

Advances in Modelling Agricultural Land Use Practices Using Earth Observation in Canada

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What information do we need to improve our measurement of factors impacting resiliency?

- In 2020, the Agricultural Climate Solutions (ACS) Data Strategy and Implementation Plan was initiated to improve modelling and monitoring of best management practices to enhance National GHG Inventory Reporting
- ACS Data Strategy has three core work areas:
 - **Using earth observation to improve farm practice data**
 - Improving GHG emissions and sequestration estimation modelling
 - Improving soil properties mapping

Crop Rotations

Land Use Change

Biomass

Woody Biomass on Ag Land

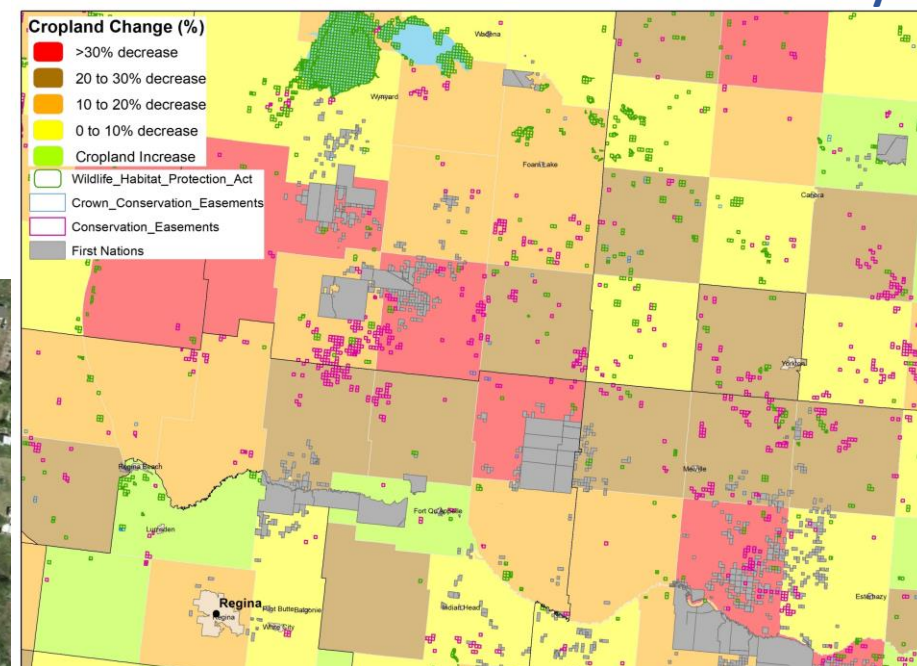
Fractional residue cover

Tillage practices

Winter cover / Cover crops

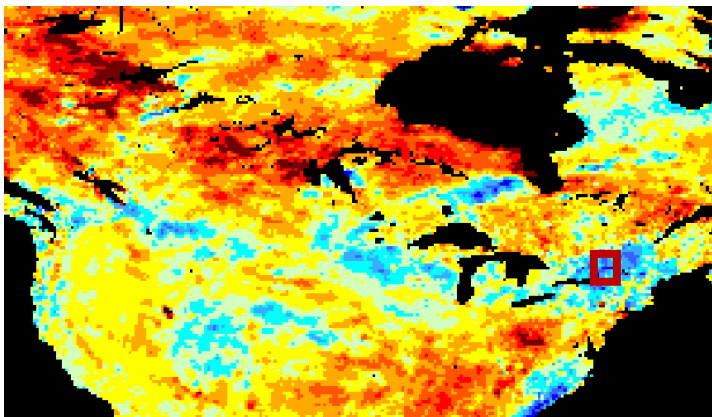
Seeding / harvest monitoring

National Grassland Inventory



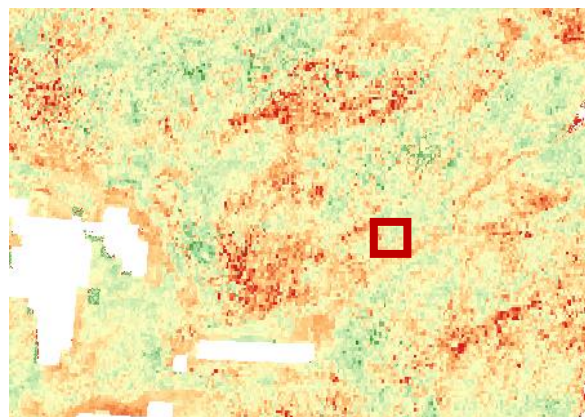
Spatial & Spectral & Temporal Characteristics

