

Integration of Photo Interpreted and LiDAR Attributes into a Polygonal Forest Inventory Framework

Knowledge Transfer and Tool Development (KTTD) Webinar

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November 2023



THE UNIVERSITY OF BRITISH COLUMBIA
Faculty of Forestry





Aims of presentation

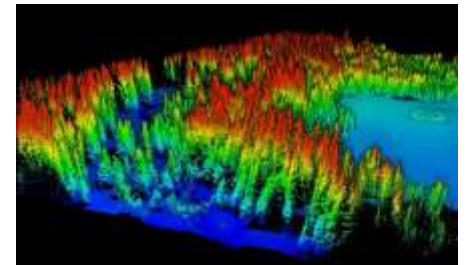
- Discuss context and objectives of project
- Explain analyses
- Present results
- Highlight considerations, limitations, and adoption of methods
- Showcase project website with background info and coding workflow

Why use Airborne Laser Scanning (ALS)?

- High resolution
- Highly accurate forest structure metrics
- Fast
- Scalable
- Reproducible
- Objective



(2)



(3)



(4)

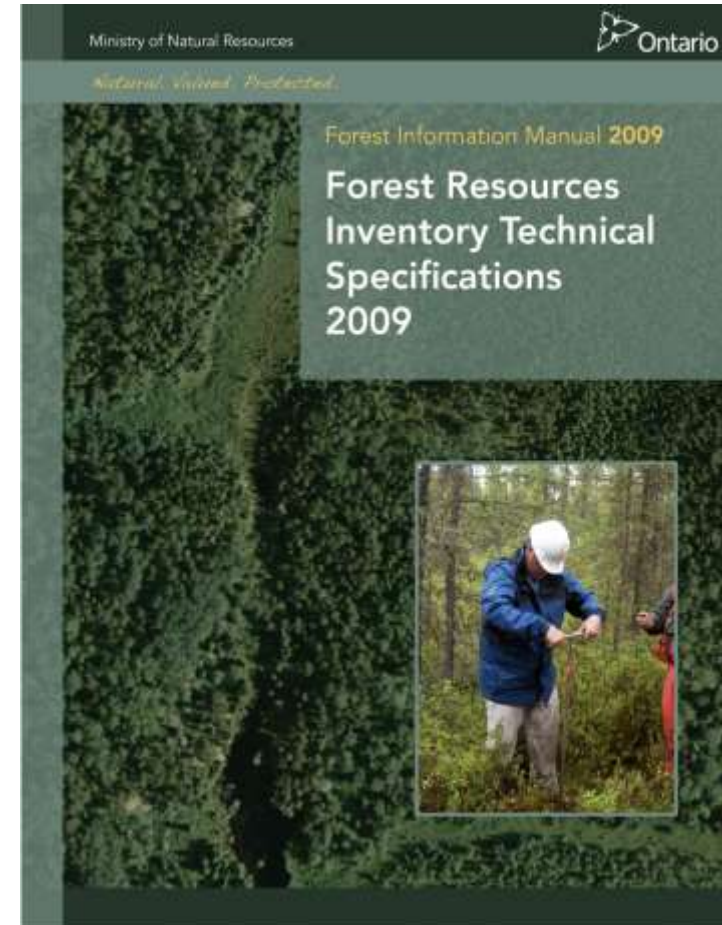
But.. ALS is raster-based



(5)

And what about forest composition?

- Age
- Species Composition
- Ecosite



(6)

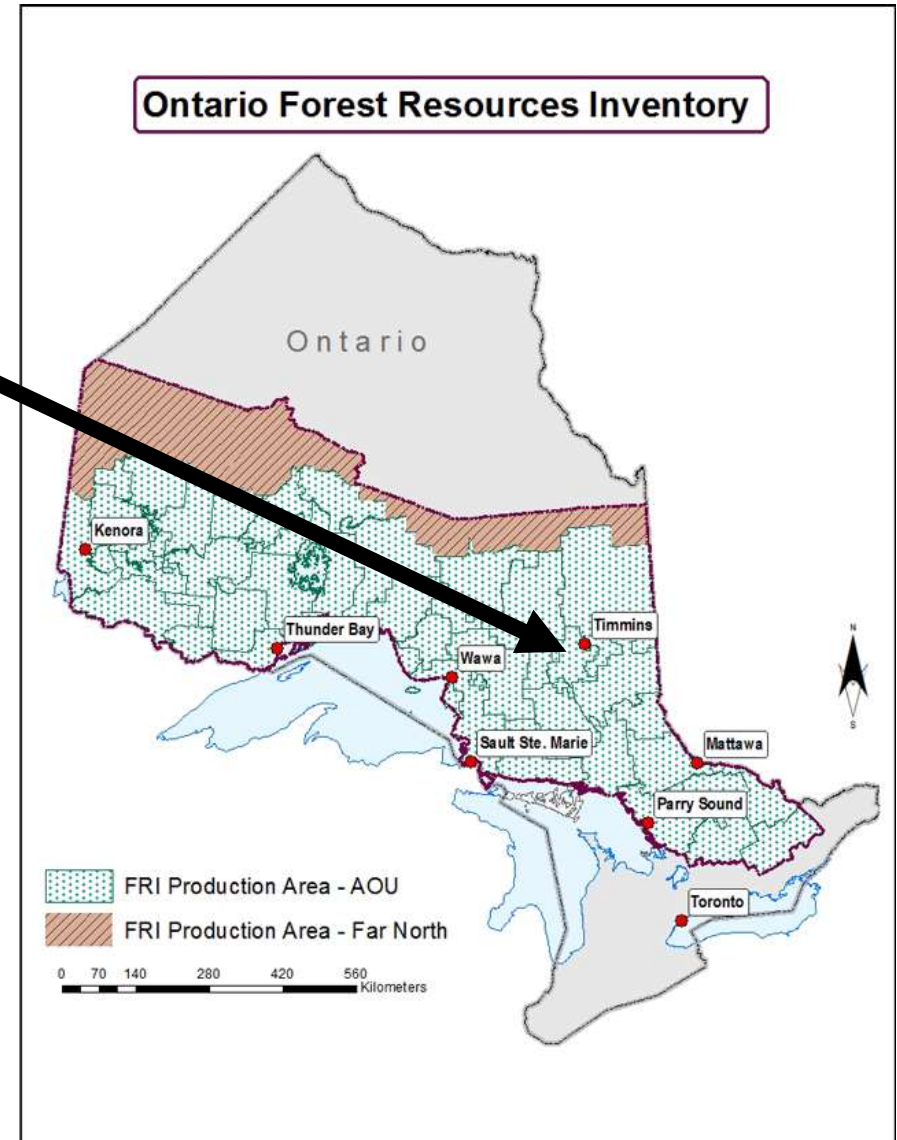
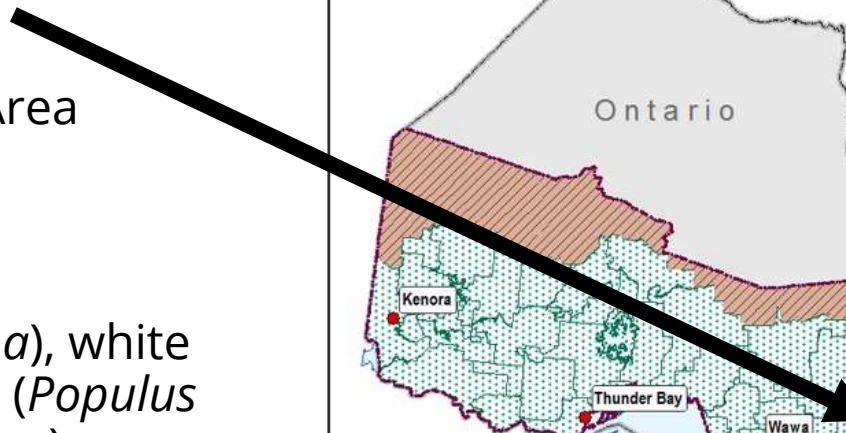
Project objectives

