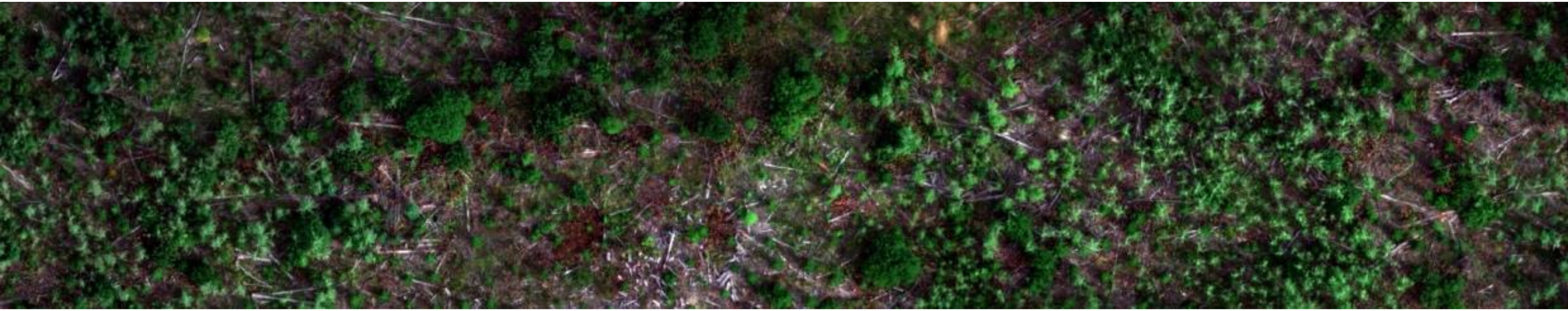
Using drones to evaluate early seral vegetation: opportunities and challenges

Matt McLean, Richard Reich, Hardy Griesbauer, Che Elkin



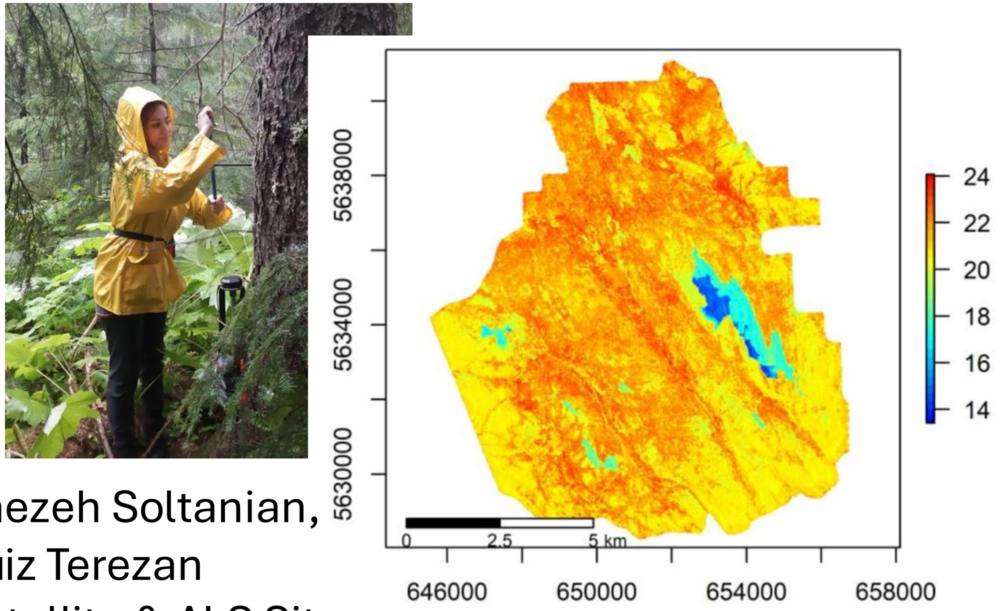
UNBC UNIVERSITY OF NORTHERN BRITISH COLUMBIA
BRITISH COLUMBIA | Ministry of Forests
CNC College of New Caledonia

2 Talks

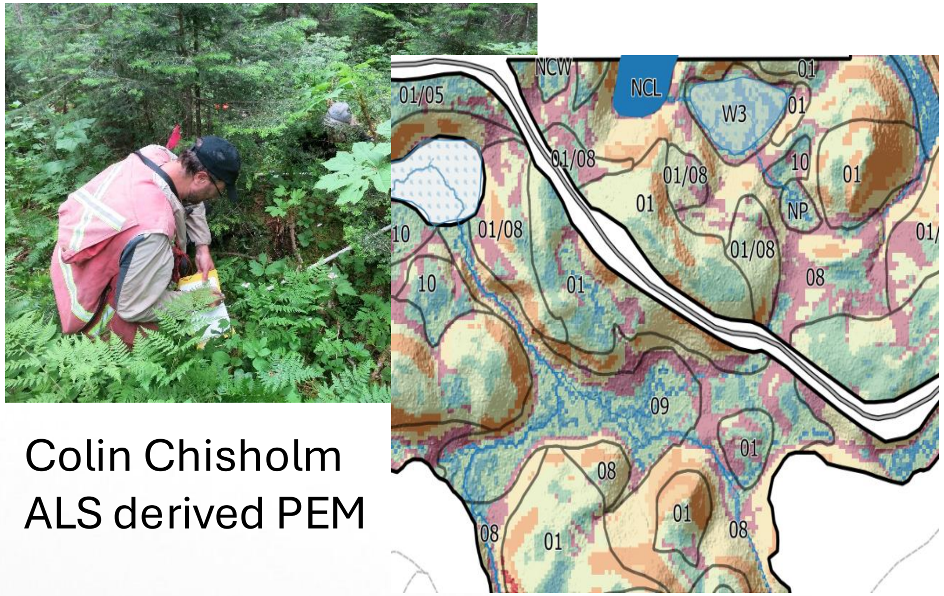
- **Developing an approach to identify and map moose browse in harvested openings in northern British Columbia**

- **Operational recommendations for using remote sensing data**

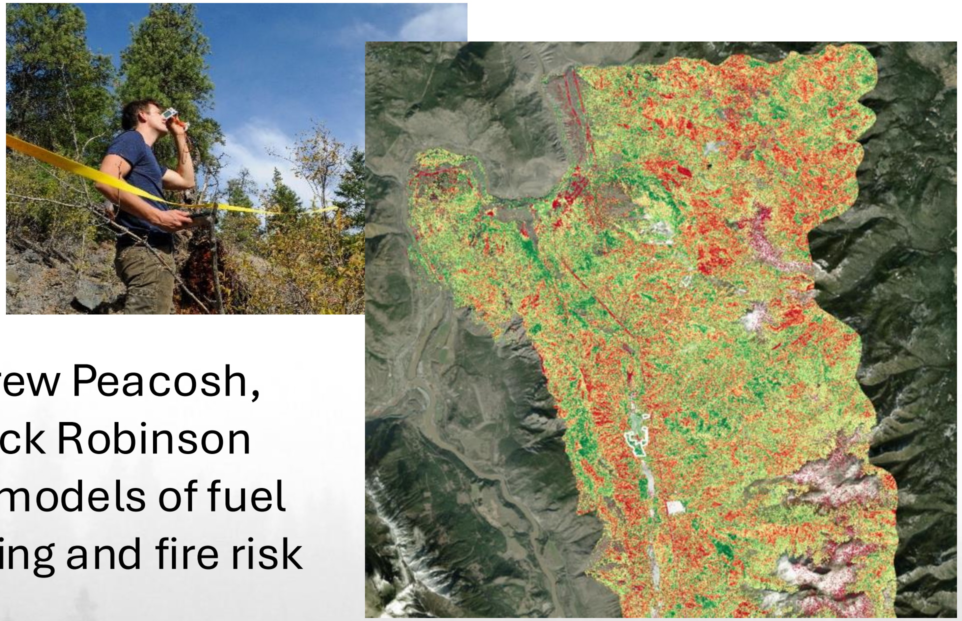
Remote sensing and forestry



Faezeh Soltanian,
Luiz Terezan
Satellite & ALS Site Index models



Colin Chisholm
ALS derived PEM



Andrew Peacosh,
Patrick Robinson
ALS models of fuel loading and fire risk

Remote sensing and forestry

Integration of Airborne Laser Scanning data into forest ecosystem management in Canada: Current status and future directions

By Tristan R.H. Goodbody[1], Nicholas C. Coops[1*], Liam A.K. Irwin[1], Claire C. Armour[1], Sari C. Saunders[2], Pamela Dykstra[3], Christopher Butson[4], and Genevieve C. Perkins[4,5]

2024, VOL. 100, N°2 — THE FORESTRY CHRONICLE

https://pubs.cif-ifc.org/doi/10.5558/tfc2024-014

Applications	Research maturity	Operational feasibility
Timber resource assessment	Mature	Realized
Wildlife habitat	Mature	Potential
Carbon / biomass assessment	Actively developing	Challenging
Forest health	Actively developing	Challenging
Silviculture and operational -level planning	Actively developing	Potential

Best practice guides

Forestry: An International Journal of Forest Research, 2024, **97**, 11–37
https://doi.org/10.1093/forestry/cpad024
Advance access publication date 10 May 2023
Review

Remote sensing in forestry: current challenges, considerations and directions

Fabian Ewald Fassnacht[1], Joanne C. White[2], Michael A. Wulder[2] and Erik Næsset[3]