Passive Microwave L-Band



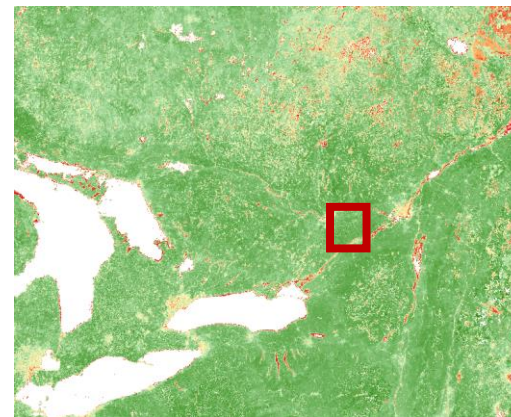
SMOS Soil Moisture 25 km

Thermal Infrared



MODIS ET Anomalies 1 km

Optical Visual-Near Infrared



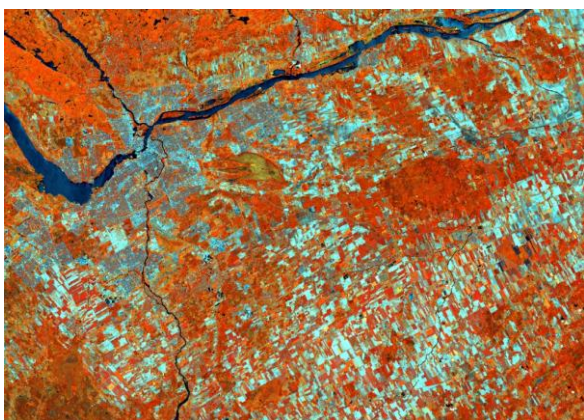
VIIRS NDVI 250 m

Optical Visual



Rapid Eye True Colour Composite 5m

Optical – Visual Near Infrared



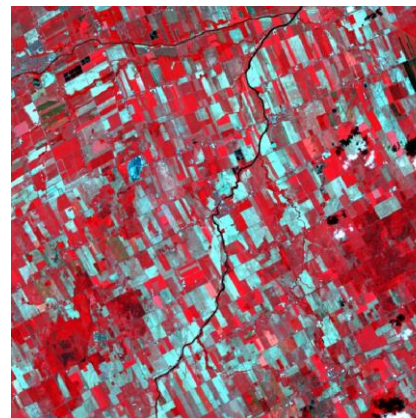
Sentinel-2 False Colour Composite 20 m

Active Microwave C-Band



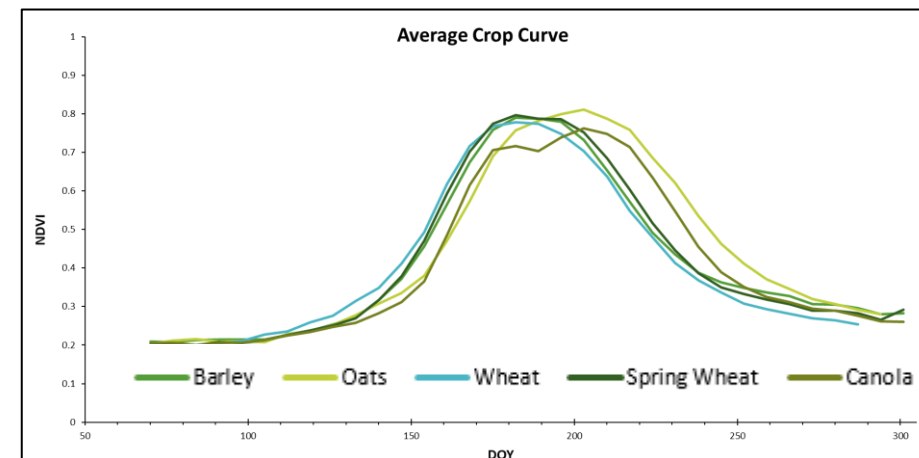
Radarsat Constellation Mission Compact Polarimetric Backscatter 30m

Hyperspectral (244 bands)





















































ENMAP False Colour Composite 30 m

Temporal Signatures of Different Crops (NDVI)

