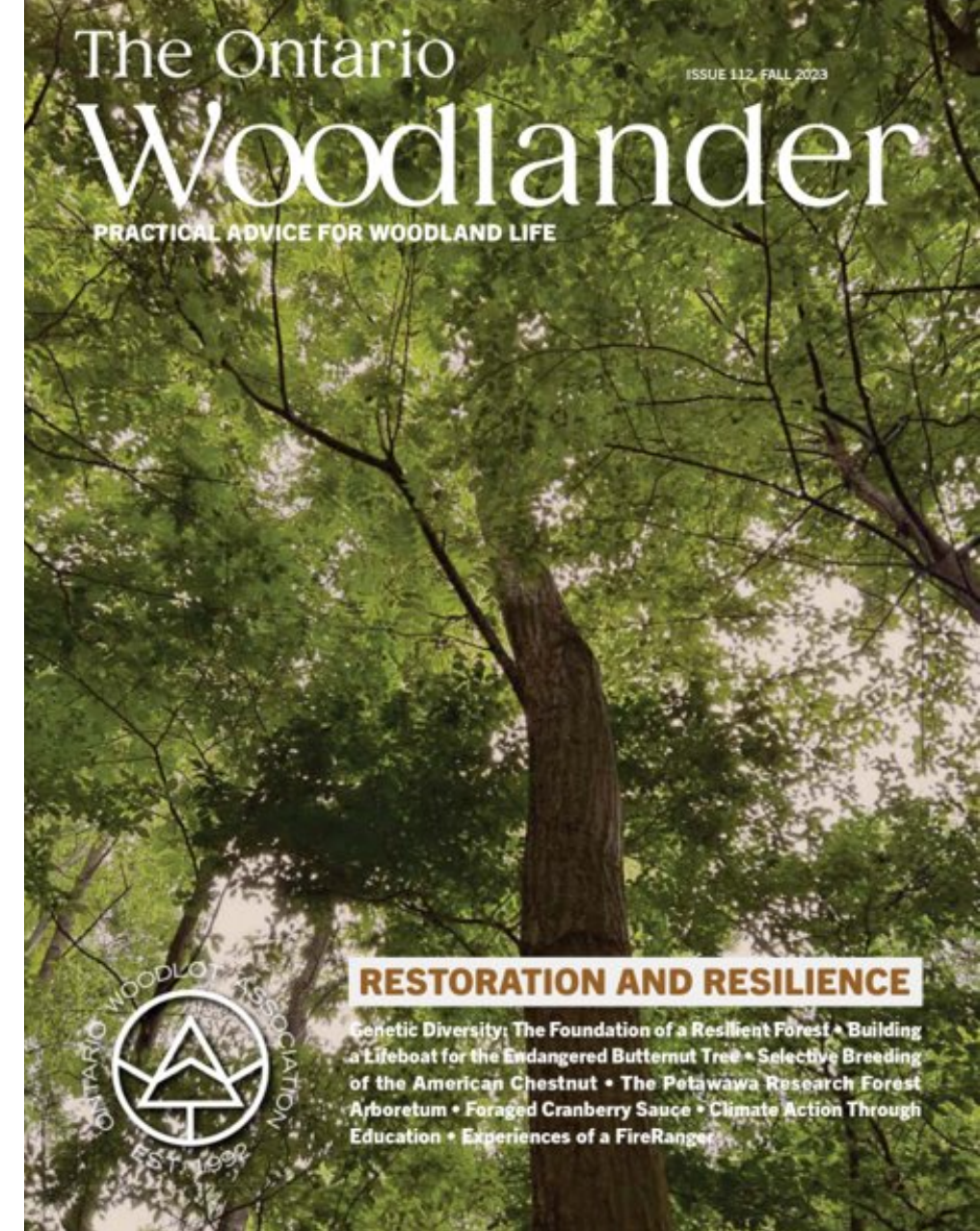
## MISSION

Helping each other to become the best possible stewards of our woodlands!

## VALUES

As an organization built by enthusiastic and engaged people, committed to using best management practices, we want our woodlots to be:

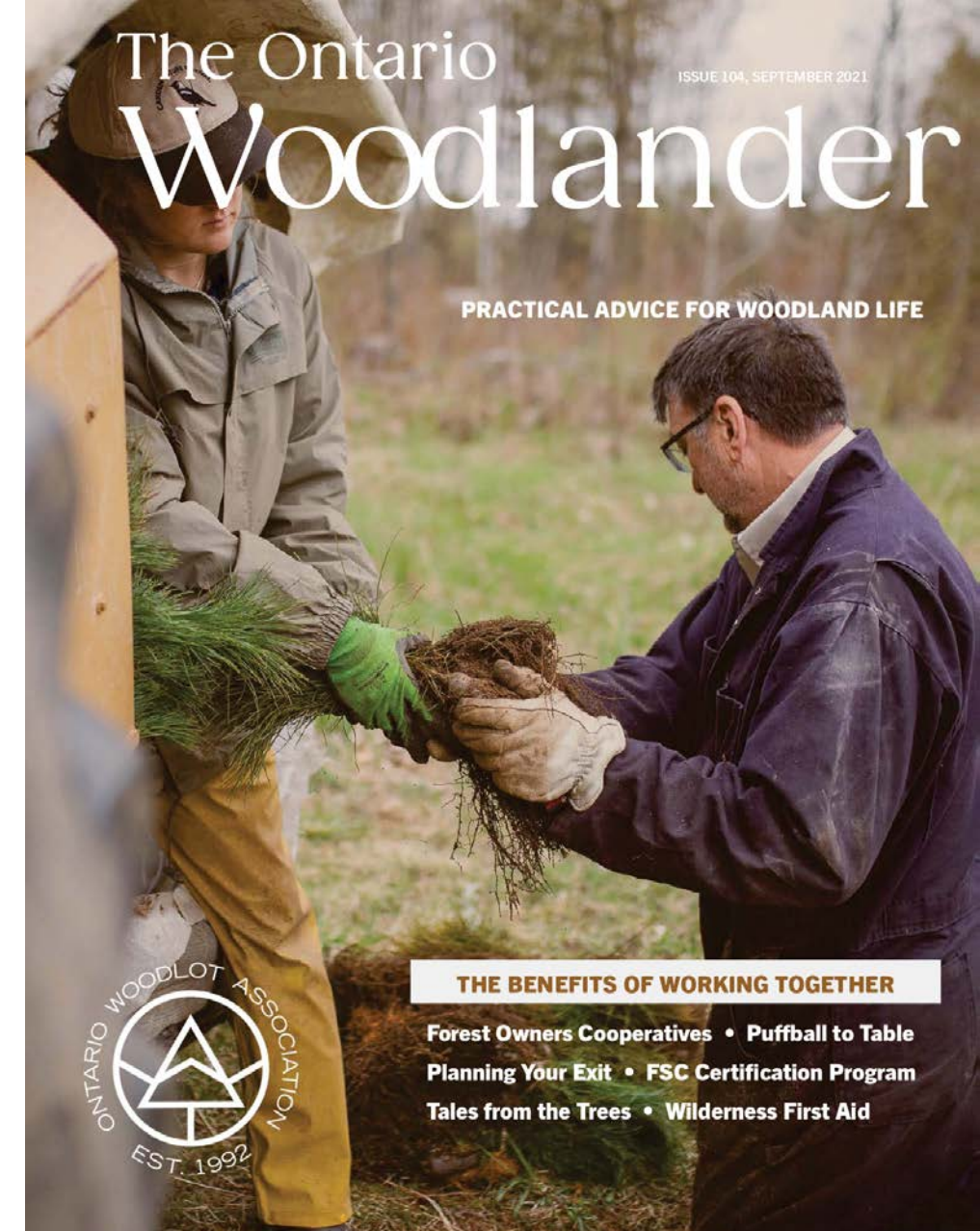
- Sustainable and productive
- Ecologically healthy and diverse
- Spiritually and physically renewing



