

Lecture 6:

Applications of SAR for Agriculture

What Applications?

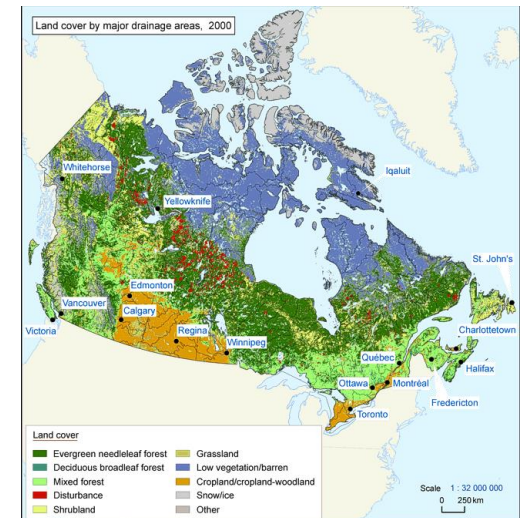
- Crop type
- Land use change
- Crop condition
- Leaf Area Index and biomass
- Crop phenology
- Soil moisture



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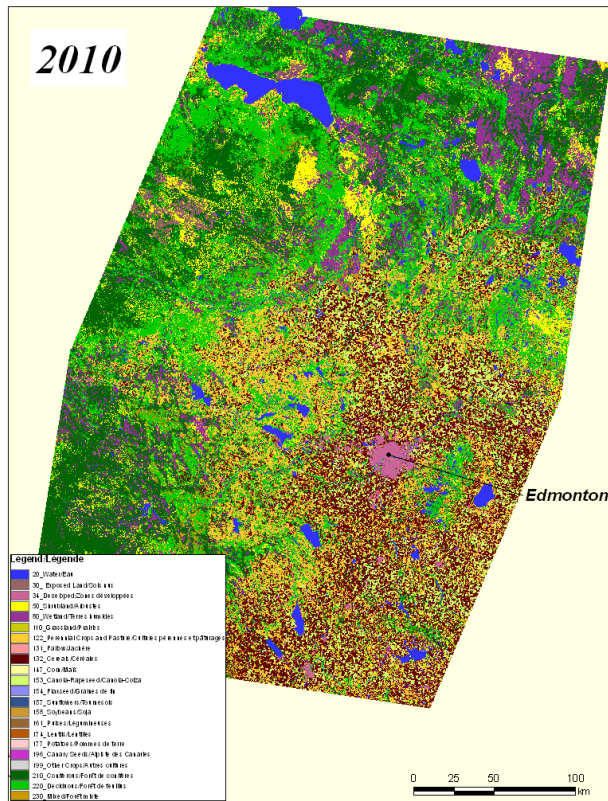
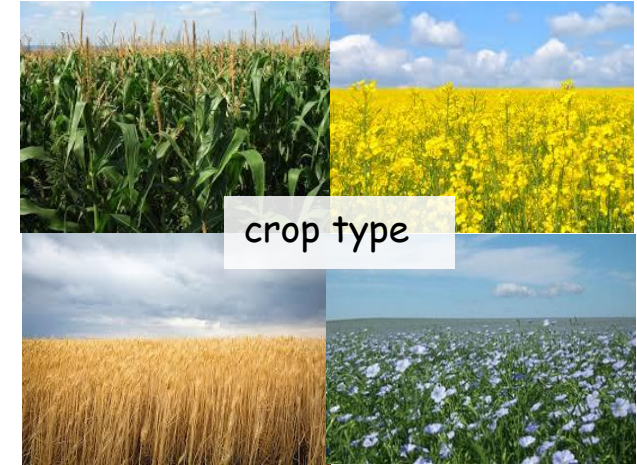


Source(s): Statistics Canada, Environment Accounts and Statistics Division.

Latifovic, R., Z.-L. Zhu, J. Chiriac, C. Giri, and I. Olthoff. 2004. "Land cover mapping of North and Central America - Global Land Cover 2000." in Remote Sensing of Environment, 89, pp 116-127.

Crop Identification

- traditionally accomplished using optical data
- when available at the right time in the growing season, optical data does very well
- but....



Optical + Single Frequency SAR (Edmonton, Canada)

Landsat 5:

2010-06-20

RADARSAT-2:

2010-05-28

2010-06-21

2010-07-15

2010-08-08

Overall accuracy

- with Landsat only (< 70%)
- including ScanSAR Narrow (VV, VH) data (89.1%)

Crop Identification

Rule Number 1: Make sure you collect the right type of data

Polarization:

- #1: **HV or VH**. The cross-polarization responds to volume scattering in the crop canopy and the amount of volume scattering is crop-type specific
- #2: **VV**. The vertically-oriented waves couple with vertical structures which either scatter or attenuate signal.
- Last: HH-polarization: usually the least helpful but can assist with separating some crops (like forages)
- Bottom line: VV-VH is the best dual polarization combination

VH/HV + VV

Crop Identification

Frequency

- more difficult to determine as we want some penetration into the canopy, but not too much
- difficult because penetration depends on canopy volume and this changes for different crops and different growth stages
- ideally a multi-frequency approach (X+C, C+L, X+C+L), which provides excellent results

Multi-temporal

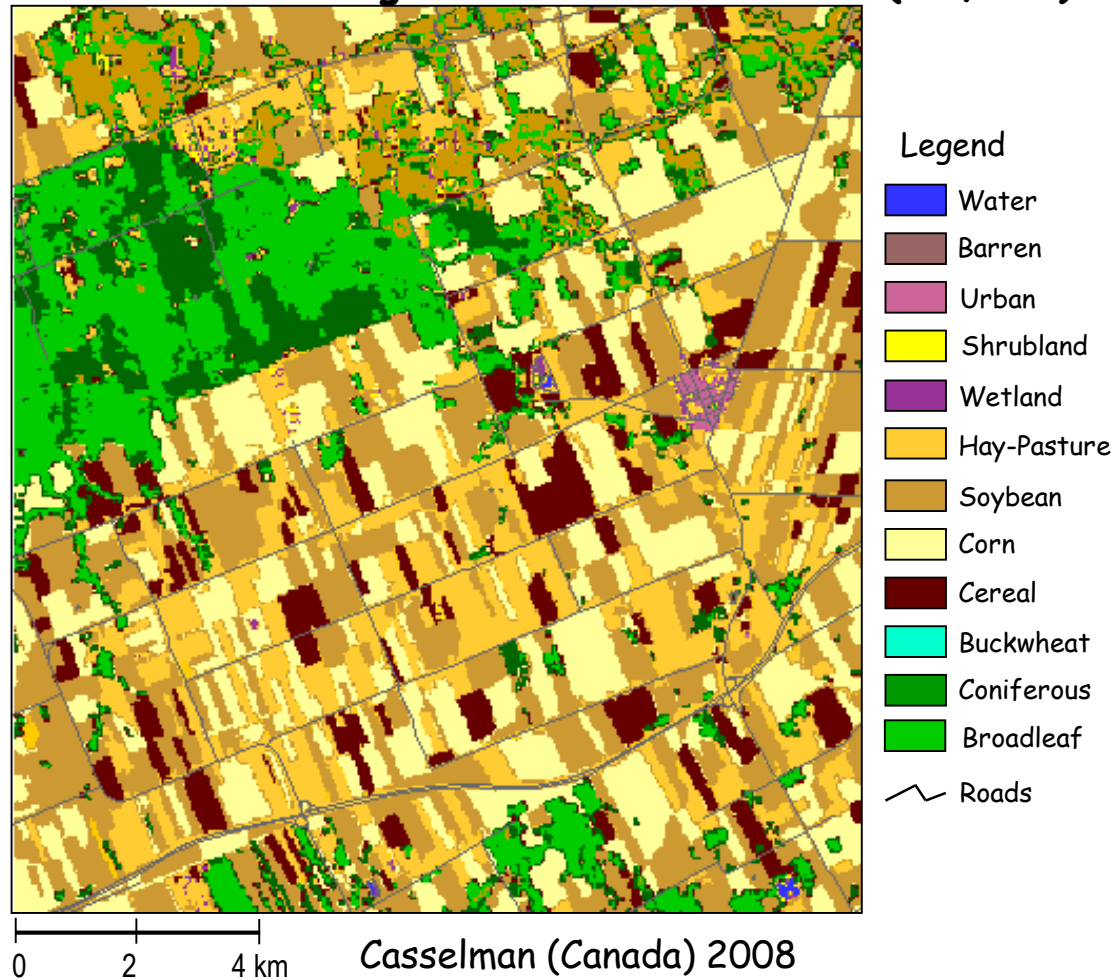
- as with optical approaches, multi-temporal data are critical
- crops may look very similar to SAR at one growth stage, but very different at another
- generally, the single best time for crop separation is when crops are in their **seed development/reproductive** stage. An acquisition at this time is important because this is when crop structure changes the most



Single Frequency Multi-polarization SAR

In general, classification is best with higher frequencies (shorter wavelengths) as this provides best opportunity for multiple scattering within the canopy

Classification using 6-date TerraSAR-X (VV, VH)



X-Band provides excellent classification results

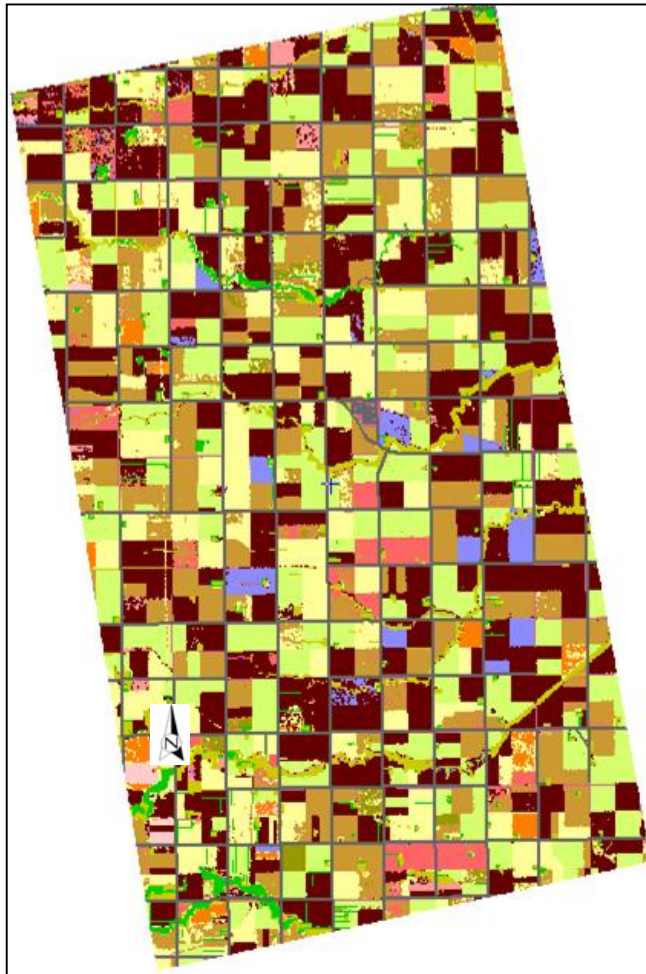
Still, best option is multi-frequency

X-Band = 84.9% (6 images)





