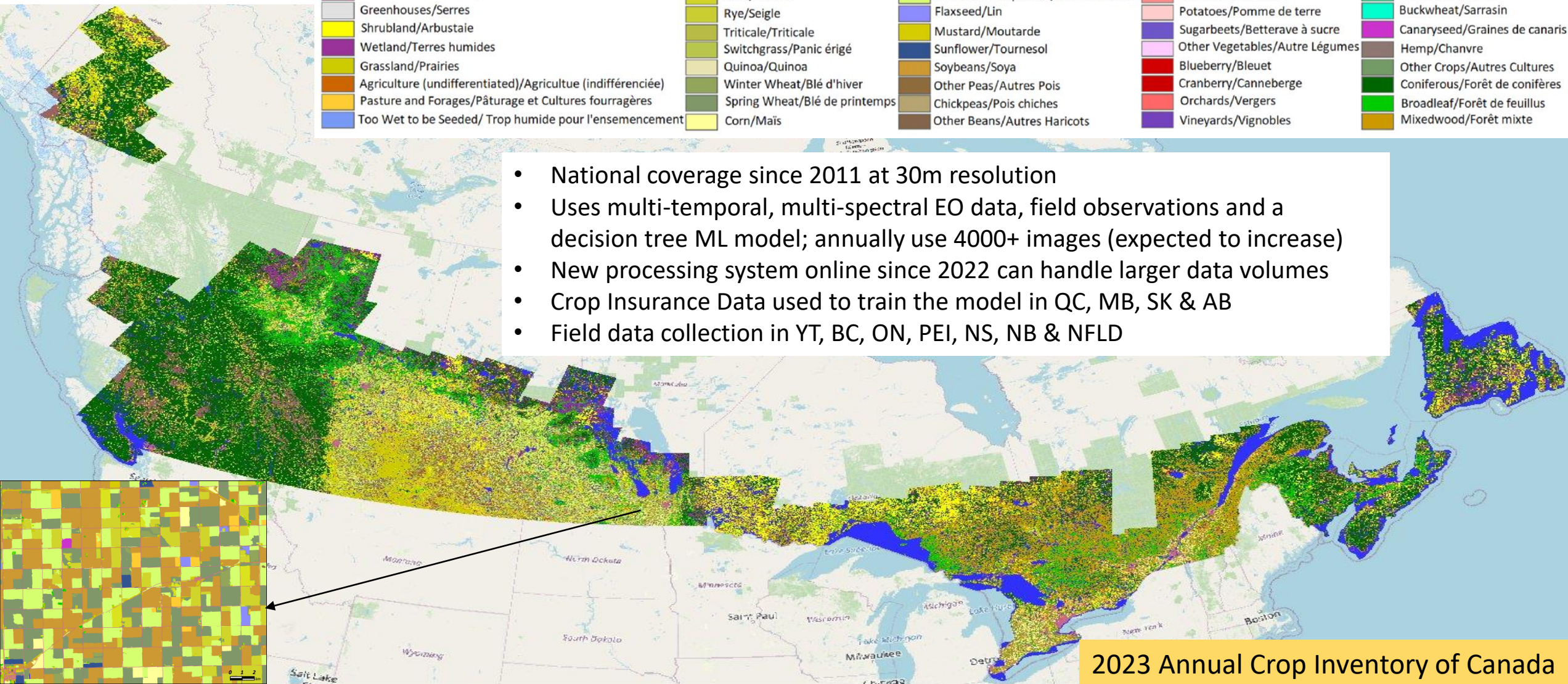


Land Use: Annual Crop Inventory

Legend/Légende

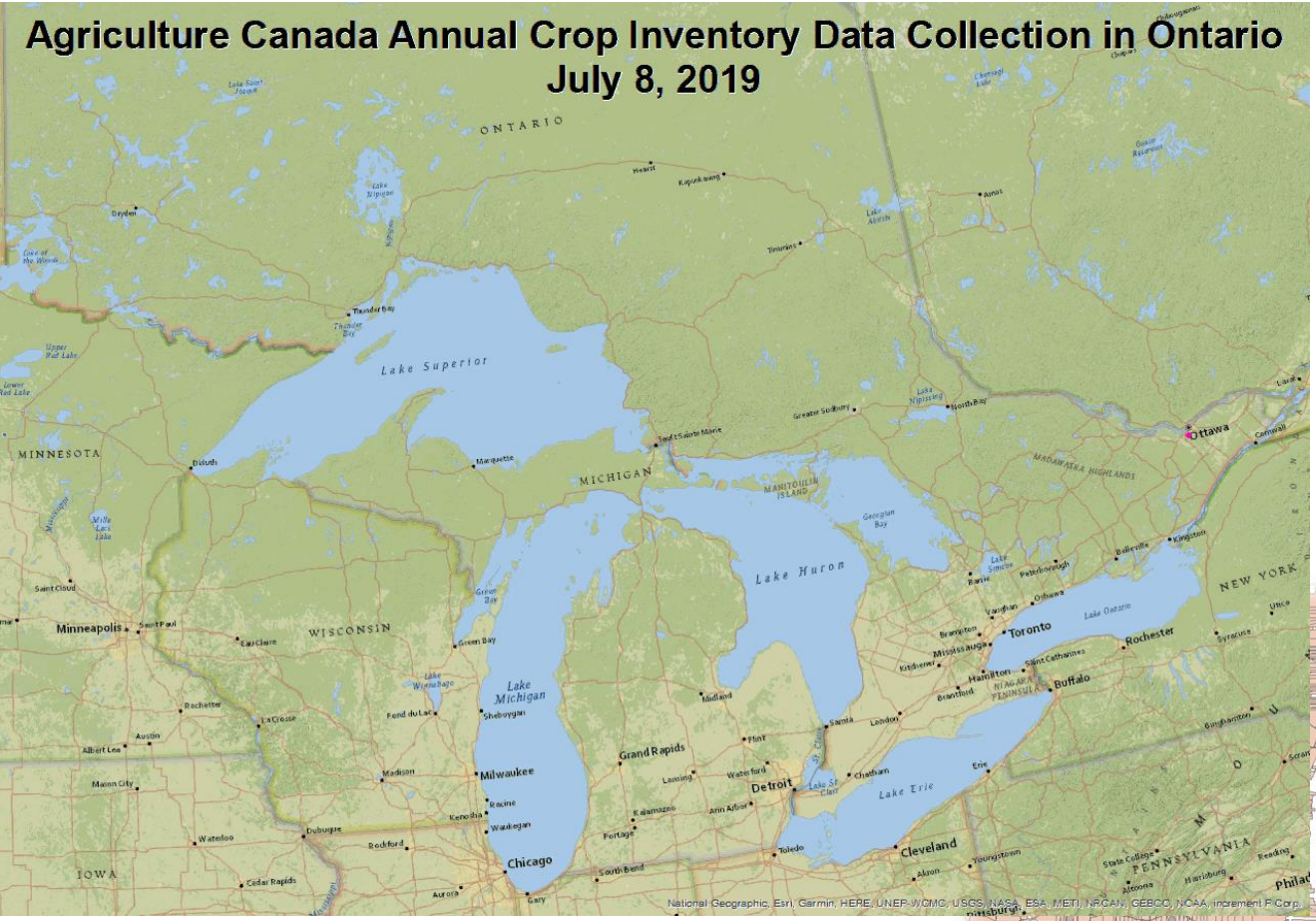
 Water/Eau	 Fallow/Jachère	 Tobacco/Tabac	 Fababeans/Fèves	 Sod/Gazon en plaques
 Exposed Land and Barren/Sols nus et terres stériles	 Barley/Orge	 Ginseng/Ginseng	 Lentils/Lentilles	 Herbs/Fines herbes
 Urban and Developed/Milieu urbain et bâti	 Oats/Avoine	 Canola and Rapeseed/Canola et Colza	 Tomatoes/Tomates	 Nursery/Pépinière
 Greenhouses/Serres	 Rye/Seigle	 Flaxseed/Lin	 Potatoes/Pomme de terre	 Buckwheat/Sarrasin
 Shrubland/Arbustaie	 Triticale/Triticale	 Mustard/Moutarde	 Sugarbeets/Betterave à sucre	 Canaryseed/Graines de canaris
 Wetland/Terres humides	 Switchgrass/Panic érigé	 Sunflower/Tournesol	 Other Vegetables/Autre Légumes	 Hemp/Chanvre
 Grassland/Prairies	 Quinoa/Quinoa	 Soybeans/Soya	 Blueberry/Bleuet	 Other Crops/Autres Cultures
 Agriculture (undifferentiated)/Agriculture (indifférenciée)	 Winter Wheat/Blé d'hiver	 Other Peas/Autres Pois	 Cranberry/Canneberge	 Coniferous/Forêt de conifères
 Pasture and Forages/Pâturage et Cultures fourragères	 Spring Wheat/Blé de printemps	 Chickpeas/Pois chiches	 Orchards/Vergers	 Broadleaf/Forêt de feuillus
 Too Wet to be Seeded/ Trop humide pour l'ensemencement	 Corn/Mais	 Other Beans/Autres Haricots	 Vineyards/Vignobles	 Mixedwood/Forêt mixte

- National coverage since 2011 at 30m resolution
- Uses multi-temporal, multi-spectral EO data, field observations and a decision tree ML model; annually use 4000+ images (expected to increase)
- New processing system online since 2022 can handle larger data volumes
- Crop Insurance Data used to train the model in QC, MB, SK & AB
- Field data collection in YT, BC, ON, PEI, NS, NB & NFLD



Collect Small Subset of Observations to Model National Level Trends

Agriculture Canada Annual Crop Inventory Data Collection in Ontario July 8, 2019



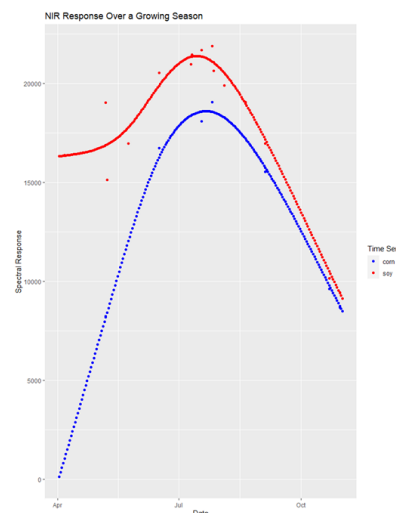
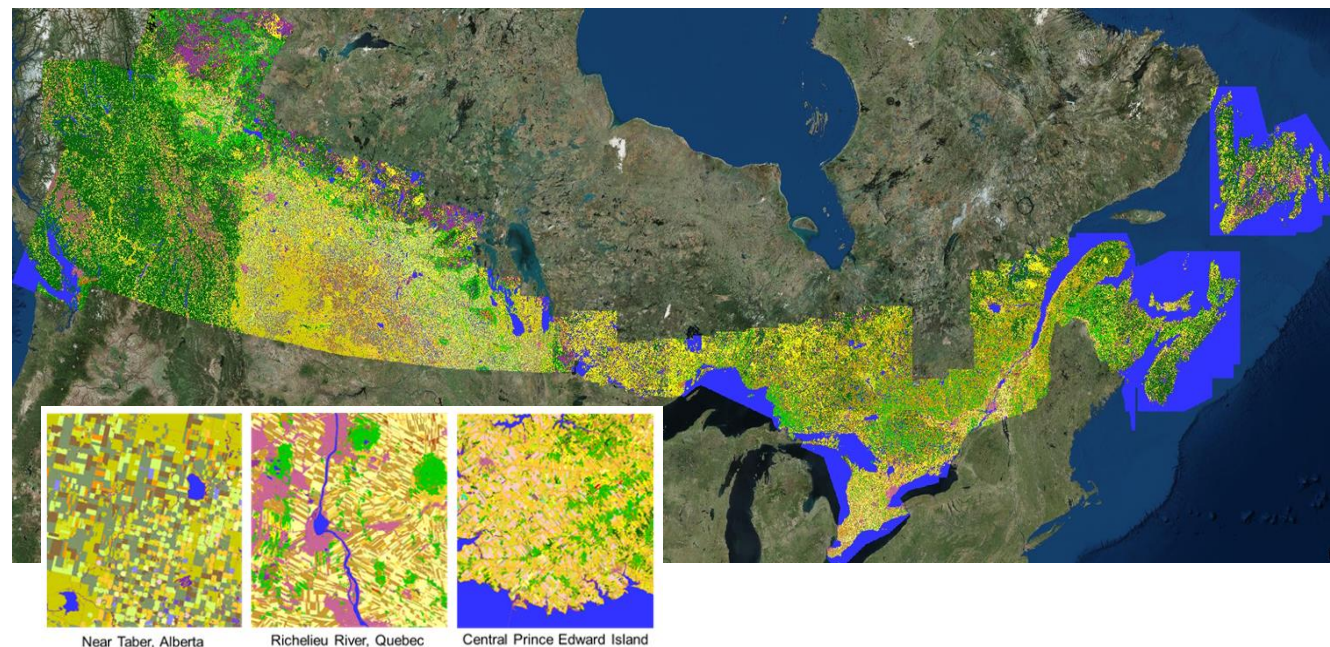
Use calibration/validation data & model to derive information over geographic regions