- Integrate ALS-based forest inventory attributes with conventional photo-interpreted FRI attributes
 - **Segment** forest stand polygons from raster-based ALS attributes
 - **Impute** forest composition attributes from conventional FRI
- Develop open-source tools
- Conduct knowledge and technology transfer

Study Area

Romeo Malette Forest (RMF)

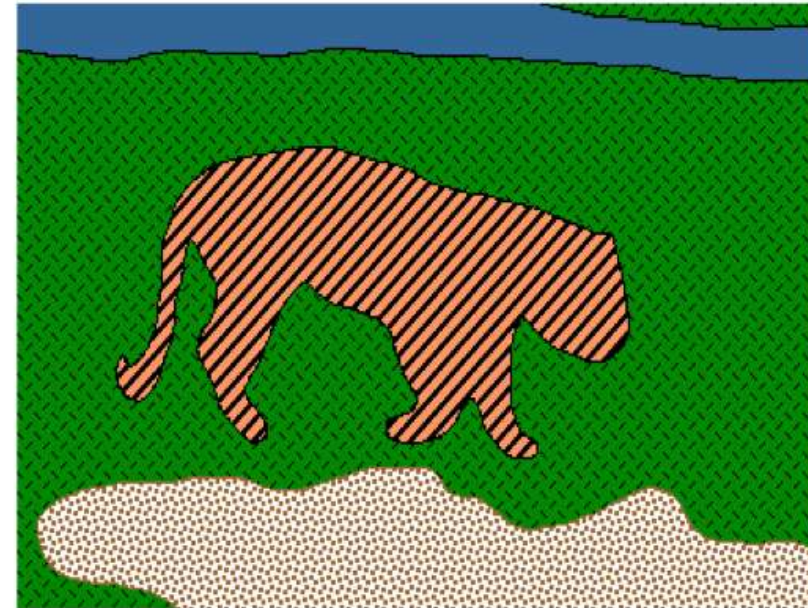
- ~630,000 ha Sustainable Forest License Area
- Boreal Shield ecozone
- ~92% of area forested land
- Dominated by black spruce (*Picea mariana*), white birch (*Betula papyrifera*), trembling aspen (*Populus tremuloides*), and jack pine (*Pinus banksiana*)
- Diverse stand ages and development stages
- ALS flown in 2018
- Enhanced Forest Inventory (EFI) attributes available



(7)

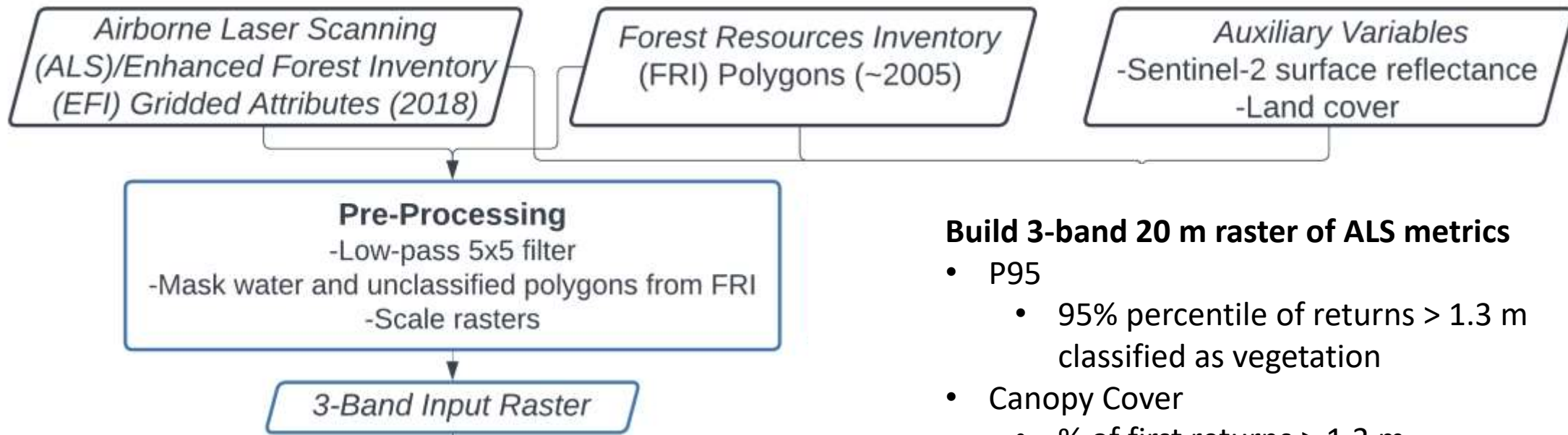
What is Segmentation?