C-Band = 75.4% (4 images)

X + C = 87.3%

Integrating Multiple Frequencies



Legend

	Soybean		Water
	Corn		Barren
	Cereal		Urban
	Canola		Shrub land
	Soybean		Wetland
	Field peas		Coniferous
	Beans		Broadleaf
	Sunflower		Roads
	Flaxseed		
	Potato		
	Fallow		
	Hay-Pasture		

X-, C- and L- Band: Carman 2009

CFIA (2006) (corn, soybean, wheat, forage/hay): **C- and L-Band 82.9%**

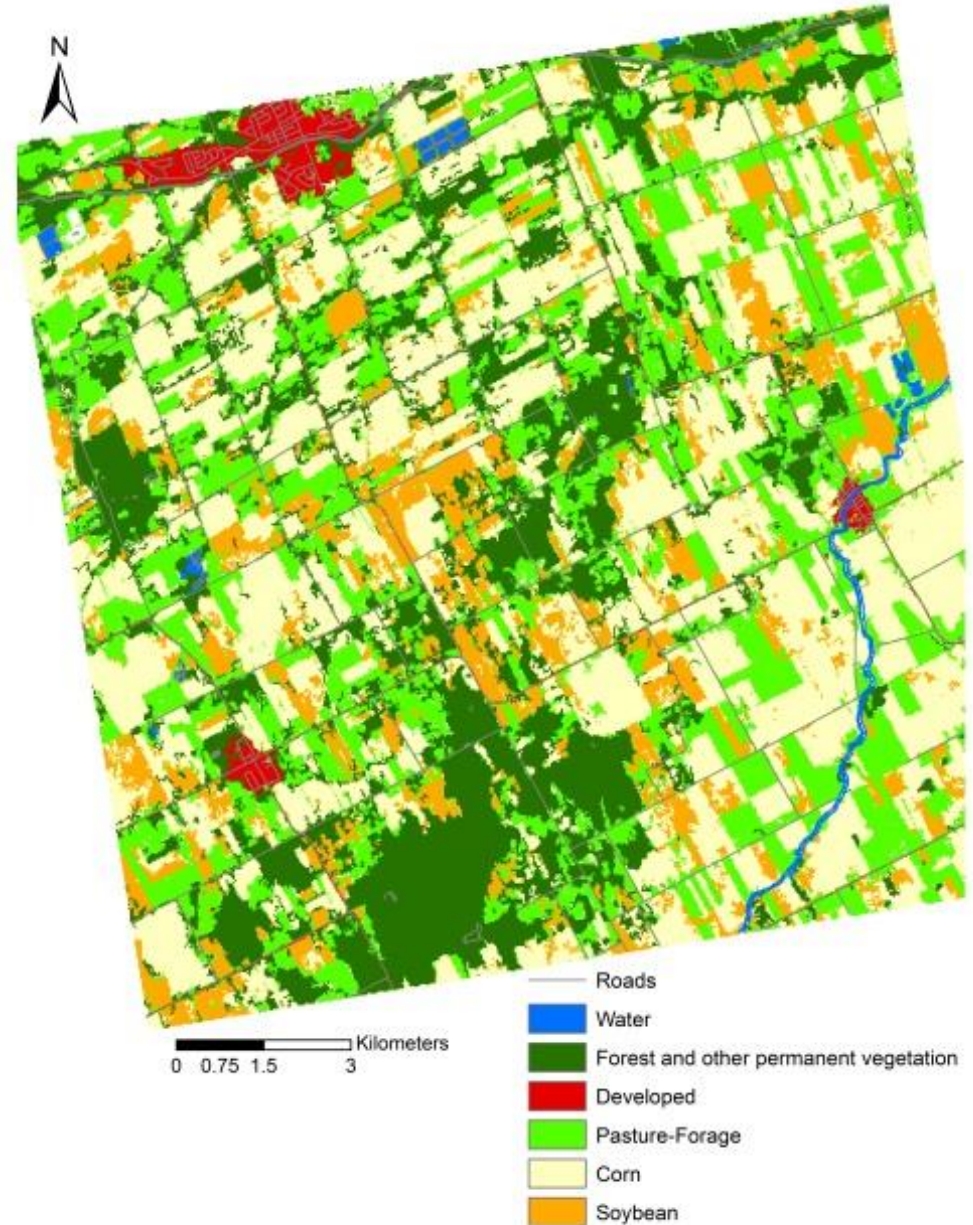
Casselman (2008) (corn, soybean, wheat, forage/hay): **X- and C-Band 87.3%**

Carman (2009) (canola, flax, beans, corn, cereals): **X-, C- and L-Band 91.4%**

Early Season Crop Identification

End of season TerraSAR-X crop
classification: Ottawa 2012
Overall accuracy: **97.2%**

Early season: Corn can be
identified at V6 or 6th leaf collar
stage (about 6 weeks after
planting)



What About Fully Polarimetric?

- some sensors offer fully polarimetric modes
- these modes allow users to synthesize many radar parameters in addition to HH, HV/VH and VV
- provide better accuracies than dual-polarizations

RADARSAT-2 Indian Head 2009

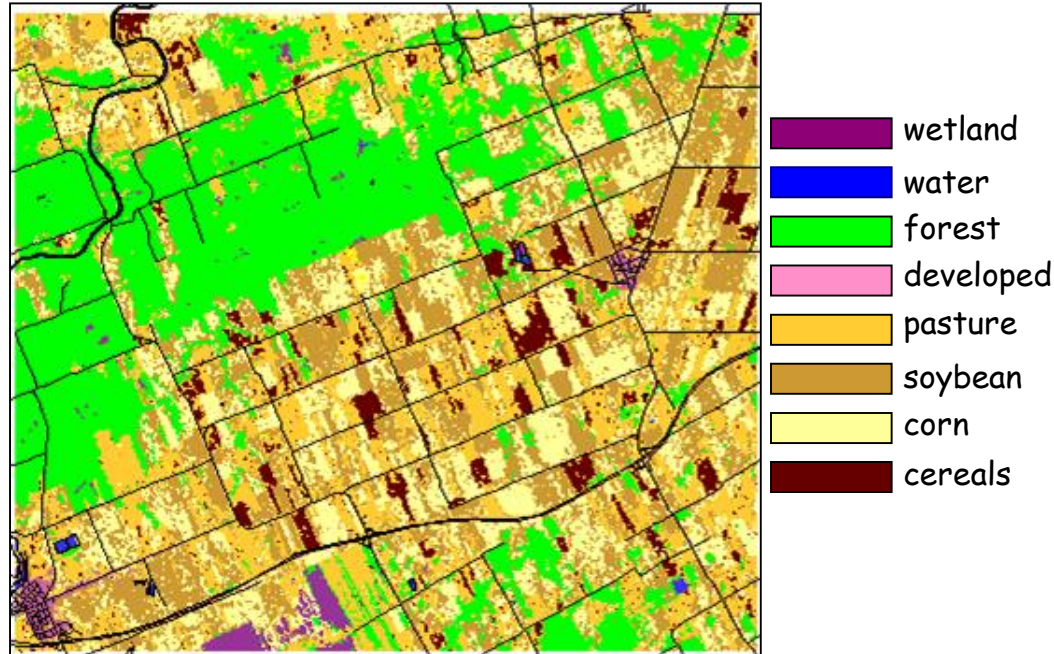
Producer's accuracies

Class	Linear intensity	Cloude decomposition
Pasture/forage	77.8	81.2
Fallow	40.7	73.1
Canola	95.3	95.4
Flaxseed	23.1	41.6
Lentils	80.9	95.3
Field peas	97.2	97.1
Cereals	97.7	97.8
Overall	87.2	89.0

RADARSAT-2 (June 15, July 6, August 9, September 2): Casselman 2008

Dates of Data Acquisition	User's Accuracy				Producer's Accuracy				Overall
	Pasture	Soy	Corn	Wheat	Pasture	Soy	Corn	Wheat	
Cloude-Pottier (E, A, α)	77.5	85.2	86.4	97.6	80.6	87.4	86.8	84.9	85.8
Freeman-Durden	85.1	93.7	89.9	93.3	85.7	92.4	94.5	83.4	90.9
Linear Polarizations (HH, HV, VV, VH)	60.4	81.8	73.6	83.8	66.2	82.9	76.1	64.0	75.4

...And Compact Polarimetry?

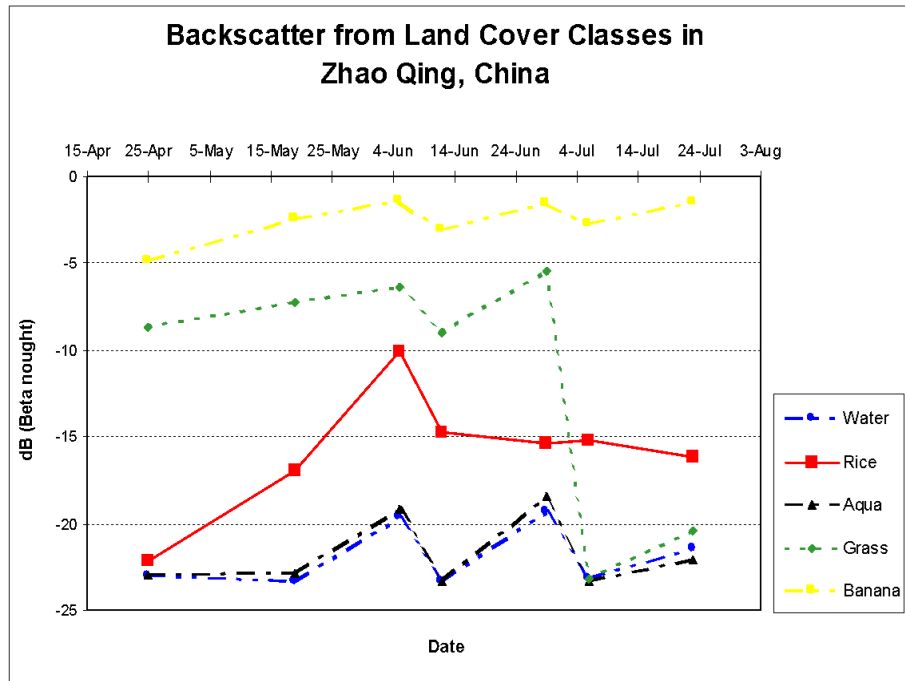


Classification generated from mDelta
mDelta: **single**, **double**, **volume**
84.3% overall accuracy

- compact Polarimetry lies in world between multi-polarization and full polarimetry
- CP can be implemented for wide swaths and is thus of significant interest for regional and national monitoring
- RADARSAT Constellation Mission (RCM) and SAOCOM-1A also have CP capabilities.