Field Data Collection

Deep Learning to Enhance Annual Crop Inventories

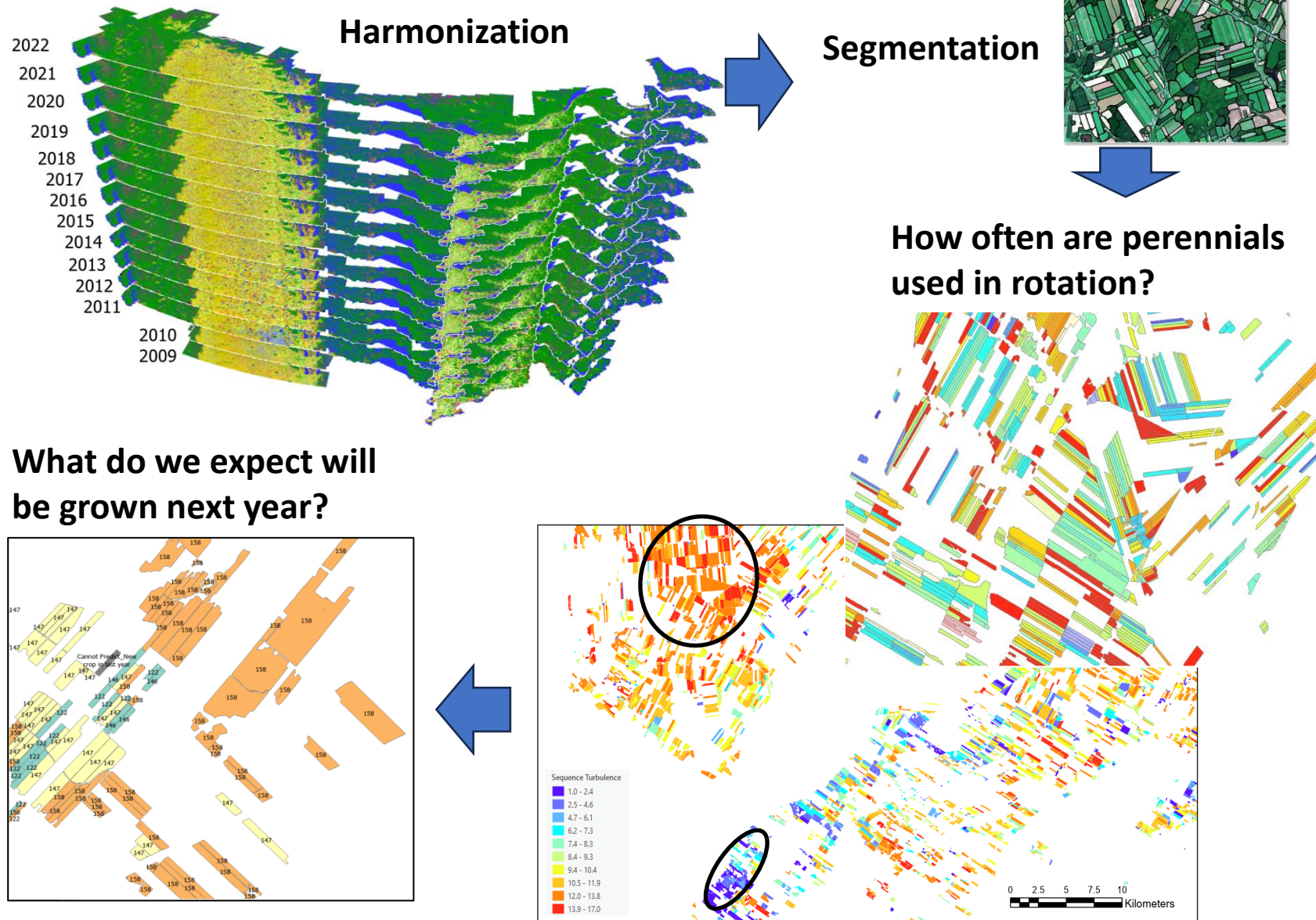
Objective

- Current model requires significant model training data on an annual basis to achieve high accuracy
- Optimization of training data can be achieved through transfer learning to leverage historical data to classify current year
- Recurrent neural networks leverage sequential nature of spectral information to capture patterns in changing crop patterns over growing season
- Annual model training data collection to focus on complex classes and areas with high degree of interannual change



