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SMAP's Active Radar Sensor for Monitoring Soil Moisture to Support Agricultural Risk Mitigation

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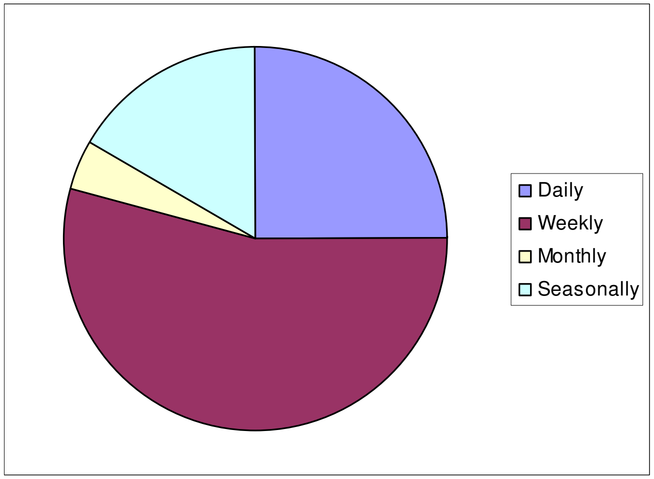
Canada

Need for Soil Moisture Information for Agriculture

- **Early assessment of emerging risk, due to too much or too little available soil water, will assist the agricultural community to develop appropriate management strategies**
  - ***Erosion risk***
  - ***Prediction of spring flooding***
  - ***Pest assessment***
  - ***Fertilizer, pesticide and seed demand***
  - ***Yield estimation***
  - ***Soil trafficability***



Source: International GEO Workshop on Synthetic Aperture Radar (SAR) to Support Agricultural Monitoring: Report of Pre-workshop Survey Findings

Supporting Agricultural Risk Management: An Integrated Passive-Active Microwave Approach to Identify Soil Moisture Extremes

GRIP Project Objectives: Segment 1 R&D (October 2007 – March 2010)