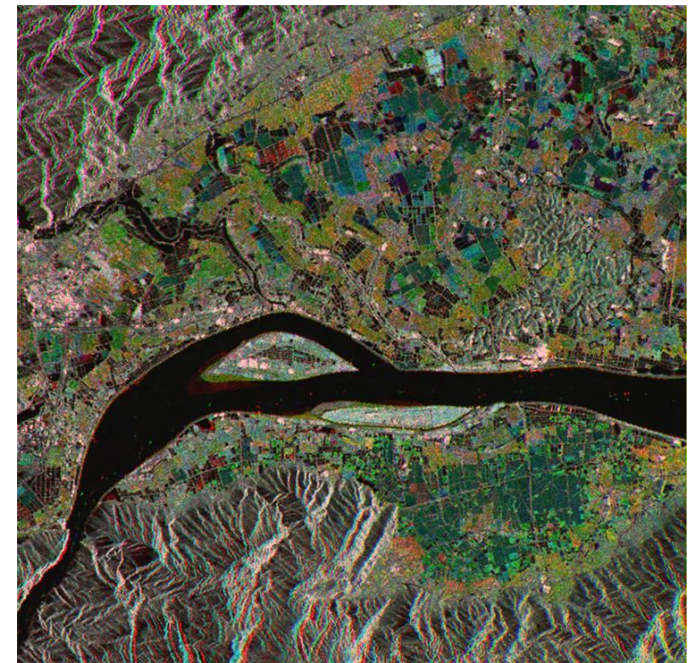
- CP parameters outperformed dual polarizations (results from 2008 and 2010)
 - small improvements in overall accuracies (1.5 to 2.7%)
 - larger improvements in individual dates (up to 21.5%)
 - large increase in accuracy for wheat (10.2% (producer's) to 11.4 (user's) for 2010)
 - smaller gains in other classes (<3%)

SAR Was “Born” to Monitor Rice

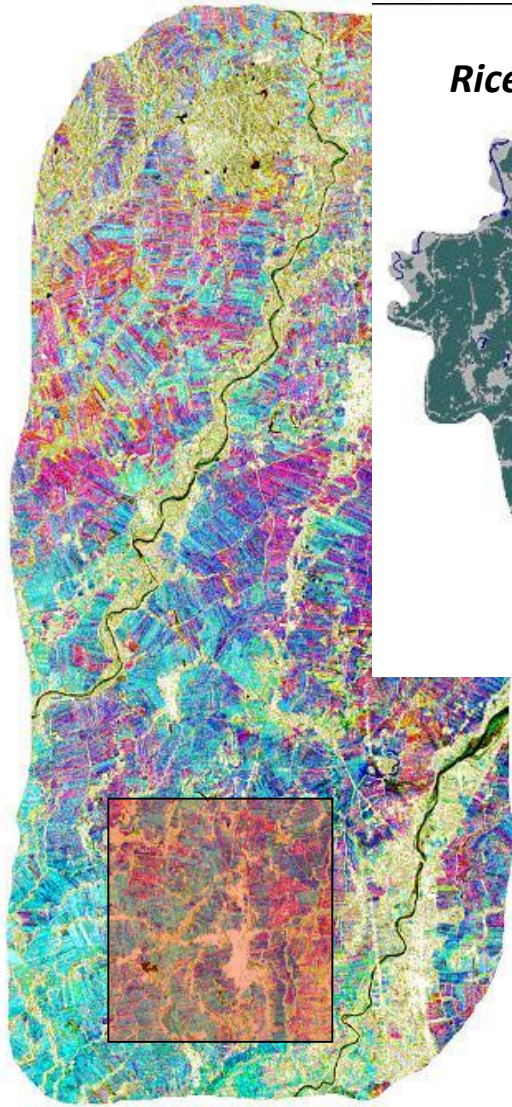


- 12 dB change in **rice** areas from beginning of growing season to peak growing season
- **Banana** target consistently bright
- **Grass** provided constant return of -5 to -8 dB, until flooded mid-season
- **Water** and aquaculture consistently dark between -19 and -24 dB

Double-bounce scattering for flooded rice paddies

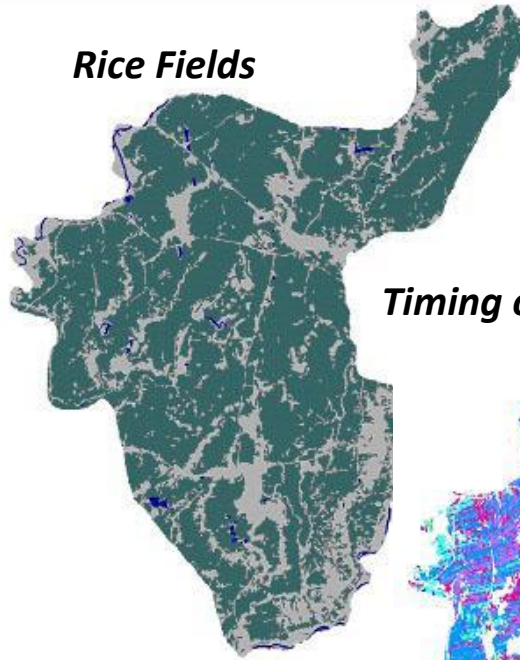


Rice Monitoring: The Philippines

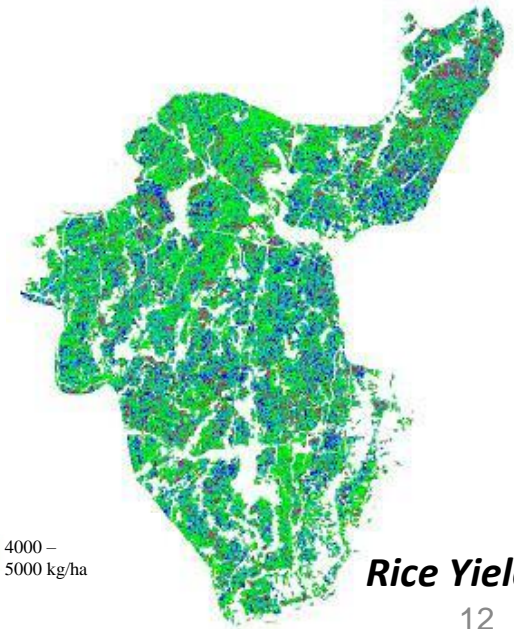
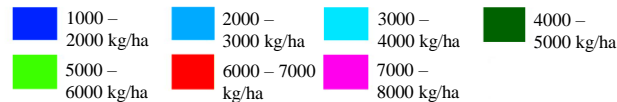
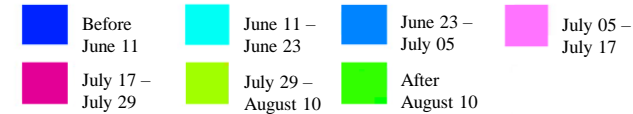
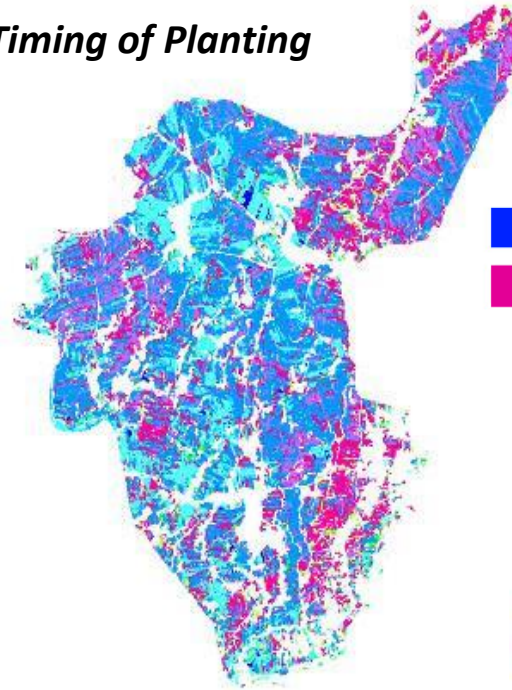


Multi-date RADARSAT-1
Santo Domingo
The Philippines (2001)

Rice Fields



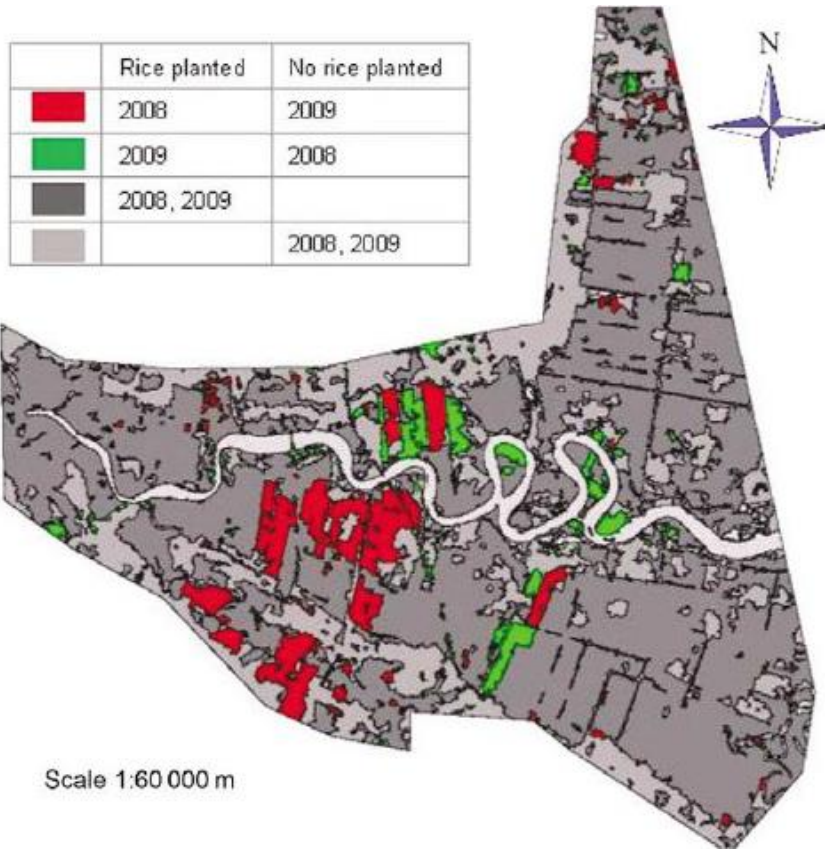
Timing of Planting



Rice Yields

Land Use Change

Rice Monitoring with TerraSAR-X Xuwen, China



- Almost 15 000 ha of rice was under cultivation in the Xuwen study site
- 10% of this land experienced change (rice to non-rice or non-rice to rice)
- Changes driven by market demand as prices of other cash crops (peanut and watermelon) were high spurring farmers to drain rice paddies to plant cash crops.