- Geographic Object-Based Image Analysis (GEOBIA)
- Pixels \rightarrow Objects



(8)

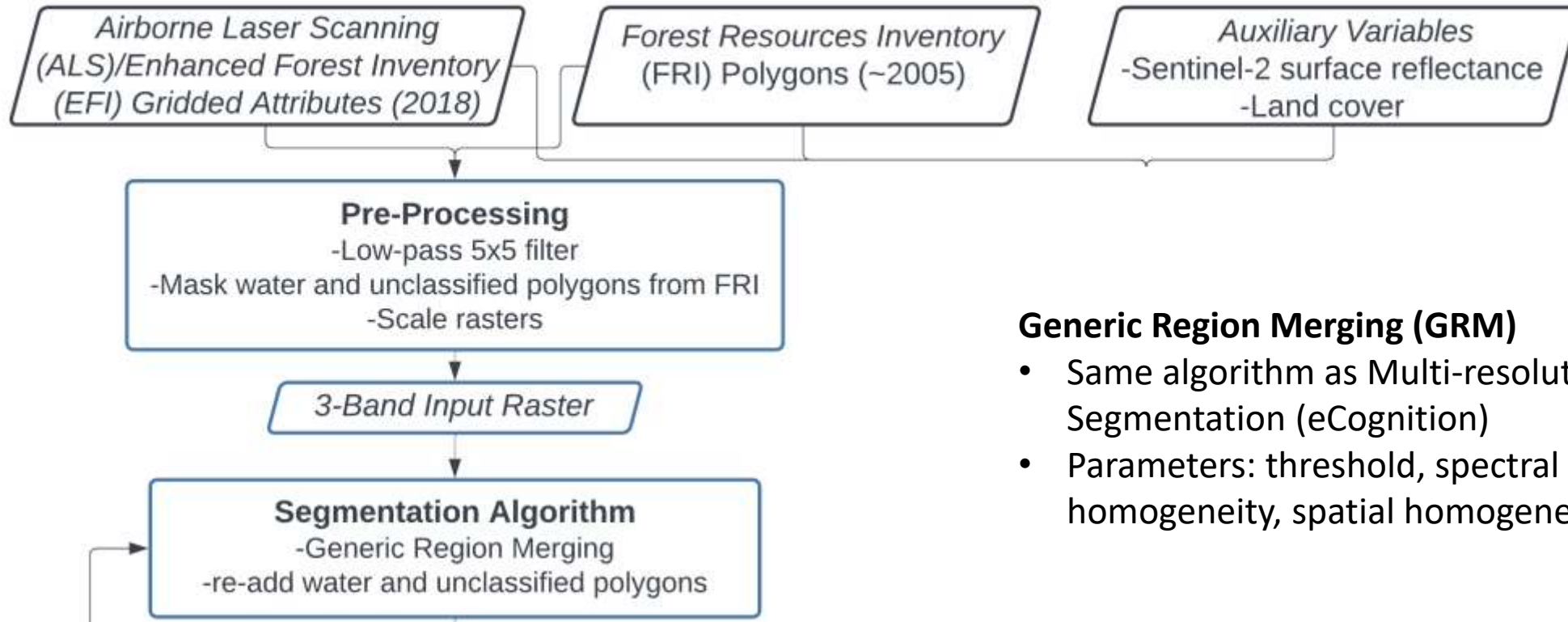
Pre-processing



Build 3-band 20 m raster of ALS metrics

- P95
 - 95% percentile of returns > 1.3 m classified as vegetation
- Canopy Cover
 - % of first returns > 1.3 m classified as vegetation
- Coefficient of Variation
 - Mean/SD