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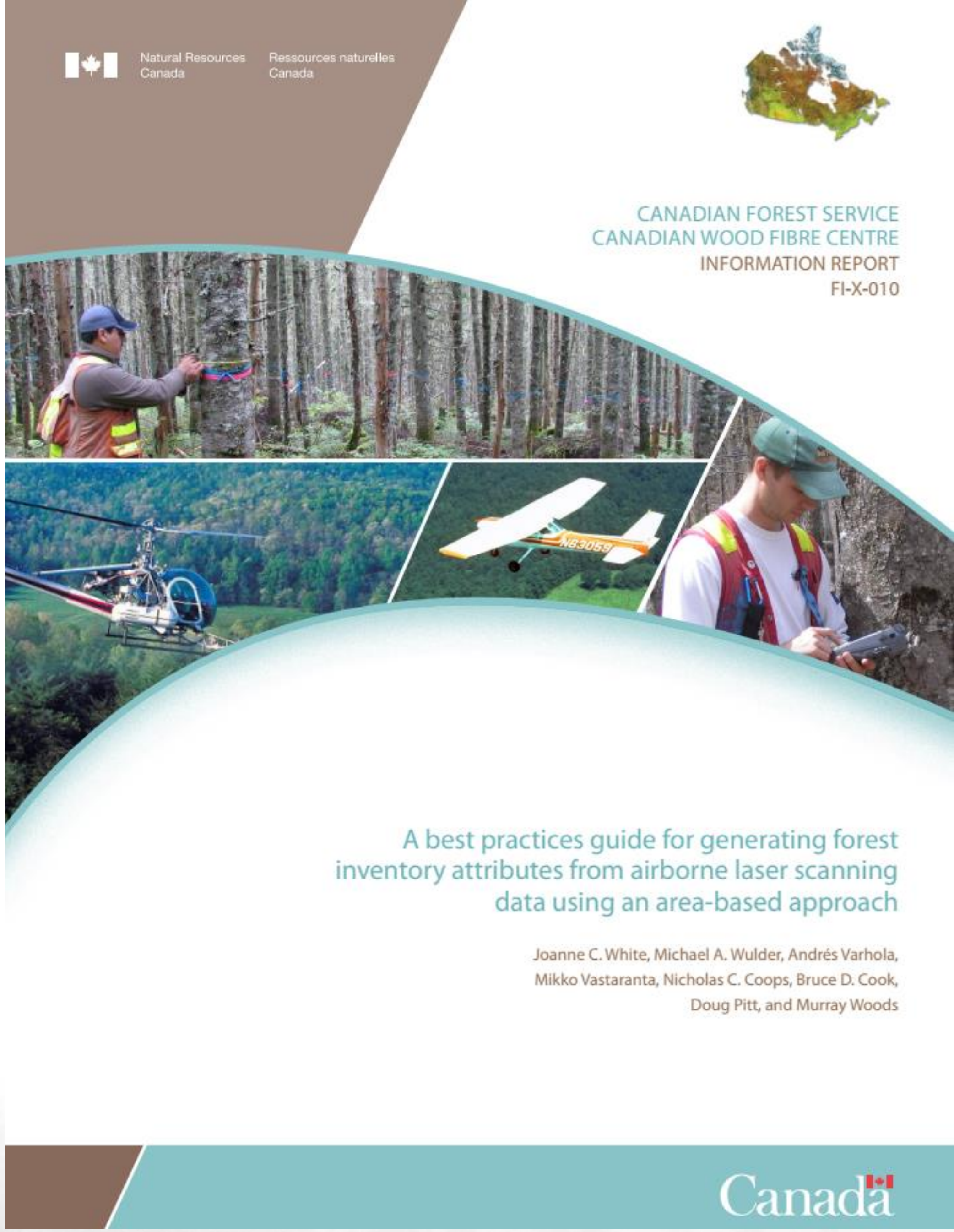
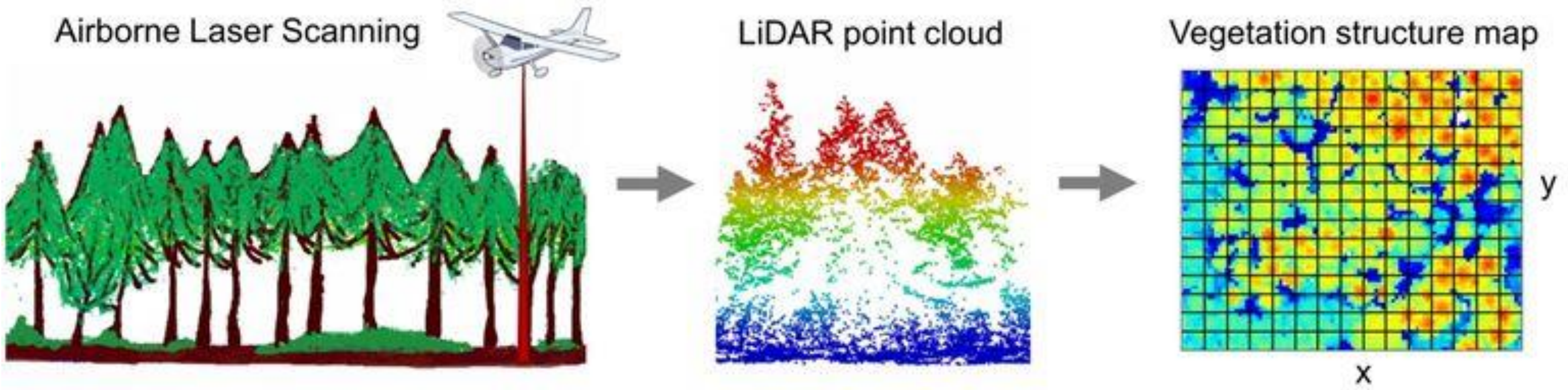
[2]Canadian Forest Service (Pacific Forestry Centre), Natural Resources Canada, 506 West Burnside Road, Victoria, British Columbia, V8Z 1M5, Canada
[3]Faculty of Environmental Sciences and Natural Resources Management, Norwegian University of Life Sciences, P.O. Box 5003, NO-1432 Ås, Norway
*Corresponding author Tel: +49 03083851773; E-mail: fabian.fassnacht@fu-berlin.de

https://doi.org/10.1093/forestry/cpad024



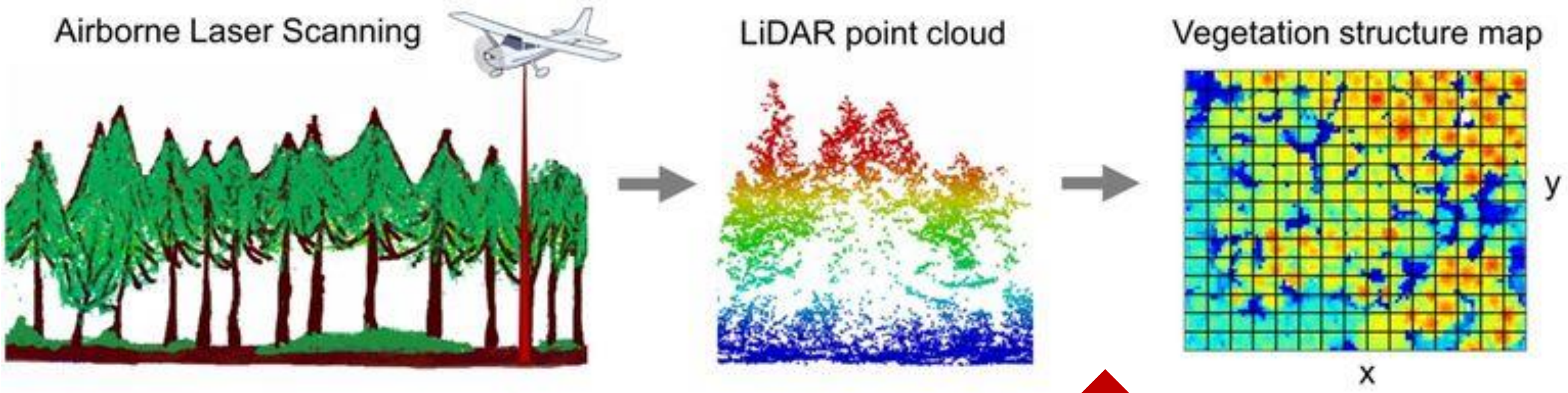
https://publications.gc.ca/collections/collection_2013/rncan-nrcan/Fo148-1-10-eng.pdf

Remote sensing in forestry: application



Brax et al. 2019 Diversity and Distributions 25(7)
https://onlinelibrary.wiley.com/doi/epdf/10.1111/ddi.12915