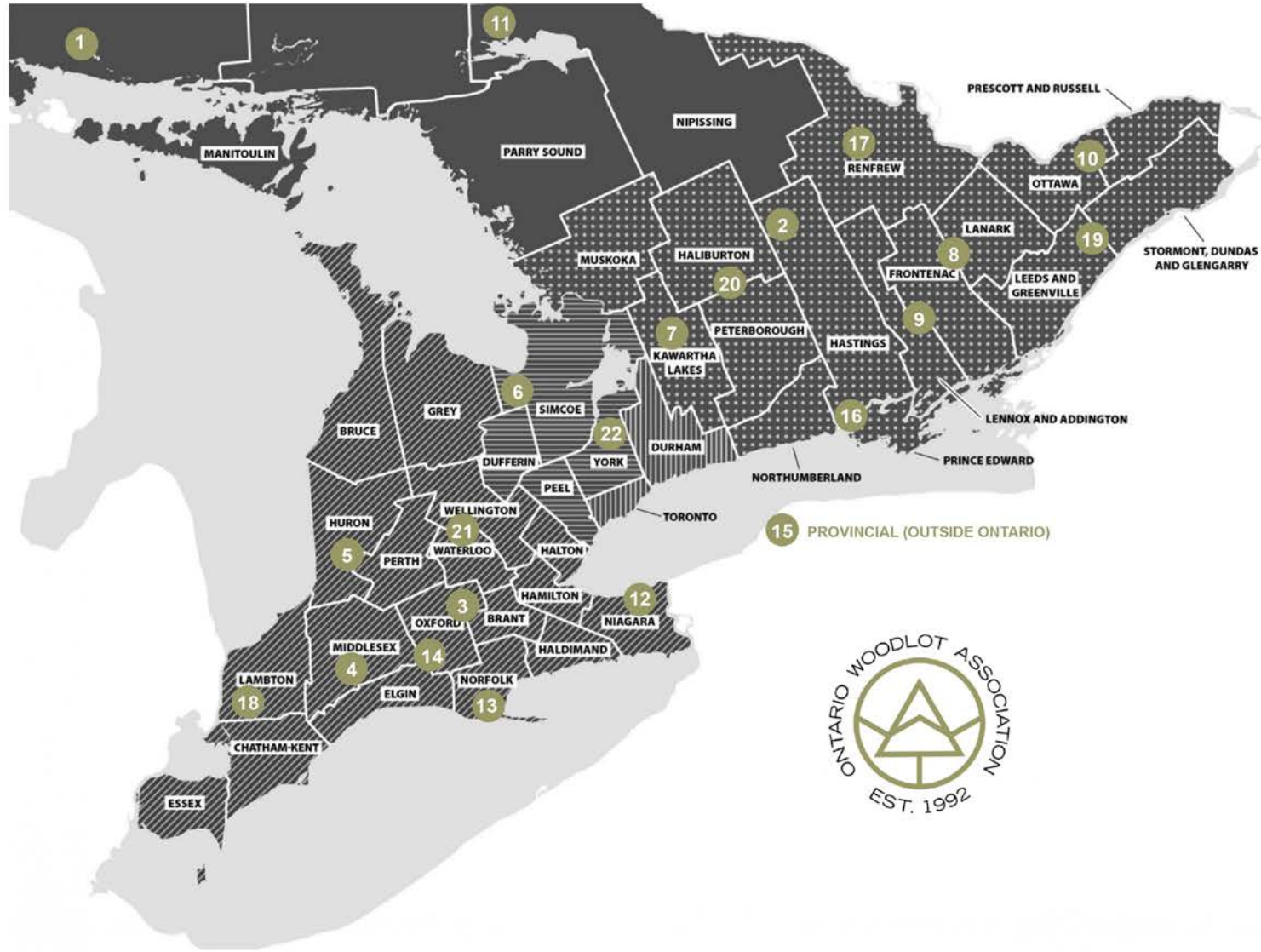
# Member Value

## Products and Services

- The Ontario Woodlander Magazine
- Monthly E-newsletter
- Modern Website, Database, Ecommerce
- Social Media (Instagram, Facebook, Linked-In, Twitter and YouTube)
- Provincial Conference and AGM (April 2024 - Huronia)
- Woodland Walk and Talk Video Series
- 100+ events annually across 22 Chapters in southern & central Ontario
- Woodlands Appreciation Week (early May)
- E-Store (artisanal wood products from and for our members)
- Forest Owners Forum/Blog
- ***Multiple Programs and Projects including our flagship Private Lands Forest Inventory Program***
  
- *Constructive advocacy on behalf of membership and woodlot owners...*



# ONTARIO WOODLOT ASSOCIATION CHAPTER MAP



## LEGEND

- 1 ALGOMA (SAULT STE MARIE/ NORTH SHORE)
- 2 BANCROFT/HALIBURTON
- 3 BRANT COUNTY WOODLOT OWNER' ASSOC.
- 4 ELGIN/MIDDLESEX WOODLOT OWNER'S ASSOC.
- 5 HURON/PERTHCOUNTIES
- 6 HURONIA WOODLAND OWNER'S ASSOC.
- 7 KAWARTHA (LINDSAY/MINDEN)
- 8 LANARK & DISTRICT CHAPTER
- 9 LIMESTONE (KINGSTON/NAPANEE)
- 10 LOWER OTTAWA VALLEY
- 11 NEAR NORTH (NORTH BAY/ HUNTSVILLE REGION)
- 12 NIAGARA
- 13 NORFOLK WOODLOT OWNERS ASSOC.
- 14 OXFORD COUNTY WOODLOT OWNERS' ASSOC.
- 15 PROVINCIAL (OUTSIDE ONTARIO)
- 16 QUINTE
- 17 RENFREW COUNTY
- 18 SOUTH WEST WOODLOT OWNERS' ASSOC.
- 19 STORMONT, DUNDAS, GLENGARRY
- 20 UPPER TRENT VALLEY (MARMORA/PETERBOROUGH)
- 21 WATERLOO/WELLINGTON WOODLOT OWNERS' ASSOC.
- 22 YORK/DURHAM CHAPTER



# A Textbook Pilot Project that has Catalyzed a Comprehensive Program!



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# Project Impetus

## Need for Forest Resource Inventory on Private Land in Ontario

Last comprehensive inventory of Southern Ontario was 1979

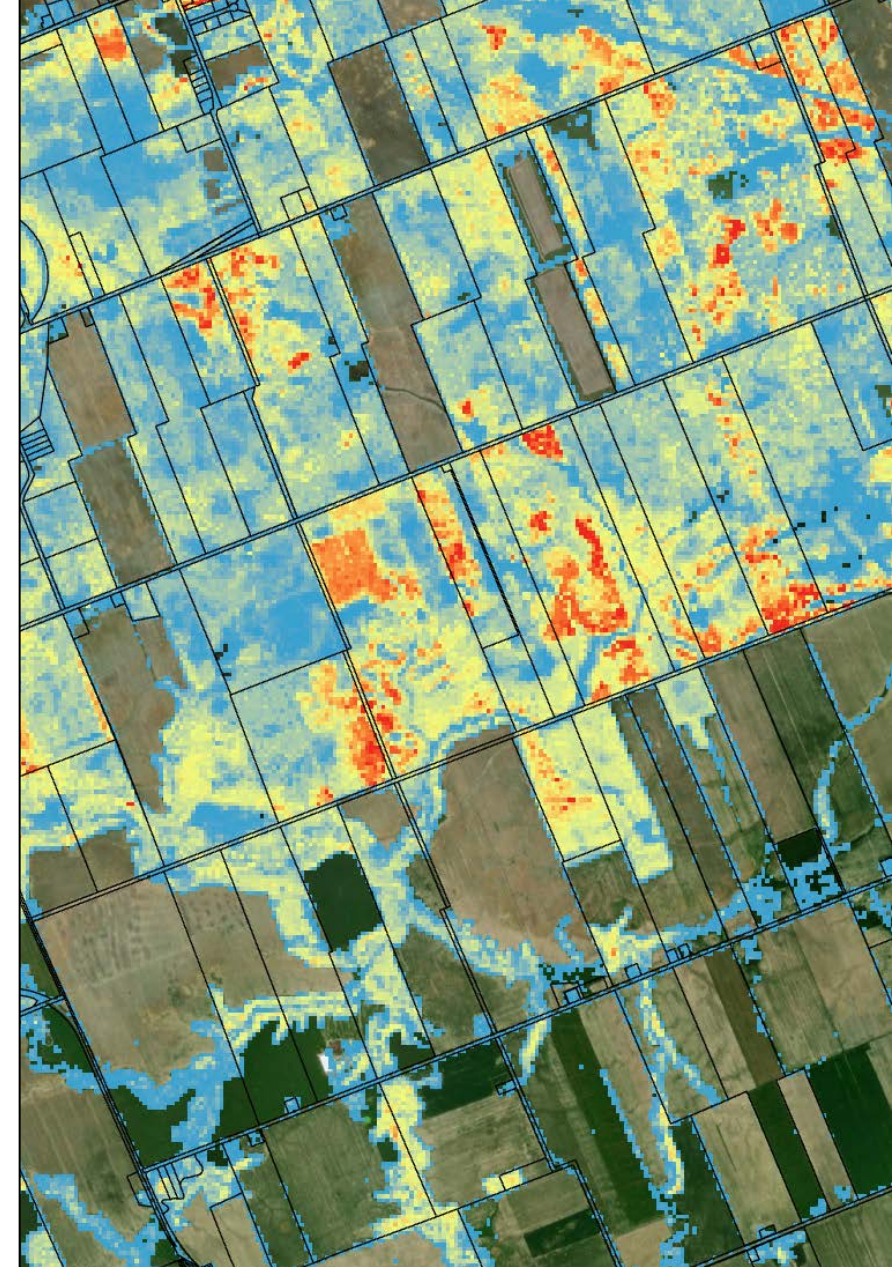
## Availability of LiDAR Data in Region

Originally acquired for terrain mapping | Digital elevation products

LiDAR enables production of an *Enhanced Forest Resource Inventory* (eFRI)

## Promote Private Land Forestry Sector in Ontario

Up to date inventory a critical tool to sustainable forest management

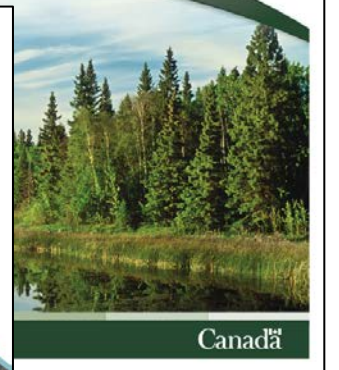
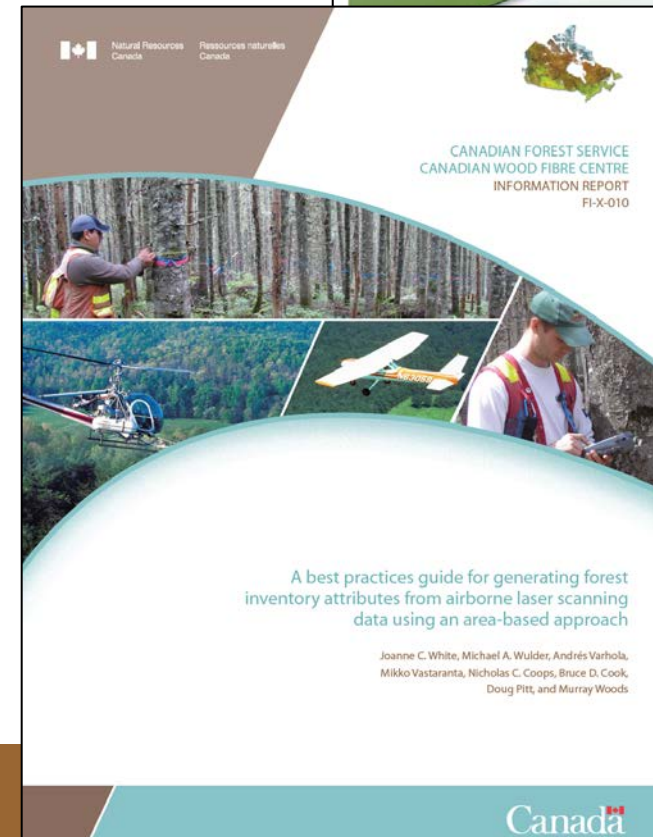


# Project Impetus

## Research Question:

Can we apply industry standard techniques to produce an adequate eFRI of an urban/rural area within Southern Ontario?

And can we model temporal change to glean relevant economic insights?