Red: Paddies planted in rice in 2008 but not 2009

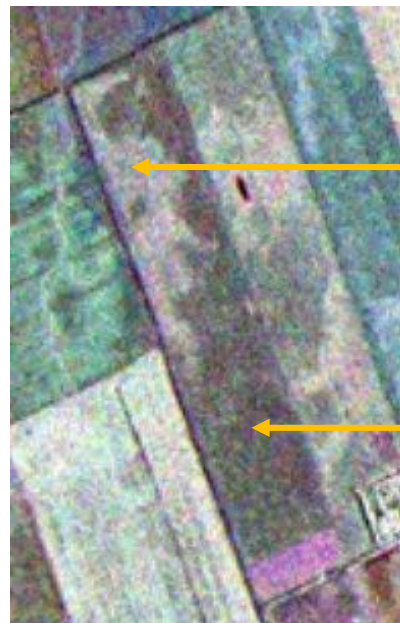
Green: planted in rice in 2009 but not 2008

Dark grey: planted in rice both years

Light grey: non-rice fields

Crop Condition

- SAR responds to changes in structure and changes in moisture
- this can be exploited to inform on condition of crops
- traditionally done using optical data, including optical indices
- optically, cloud-cover is dealt with by integrating data in time to create 7- or 10-day mosaics
- **Question** : Can SARs be used to provide information on crop condition to fill gaps and provide crop condition information at field scales?



Barley

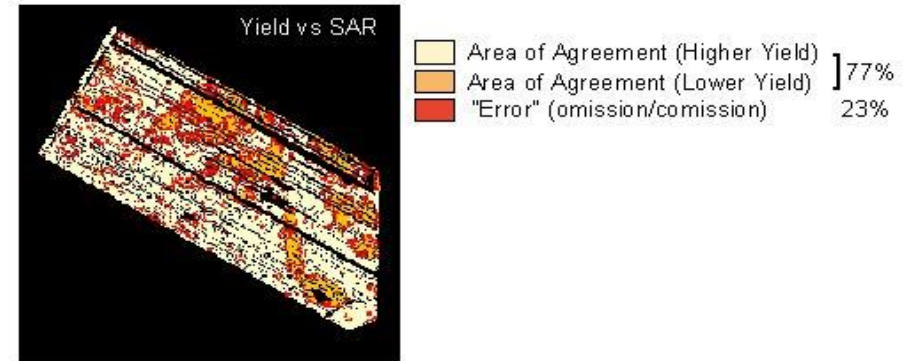
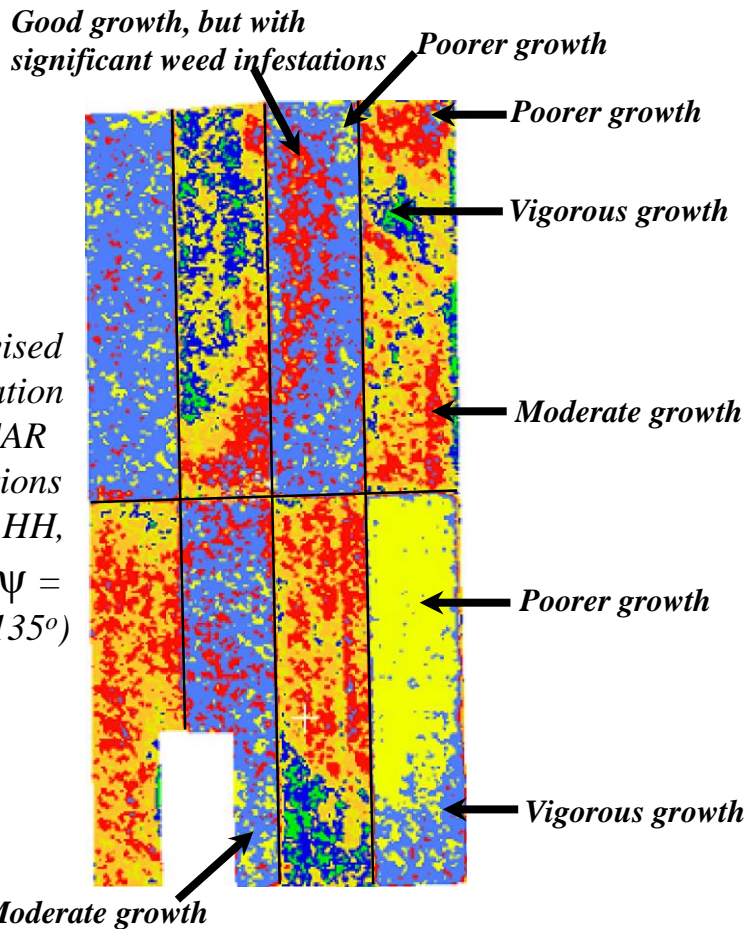
Poor growth affected by N losses due to poor soil drainage

Barley

Healthy growth

Airborne SAR (VV, VH, HH)
June 28, 2000
Indian Head, SK

Crop Condition - SAR Classification using Linear and Circular Polarizations

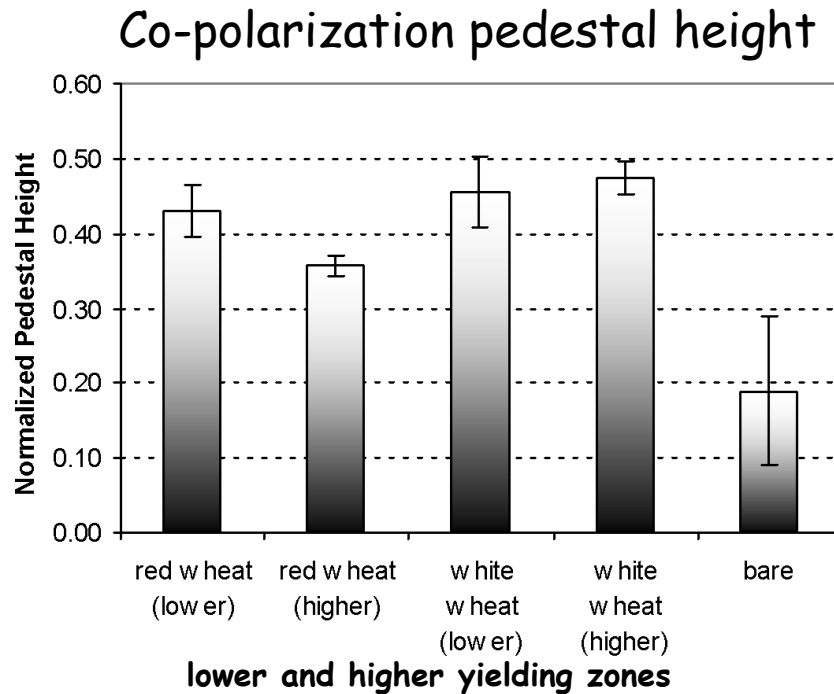


A classified image of a wheat fields was generated using HH, VV and HV polarizations from CV-580 data acquired over Clinton, Ontario (Canada) on June 30, 1999.

These classes were then compared to classes generated from crop yield monitor data (bushels per acre).

A good relationship was established between regions of high and low yield and radar response.

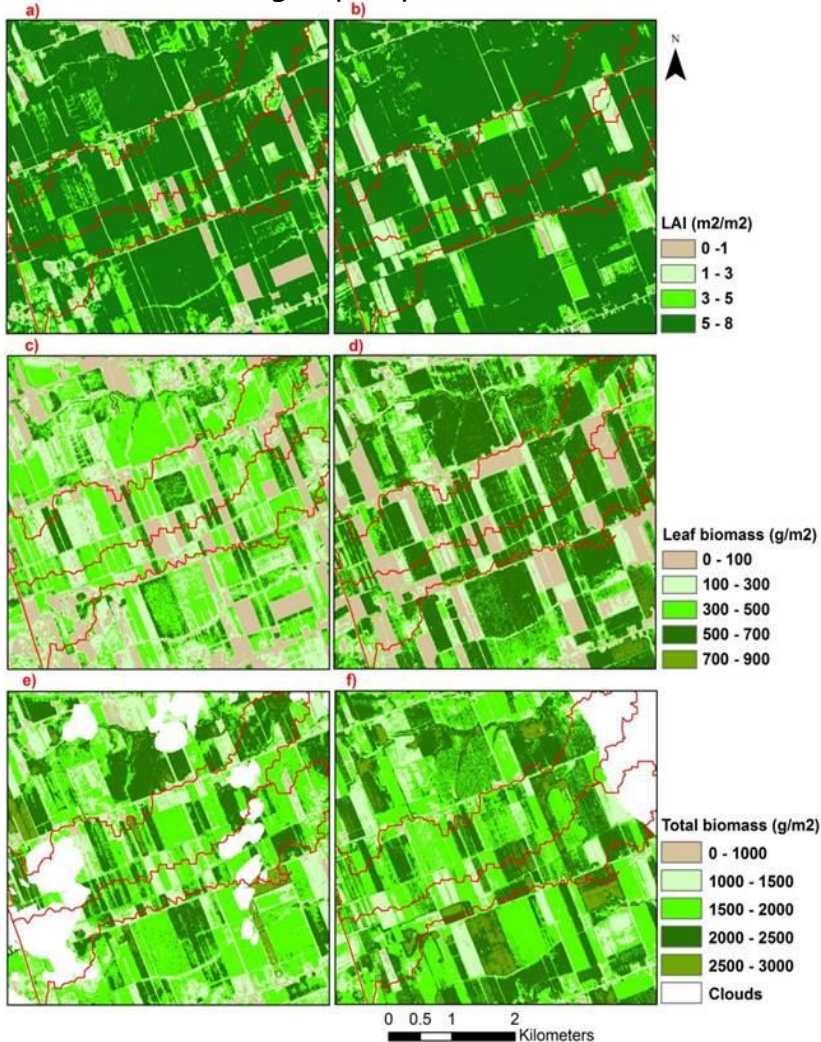
Crop Condition - Pedestal Height



- co-polarization pedestal height is larger for the cropped (wheat) fields relative to the bare field
- the low pedestal height for the bare field is typical of surface scatterers where the degree of polarization is high

Crop Condition and Productivity

Corn and Soybean Productivity (LAI and Biomass)
Using RapidEye Satellite



2012 (very dry year)

2013 (very wet year)

- Leaf Area Index and biomass are strong indicators of productivity and can be linked through process models to crop yield
- these indicators can be assimilated into crop growth models to improve model estimates (of yield, biomass etc.). However, operationally, data must be delivered consistently especially in the rapid early stages of crop growth
- there is a strong statistical relationship between backscatter and LAI/biomass
- **Note:** SAR parameters affected by volume scattering are, by far, most sensitive to crop condition:
 - HV or VH intensity (backscatter)
 - volume scattering components of SAR decompositions
 - indicators of unpolarized and random scattering (such as entropy)

How Are LAI and Biomass Estimated from SAR?