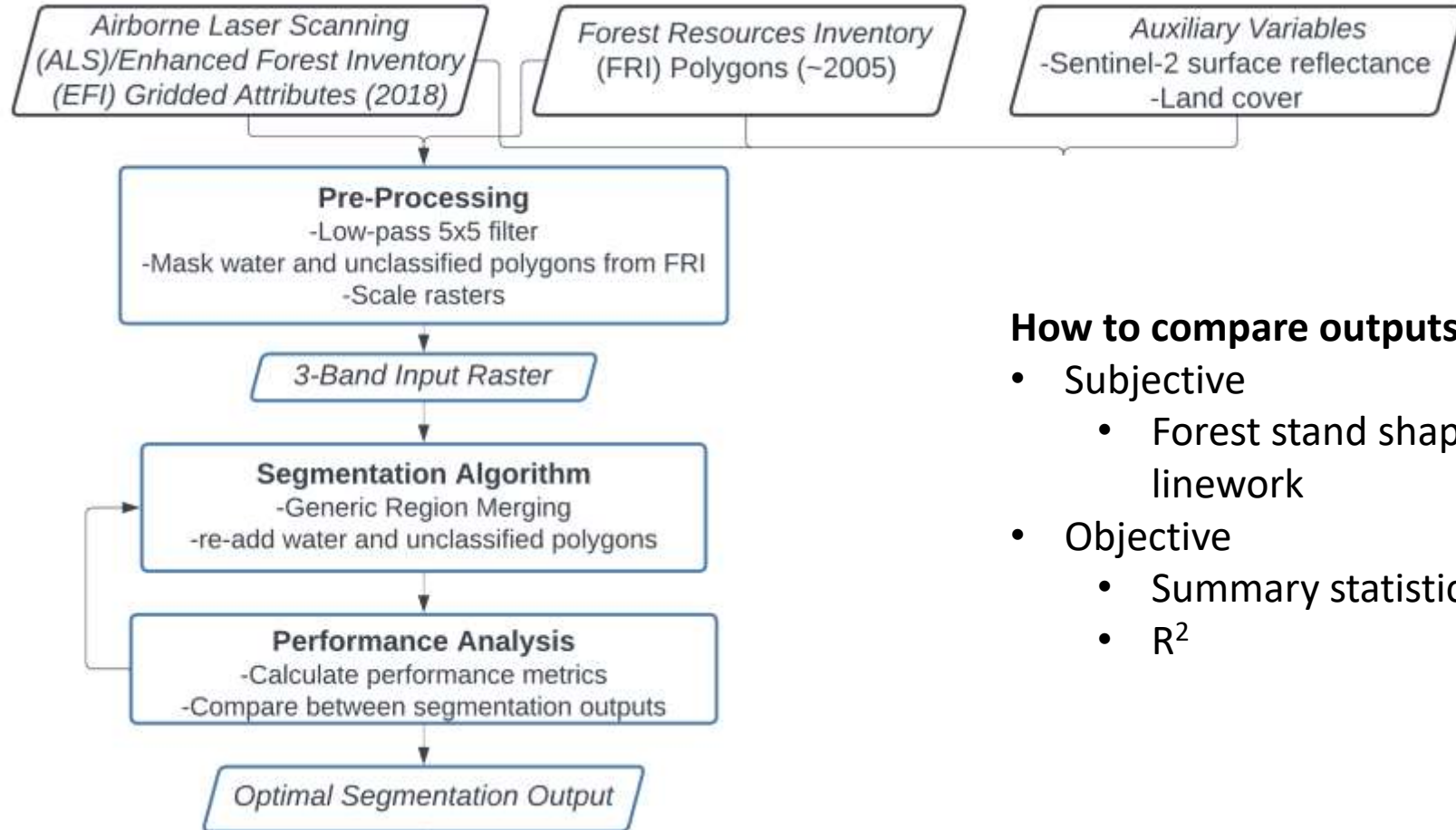
Segmentation algorithm



Generic Region Merging (GRM)

- Same algorithm as Multi-resolution Segmentation (eCognition)
- Parameters: threshold, spectral homogeneity, spatial homogeneity

Performance analysis

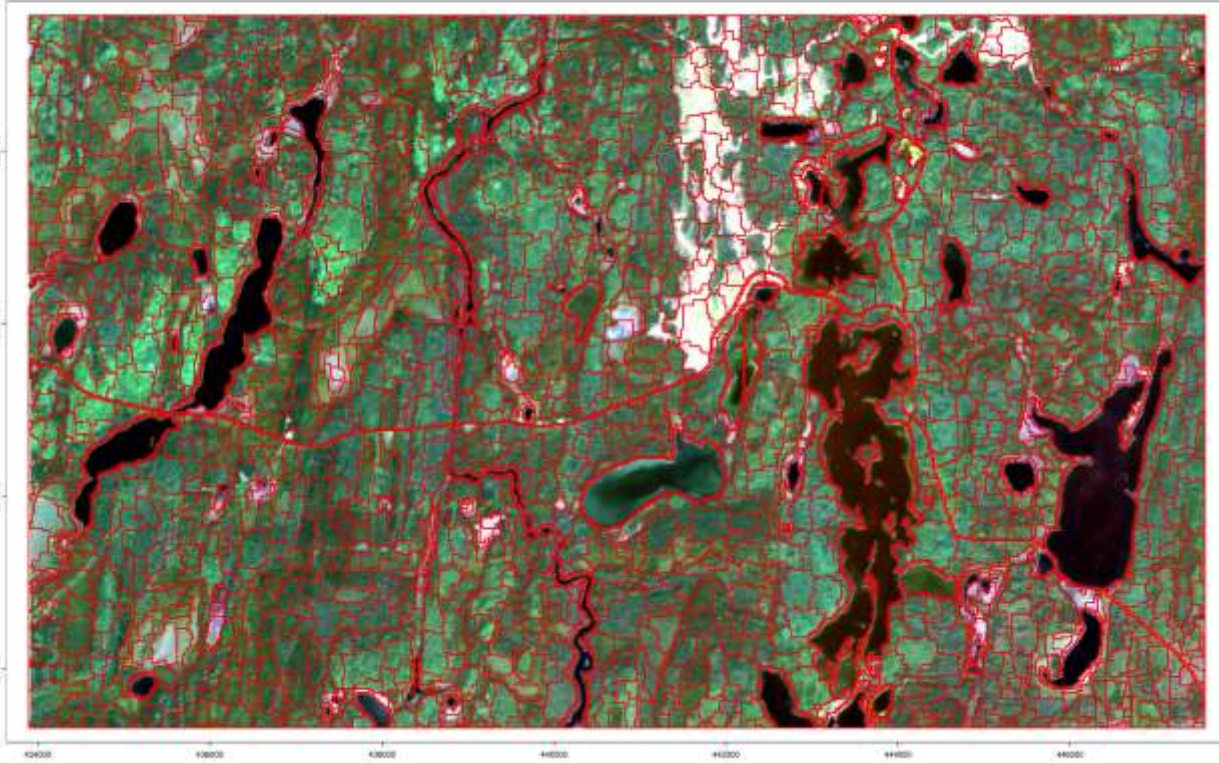


How to compare outputs?