# Project Context

## Study Area

United Counties of Prescott and Russell (UCPR) | 2014 km<sup>2</sup> area

## Raster (20 m) Area-Based FRI that is T2 Crown Land FRI (MNRF) Equivalent

All industry-standard attributes by size-class (per ha) and with leading species or species groups information

## Airborne LiDAR Data

Collected May 8 – 11<sup>th</sup>, 2015

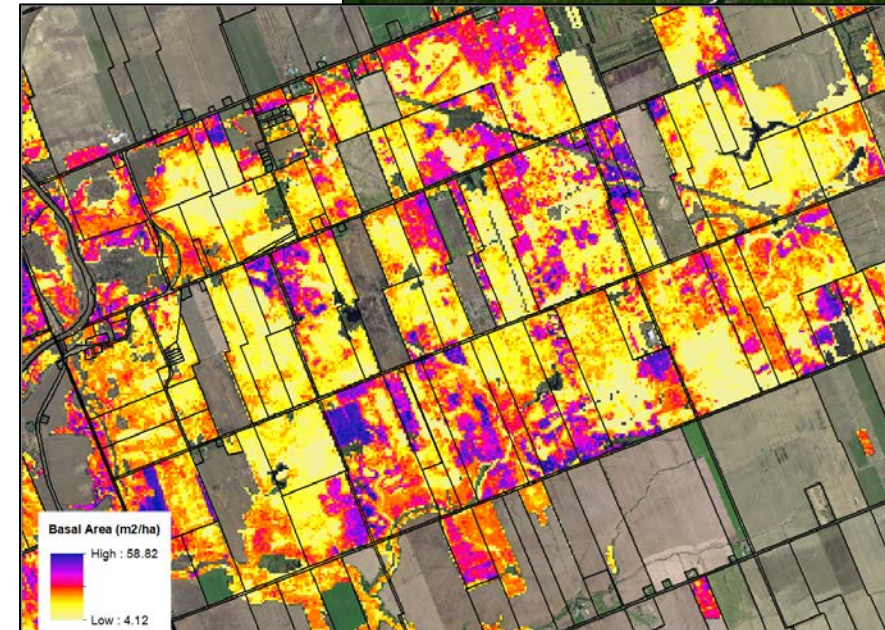
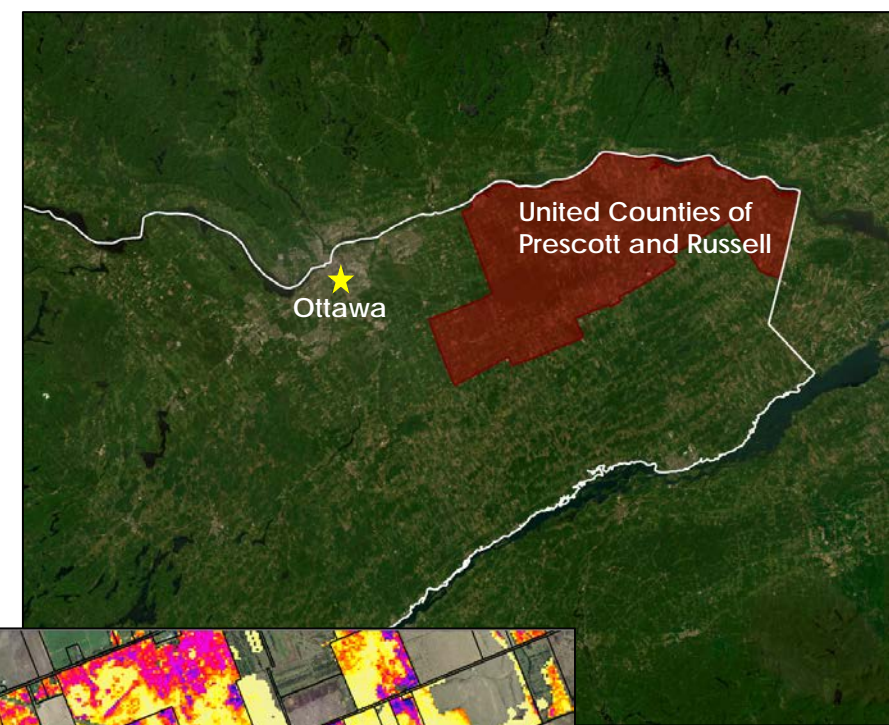
Flight Alt: 1350 m

Point Density: 4 pts/m<sup>2</sup> (linear mode)

## Challenges

Leaf-off data

Outdated data



# Project Context

## Existing FRI Generated from 2015 LiDAR Dataset

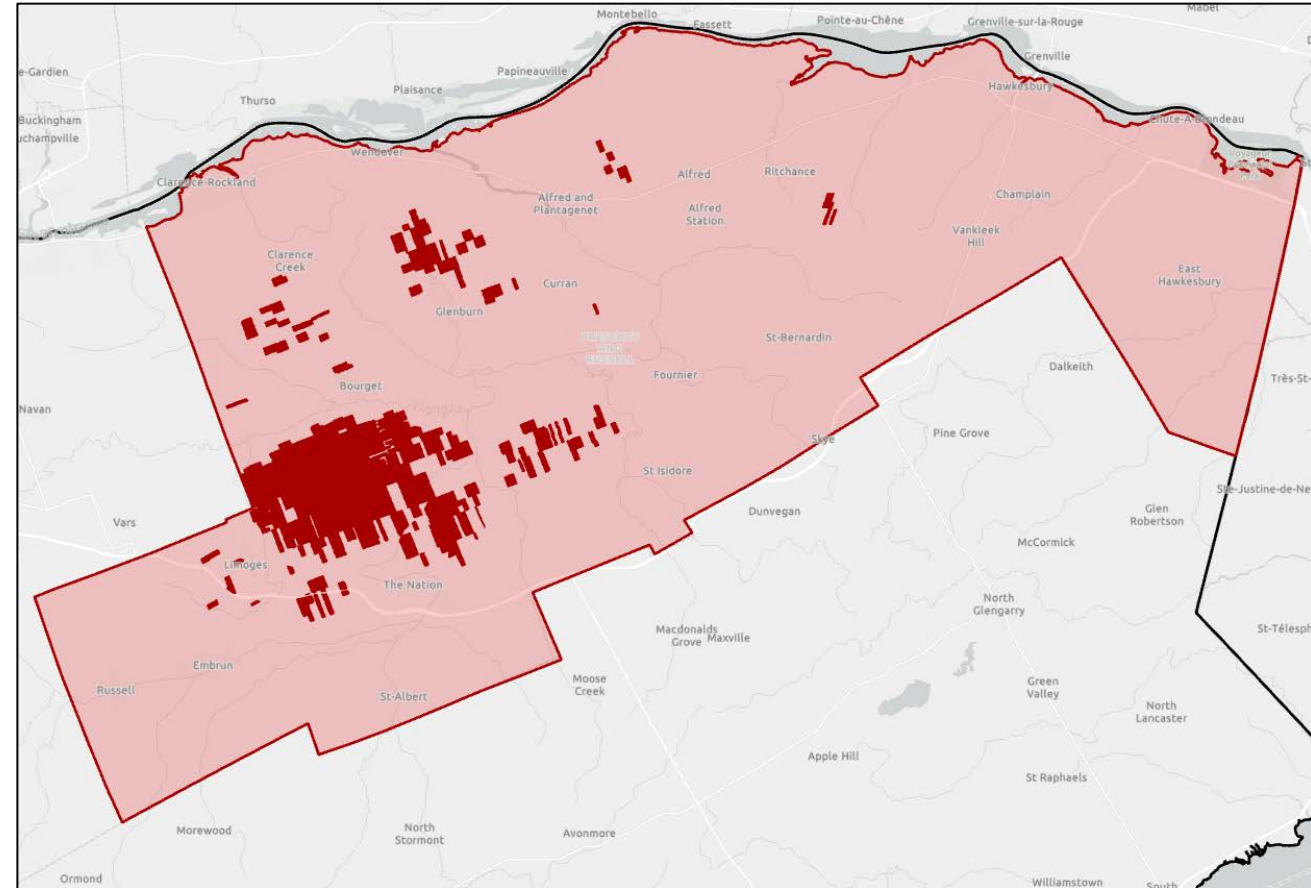
Larose Forest properties calibrated in 2015-2016

200 calibration plots

Formed a basis for wider county inventory

## Calibration Plot Information

Strata	# of targeted plots
Red and White Pine	45
Upland/Lowland Hardwoods	35
White Spruce Plantations	40
Intolerant Hardwoods	30
Other Conifers	25
Low Priority Conditions	25
<b>Total</b>	<b>200</b>