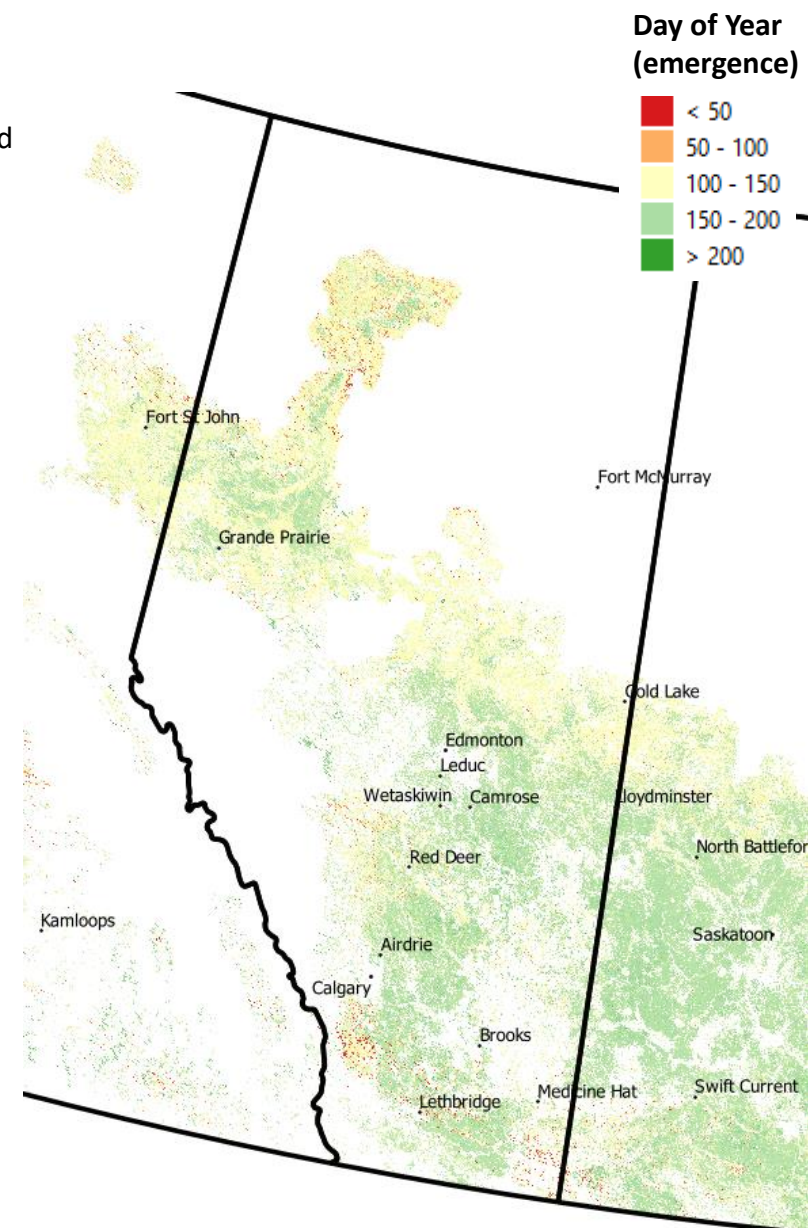
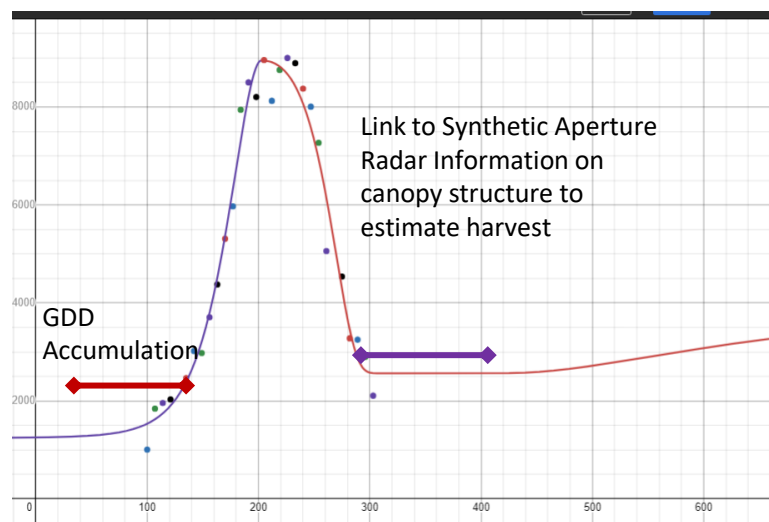
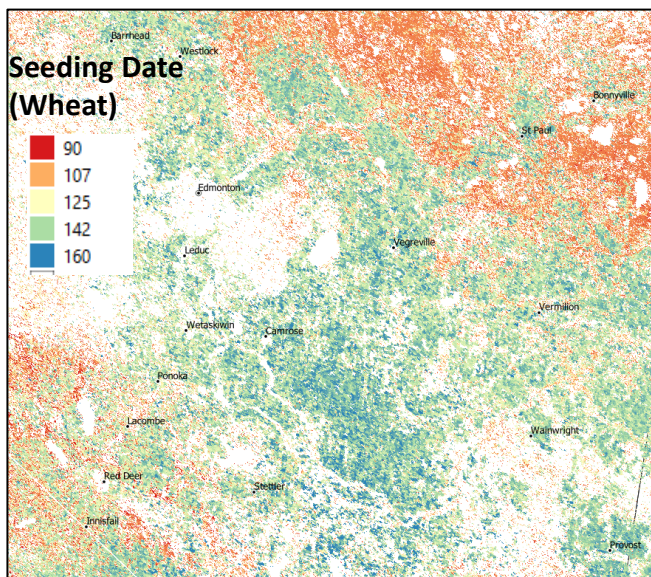
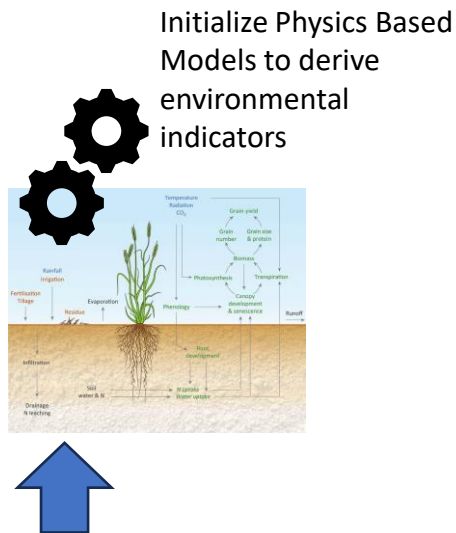
Land Use Change: Sustainable Crop Rotations

- Multi – year space based crop inventory has been harmonized between growing seasons to analyze change
- Field boundary delineation using foundation model imagery (Alpha Earth) and encoder-decoder (Segment Anything), updated annually
- Rotational sequence extracted for 2011 – 2025 and analytical metrics extracted (turbulence, Shannon diversity)
- Can be used to identify rotation sequences associated with carbon sequestration



Identifying Seeding Dates

- Seasonal cycles of vegetation green-up and senescence can be leveraged to calculate metrics of growth stage and trends in seeding practices
- Traditional EO approaches use curve-fitting to calculate metrics; combine with meteorological data to translate EO metrics into practices data
- Machine Learning approach is being tested to evaluate improvements in seeding date estimation



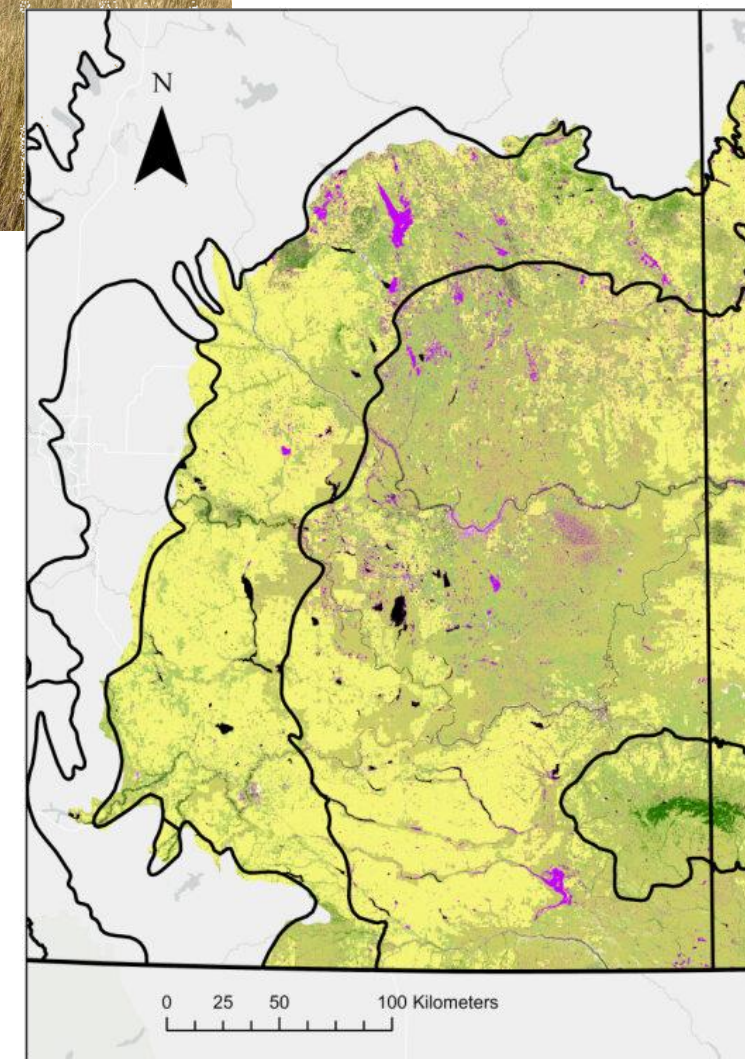
Perennial Agriculture

- Separate native grassland from perennial seeded forage. **This is generally a difficult class to identify from EO**
- Grassland systems show **high temporal and spatial variability** compared to annual crops
- Perennial systems – leverage long term, multi-year, multi-frequency satellite data sets, changes in moisture and soil structure associated with short term and long term perennial cover