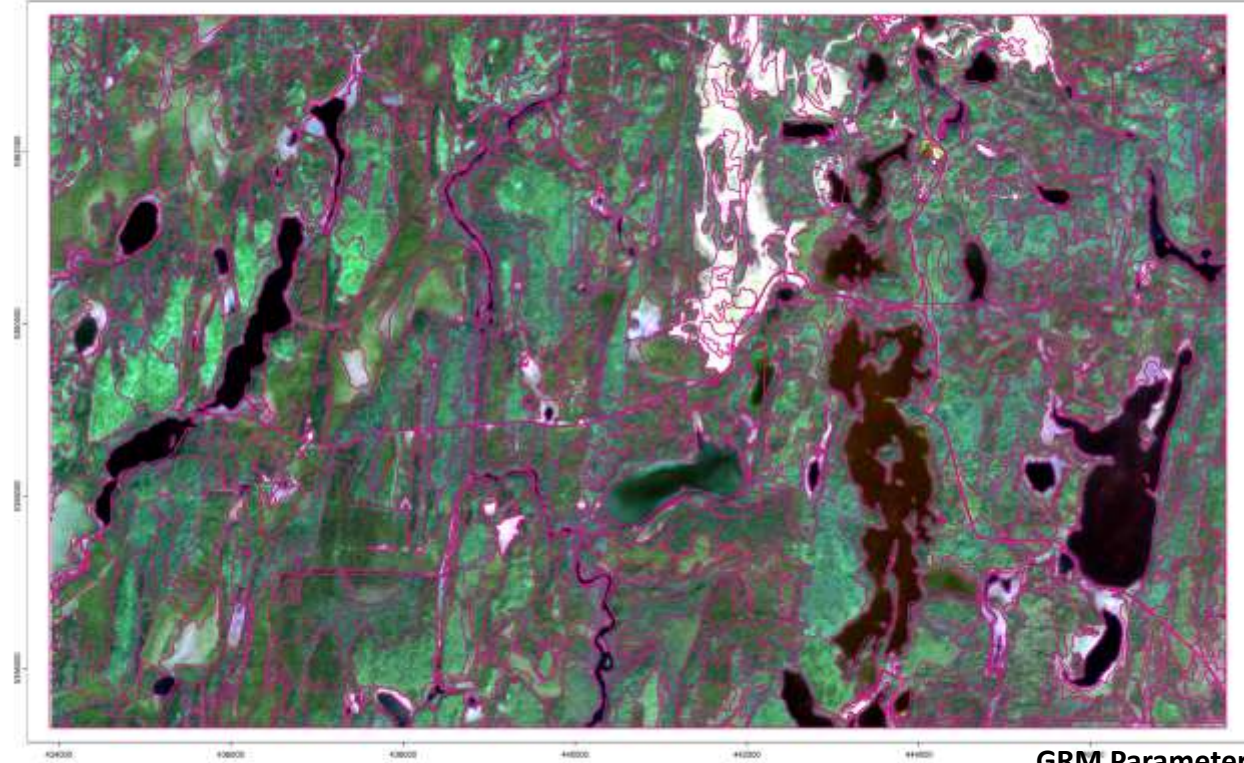
- Subjective
 - Forest stand shape and linework
- Objective
 - Summary statistics
 - R^2



GRM Polygons Overlaid on True Color Image



FRI Polygons Overlaid on True Color Image



GRM Parameters

Threshold: 10

Spectral homogeneity: 0.1

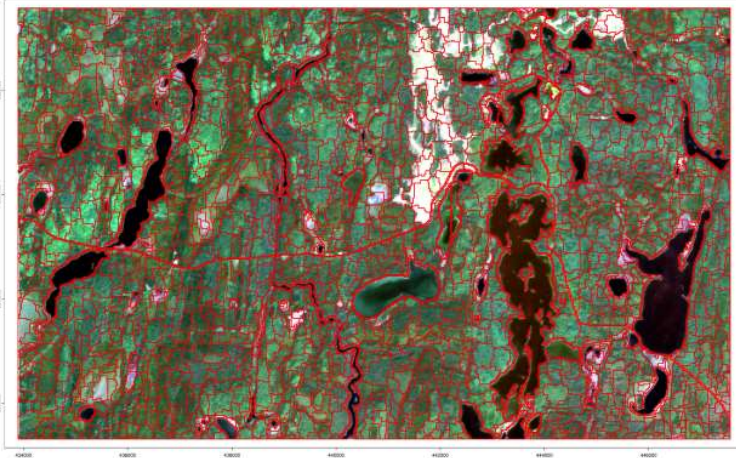
Spatial homogeneity: 0.5

Segmentation summary

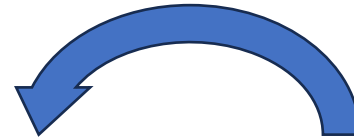
- Optimal results from GRM algorithm
- Fast and easy to reproduce
- Segmentation is subjective
- Semi-automatic
- Already being implemented in Ontario

What is Imputation?

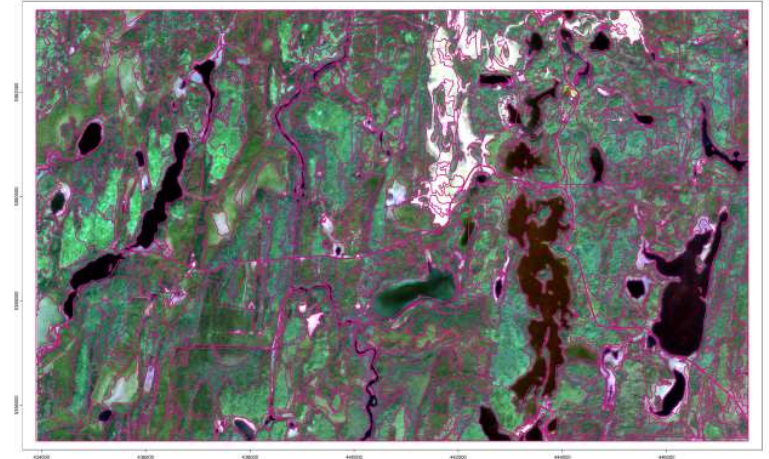
GRM Polygons Overlaid on True Color Image



IMPUTATION



FRI Polygons Overlaid on True Color Image



ID	Top Height	...ALS/EFI Metrics	Age	Species Class
1				
2				
3				
4				
...				

ID	Top Height	...ALS/EFI Metrics	Age	Species Class
1				
2				
3				
4				
...				