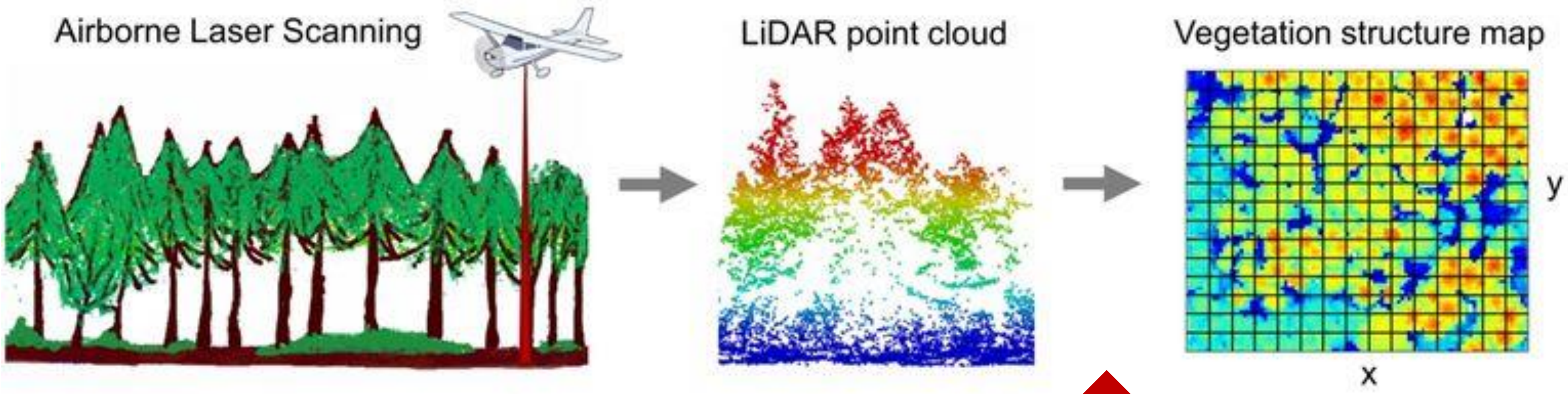
Remote sensing in forestry



Optimal modeling processes for early seral vegetation identification

Remote sensing in forestry

Operational planning for the effective use of remote sensing in forestry



Optimal modeling processes for early seral vegetation identification

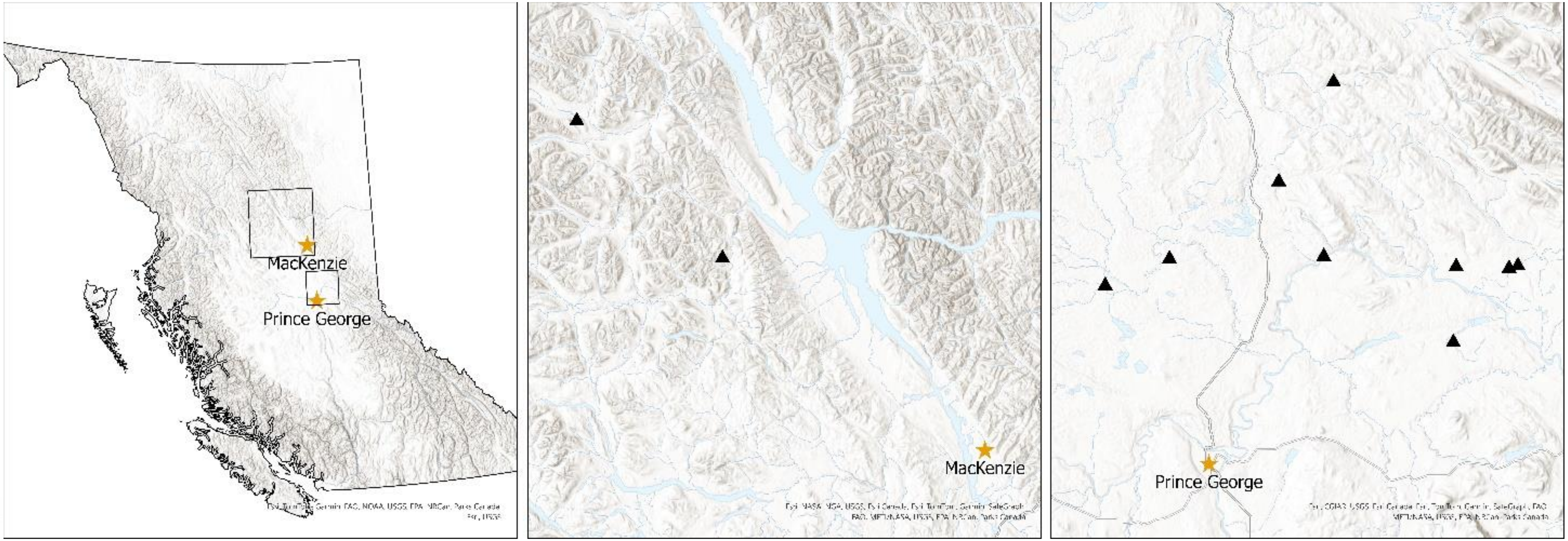
Remote sensing of vegetation following harvest

- Seedlings
- Ground cover
- Brush competition
- Wildlife forage

Moose browse

1. Trembling aspen (*Populus tremuloides*) under 3m in height
2. Paper birch (*Betula papyrifera*) under 3m in height
3. Highbush cranberry (*Viburnum edule*)
4. Willow species (*Salix* spp.)
5. Red-osier dogwood (*Cornus stolonifera*)

Study sites



11 sites

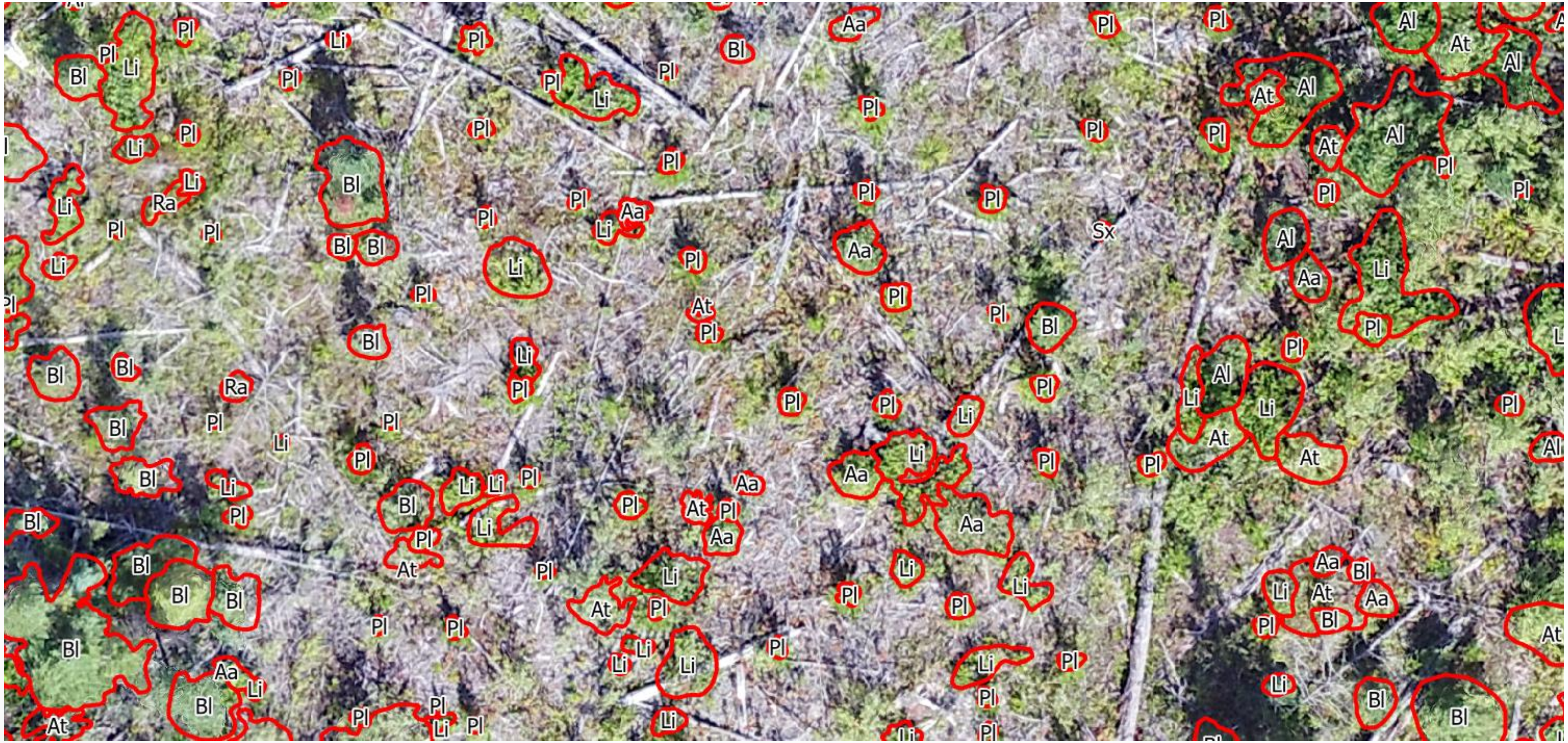
Study sites

Site \ Attribute	Leading Species	Planted	Brushed	Previous Dominant	BEC Zone	BEC Subzone
200rd	Pl (33%)	May 2016	NA	PLI	SBS	mk
700rd	Cs (32%)	July 2017	August 2014	SW	SBS	wk
Alezza	Sx (42%)	June 2019	NA	SX	SBS	wk
Bend05km	Sx (50%)	July 2013	August 2015	BL	SBS	vk
ChiefLake	Pl (23%)	June 2013	August 2018	--	SBS	mk
ConifexH47	Li (23%)	July 2017	NA	SX	ESSF	mv
ConifexK14	Bl (42%)	August 2017	NA	PLI	BWBS	dk
NorthFraser11	Sx (42%)	June 2008	August 2010	PLI	SBS	mk
NorthFraser41	Ri (21%)	July 2017	August 2018	SX	SBS	wk
NorthFraser50	Sx (44%)	July 2016	August 2015	BL	SBS	wk
Olson5km	Bl (32%)	June 2015	NA	PLI	SBS	mk

Data collection

- Drone / UAV / RPAS
  - DJI Matrice 210
- Camear
  - High-resolution RGB data
  - Micasense RedEdge-M