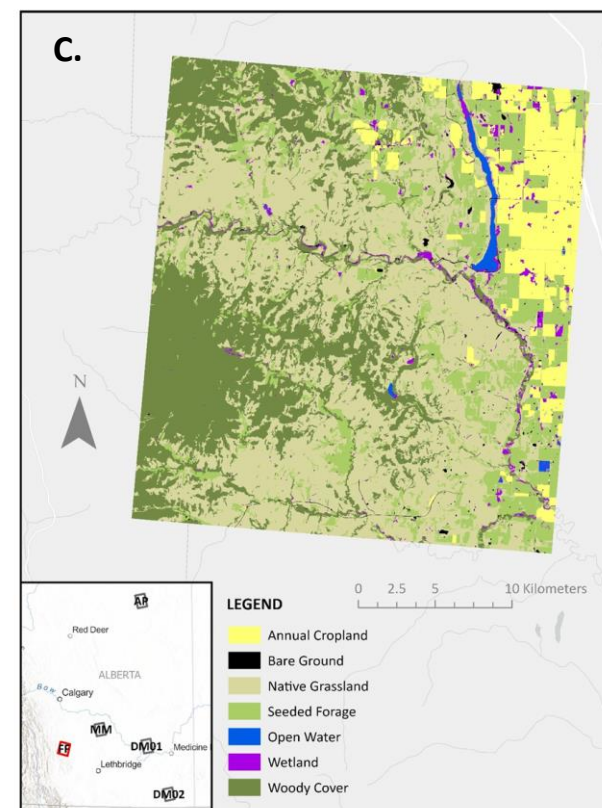
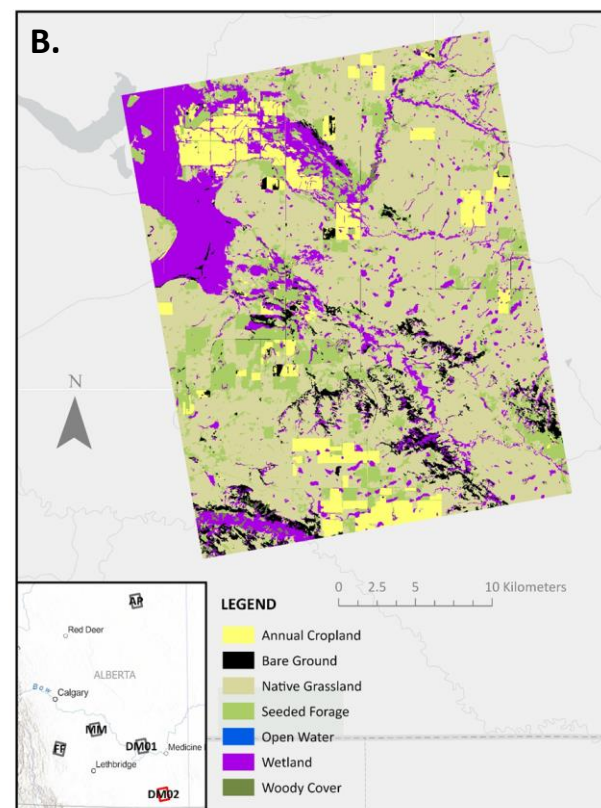
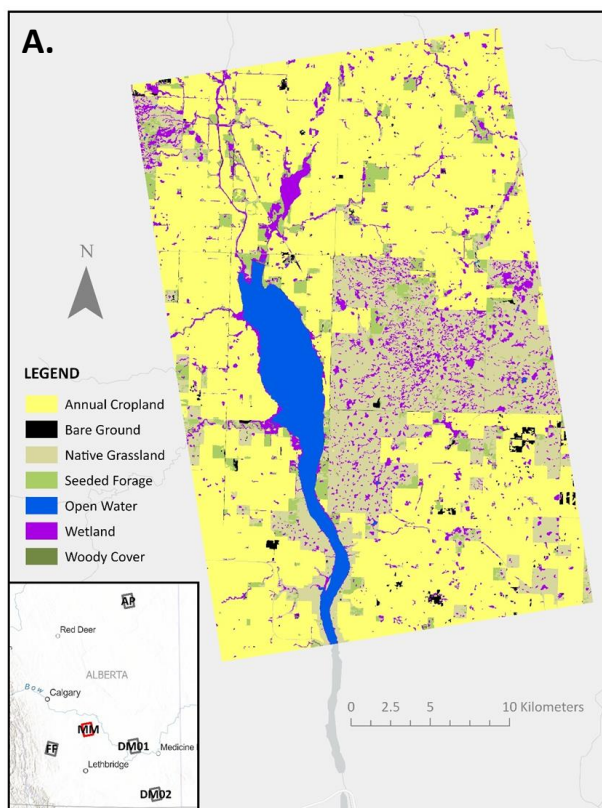


Lindsay, E., D.J. King, A.M. Davidson and B. Daneshfar. 2019. [Canadian prairie rangeland and seeded forage classification using multi-season Landsat 8 and summer Radarsat-2 data](#). *Rangeland Ecology and Management*, 72: 92-102.

Lindsay, E. J., et al. 2026. [Compact polarimetric response of native grassland and seeded forage across a gradient of Southern Alberta Prairie ecoregions](#). *Canadian Journal of Remote Sensing* 52(1).



Creating the National Grassland Inventory



A. Random forest classification for the Alberta Moist Mixed study site:
88.9% Overall Accuracy

B. Random forest classification for the Alberta Dry Mixed study site:
92.6% Overall Accuracy

C. Random forest classification for the Alberta Foothills Fescue study site:
89.1% Overall Accuracy

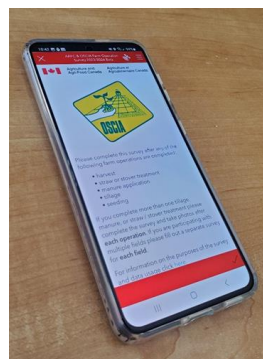
- Ground samples collected from crop insurance, managed government pastures/rangelands and detailed field sampling from Canadian Forage and Grassland Association to identify Native Grassland and Seeded Forage
- Used Sentinel-2 image composites (mean, min, max surface reflectance R, G, NIR) for 3 time periods for three growing seasons (2019, 2020, 2021):
 - Spring (T1) – snowmelt and vegetative growth
 - Mid Summer (T2) – peak biomass and onset of dryness, heavy grazing
 - Late Summer (T3) – vegetation dormant (dry ecosystems)
- Sentinel-1 image composites (mean, min, max backscatter VV, VH, VH/VV) monthly composites for 5 months (May to September) for three growing seasons (2019, 2020, 2021)

Fractional Residue Cover

- U-Net architecture used to build cell phone app to collect and classify residue coverage within fields
- Photos used to train Sentinel-2 model in Google Earth Engine to generate maps or fraction of residue cover
- CNN is able to classify complex imagery (containing small green plants, soils of different colors, cracked soils, stones in photos, different residue types (including corn, soybean, wheat, alfalfa, potatoes) etc.)