# 2021 United Counties of Prescott and Russell Inventory

## Evaluate Applicability of Calibration Plots to Landscape

Principal components analysis

## Generate Landscape Species Information

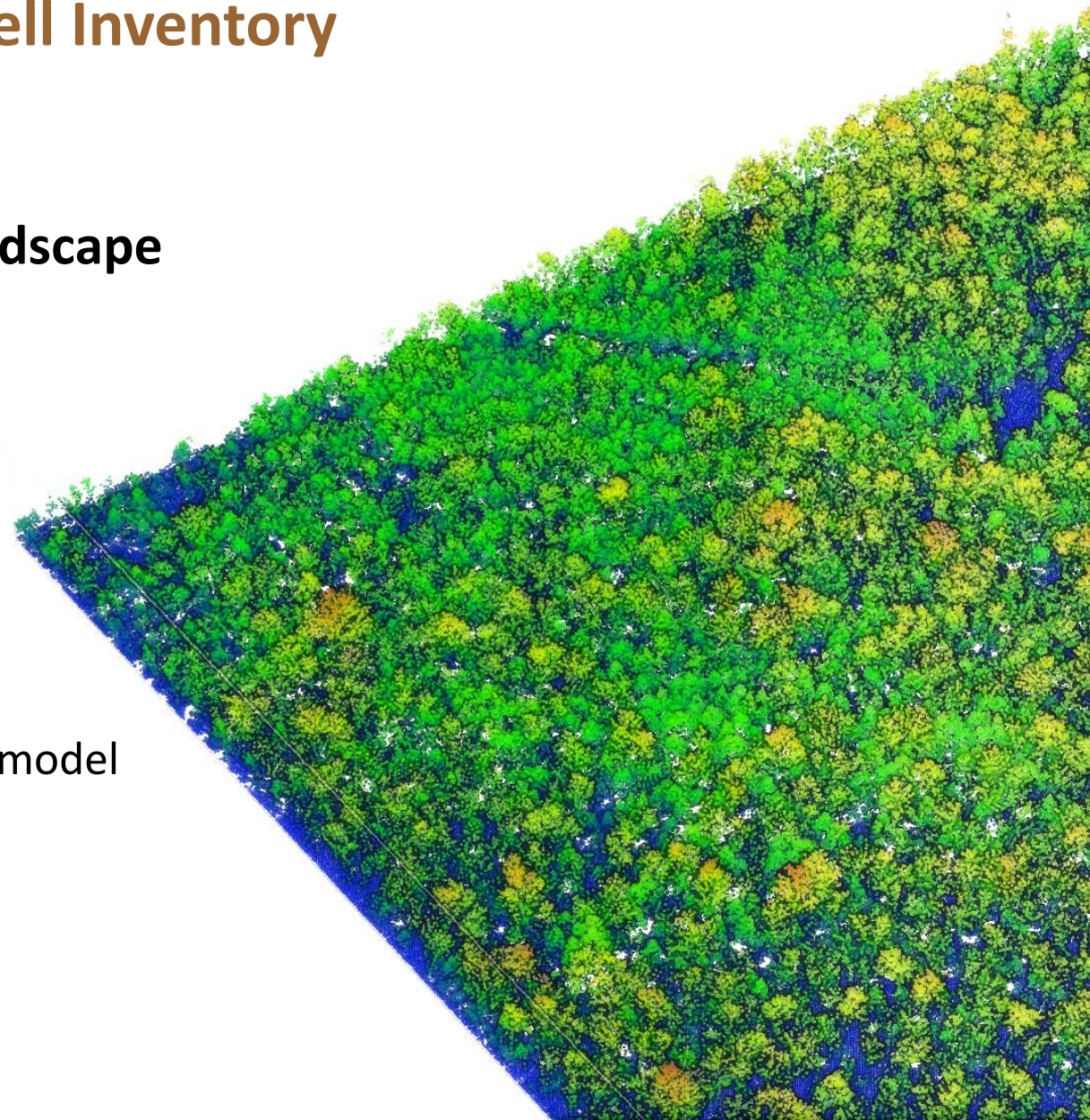
Leading species/species groups

## Determine Forest Cover Change on Landscape

Analysis of forest cover with NDVI/Canopy height model

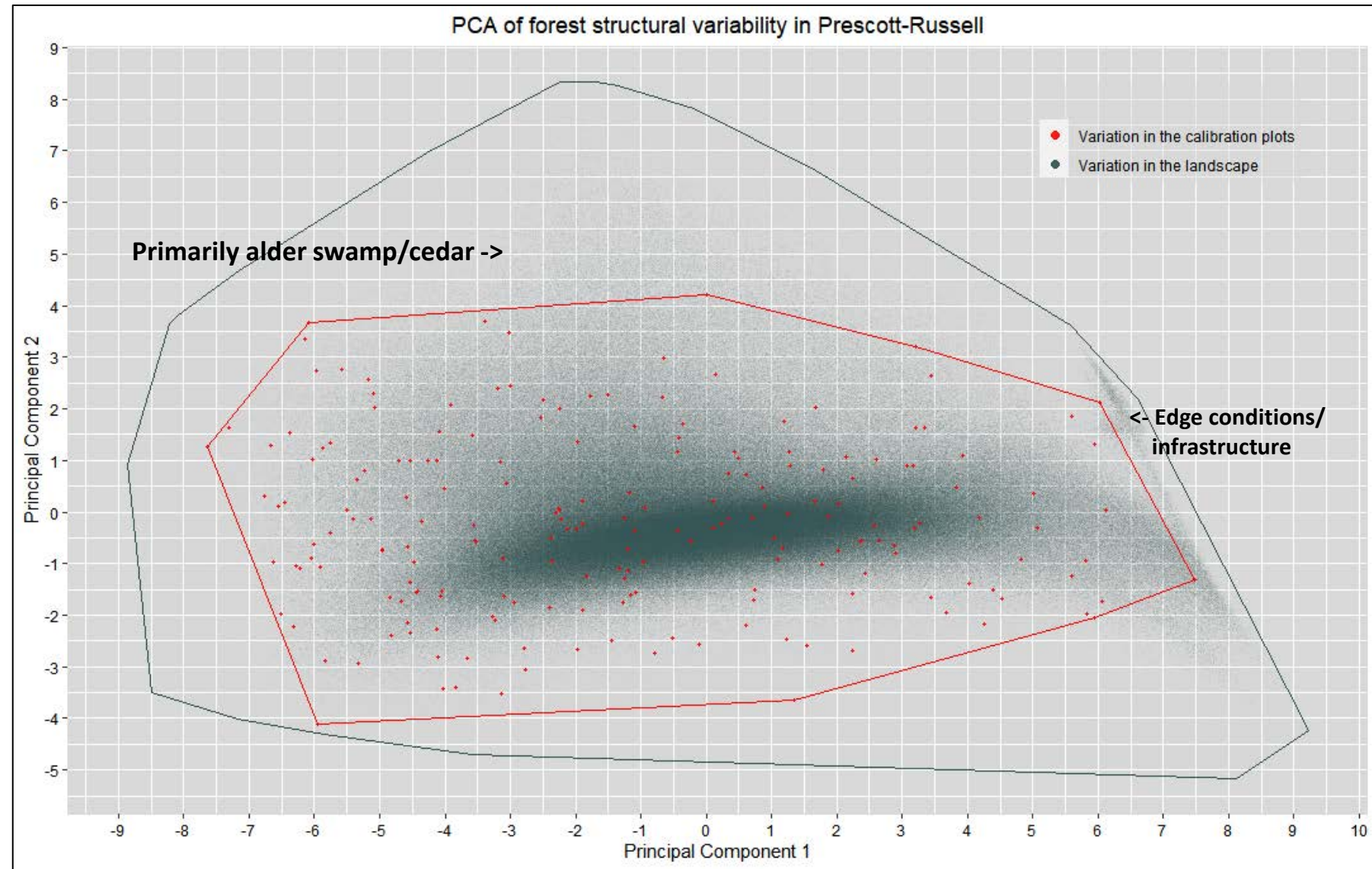
## “Grow” the Inventory from 2016 – 2021