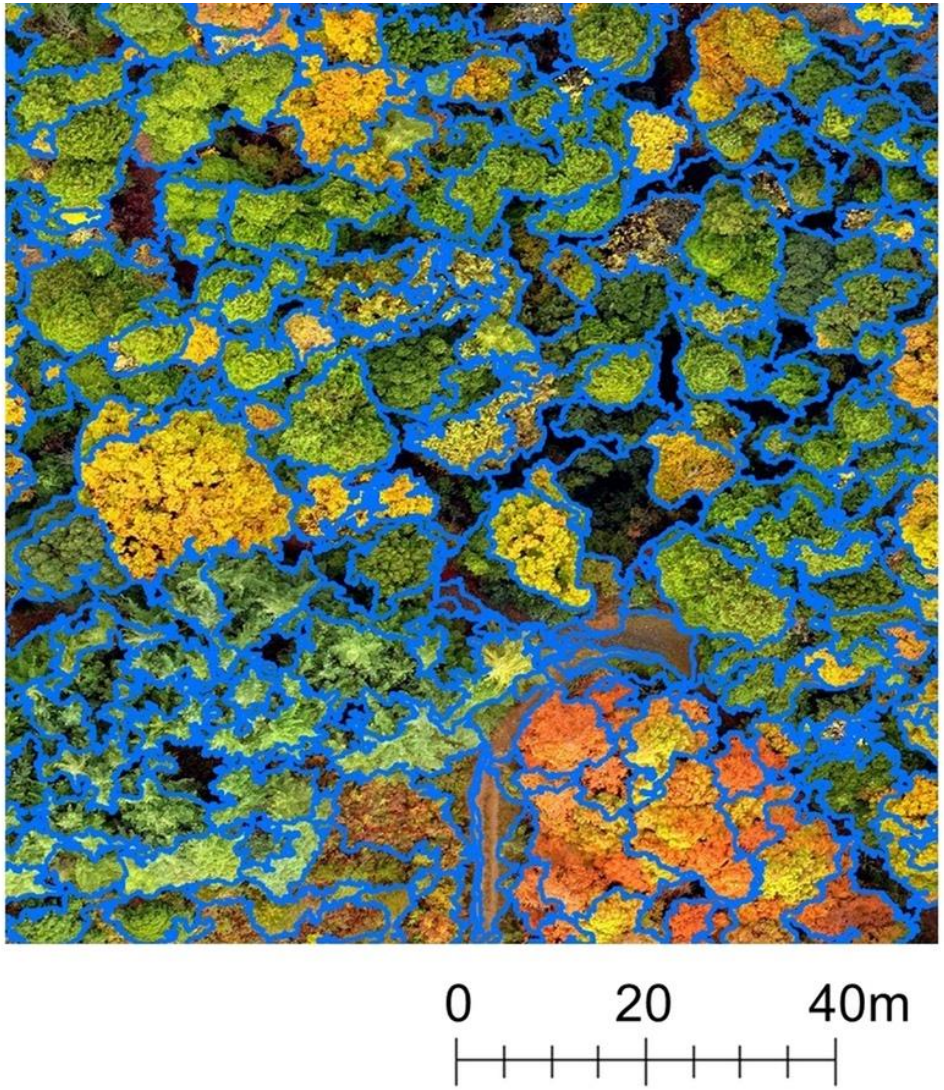
Manual delineation of trees and veg



- Field identification of species
- Office delineation of vegetation polygons (crown)

Detecting and classifying vegetation

- Segmentation
  - Process of breaking up an image into "objects"
- Classification
  - Process of identifying the "objects"

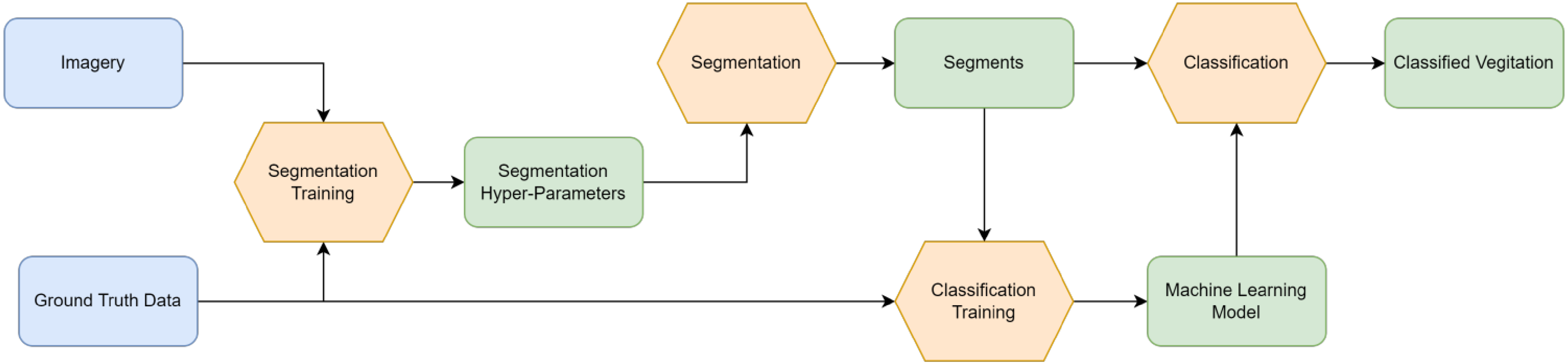


Onishi & Ise 2021 Nature

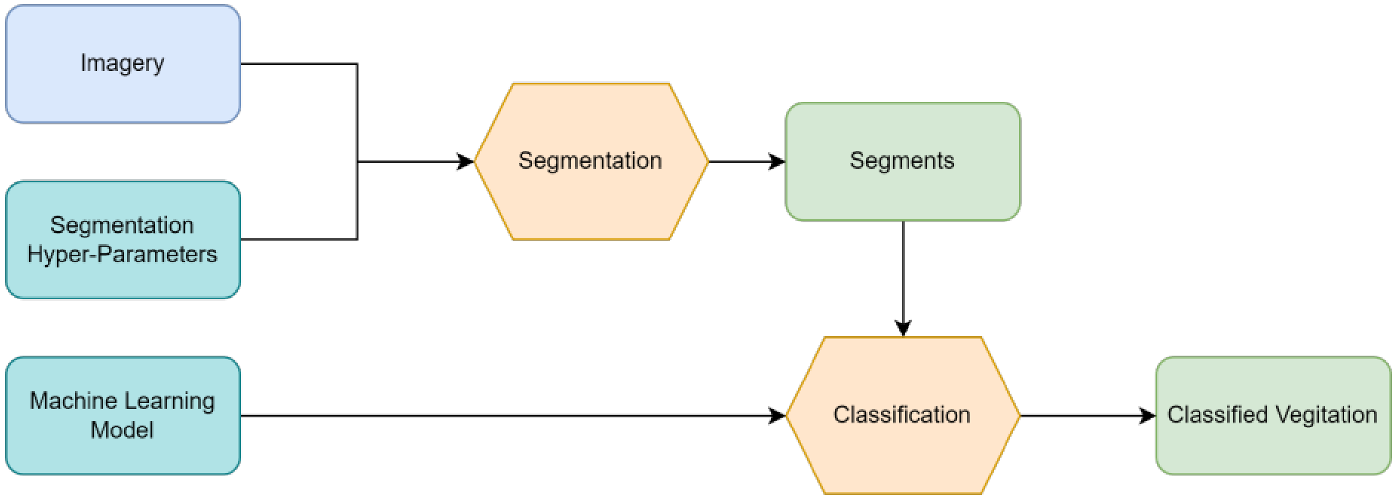
https://www.nature.com/articles/s41598-020-79653-9

Data processing

Training

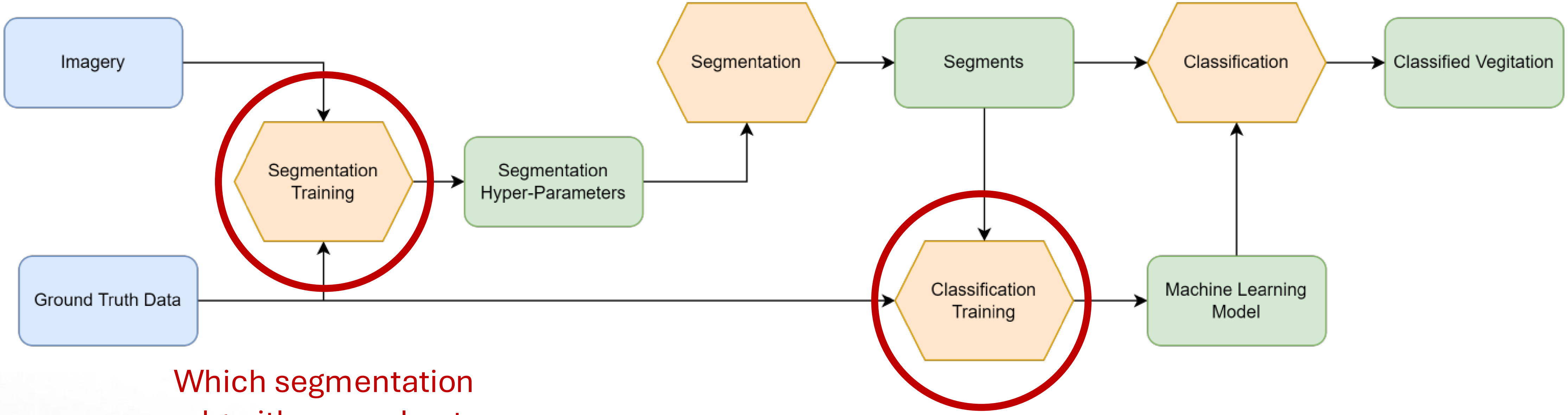


Application of Model



Data processing

Training



Which segmentation algorithms are best at delimitating vegetation objects?