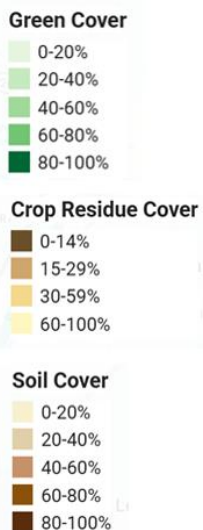
Data collection

- Training / Validation Data
 - +3000 images of crop residue
 - INRS - QC
 - AAFC - ON, MB, NB
 - USGS - Iowa, Delaware



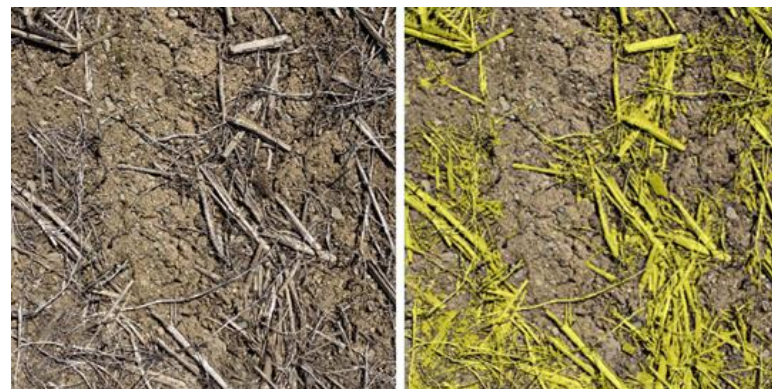
Cell phone app to collect tillage and residue observations

Work by Heather McNairn, Maryam Rahimzad, Saeid Homayouni, Samantha Schultz, Xianfeng Jiao, Omar Gaweesh



EMILI Site - Manitoba
October 1, 2024

EMILI Site - Manitoba
October 8, 2024



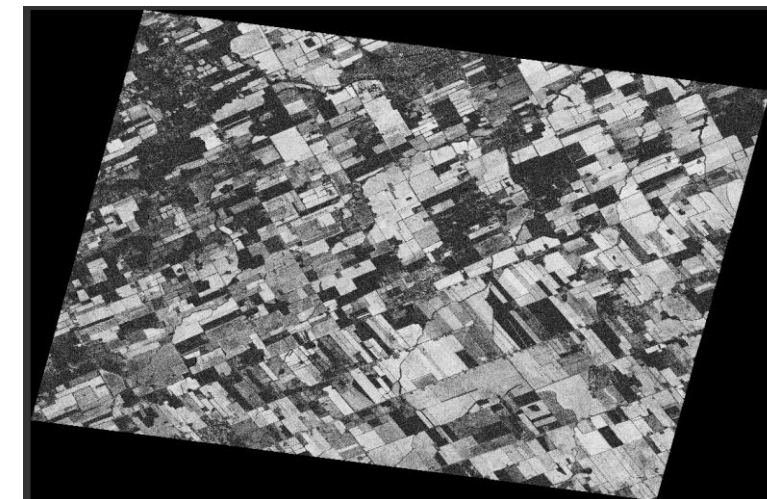
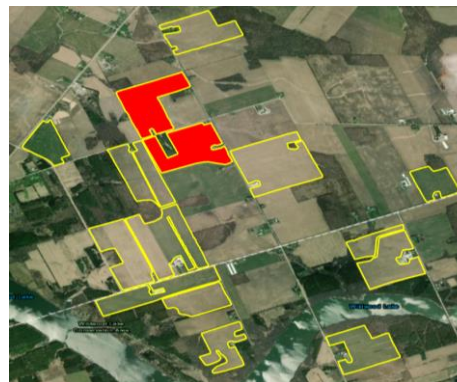
Fractional Tillage Cover

- Synthetic Aperture Radar (SAR) is sensitive to changes in surface roughness associated with soil and canopy disturbance
- Sentinel-1 C-Band SAR has regular acquisition cycle that can be leveraged to calculate changes in coherence (CCD) between image pairs.
- Analysis continues to demonstrate that a drop in coherence is indicative of a tillage event

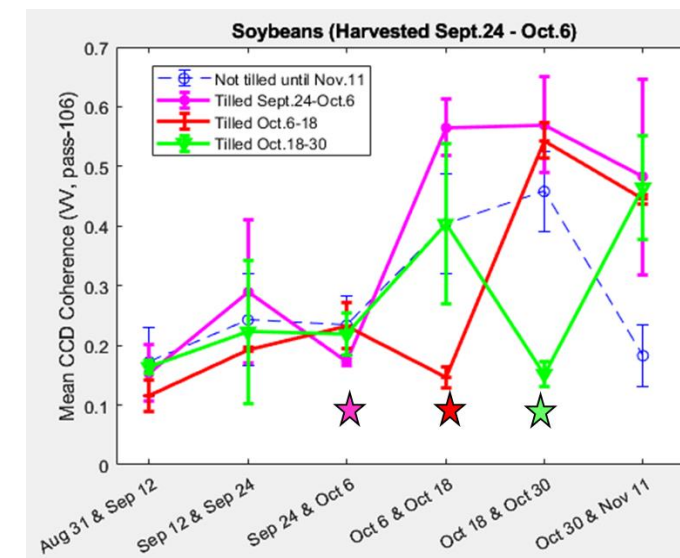
Data Processing and Results

- Validation Data Collected via Survey App
 - +300 field activities (2023-2025)
 - Southern Ontario
 - Eastern Ontario
 - Grosse Isle, Manitoba
- +250 Sentinel-1 SLC images to generate InSAR coherence products
- 9 tillage alerts / site / year (August – December)

Work by Heather McNairn, Xianfeng Jiao, Samantha Schultz, Omar Gaweesh

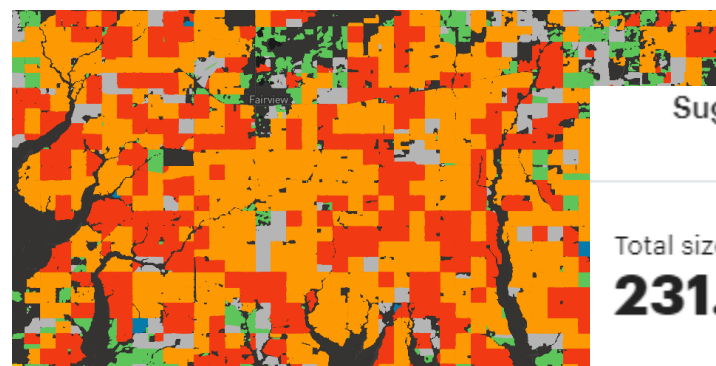
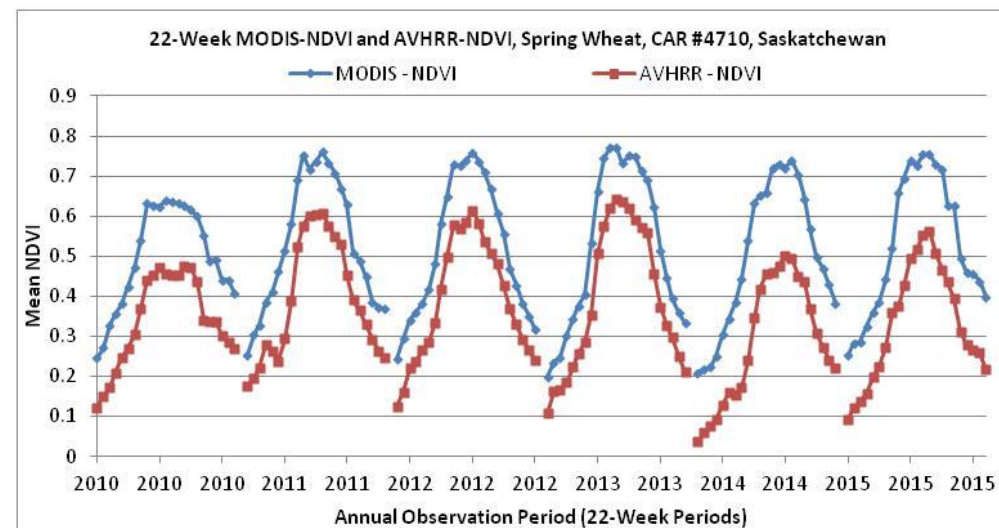


CCD product created using ICEYE SLC data over eastern Ontario test site. Bright areas indicate high coherence (no change); dark areas indicate loss of coherence (change).