Missing values

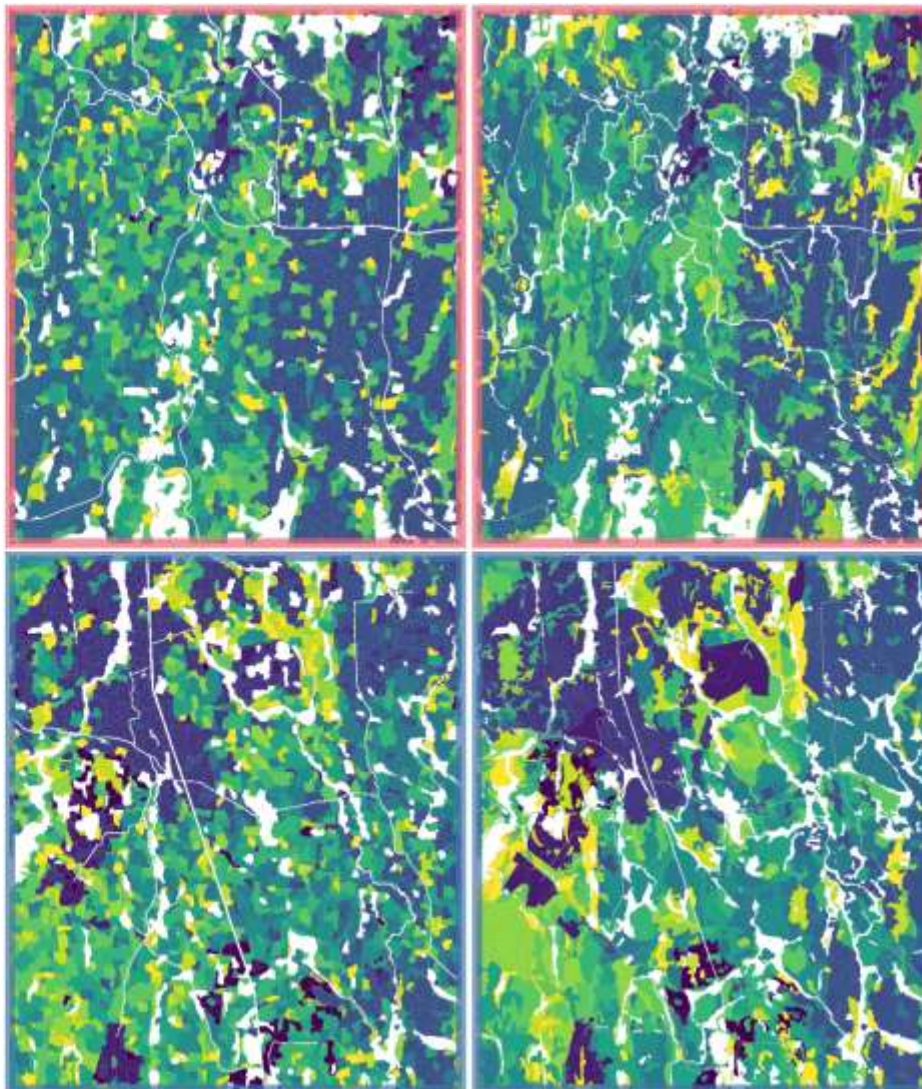
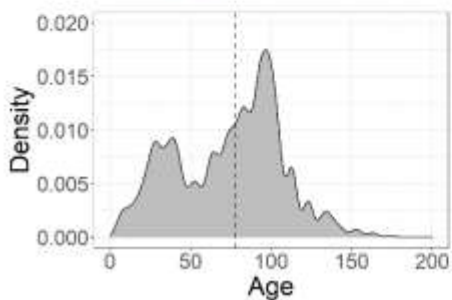
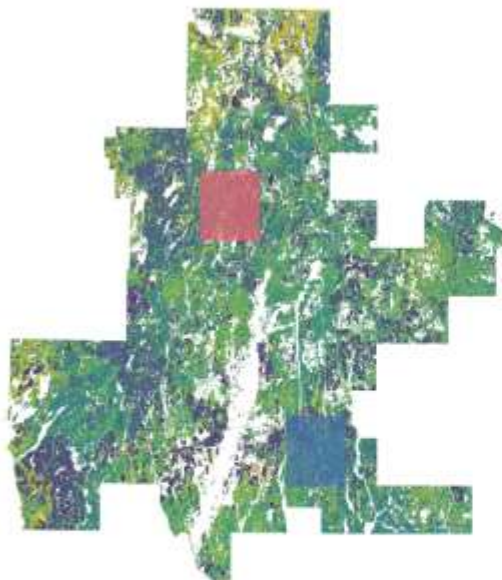
X-Variables

Y-Variables

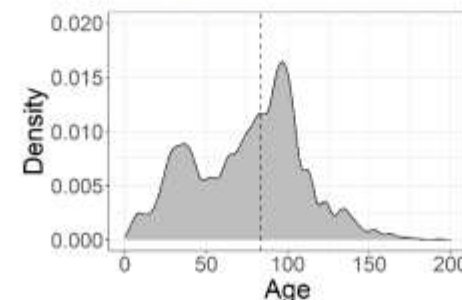
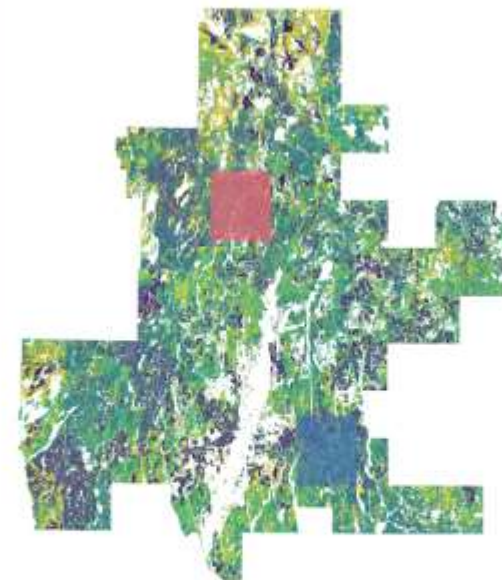
X-Variables (Imputation Predictors)		
Category	Variable	Description
ALS	cc	Canopy cover. Percent of first returns height > 2 m.
ALS	avg	Mean returns height > 1.3 m classified as vegetation.
ALS	qav	Average square of returns height > 1.3 m classified as vegetation.
ALS	sd	Standard deviation of returns height > 1.3 m classified as vegetation.
ALS	rumple	Ratio of canopy outer surface area to ground surface area.
ALS	pcum8	Cumulative percentage of returns found in 80th percentile of returns height.
EFI	lor	Lorey's height. Mean tree height weighted by basal area.
EFI	ba	Basal area. Tree cross-sectional area at breast height.
EFI	qmdbh	Quadratic mean of diameter at breast height.
EFI	agb	Above-ground biomass. Total tree biomass per hectare.
EFI	top_height	Top height. Mean height of largest 100 trees (diameter at breast height) per hectare.
Sentinel-2	red_edge_2	Cloud-free composite of Sentinel 2 band 6 (740 nm) surface reflectance.
Centroid	x	X-coordinate of polygon centroid in UTM projection.
Centroid	y	Y-coordinate of polygon centroid in UTM projection.