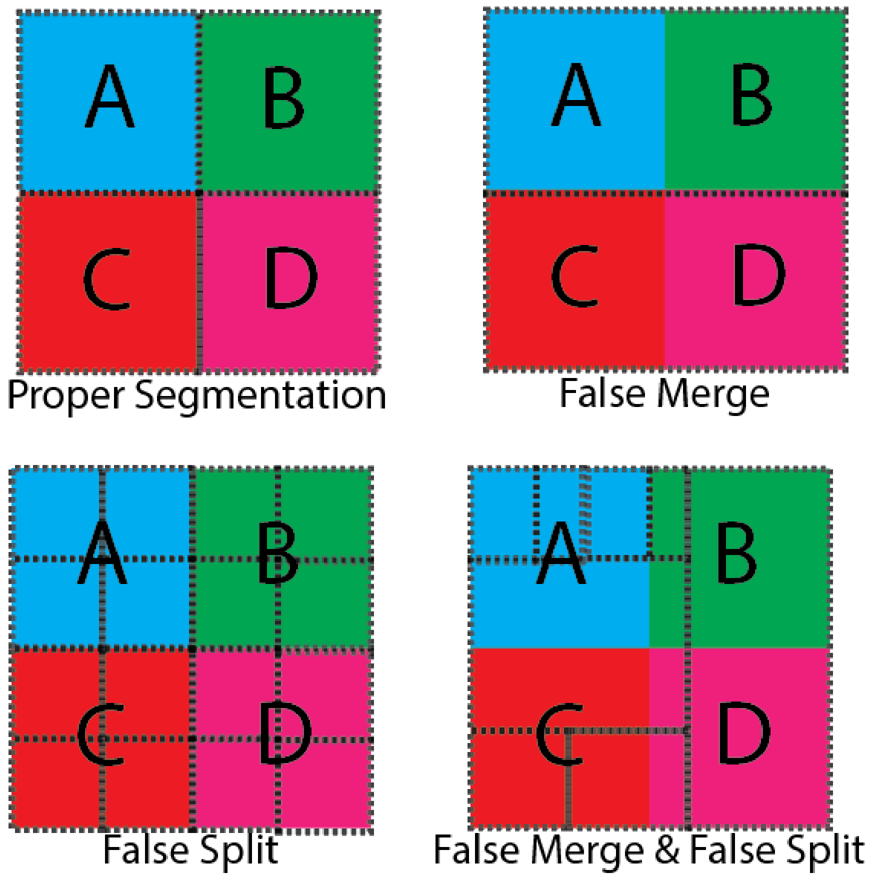
What machine learning models are best at accurately identifying vegetation objects?

Segmentation

Algorithms

- SLIC: Simple Linear Iterative Clustering
- Quick Shift
- F-Graph: Felzenszwalb's Efficient Graph
- Mean Shift

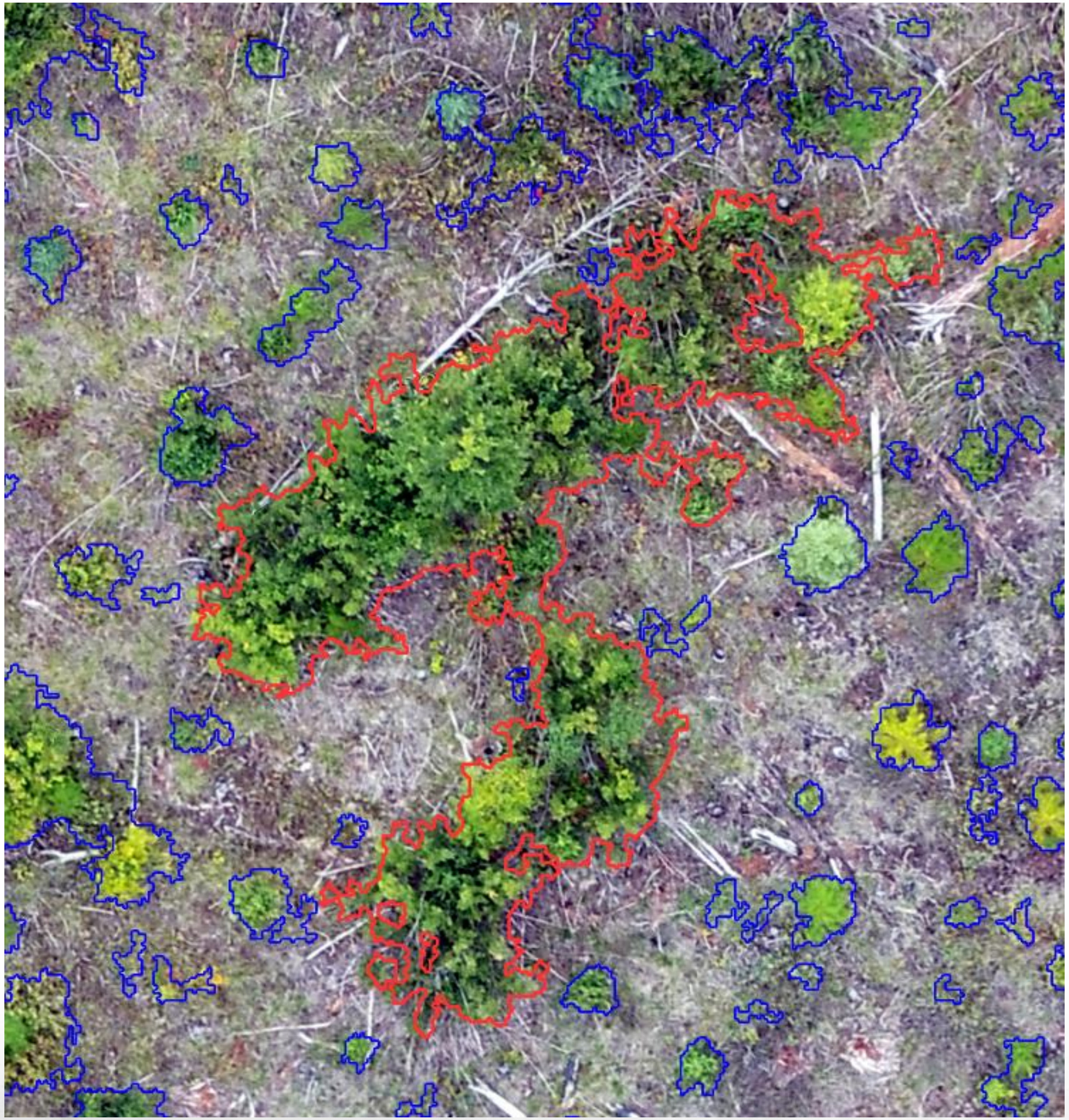
- Object identification (YOLO)