Importance of consistent, well calibrated data & models

- Earth observation derived data is widely available, and information derived from it varies considerably in quality & fit for purpose
- Deriving insights that are accurate requires data that are consistent in time and locally calibrated
 - Global data sets rarely provide detail and precision for understanding national or local level processes
 - Data must be processed to consistent standards so that it is comparable over time
- Foundation models need to be locally refined to enable consistent information extraction



Sugarcane data for the year 2020
Canada, all regions

Total size of fields

231.8 ha

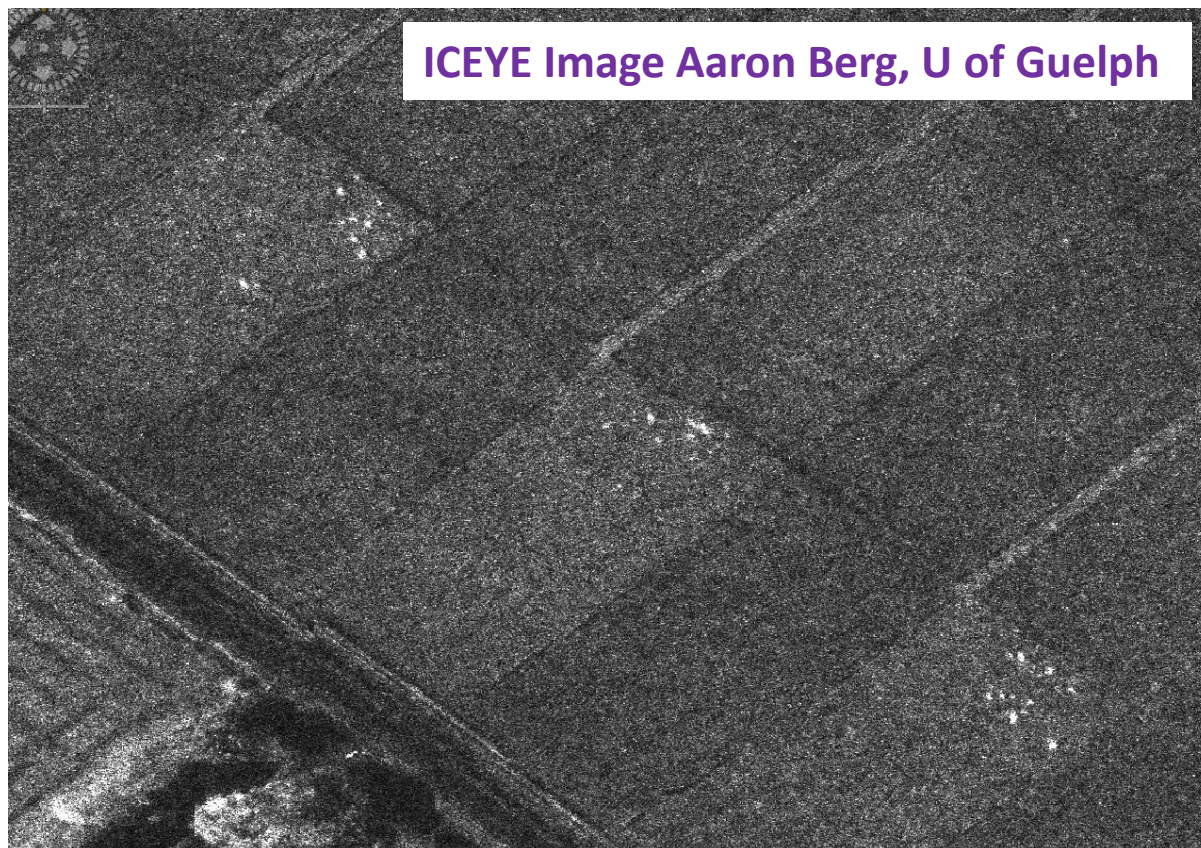
Total number of fields

46

Region ranking

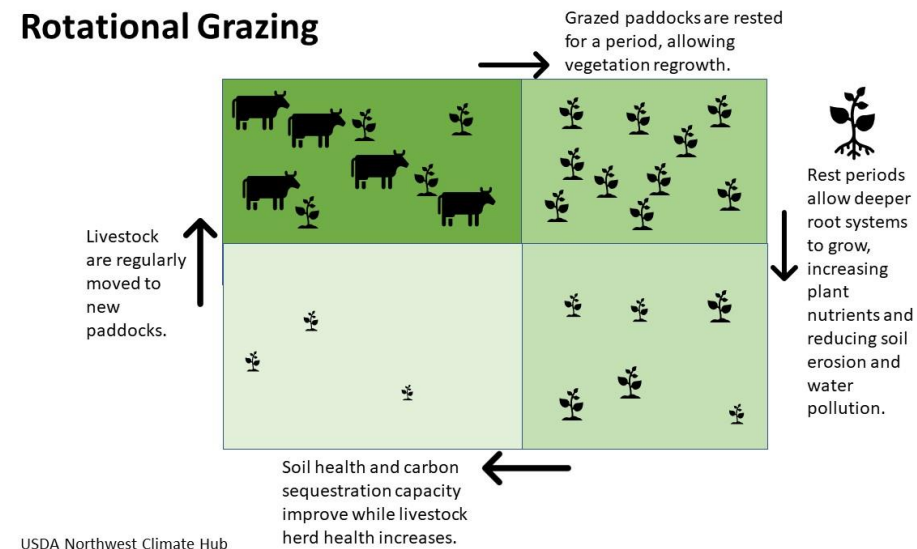
#	Region	Size	Number
1	Ontario	208.4	29
2	Manitoba	11.8	12
3	British Columbia	11.3	4
4	Quebec	0.3	1

What else do we need to measure?



- Continue to push boundaries of what can be measured, and new satellites and new methods of training/validation collection can contribute to this

Rotational Grazing



Can't model impact of improvements in agriculture if we don't know where and when these improvements are occurring

EO isn't the solution to everything; creative solutions (AI & fusing non traditional data sets) are needed to get information we don't yet have spatially

It takes a village.....

- Annual Crop Inventory, Weekly NDVI, Crop Rotations are all published online and are updated annually; Grassland inventory will be published online for Prairies in coming year
- Seeding dates (version 1) available internally
- Tillage/Residue work will be further validated, scaled to national mapping
- Other data sets: crop yield, biomass, soil moisture, evapotranspiration, land use change, disease/pest risks