Y-Variables (Imputation Responders)		
Category	Variable	Description
Age	age	Forest stand age in 2018 derived from FRI YRORG attribute (year of forest stand origin).
Species	3 class	Three functional groups classification: hardwood, mixedwood, softwood.
Species	5 class	Five functional groups classification: black spruce-dominated, jack pine-dominated, mixed conifer, mixedwood, hardwood.
Species	sp1	Leading species derived from FRI SPCOMP attribute (species composition).
Species	sp2	2nd leading species derived from FRI SPCOMP attribute (species composition).

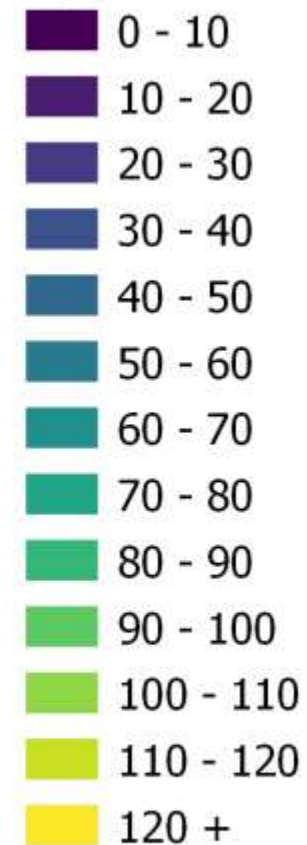
A) GRM



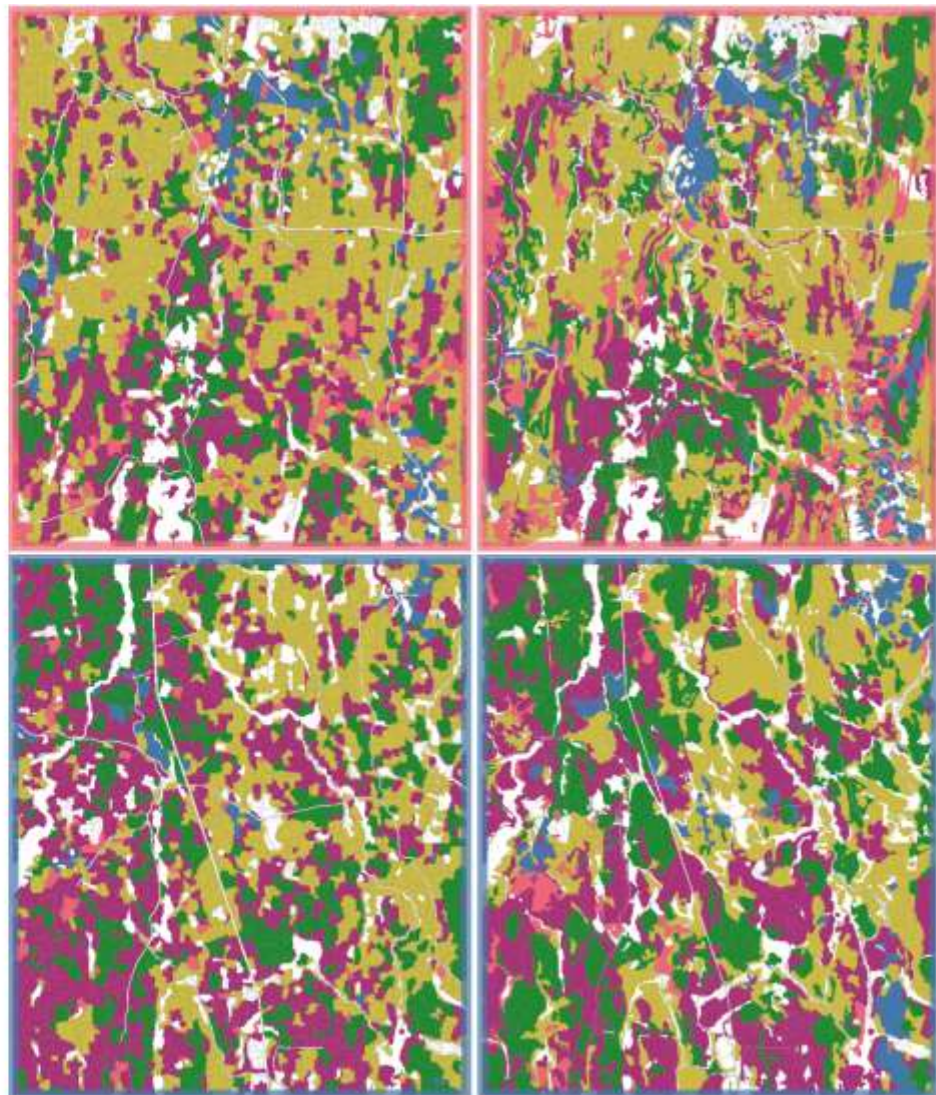
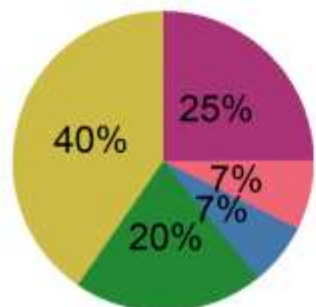
B) FRI



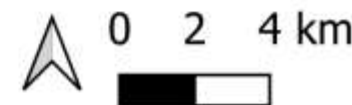
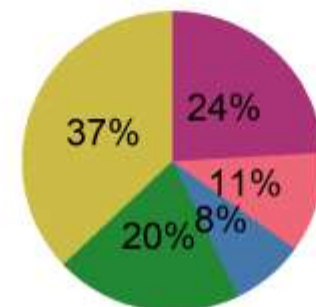
Age



A) GRM



B) FRI





Imputation summary

- Spatial and overall distributions match between GRM/FRI
- All FRI metrics imputed together – more than shown here!