Segmentation

False mergers

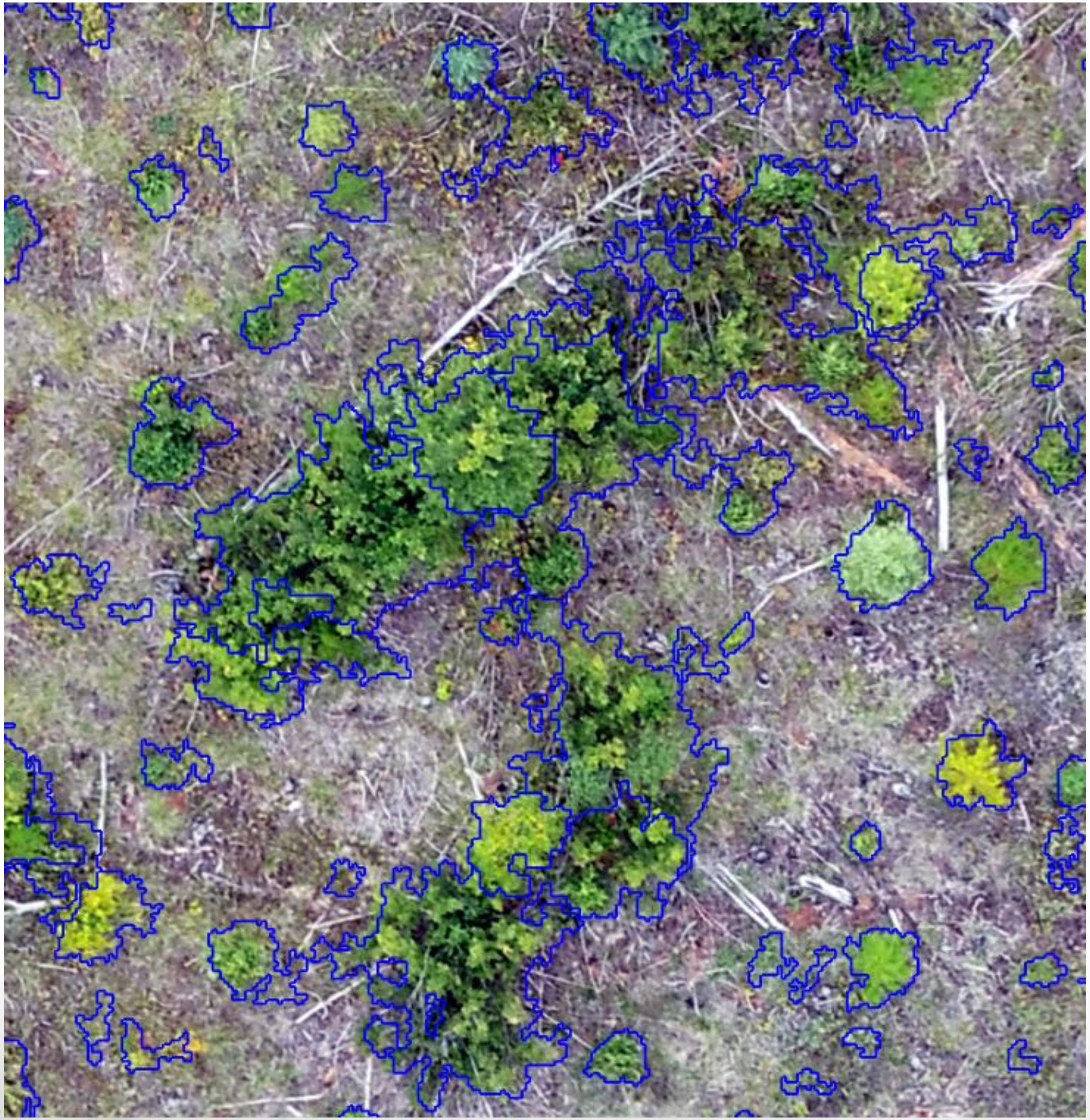
Fales splits



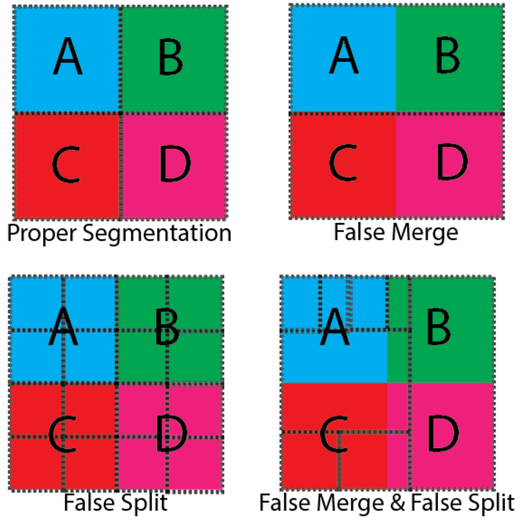
Segmentation

False mergers

Fales splits



Segmentation



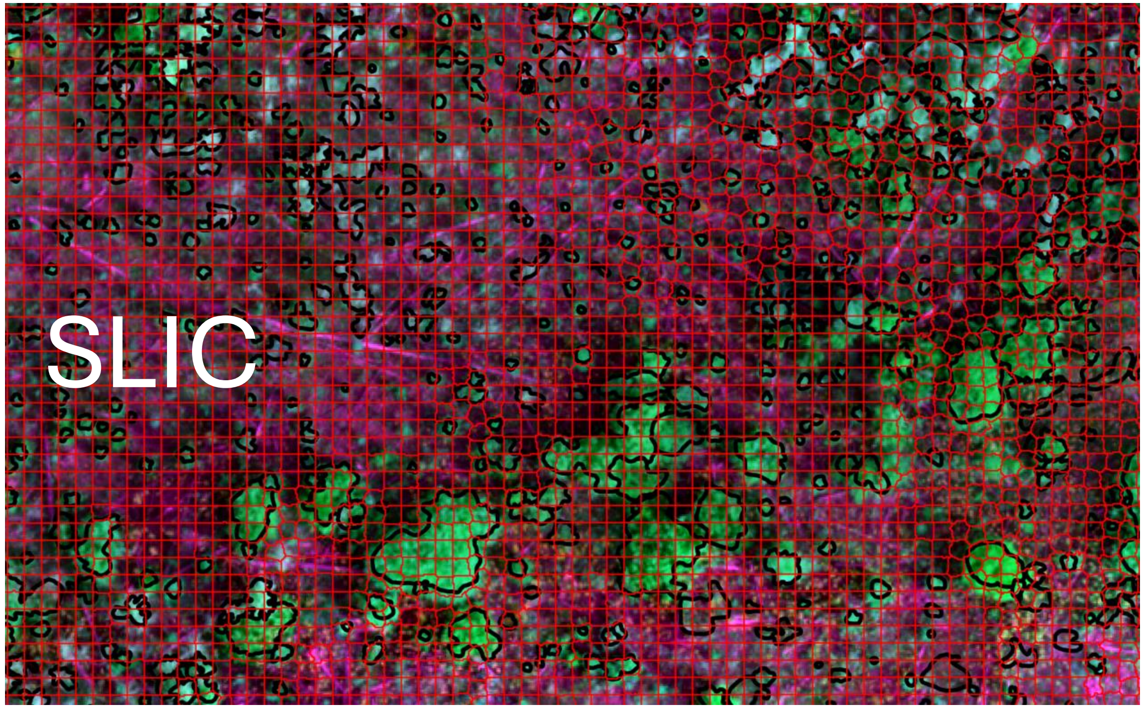
How can segmentation accuracy be assessed?

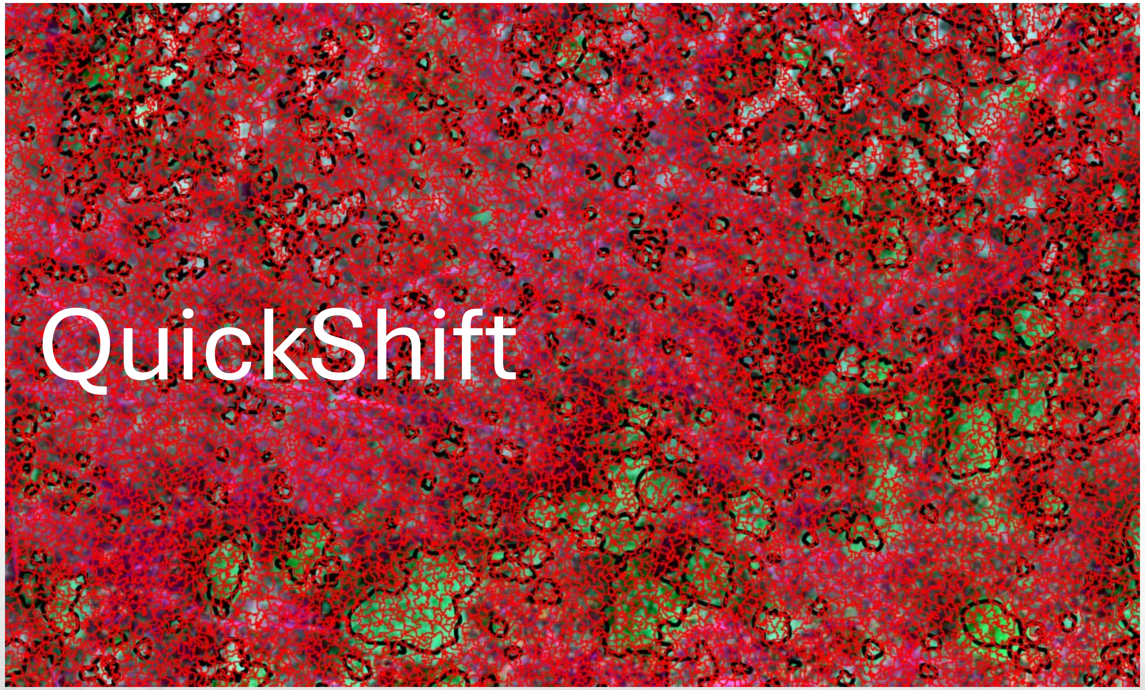
Metrics

1. “Small Segments” : Strongly penalize false mergers
2. “Average of Metrics” :Equal weighting of FM, FS and pixel error
3. “Weighted Small Segments”: Penalize false mergers
4. “Weighted Average of Metrics”: Equal weighting, slightly penalize false mergers

Segmentation Results

- SLIC performed best, QuickShift a very close second





Segmentation Results

Negative values worse

Average:
Site specific calibration

Aggregate:
Same calibration across sites

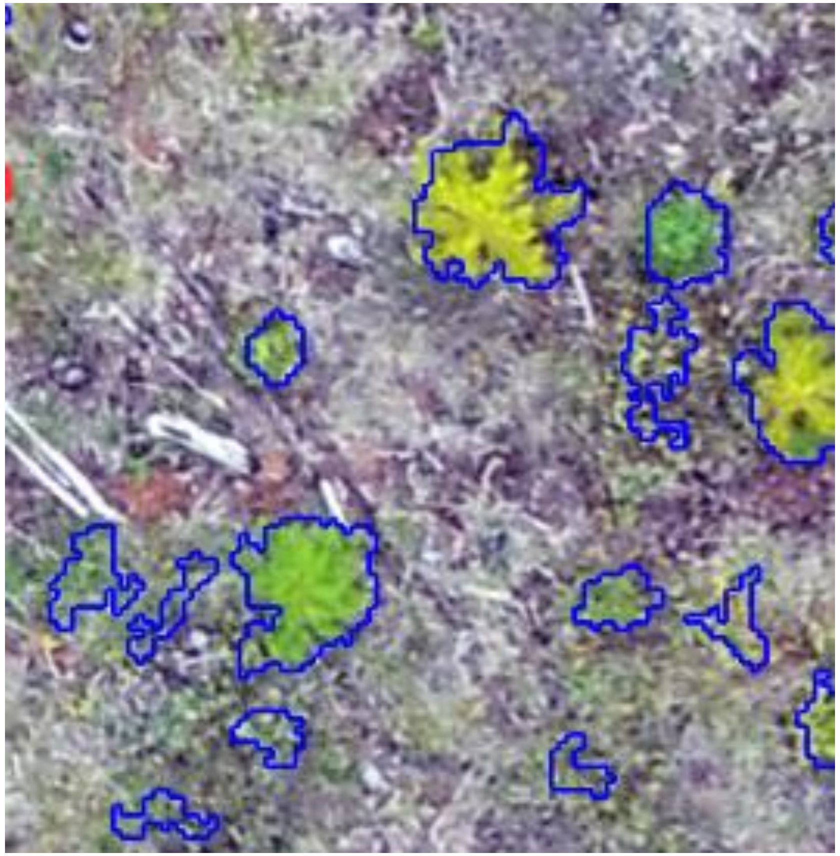
Average Scores				
Metric 1				
	SLIC	**QuickShift**	**F_Graph**	**MeanShift**
Average	-0.11367	-0.07550	-0.08227	-1.89704
Aggregate	-0.1161	-0.0763	-0.0897	-1.897
Metric 2				
	SLIC	**QuickShift**	**F_Graph**	**MeanShift**
Average	-0.48293	-0.50196	-4.79493	-3.33711
Aggregate	-5.0441	-5.6223	-5.3433	-3.3371
Metric 3				
	SLIC	**QuickShift**	**F_Graph**	**MeanShift**
Average	-0.30448	-0.34644	-2.334	-2.91146
Aggregate	-2.5232	-2.765	-2.7298	-2.9115
Metric 4				
	SLIC	**QuickShift**	**F_Graph**	**MeanShift**
Average	-0.29074	-0.33147	-2.87894	-4.15706
Aggregate	-3.1395	-3.2964	-3.2869	-4.1571