Model growth over time in UCPR



# Principal Component Analysis

**PC 1 and 2 Cover 86% of Variability on the Landscape**



# Inventory Modelling Results

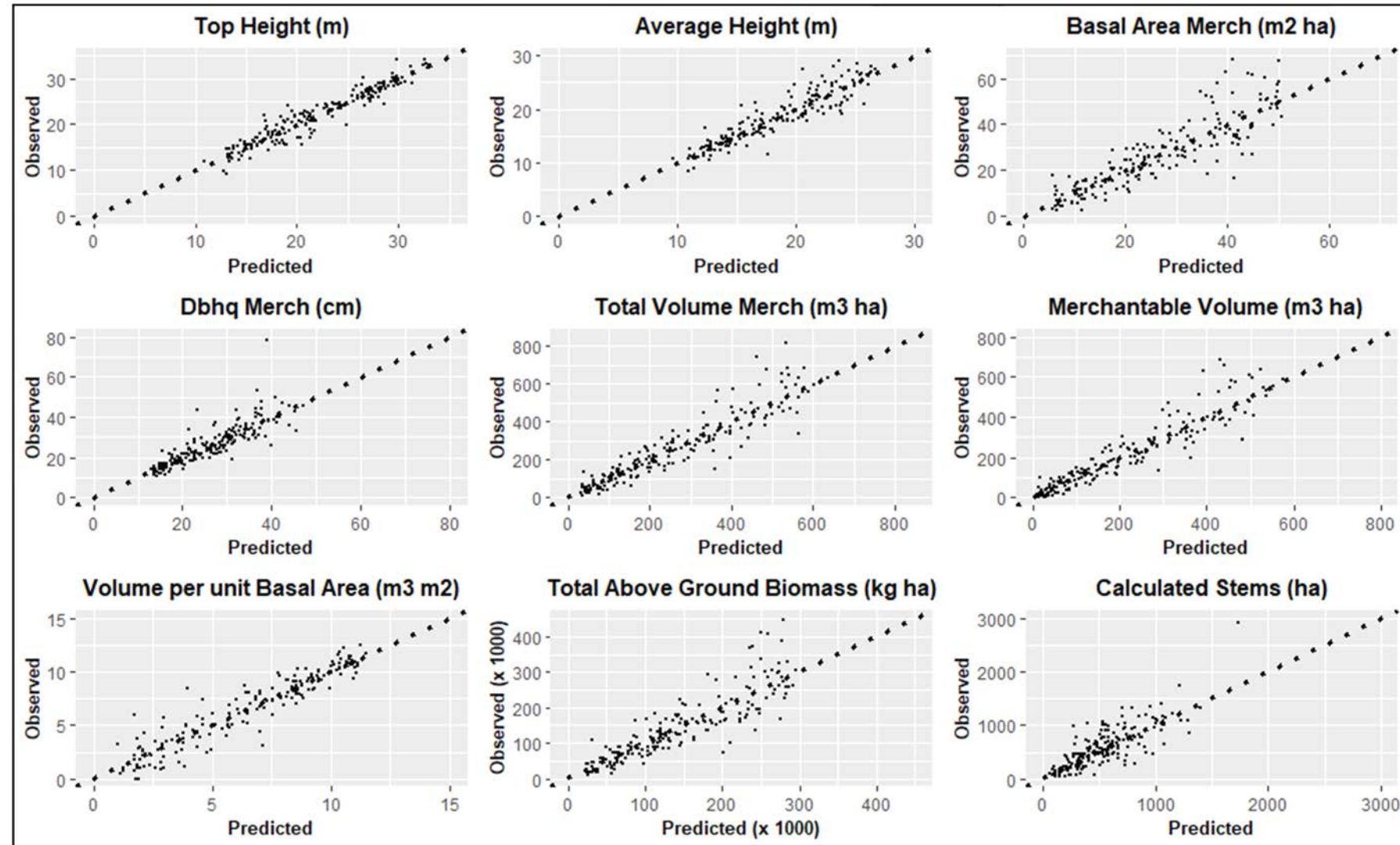
## Machine Learning

Random Forest

## Structure Based Modelling

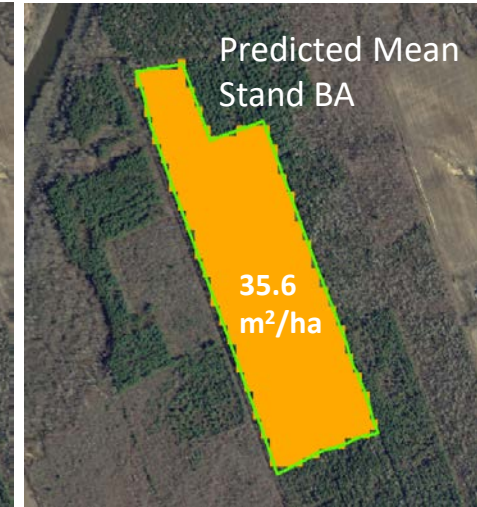
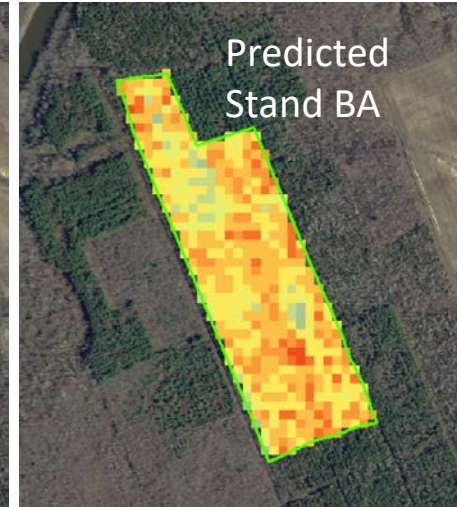
No species information

Based on Plots not Stands



# Inventory Validation Results

Compartment	Forest Type	Cruising Summary		LiDAR Summary
		Sample Pts	BA (m <sup>2</sup> ha)	BA (m <sup>2</sup> ha)
204	White Pine	17	45.2	46.9
16	Hwd	16	26.6	23.2
17	Red Pine	3	40	38.4
198	White Pine	18	43	39.2
230	Hwd	4	24.5	21.8
209	White Spruce	6	33	34.2
264	SwPr	8	37	32.2
256	PrPw	9	42.4	42.2
265	Sn	3	34	31.9
255	Red Pine	5	39.6	41.7
255	PwSw	19	32.5	35.6

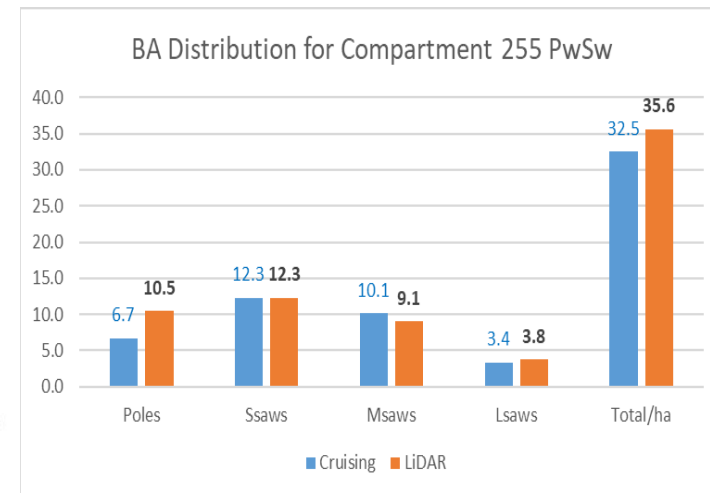
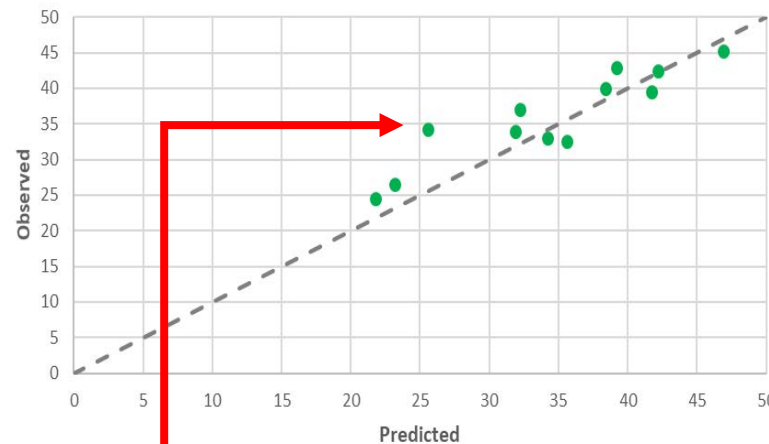


RMSE m <sup>2</sup> ha	2.7
RMSE%	8%
MeanBias m <sup>2</sup>	1.0
Bias%	3%

Not Included above

Compartment	Forest Type	Sample Pts	Cruised BA	LiDAR BA
210	Hwd	9	34.2	25.6*

Stand Level Predicted vs Observed for BAmerch (m<sup>2</sup>/ha)



\* RMSE 3.6 m<sup>2</sup>/ha RMSE% = 10%

# Species

## Time-Series Sentinel-2 Multispectral Satellite Data

### All Species Information from 2020-2021

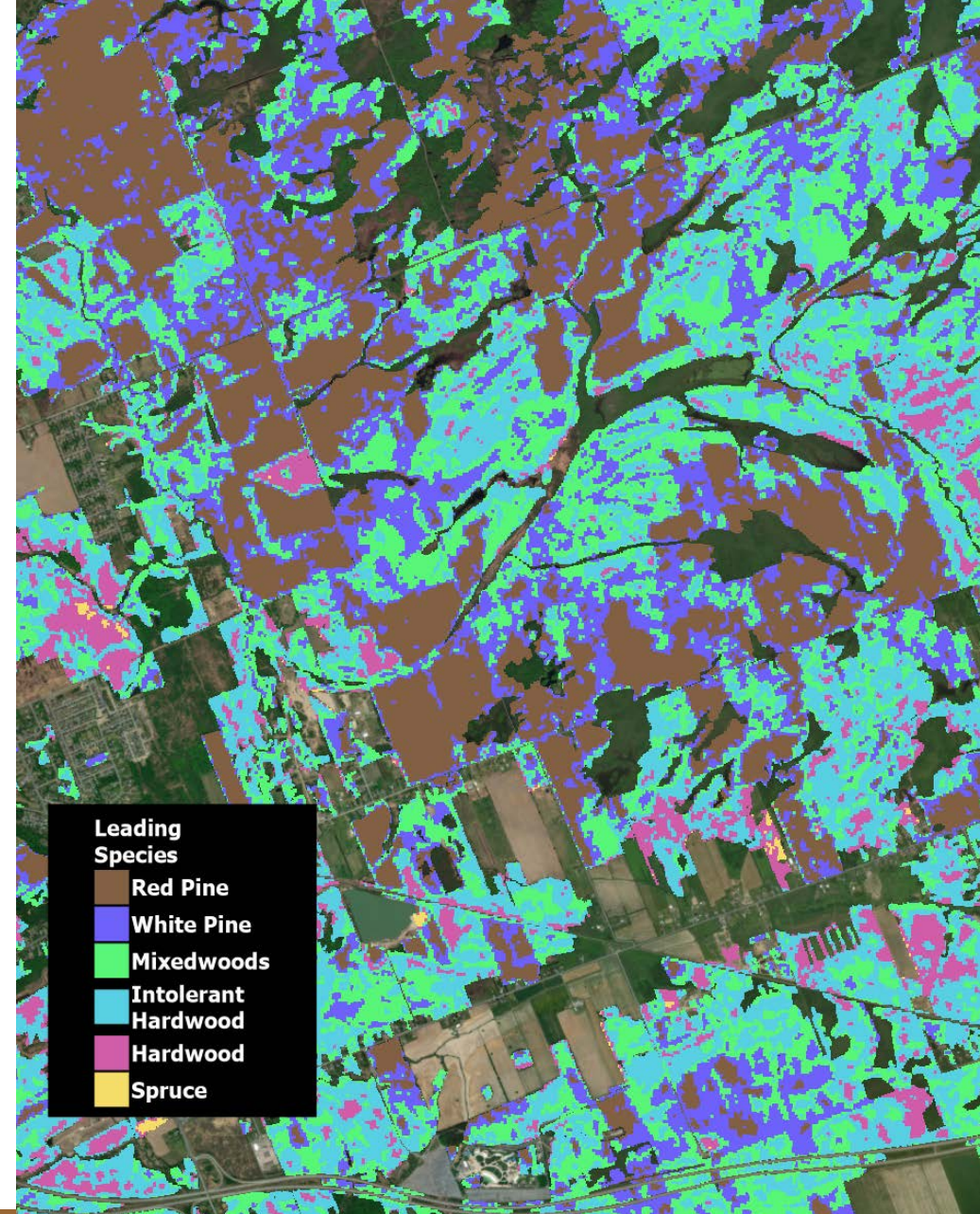
Training samples (2021)

Imagery (Dec 2020, April/June/July/Sept/Oct 2021)

### Predicted Forest Type/Leading Species

White pine (88% TPR $n = 23$ )	Mixedwoods (79% TPR $n = 20$ )
Red pine (93% TPR $n = 27$ )	Hardwoods (76% TPR $n = 18$ )
Spruce (82% TPR $n = 18$ )	
Other conifer (66% TPR $n = 13$ )	