- several modelling approaches, each with advantages and disadvantages
 - empirical
 - semi-empirical
 - physical

SAR modelling with Water Cloud Model (Semi-Empirical)

$$\sigma^0 = AL^E \cos \theta (1 - \exp(-2BL / \cos \theta)) + \sigma_{soil}^0 \exp(-2BL / \cos \theta)$$

Total backscattered by the whole canopy (σ^0) at incidence angle (θ)

$$\sigma_{veg}^0 = AL^E \cos \theta (1 - \tau^2)$$

$$\tau^2 = \exp(-2BL / \cos \theta)$$

Vegetation component

$$\sigma_{soil}^0 = C + DM_s$$

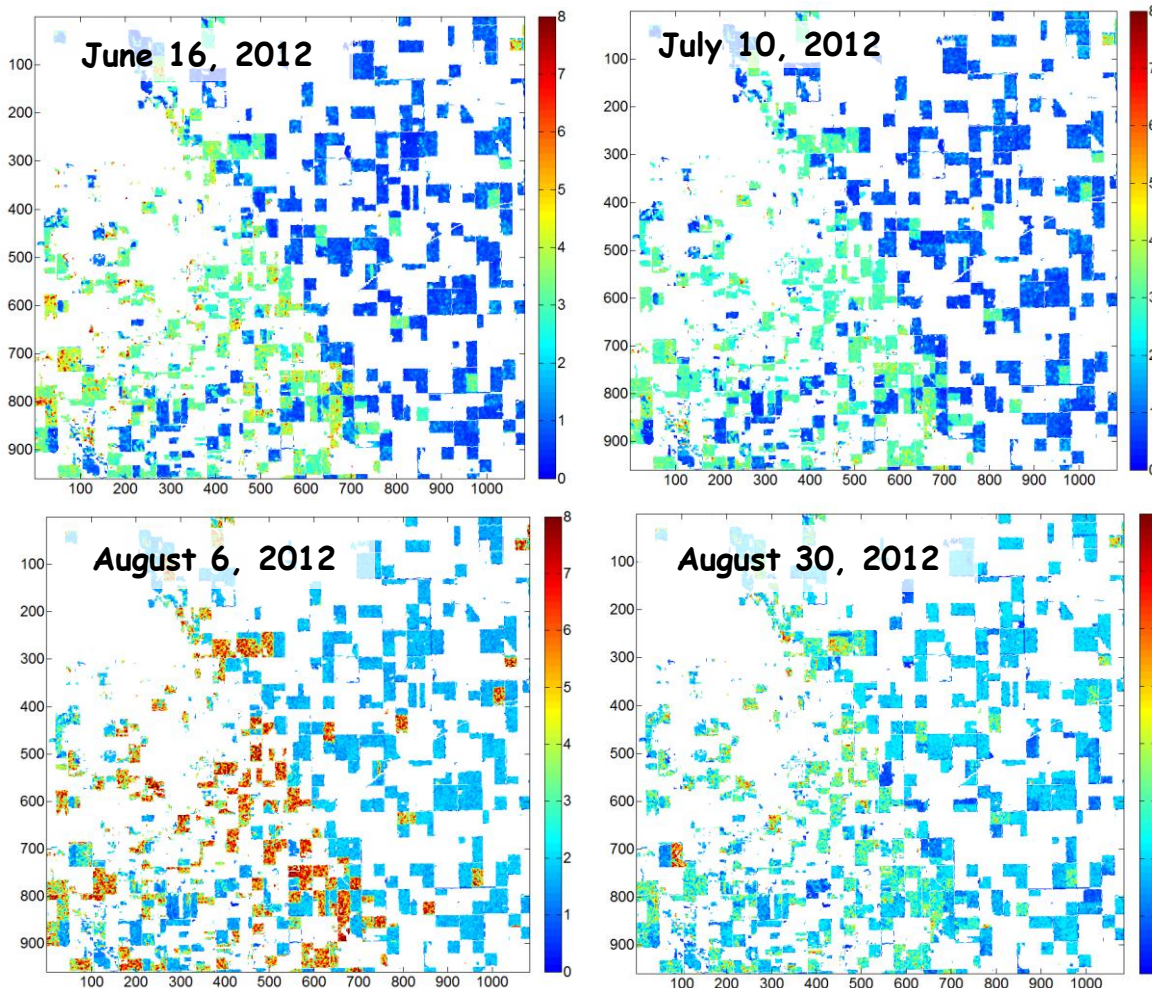
Soil component

τ^2 is the two-way attenuation through the canopy layer

L is the LAI or biomass (expressed in m^2/m^2 or g/m^2)

A,B,C,D and E are model coefficients defined by experimental data (A,B, E depend on canopy type)

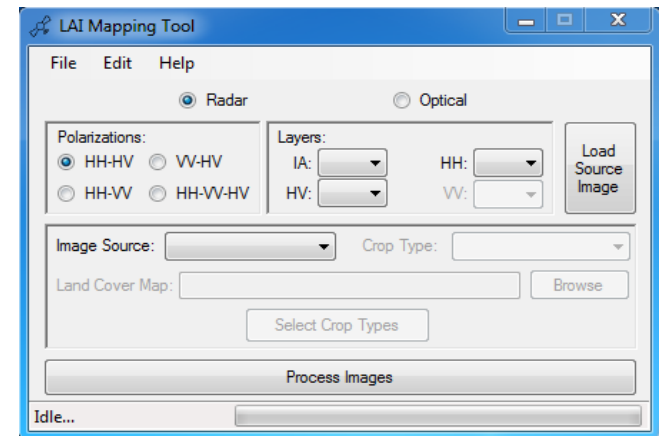
Leaf Area Index from RADARSAT-2



Manitoba, 2012

LAI and biomass estimates for corn, soybeans and wheat

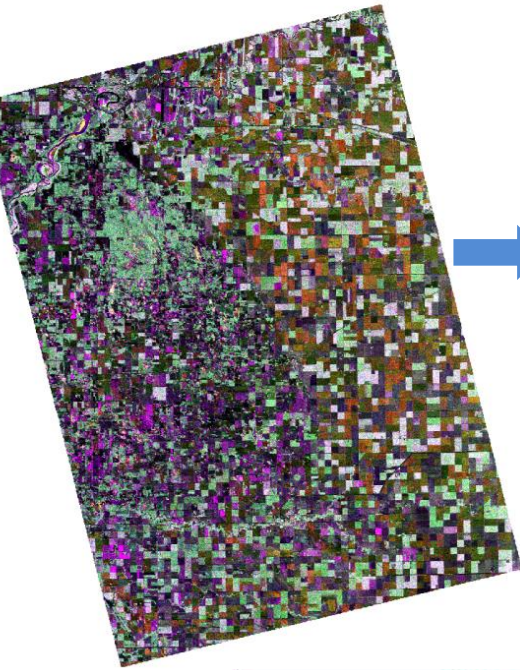
Accuracies with C- and L-band similar (or better than) accuracies using optical data



	R		
Corn HH-HV	0.84	0.65	0.83
Corn VV-HV	0.75	0.62	0.81
Soybeans HH-HV	0.64	0.44	0.80
Soybeans VV-HV	0.63	0.44	0.80

Estimating Crop Biomass from RADARSAT-2

June 27, RADARSAT-2



LAI Mapping Tool

File Edit Help

☒ Radar ☐ Optical

Polarizations:
☒ HH-HV ☐ WV-HV
☐ HH-WV ☐ HH-WV-HV

Layers:
IA: HH:
HV: WV:

Load Source Image

Image Source: Crop Type:

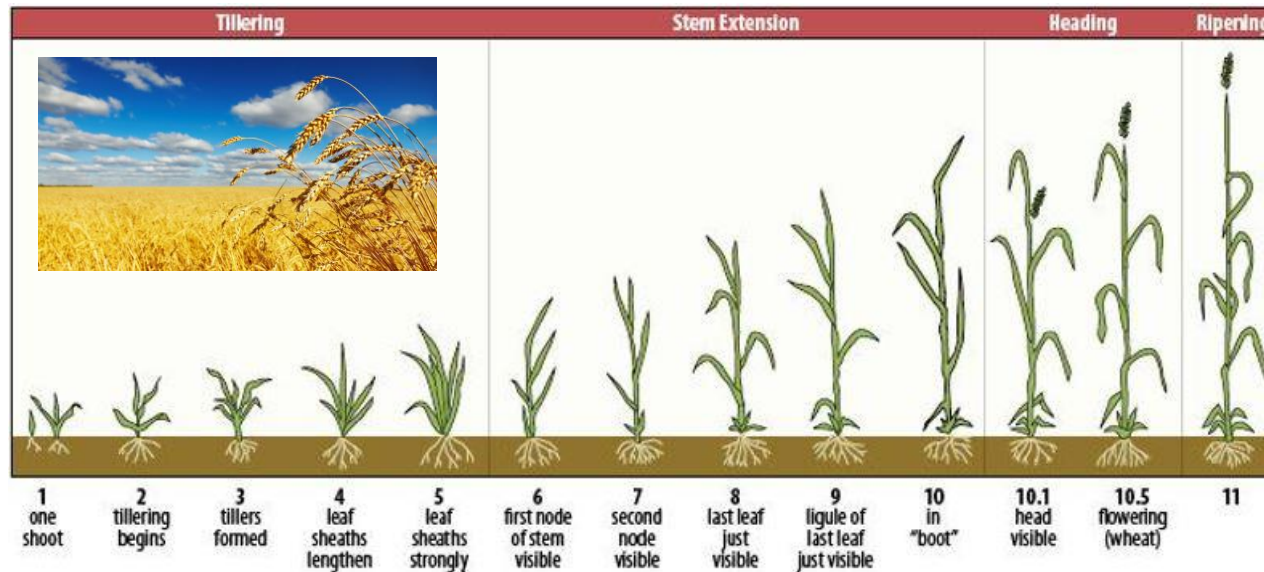
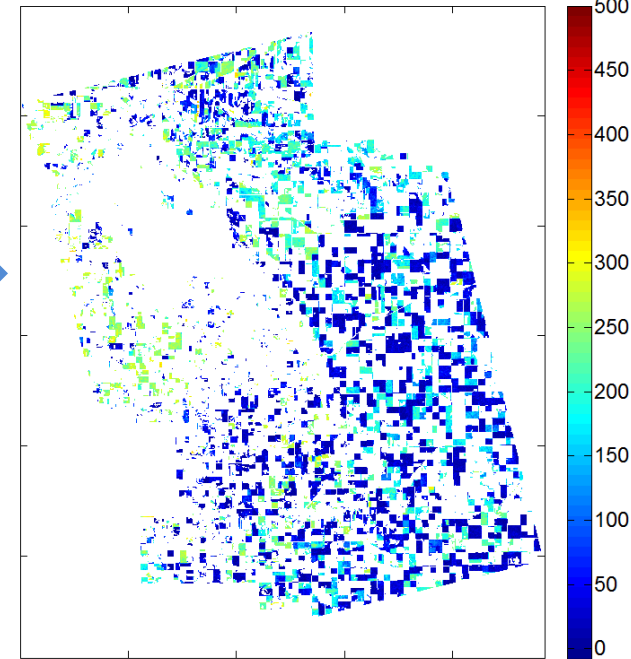
Land Cover Map: Browse

Select Crop Types

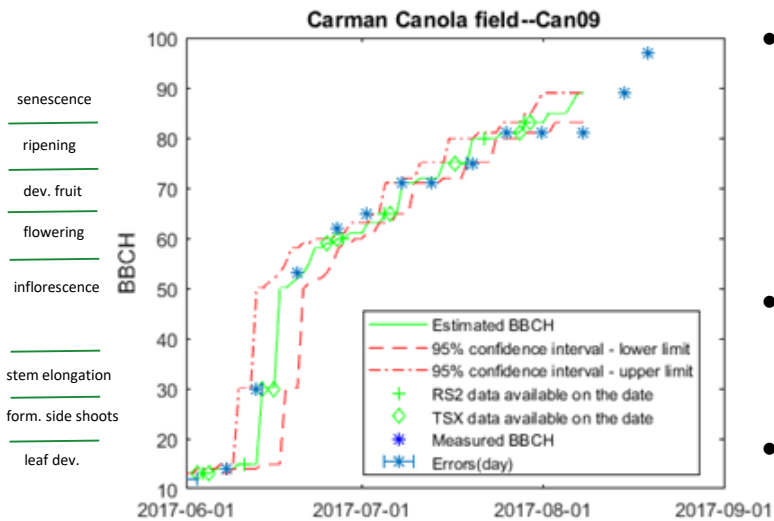
Process Images

Idle...

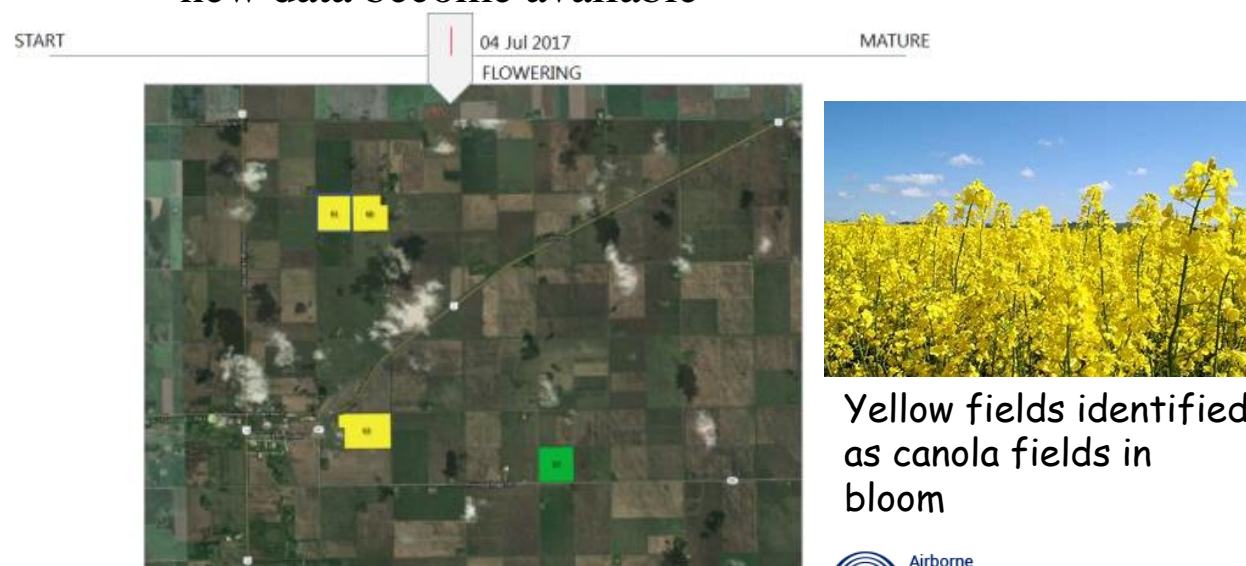
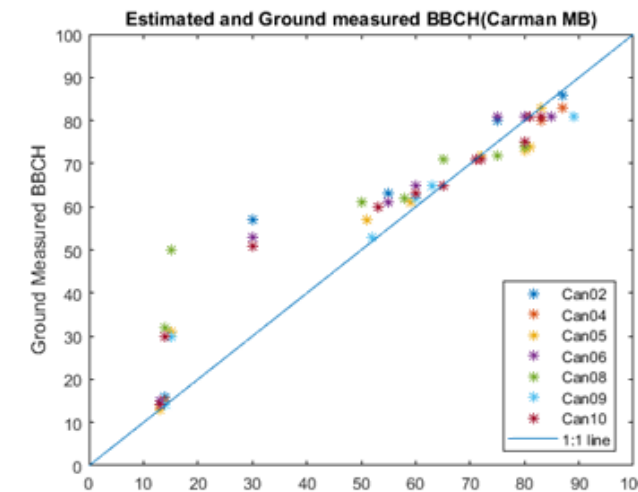
June 27, Biomass



Forecasting Crop Phenology using Machine Learning



- AAFC collaborated with A.U.G. Signals who developed a machine learning algorithm to identify and forecast crop growth stage (BBCH scale), on a daily time step
- Input data are RADARSAT-2 and TerraSAR-X imagery
- The machine learning algorithm updates existing estimates of growth stages and improves forecasts as new data become available



Airborne
Underwater
Geophysical
Signals

Methods to Estimate Soil Moisture

Empirical models

- simplest approach and models are easy to invert
- requires extensive field data and statistical models are usually not robust

Change detection

- easy to apply
- assumes that soil moisture changes over time but that roughness changes are small
- relies on good relative calibration and images must all be acquired using the exact same radar configuration (only moisture changes)
- provides only relative changes, unless change is calibrated with ground data

Semi-empirical models (such as Oh or Dubois models)

- more robust than empirical, but coefficients may not always be valid under new circumstances
- have specific ranges of validity upon which models were developed
- relatively easy to invert

Physical scattering models (such as the Integral Equation Model)

- model scattering behaviour
- also have a range of validity
- complex to invert

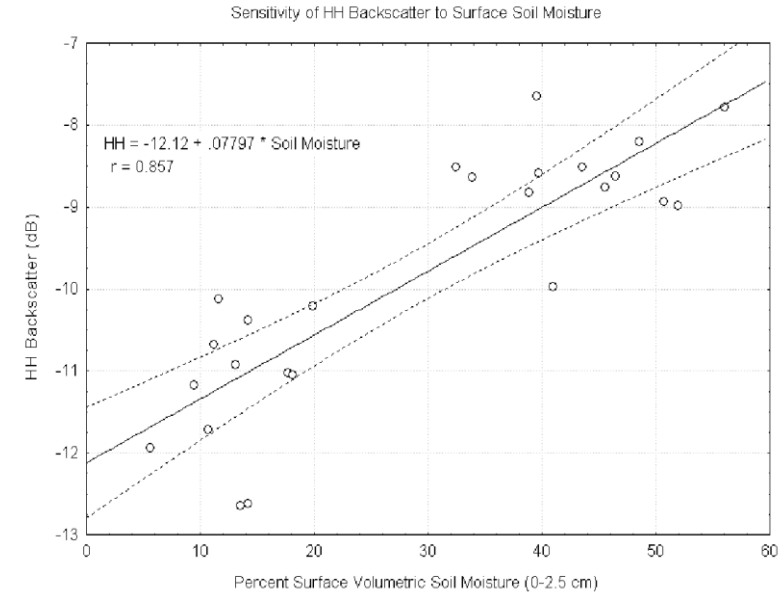
How Do I Start?