Classification

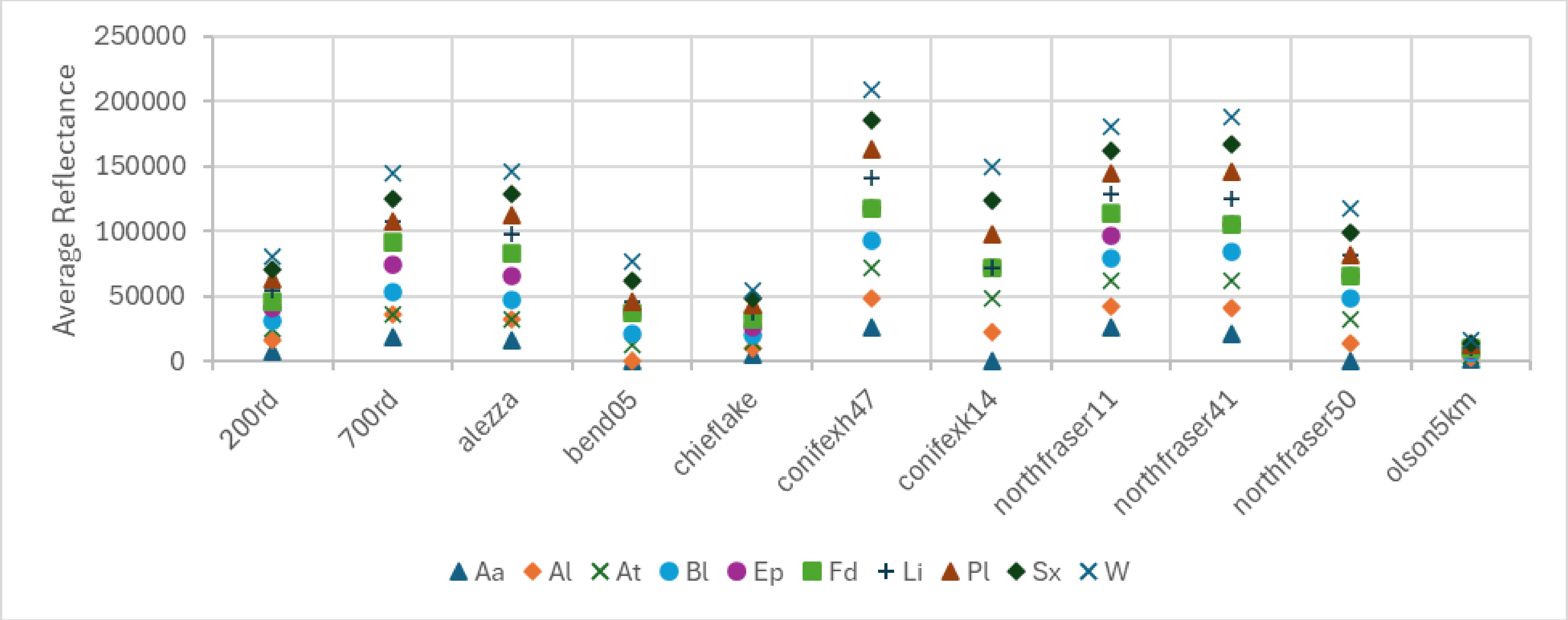
Machine learning algorithms

1. SVM: Support vector machines
2. RF: Random Forest
3. KNN: K Nearest Neighbors
4. MNB: Multinomial Naïve Bayes Classifier

- Impact of balanced sampling
- Site specific or global model



Study sites



Samples in each Site											
	200rd	700rd	Alezza	Bend05km	ChiefLake	ConifexH47	ConifexK14	NorthFraser11	NorthFraser41	NorthFraser50	Olson5km
All	11529	3774	5649	1521	12861	1398	1077	8331	1677	1107	2862
Target	2031	1977	2064	636	1491	261	513	3453	270	468	567

Classification Results

Site specific training

Accuracy **No oversample**		Site Classification Accuracy (Target Species Only)										
		200rd	700rd	Alezza	Bend05km	ChiefLake	ConifexH47	ConifexK14	NorthFraser11	NorthFraser41	NorthFraser50	Olson5km
Algorithm	RF	59%	90%	56%	62%	46%	38%	82%	78%	35%	67%	43%
	SVM	61%	91%	69%	64%	44%	37%	81%	79%	18%	71%	43%
	MNB	35%	57%	43%	49%	26%	34%	60%	34%	45%	52%	28%
	KNN	48%	88%	56%	63%	30%	28%	70%	70%	27%	64%	29%

Classification Results

Aggregate (global) training

Accuracy SMOTE		Site Group				
		α	β	γ	δ	ε
Algorithm	RF	62%	70%	77%	76%	74%
	SVM	64%	71%	77%	75%	74%
	MNB	40%	52%	62%	59%	58%
	KNN	44%	56%	66%	63%	62%

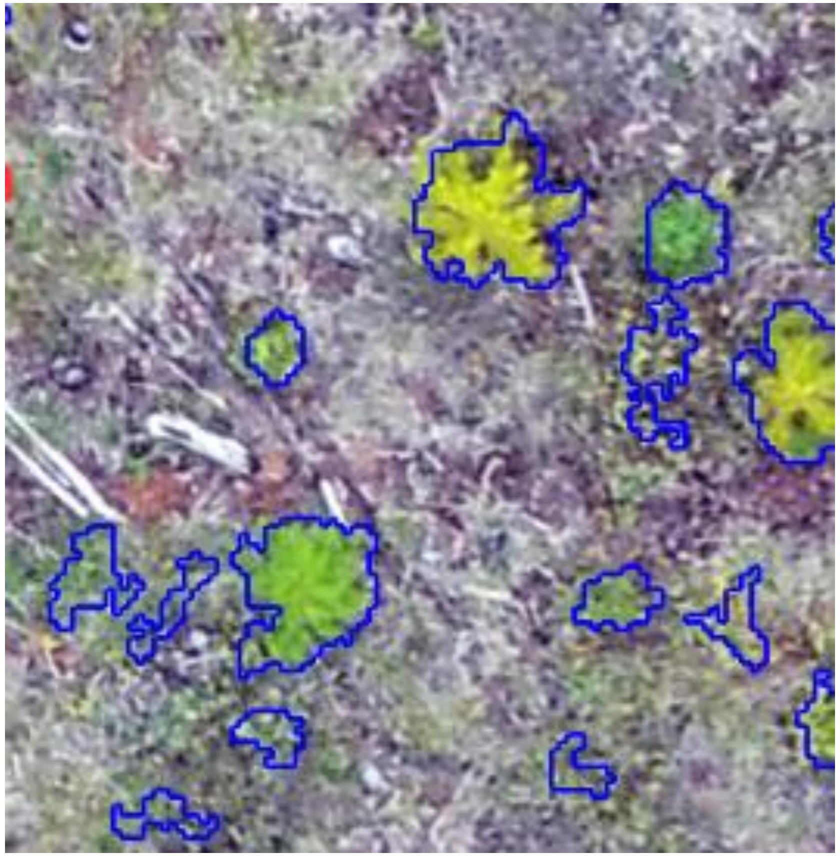
All 11 sites

Classification Results

- Support Vector Machines (SVM) performed best for single sites

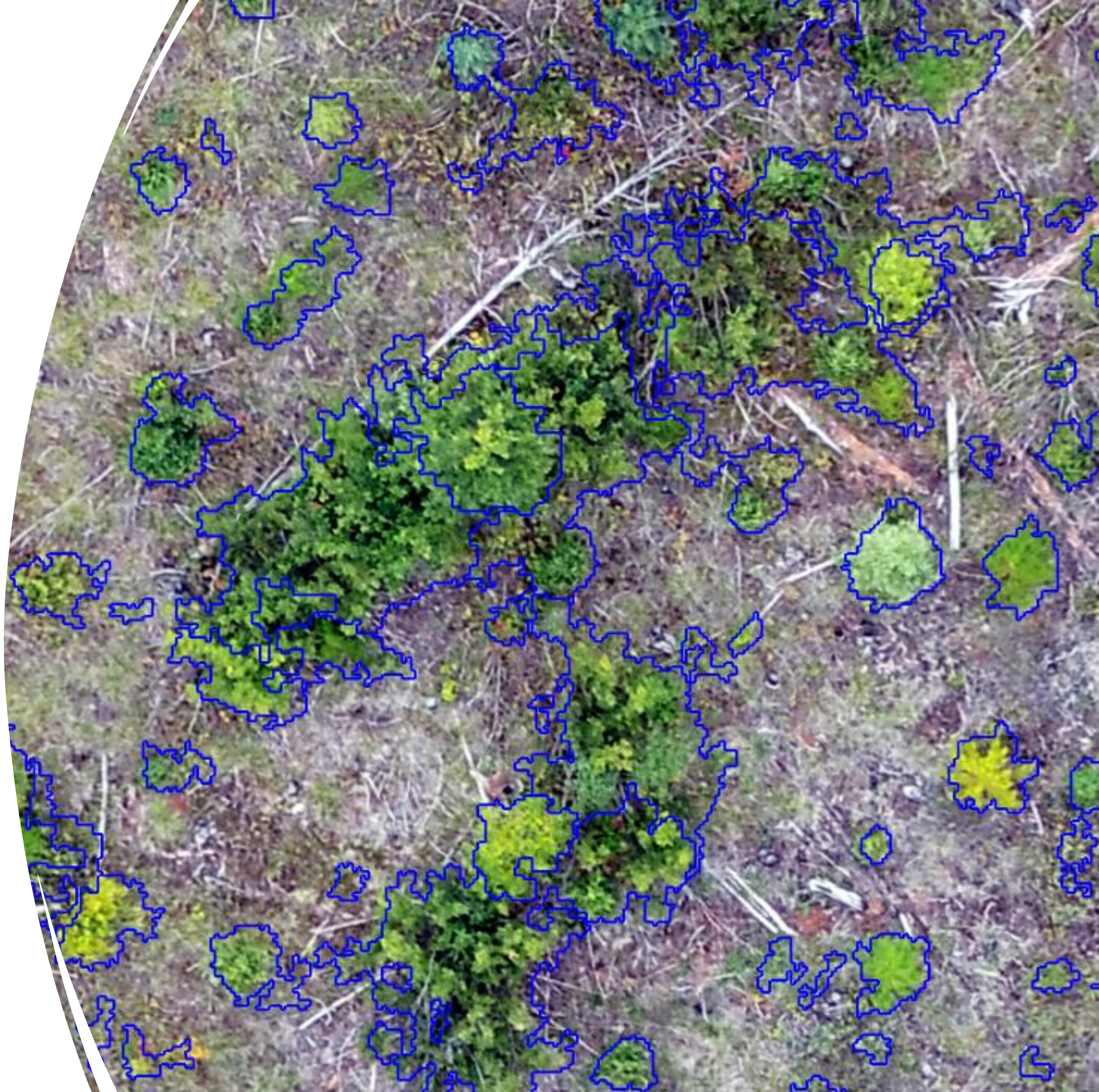
- Random Forest (RF) performed better on groups of sites