TPR = True Positive Rate  
% chance of correct classification



# Forest Cover Change Analysis

## Need to Determine Loss in Forest Cover

Conversion to agriculture or urban development

## Normalized Difference Vegetation Index (NDVI)

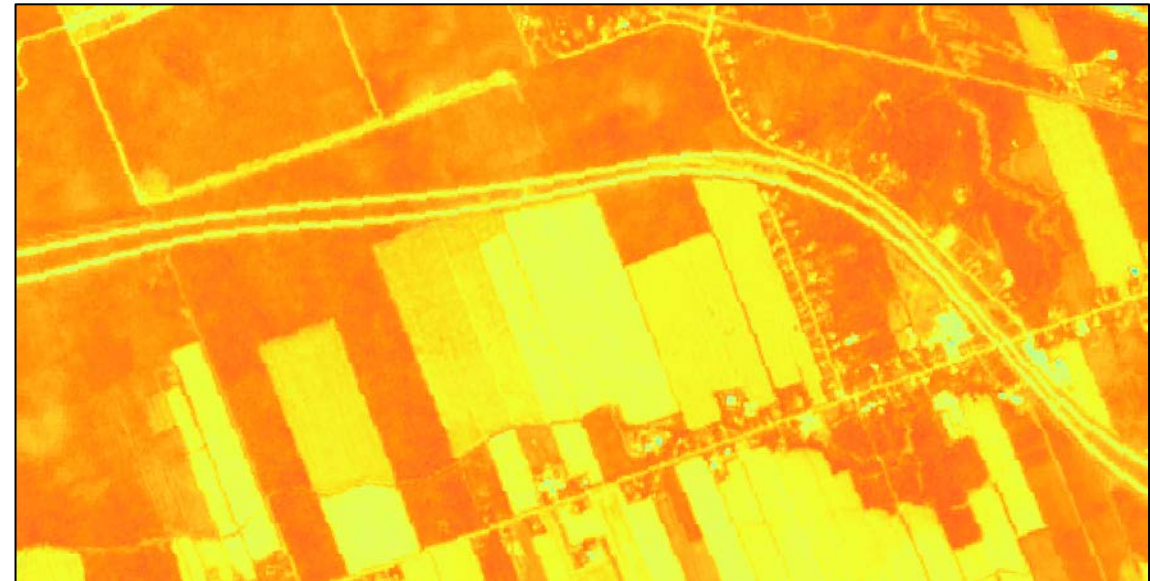
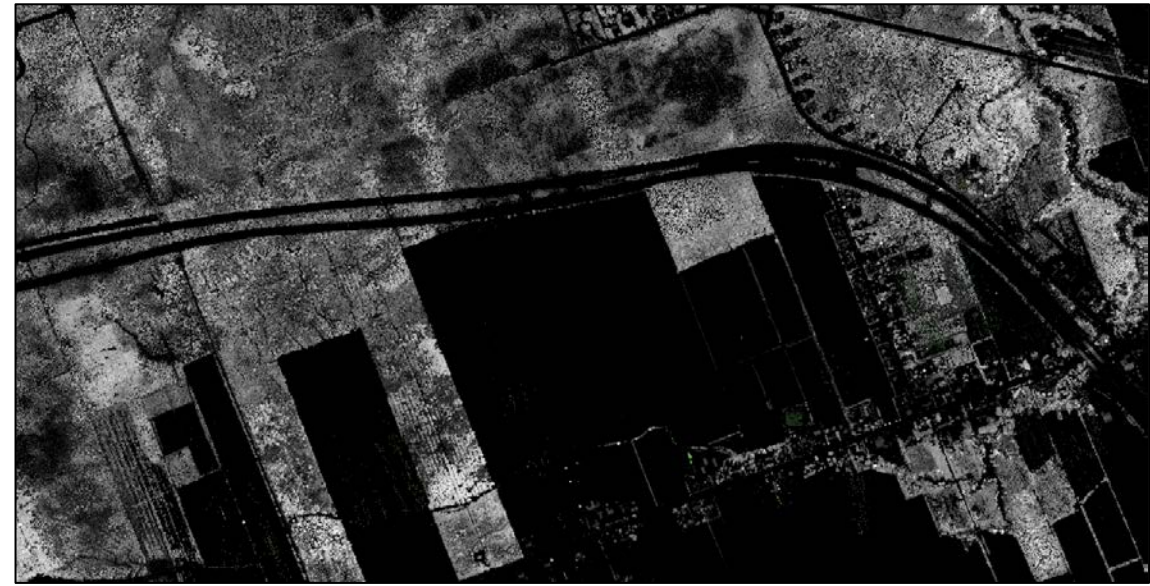
Sentinel-2 Imagery (Band 4 and 8)

Early season (May 18<sup>th</sup>) before most crops

## Combine with 2015 Canopy Height Model

Vegetation cutoff > 3m

Updated NDVI layer highlights areas no longer photosynthesizing





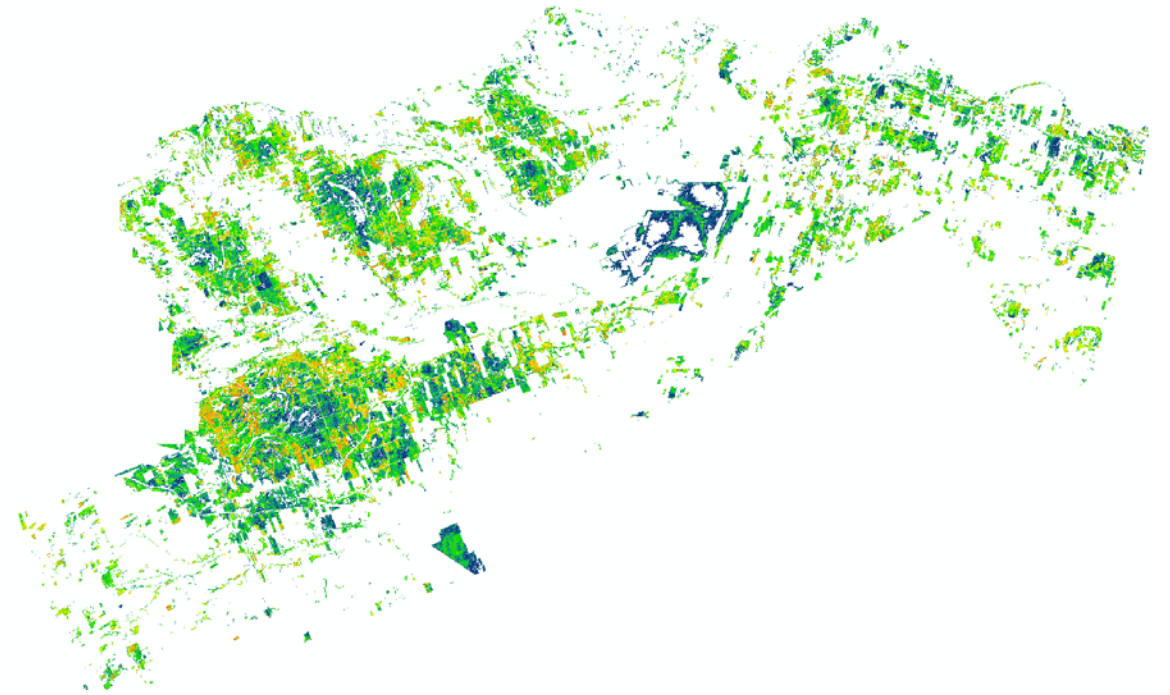
# Growing the Inventory to 2021

## 126 Variable-Radius Plots

Measuring DBH, height, species

Stratified by basal area class and forest type

5-10	Red Pine
10-20	White Pine
20-30	Spruce
30-40	Tolerant Hardwood
40+	Intolerant Hardwood



## Compared a Parametric vs Non-Parametric Approach to Predicting Growth

Polynomial linear regression vs machine-learning model (Random Forest)

## Predicted Growth Increment from 2015-2021 (6 years)

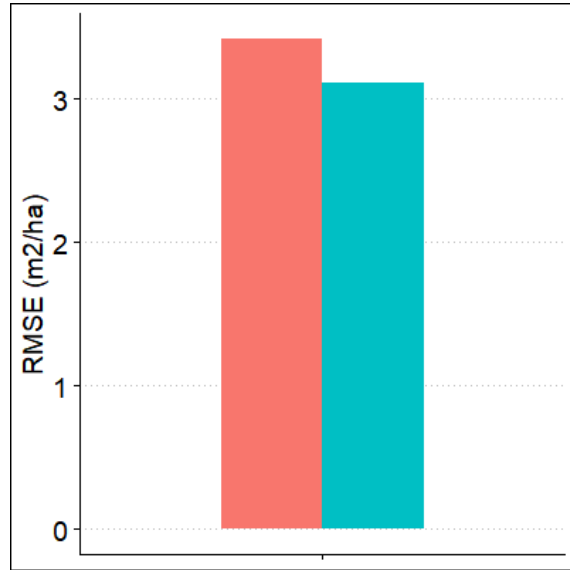
Basal Area, Volume, Height, Quad Mean Diameter, Biomass

# Growing the Inventory to 2021 – Validation Results

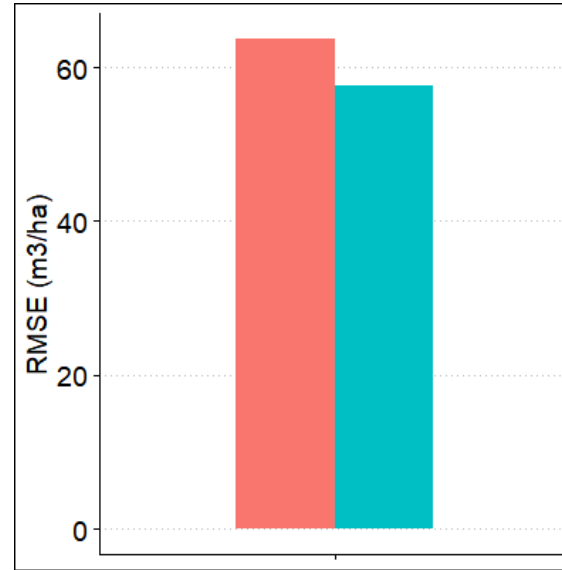
$n = 32$



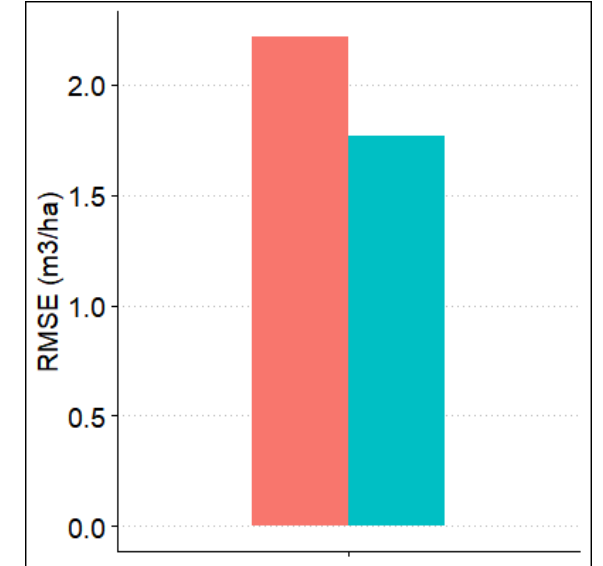
## Basal Area Models



## Volume Models



## Average Height Models

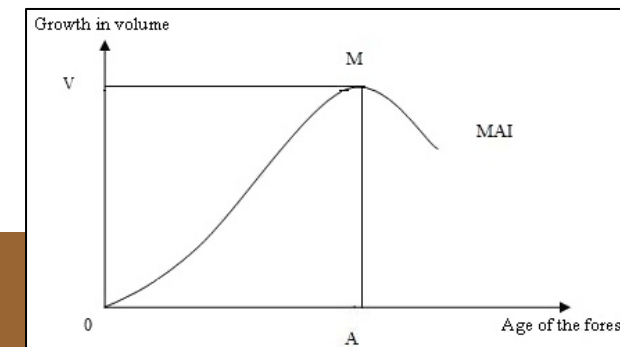


<b>Regression</b>	<b>Random Forest</b>
RMSE % : <b>11.7%</b>	RMSE % : <b>10.1%</b>
Adj. R2 : <b>0.62</b>	R2 : <b>0.64</b>