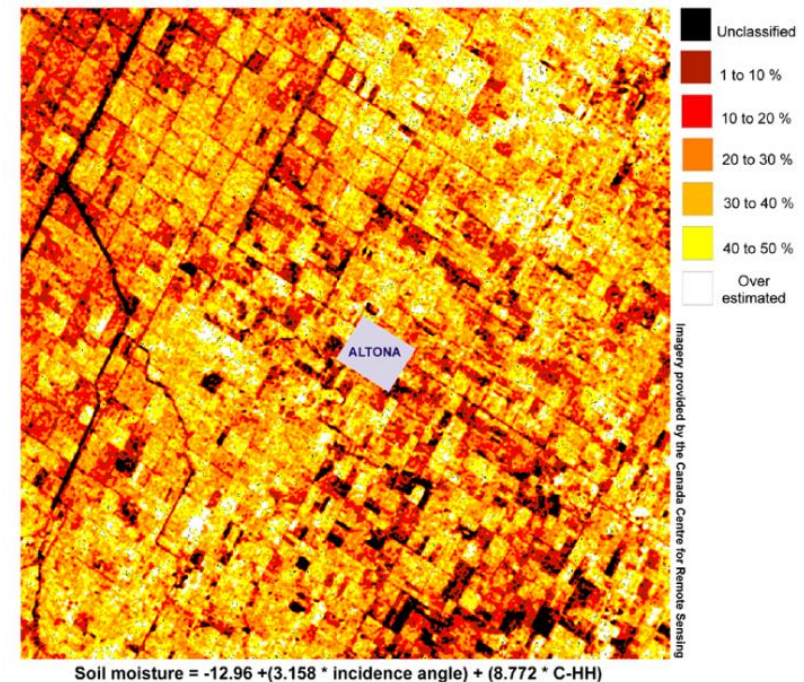
Rule Number 1: Make sure you collect the right type of data

- **Frequency**
 - longer wavelengths are preferred
 - greater penetration
 - reduces roughness effects
- **Polarization**
 - a polarization that responds to surface scatter (HH or VV) is preferred
 - semi-empirical and physical models will require specific polarizations
- **Incident angles**
 - empirical approaches: stick to steep angles where roughness effects are reduced
 - semi-empirical or physically modelling: angle is parameterized in model so choice is less critical
 - change detection: very important to stick with same repeat angle

Empirical Models



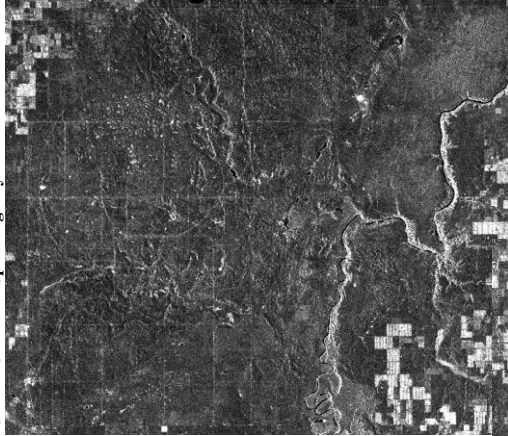
- a statistical model is developed based on the regression of volumetric soil moisture against radar backscatter
- regression coefficients developed from field measurements
- model is then inverted to predict soil moisture across the entire image



Change Detection

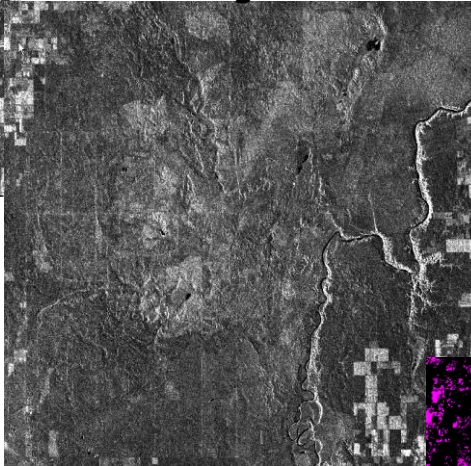
Both S1 Ascending
RADARSAT images
acquired 24 days apart

S1 Ascending 25-September-2004



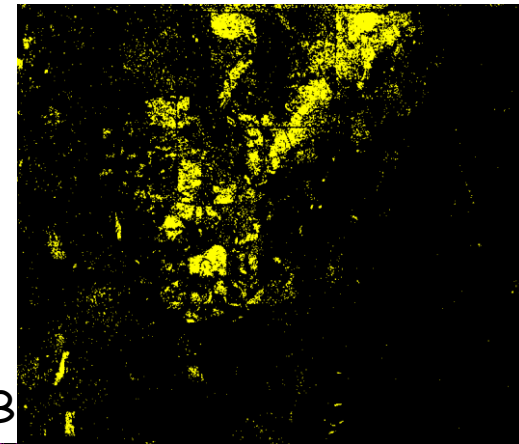
No rain 7 days
prior to acquisition

S1 Ascending 19-October-2004

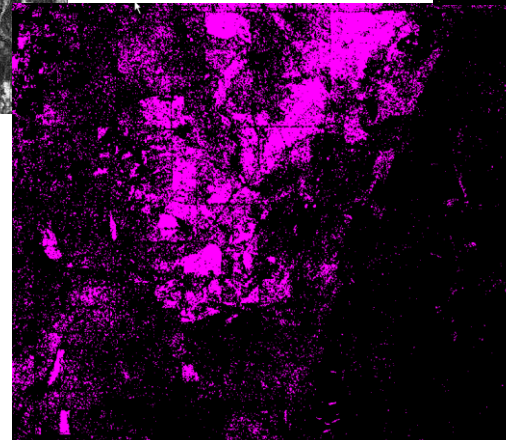


Rain day
before acquisition

Change Image
Threshold of 7dB



Change Image
Threshold of 5dB



Colour identifies
areas of
significant change
in soil moisture in
this 24-day period

Semi-empirical Models

- backscatter is related to sensor (frequency, incidence angle, polarization) and target (dielectric and random roughness) characteristics
- models mathematically relate backscatter to these variables
- coefficients are derived from extensive field work (often using scatterometer measurements)
- most models relate soil, incidence angle and frequency characteristics to backscatter at a single polarization or polarization ratio
- sensor parameters are known and two equations are solved iteratively for either dielectric or roughness
- models include one roughness variable - rms (correlation length is usually ignored)
- dielectric mixing models are related to derive volumetric soil moisture for dielectric

Semi-empirical Models

Dubois Model

$$\sigma_{hh}^o = 10^{-2.75} (\cos^{1.5} \theta / \sin^5 \theta) 10^{0.028 \epsilon_r \tan \theta} (ks \sin \theta)^{1.4} \lambda^{0.7}$$

$$\sigma_{vv}^o = 10^{-2.35} (\cos^3 \theta / \sin^3 \theta) 10^{0.046 \epsilon_r \tan \theta} (ks \sin \theta)^{1.1} \lambda^{0.7}$$

λ = wavelength (cm)

σ^o = backscatter (sigma)

θ = incidence angle (radians)

ϵ_r = real part of the dielectric constant

k = is the wave number ($k=2\pi/\lambda$)

s = root mean square height (cm)

Oh Model

$$\alpha = \sigma_{hh}^o / \sigma_{vv}^o = [1 - (2\theta/\pi)^{1/3} \Gamma_o \exp(-ks)]^2$$

$$\beta = \sigma_{hv}^o / \sigma_{vv}^o = 0.23 \sqrt{\Gamma_o} (1 - \exp(-ks))$$

$$\Gamma_h = \left| \frac{\cos \theta - \sqrt{\epsilon_r - \sin^2 \theta}}{\cos \theta + \sqrt{\epsilon_r - \sin^2 \theta}} \right|^2$$

$$\Gamma_v = \left| \frac{\epsilon_r \cos \theta - \sqrt{\epsilon_r - \sin^2 \theta}}{\epsilon_r \cos \theta + \sqrt{\epsilon_r - \sin^2 \theta}} \right|^2$$

$$\Gamma_o = \left| \frac{1 - \sqrt{\epsilon_r}}{1 + \sqrt{\epsilon_r}} \right|^2$$

σ^o = backscatter (sigma)

θ = incidence angle (radians)

ϵ_r = real part of the dielectric constant

k = is the wave number ($k=2\pi/\lambda$)

s = root mean square height (cm)

Integral Equation Model - IEM

- Integral Equation Model (IEM): a model adapted to randomly dielectric rough surfaces to simulate the backscattering behaviour for the wide range of surface roughness values.
- 3 unknowns: rms, correlation length, dielectric \rightarrow requires 3 measures of backscatter
- a calibrated version of IEM is available: reduces the model parametrization from three unknowns (dielectric constant; roughness rms; correlation length) to two unknowns (dielectric constant; roughness rms)
- calibration involves an optimum roughness correlation length ℓ_{opt}
- this parameter was obtained by forcing the IEM until a good agreement is reached between simulations and SAR image data; calculations were performed using measured rms roughness height and soil moisture content

$$\ell_{\text{opt}2} = \delta(\sin\theta)^{\mu} \text{rms}^{\eta\theta + \xi}$$

$$\bar{\sigma}_{\text{VV}} = 3.289$$

$$\bar{\sigma}_{\text{HH}} = 4.026$$

$$\bar{\xi}_{\text{VV}} = 1.222$$

$$\bar{\xi}_{\text{HH}} = 1.551$$

$$\eta_{\text{HH}} = \eta_{\text{VV}} = -0.0025$$

$$\mu_{\text{HH}} = \mu_{\text{VV}} = -1.744$$

Physical Model: Integral Equation Model

IEM formulation

$$\begin{aligned}\sigma_{pp}^o = & \frac{k^2}{2} |f_{pp}|^2 \exp(-4k^2 s^2 \cos^2 \theta) \sum_{n=1}^{+\infty} \frac{(4k^2 s^2 \cos^2 \theta)^n}{n!} W^n(2k \sin \theta, 0) \\ & + \frac{k^2}{2} \operatorname{Re}(f_{pp}^* F_{pp}) \exp(-3k^2 s^2 \cos^2 \theta) \sum_{n=1}^{+\infty} \frac{(2k^2 s^2 \cos^2 \theta)^n}{n!} W^n(2k \sin \theta, 0) \\ & + \frac{k^2}{8} |F_{pp}|^2 \exp(-2k^2 s^2 \cos^2 \theta) \sum_{n=1}^{+\infty} \frac{(k^2 s^2 \cos^2 \theta)^n}{n!} W^n(2k \sin \theta, 0)\end{aligned}$$

where

$$\begin{aligned}f_{hh} &= \frac{-2R_h}{\cos \theta} & R_h &= \frac{\cos \theta - \sqrt{\epsilon_r - \sin^2 \theta}}{\cos \theta + \sqrt{\epsilon_r - \sin^2 \theta}} & F_{vv} &= -2 \frac{\sin^2 \theta}{\cos \theta} \left[\left(1 - \frac{\epsilon_r \cos^2 \theta}{\mu_r \epsilon_r - \sin^2 \theta} \right) (1 - R_v)^2 + \left(1 - \frac{1}{\epsilon_r} \right) (1 + R_v)^2 \right] \\ f_{vv} &= \frac{2R_v}{\cos \theta} & R_v &= \frac{\epsilon_r \cos \theta - \sqrt{\epsilon_r - \sin^2 \theta}}{\epsilon_r \cos \theta + \sqrt{\epsilon_r - \sin^2 \theta}} & F_{hh} &= -2 \frac{\sin^2 \theta}{\cos \theta} \left[4R_h - \left(1 - \frac{1}{\epsilon_r} \right) (1 + R_h)^2 \right]\end{aligned}$$