- Groups of sites reflect real world application



Take home messages

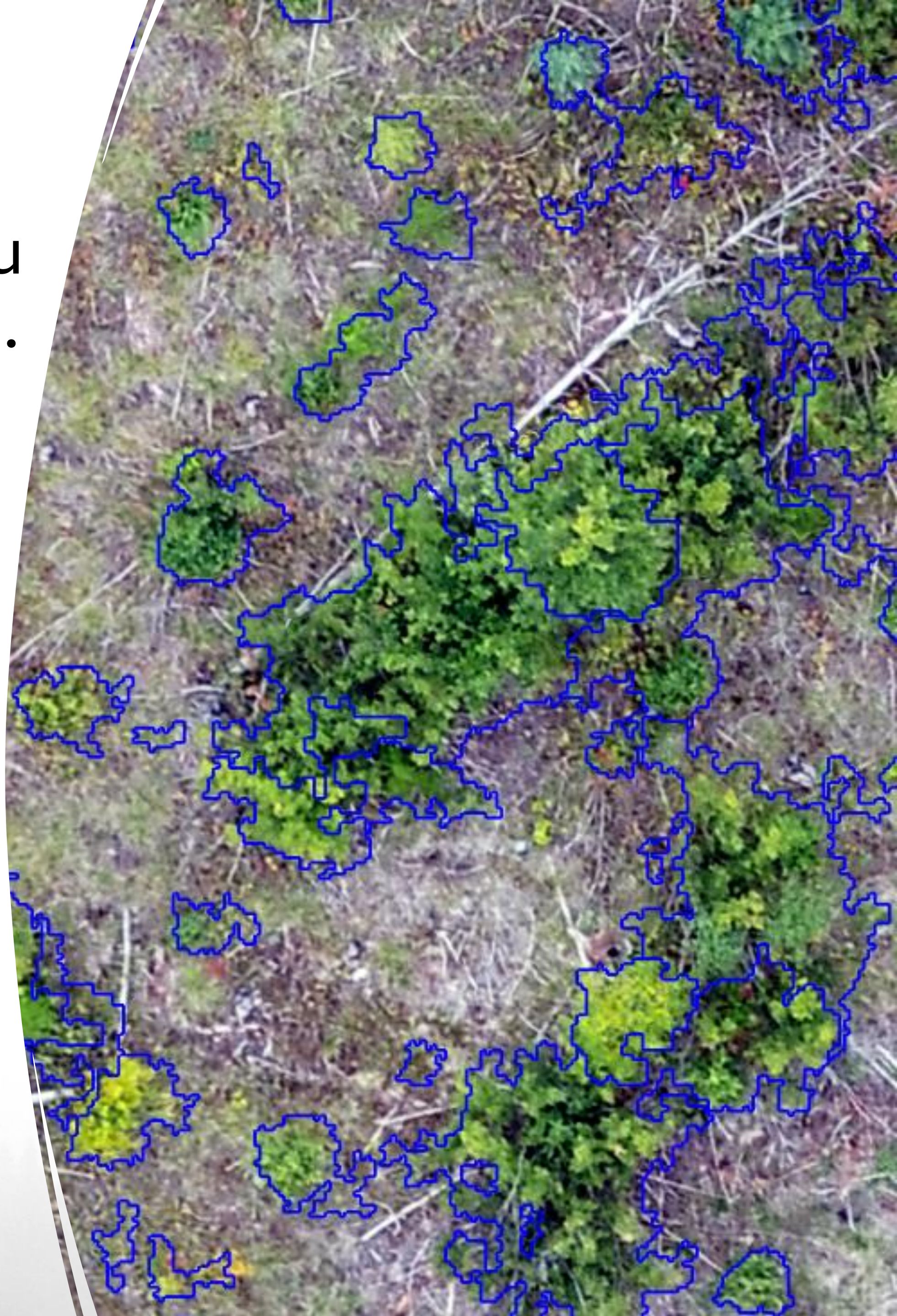
- Vegetation in recently harvested blocks can be identified and assessed using UAV imagery
    - If good remotes sensing data is used, and accurate empirical training data is collected.



Take home messages

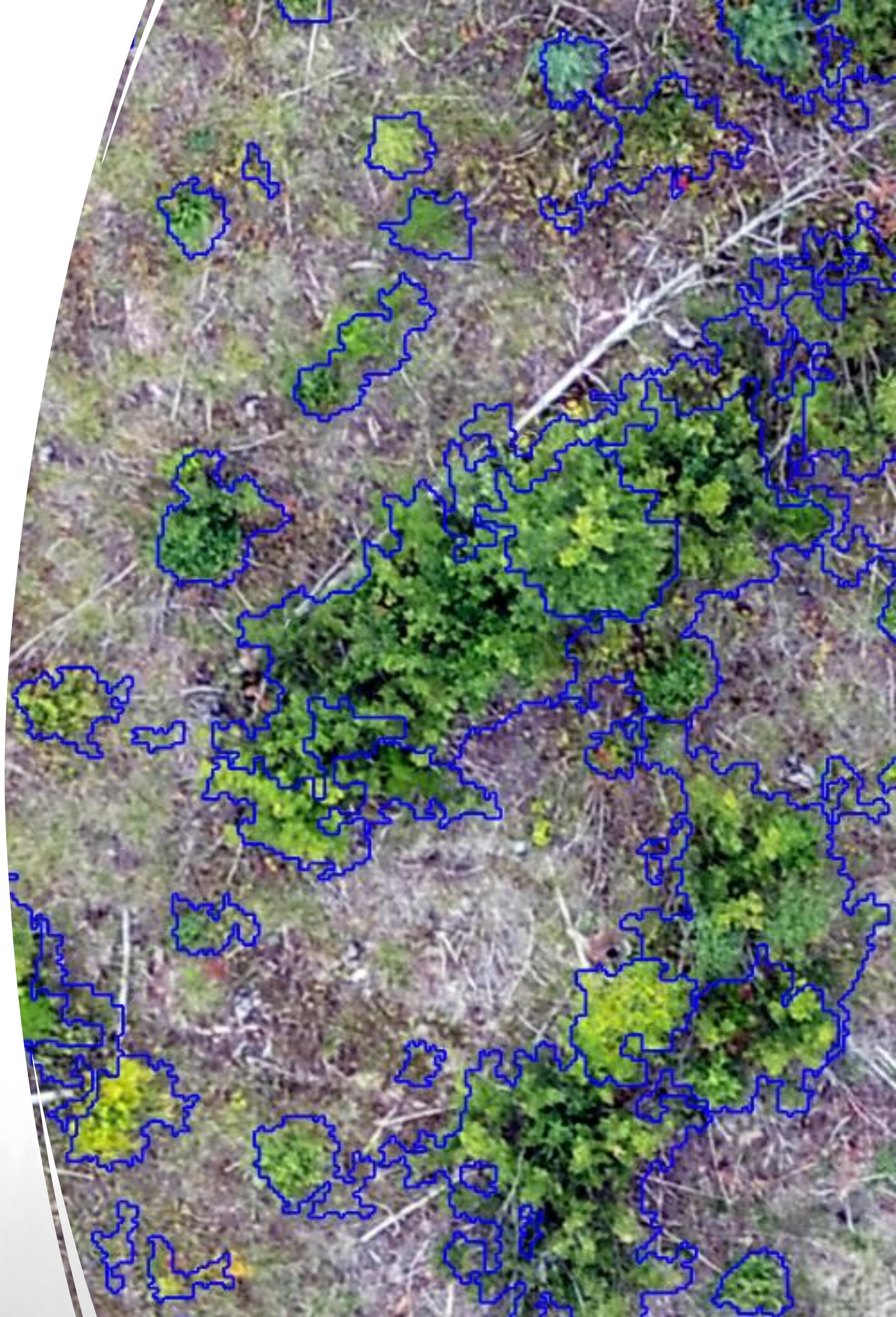
- Be very clear about the question/problem you are using the remote sensing data to address.
  - % ground cover
  - # of individuals (e.g. aim to count trees?)
  - Individual species

- Consider
  - When data is being collected
  - Level of detail needed
  - Amount of data needed (training)
  - The importance of balanced sampling



Take home messages

- Remote sensing and effective machine learning require high quality data. Be strategic.
- Training data needs to reflect implementation data. Consider:
- When data is collected
  - Phenological cycles are important (time of year should be the same)
  - Vegetation health and vigor can differ and can result in individuals looking different.
  - Weather can impact sensors, but also plants
- Where data is collected
  - Site conditions matter. Species will present different in sites that are environmentally different.



Questions?

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