<b>Regression</b>	<b>Random Forest</b>
RMSE % : <b>27.6%</b>	RMSE % : <b>25.3%</b>
Adj. R2 : <b>0.23</b>	R2 : <b>0.41</b>

<b>Regression</b>	<b>Random Forest</b>
RMSE % - <b>10.0%</b>	RMSE % : <b>8.0%</b>
Adj. R2 - <b>0.76</b>	R2 - <b>0.40</b>

**Parametric (Regression) Approach Chosen as it Extrapolates Beyond Training Data Better Than Non-Parametric**



# 2021 UCPR – Economic Analysis – Red Pine Plantation Management

## Combination of Modelled Attributes

Stand density (# trees/ha)

Mean diameter (cm/ha)

Average height (m)

Basal Area (m<sup>2</sup>/ha) \*non-plantation

## Density Management

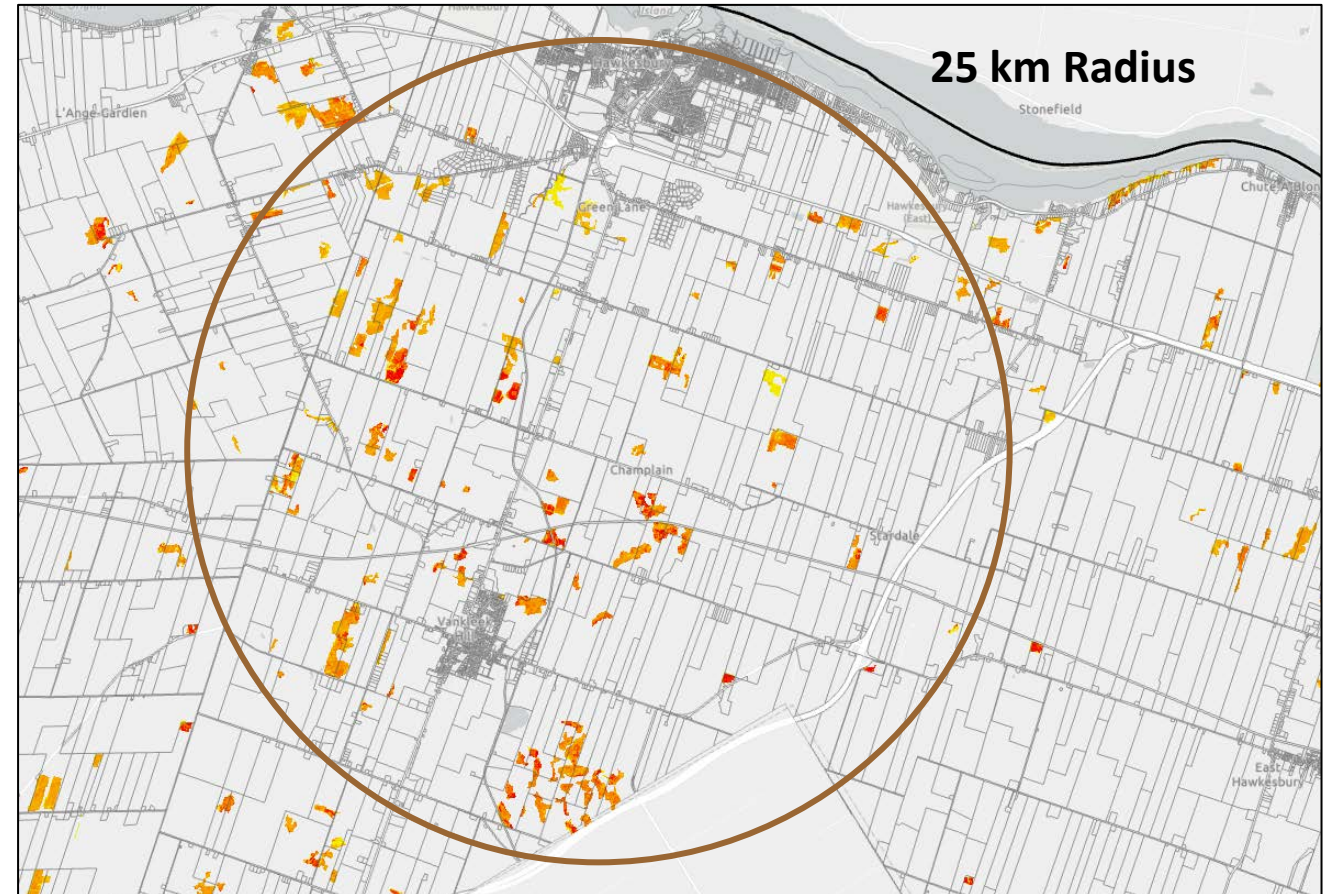
Highlight areas on landscape in need of intervention

Managing at parcel-level (not stands)

## Network Analysis

Target high-density stands with close proximal relationship (OWA Cooperatives)

Determine transportation costs to mill



# 2021 UCPR – Economic Analysis - Case Study

## Property Details

Forest Type: Red Pine Plantation

Density: 1825 trees/ha

Age: Unknown

Average Height: 27.6 m

Average Diameter: 26.8 cm

Forested Area: 21 ha

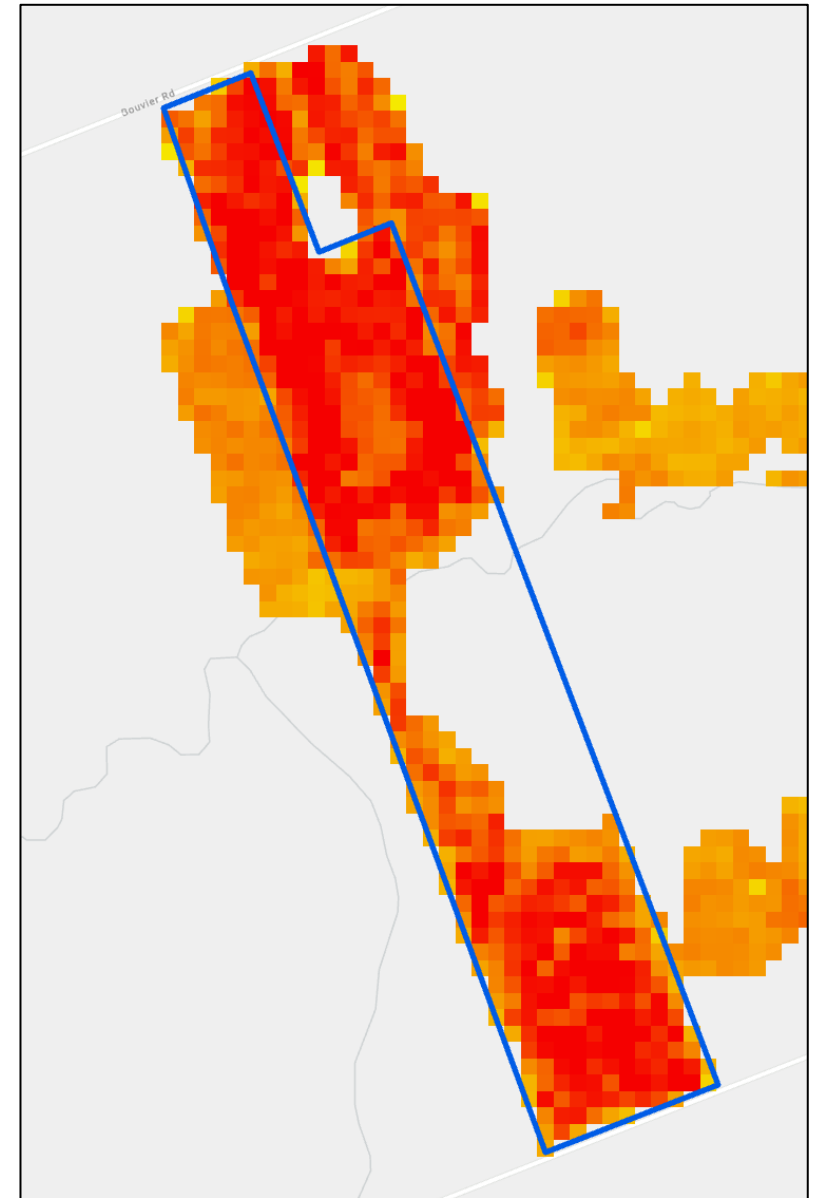
## Overstocked Stand

High average diameter

High # trees/ha

Competition for resources -> Senescence/Slow Growth

Capture value and long-term health with thinning treatment



# 2021 UCPR – Economic Analysis - Case Study

## Property Details

Forest Type: Red Pine Plantation

Density: 1825 trees/ha

Average Diameter: 25.8 cm

Age: Unknown

Average Height: 26.6 m

Forested Area: 21 ha

## Treatment Details

Thin to 700 trees/ha (1125 trees/ha removed)