Integration of Photo Interpreted and LiDAR Attributes into a Polygonal Forest Inventory Framework

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2023-05-04

1 Introduction

Welcome! This website serves as the information hub for the *Integration of Photo Interpreted and LiDAR Attributes into a Polygonal Forest Inventory Framework* project. The project is led by Prof. Nicholas Coops from 2021-2023 and made possible through a [Forestry Futures Trust Ontario](#) grant. Here you will find details about the project partners, project objectives, and analyses completed including coding demos and results. For further inquiries please feel free to [email me](#).

1.1 Project Summary

The acquisition of Airborne Laser Scanning (ALS) Single Photon Lidar over the forested area of Ontario is redefining how forest attributes are predicted and monitored throughout the Province. A key question remains however, of how to aggregate these area-based (raster) estimates of forest attributes into traditional strategic or tactical-level inventory polygons. This project is designed to address this need. Outcomes of the project will be open source segmentation and attribute prediction tools to develop a polygon based forest inventory inclusive of both ALS and interpreted forest stand attributes as well as knowledge transfer activities and demonstration at a number of forest management units.

1 Introduction

1.1 Project Summary

1.2 Project Partners

2 People

2.1 University of British Columbia

2.2 GreenFirst Forest Products

2.3 Ontario Ministry of Natural Re...

2.4 Laval University

3 Project Details

3.1 Objective

3.2 Themes

3.3 Description

3.4 Study Area

3.5 Methodology

3.6 Knowledge & Technology Tran...

4 Segmentation: Romeo Malette Forest

4.1 Introduction

4.2 Generic Region Merging Para...

4.3 Data Requirements

4.4 Set Code and File Parameters

4.5 Pre-processing

4.6 Execute GRM Segmentation

4.7 Post-processing

4.8 Performance Analysis

4.9 Results: GRM Algorithm

4.10 Results: Summary Statistics

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 - 4.15 ...

4 Segmentation: Romeo Malette Forest

4.1 Introduction

Forest stand polygons are familiar to forest managers, used by many forest planning and valuating workflows and software, and thus are preferable for management and monitoring. As the EFI becomes more prevalent, there is an immediate need to create a systematic workflow to convert raster-based metrics into a familiar polygonal format with the goal of ensuring usability and a seamless transition from the traditional forest inventory to the EFI. Although it is straight-forward to average EFI attributes over existing inventory polygons, these polygons are out of date (Bilyk et al., 2021) and do not represent the current conditions of dynamic forested environments. Manual delineation of forest stands is challenging since there are a lack of expert photo interpreters, the process is slow and expensive, and the subjective nature of the delineation makes monitoring of resources through time difficult (Wulder et al., 2008). Thus, to improve forest inventories our first step is to automatically delineate forest stand polygons from ALS data representing current conditions.

Segmenting grid data (such as metrics derived from ALS) into meaningful polygonal objects is a well-documented process of geographic object-based image analysis. [Generic Region Merging \(GRM\)](#), available from Orfeo Toolbox, is a region merging algorithm which has three options for homogeneity criterion: Baatz & Schape, Eclidean Distance, and Full Lambda. The Baatz & Schape criterion (Baatz and Schäpe, 2000), is the same algorithm used by the popular subscription based Multi-resolution Segmentation (eCognition software), and thus GRM provides an open-source framework to access the most popular segmentation method for remote sensing applications (Blaschke, 2010).

How do we know if the segmentation is "good"? There are no universal criteria to assess the ability of segmentation algorithms to accurately delineate features in data. Judging performance depends on the application, and may include factors such as radiometric variation within segments, contrast to other segments, segment shape, size and distribution, number of segments, and other application specific metrics such as number of landcover classes within each segment, or classification accuracy. In terms of applying segmentation to ALS data in order to generate representative forest stand polygons, we assess the segmentation results in terms of ease, efficiency, and replicability of the algorithm (thus choosing GRM), segment shape, number of segments, line work (not having multiple sets of parallel lines), and

Acknowledgements

We would like to thank:

- Chris McDonell
 - GreenFirst Forest Products
- Forestry Futures Trust Ontario

Journal Article

- Berman, E. E., Coops, N. C., Robere-McGugan, G., Sinclair, I., McCartney, G., & Achim, A. (2023). Updating forest stand inventories: Integration of photo-interpreted and airborne laser scanning forest attributes using Generic Region Merging segmentation and kNN imputation. *Canadian Journal of Remote Sensing*, Under review.

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🌐: bermane.github.io/ontario-inventory



References

- (1) Bilyk, A., Pulkki, R., Shahi, C., & Larocque, G. R. (2021). Development of the ontario forest resources inventory: A historical review. *Canadian Journal of Forest Research*, 51(2), 198–209. <https://doi.org/10.1139/cjfr-2020-0234>
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- (3) <https://geodetics.com/lidar-point-clouds/>
- (4) <https://es.red-leaf.com/provincia/ontario/>
- (5) <https://evolve-mma.com/blog/how-to-improve-ring-generalship-for-boxing/>
- (6) OMNRF. (2009). Forest Resources Inventory Technical Specifications 2009. In *Forest Information Manual 2009*. <https://www.ontario.ca/environment-and-energy/forest-resources-inventory-technical-specifications>
- (7) <https://www.ontario.ca/page/forest-resources-inventory>
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