For exponential roughness autocorrelation function

$$W^n(2k \sin \theta, 0) = \left(\frac{\ell}{n} \right)^2 \left[1 + \left(\frac{2k\ell \sin \theta}{n} \right)^2 \right]^{-1.5}$$

σ_{pp}^o = backscatter at polarization pp (sigma)

θ = incidence angle (radians)

ϵ_r = real part of the dielectric constant

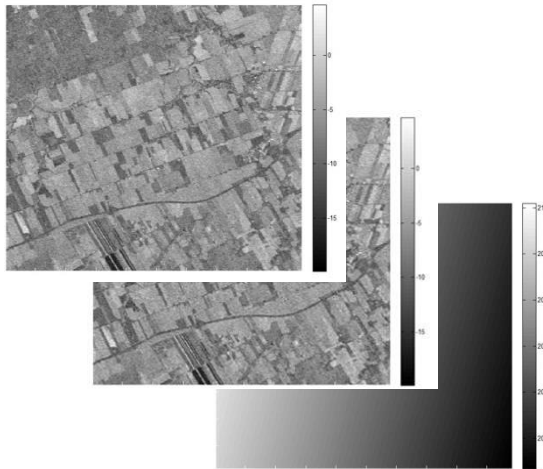
k = is the wave number ($k=2\pi/\lambda$)

s = root mean square height (cm)

ℓ = roughness correlation length (cm)

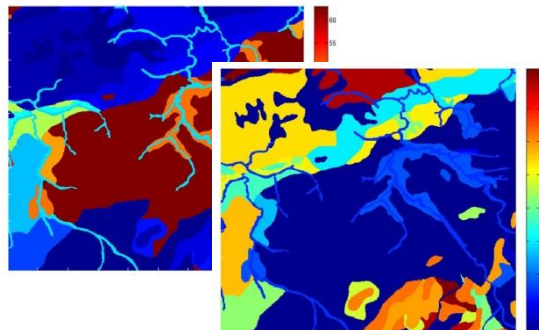
Physical Modeling Approach

Input Data



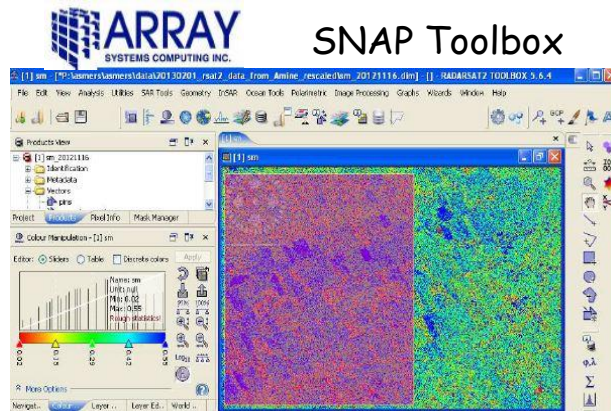
Radar Data
(HH and VV Backscatter)
(Radar Angle)

Soils Data
(Clay and Sand Fractions)



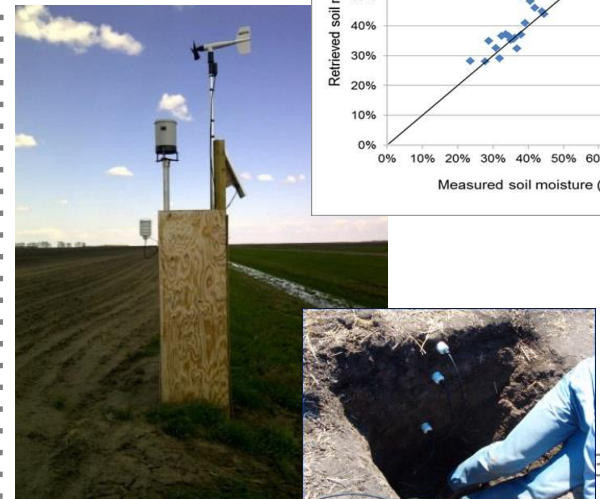
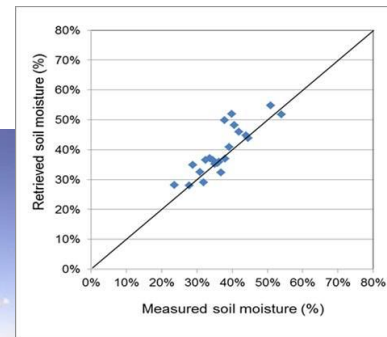
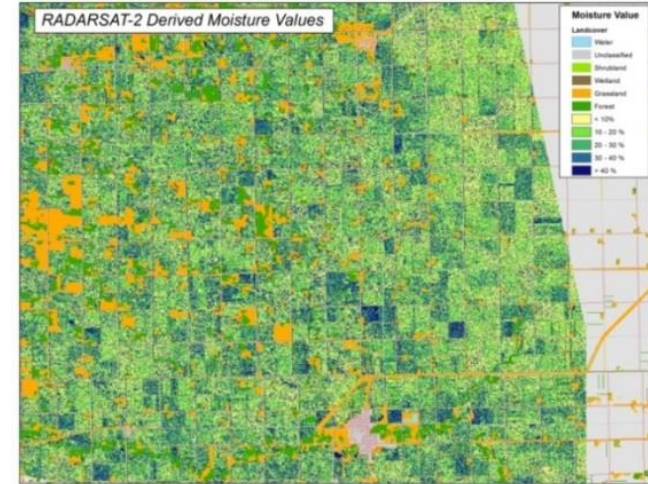
Data Processing

IEM with Fresnel Equations
(estimates real dielectric)



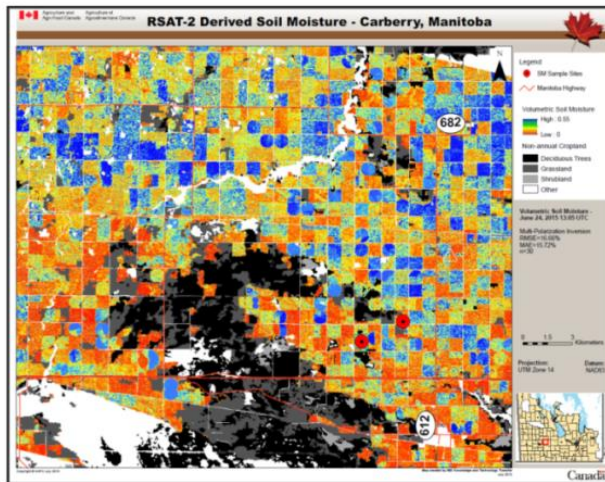
Dielectric Mixing Model
(estimate water fraction
by volume)

Output and Validation



Soil Moisture – Reducing Flood Risk

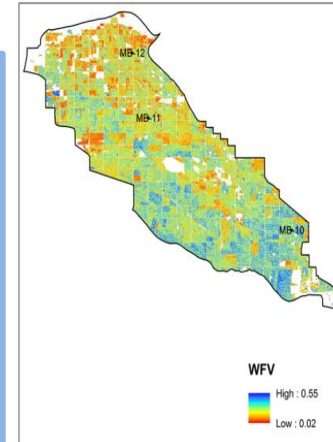
Percent soil moisture
(**wet=blue**)



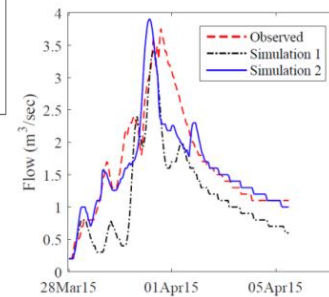
2011: total costs from the Manitoba Flood topped **\$1 billion**

2014: Excess moisture insurance payments to farmers who were unable to seed ~**\$65 million** (2,400 claims)

Better forecasting means improved early response, mitigation and recovery



Soil moisture from RADARSAT-2 integrated into hydrological model, improving stream flow forecasts

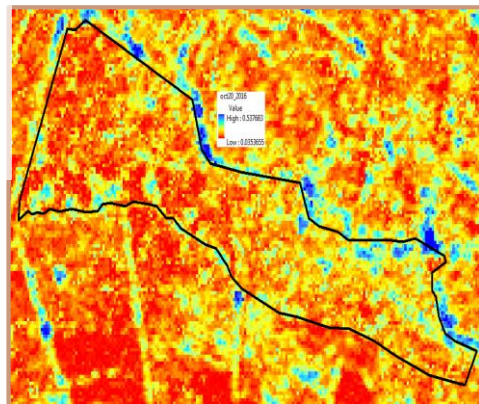


Data: Canada's RADARSAT-2
Method: physical radar model

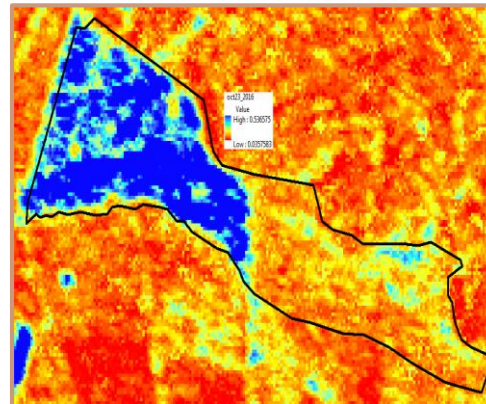
Precision Irrigation in Chile

Maps of percent soil moisture from RADARSAT-2 (**wet=blue**)

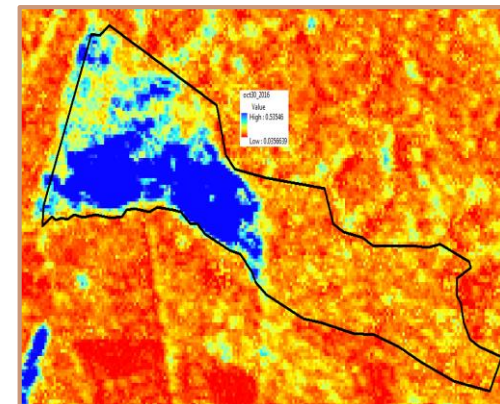
Dry conditions:
20 October



Irrigation occurs:
23 October



Post-irrigation drying:
30 October



Survival of chicory seedlings depends on adequate access to soil moisture



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