Rule of thirds -> remove only 610 trees/ha in single thinning treatment

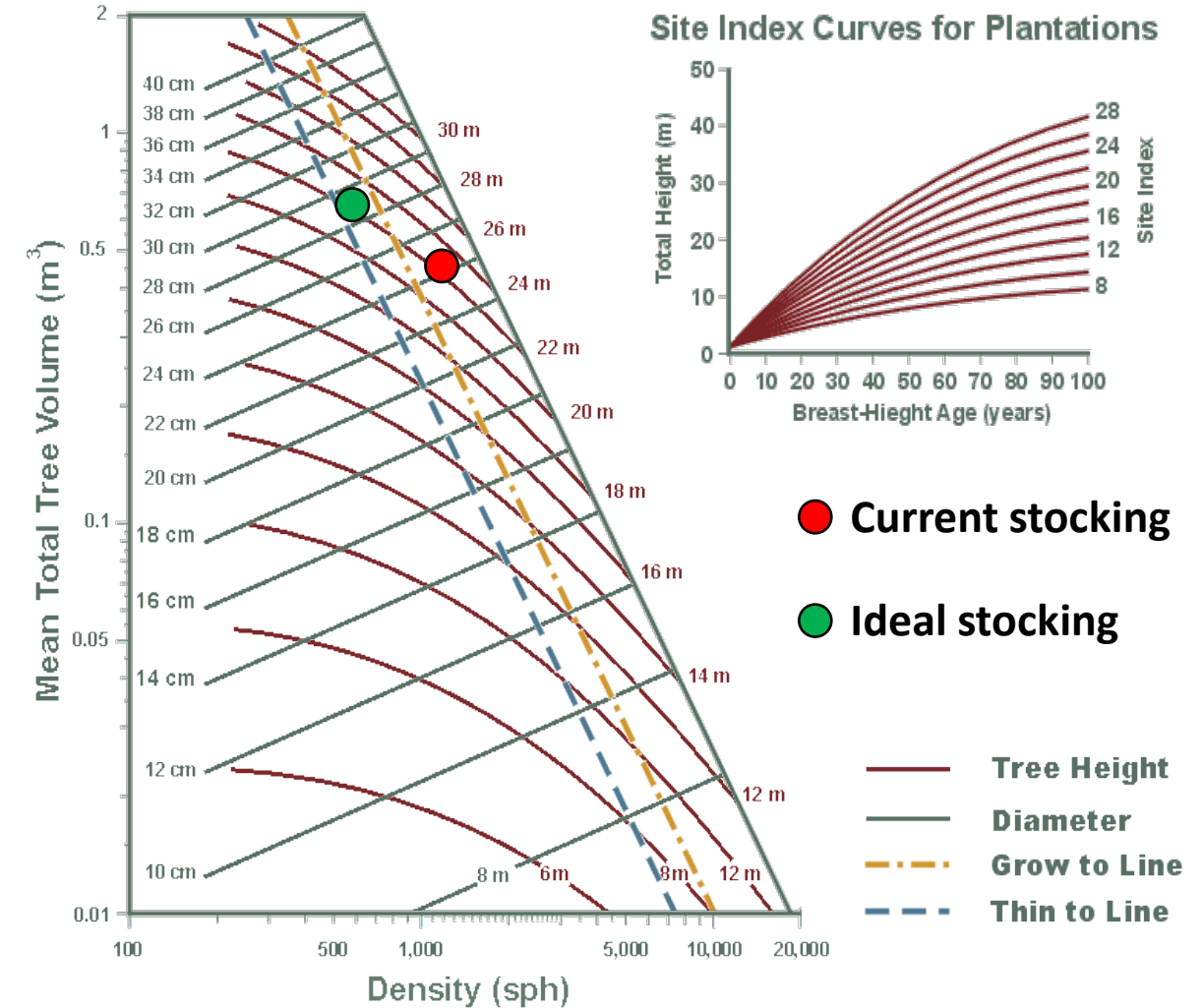
Average vol per tree (y-axis) =  $0.45 \text{ m}^3$

Harvest vol per ha =  $610 \times 0.45 = 274.5 \text{ m}^3$

Market price for Pr sawlogs **\$80/tonne (Nov 2023)**

$274.5 \text{ m}^3 = 140.25 \text{ tonne} \times \$80 = \text{\$11,200 Revenue}$

## Density Management Diagram Red Pine Plantations



# Take Aways from Private Land Inventory Production

## Municipal LiDAR Data is Adequate

Leaf-off LiDAR flown for terrain mapping can adequately measure forest characteristics in both hardwood and conifer

## Growing an Inventory Forward is Not Ideal

Better to have LiDAR acquisition/calibration under 5 years of inventory  
Modelling on top of modelling  
Does not capture recruitment into smaller size classes

## Corn is an Issue

Setting height cutoff above 4m and early season NDVI can produce excellent forest cover mask

## Provides Powerful Economic Decision-Making Tools

Stem densities for plantations, basal areas by size class for hardwoods  
Spatial analysis can determine feasibility for access/transportation  
Parcel information is critical

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ARTICLE

## Evaluating the impact of leaf-on and leaf-off airborne laser scanning data on the estimation of forest inventory attributes with the area-based approach

Joanne C. White, John T.T.R. Arnett, Michael A. Wulder, Piotr Tompalski, and Nicholas C. Coops

**Abstract:** In this study, we explored the consequences of using leaf-on and leaf-off airborne laser scanning (ALS) data on area-based model outcomes in a lodgepole pine (*Pinus contorta* var. *latifolia* Engelm.) dominated forest in the foothills of the Rocky Mountains in Alberta, Canada. We considered eight forest attributes: top height, mean height, Lorey's mean height, basal area, quadratic mean diameter, merchantable volume, total volume, and total aboveground biomass. We used 787 ground plots for model development, stratified by ALS acquisition conditions (leaf-on or leaf-off) and dominant forest type (coniferous or deciduous). We also generated pooled models that combined leaf-on and leaf-off ALS data and generic models that combined plot data for all forest types. We evaluated differences in ALS metrics and leaf-on and leaf-off model outcomes, as well as the impacts of pooling leaf-on and leaf-off ALS data, creating generic models, and of applying leaf-on models to leaf-off data (and vice versa). In general, leaf-off and leaf-on ALS metrics were not significantly different ( $p < 0.05$ ), except for the 5th percentile of height (coniferous) and canopy density metrics (deciduous). Overall, coniferous leaf-on and leaf-off models were comparable, with differences in relative root mean square error (RMSE) and bias of  $<2\%$  for all attributes except volume, which differed by  $<4\%$ . RMSE and bias for deciduous leaf-on and leaf-off models for height attributes and quadratic mean diameter differed by  $<2\%$ , whereas models for volume and biomass differed by  $<7\%$ . These results affirm that leaf-off data can be used in an area-based approach to estimate forest attributes for both coniferous and deciduous forest types. Relative RMSE and bias for pooled models (combining leaf-on and leaf-off ALS data) differed by  $<2\%$  relative to leaf-on and leaf-off models, suggesting that in the forests studied herein, combining leaf-on and leaf-off data in an area-based approach does not adversely impact model outcomes. Generic models that did not account for forest type had large errors for volume and biomass (e.g., the relative RMSE for merchantable volume was twice as large as forest type specific models). Likewise, the mixing of leaf-on models with leaf-off data and vice versa resulted in large RMSE and bias for both forest types, and therefore mixing of models and data types should be avoided.

**Key words:** airborne laser scanning, lidar, forest inventory, leaf-off, area-based approach.

**Résumé :** Dans cette étude, nous explorons les conséquences de l'utilisation des données de balayage laser aéroporté (BLA) acquises avec ou sans feuilles, sur les résultats d'un modèle par surface dans une forêt dominée par le pin tordu latifolié (*Pinus contorta* var. *latifolia* Engelm.) dans les contreforts des montagnes Rocheuses en Alberta, au Canada. Nous avons examiné huit caractéristiques de la forêt : la hauteur dominante, la hauteur moyenne, la hauteur moyenne de Lorey, la surface terrière, le diamètre moyen quadratique, le volume marchand, le volume total et la biomasse aérienne totale. Nous avons utilisé 787 placettes au sol pour l'élaboration du modèle, stratifiées par les conditions d'acquisition du BLA (avec ou sans feuilles) et le type forestier dominant (conifères ou feuillus). Nous avons également généré des modèles regroupés qui combinent les données de BLA avec feuilles aux données sans feuilles, et des modèles génériques qui combinent les données des placettes de tous les types forestiers. Nous avons évalué les différences dans les mesures de BLA et les résultats des modèles avec ou sans feuilles, ainsi que les impacts du regroupement des données de BLA avec et sans feuilles, de la création de modèles génériques et de l'application des modèles étalonnés avec feuilles aux données sans feuilles (et vice versa). En général, les mesures de BLA avec et sans feuilles n'étaient pas significativement différentes ( $p < 0,05$ ), sauf pour le 5<sup>e</sup> percentile de hauteur (conifères) et pour les mesures de densité du couvert (feuillus). Dans l'ensemble, les modèles de conifères avec et sans feuilles étaient comparables : les écarts de l'erreur quadratique moyenne (EQM) et du biais relatifs étaient  $<2\%$  pour tous les attributs, sauf pour les volumes pour lesquels ils étaient  $<4\%$ . Dans le cas des modèles de feuillus, avec et sans feuilles, les écarts de l'EQM et du biais relatifs pour les attributs de hauteur et le diamètre moyen quadratique étaient  $<2\%$ , tandis qu'ils étaient  $<7\%$  pour le volume et la biomasse. Ces résultats confirment que les données sans feuilles peuvent être utilisées dans une approche par surface pour estimer les caractéristiques de la forêt pour les deux types forestiers, soit les conifères et les feuillus. Les écarts de l'EQM et du biais relatifs pour les modèles regroupés (combinant des données avec et sans feuilles) étaient  $<2\%$  par rapport aux modèles avec et sans feuilles, ce qui indique que dans les forêts étudiées, le fait de combiner les données avec et sans feuilles dans une approche par surface ne nuit pas aux résultats du modèle. Les modèles génériques, qui ne tenaient pas compte du type forestier, avaient de grandes erreurs de volume et de biomasse (p. ex., l'EQM relative du volume marchand était deux fois plus grande que pour les

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J.C. White and M.A. Wulder, Canadian Forest Service (Pacific Forestry Centre), Natural Resources Canada, 506, West Burnside Road, Victoria, BC V8Z 1M5, Canada.

J.T.T.R. Arnett, P. Tompalski, and N.C. Coops, Department of Forest Resources Management, 2424 Main Mall, University of British Columbia, Vancouver, BC V6T 2Z4, Canada.

Corresponding author: Joanne C. White (e-mail: joanne.white@canada.ca).

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# Discussion and Questions

*Thanks!*



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