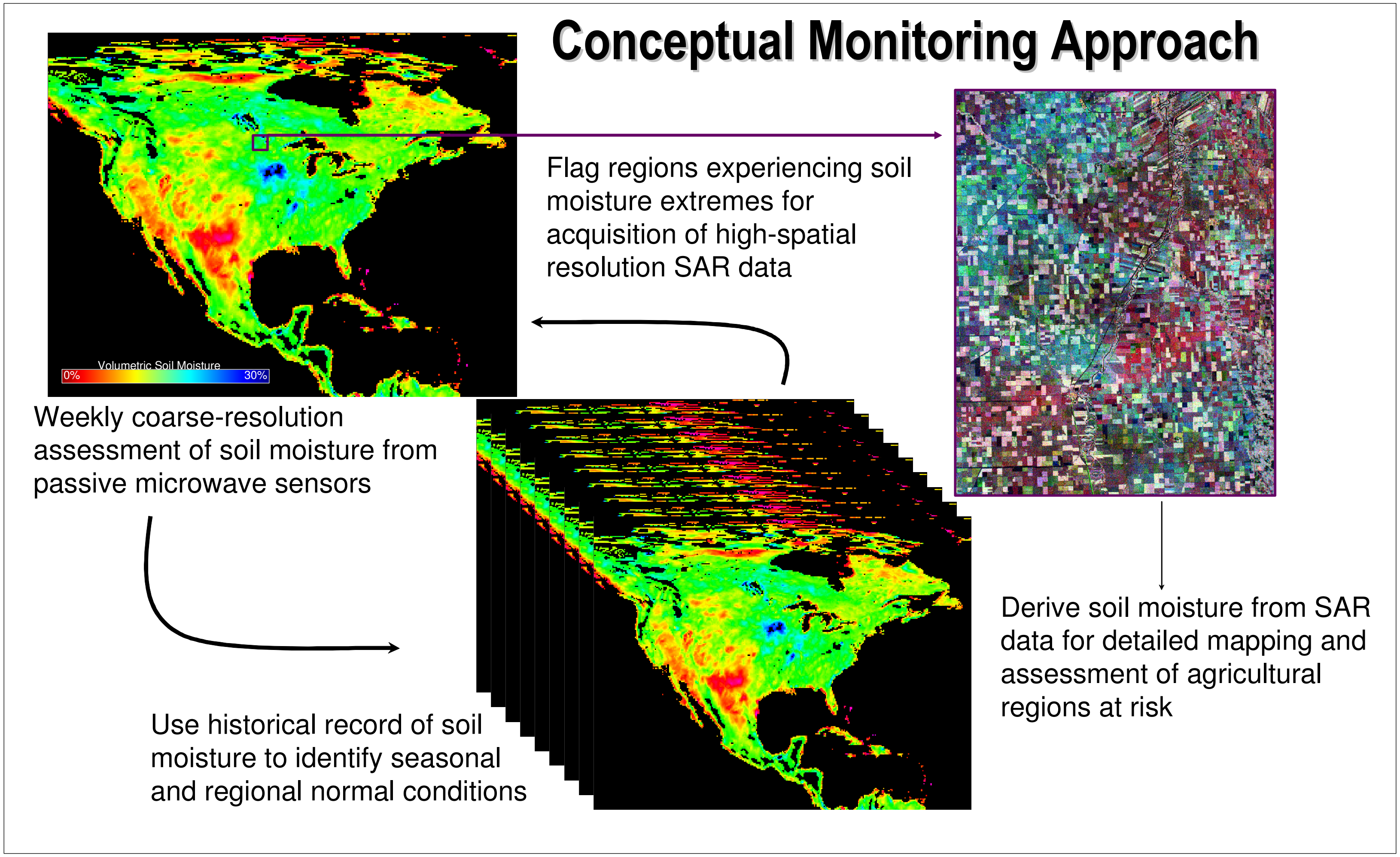
- To develop, test and evaluate methods to quantify surface soil moisture using active synthetic aperture radar (SAR) satellite sensors.
- To develop a method to flag regions experiencing extreme soil moisture conditions using passive microwave data, in order to cue collection of spatially detailed SAR data.

Segment 2 Demonstration (not funded)

- To demonstrate the assessment of risk due to extreme soil moisture conditions using integrated active and passive microwave soil moisture products, over sites in the Prairies.

Project Team:
- Research Branch (Dr. Heather McNairn, Dr. Amine Merzouki, Catherine Champagne, Anna Pacheco, Dr. Jiali Shang, co-op students)
- Agri-Environmental Services Branch (John Fitzmaurice, Zhirong Yang, Grant Wiseman, Allan Howard, Ian Jarvis)
- CCRS (Dr. Ridha Touzi, Dr. Brian Brisco, Dr. Bob Hawkins, Dr. Francois Charbonneau)
- University of Guelph (Dr. Aaron Berg)
- University of Manitoba (Dr. Paul Bullock)
- University of Calgary (Dr. Michael Collins)
- Government of Saskatchewan, Environment (Dr. Magfur Rahman)

Concept of Integrated Active and Passive System



SAR for Soil Moisture Estimation

- There is a strong correlation between soil dielectric and radar backscatter. However, deriving soil moisture estimates from backscatter is challenging and there are several limitations.

- **Surface roughness has a significant impact on radar scattering**
  - Roughness effects can be minimized using steep incidence angles, but cannot be eliminated
  - Radar models describe roughness using one or more descriptors: root mean square variance (rms), correlation length (l), autocorrelation function (gaussian, exponential)
  - Measurement of rms and l is very tricky on tilled fields
  - Radar will penetrate surface and therefore “optical roughness” (as measured by field instruments) may or may not be representative of what the radar sees
  - Radar also views surface “off-nadir” and therefore appropriate representation of roughness can be difficult to capture in the field

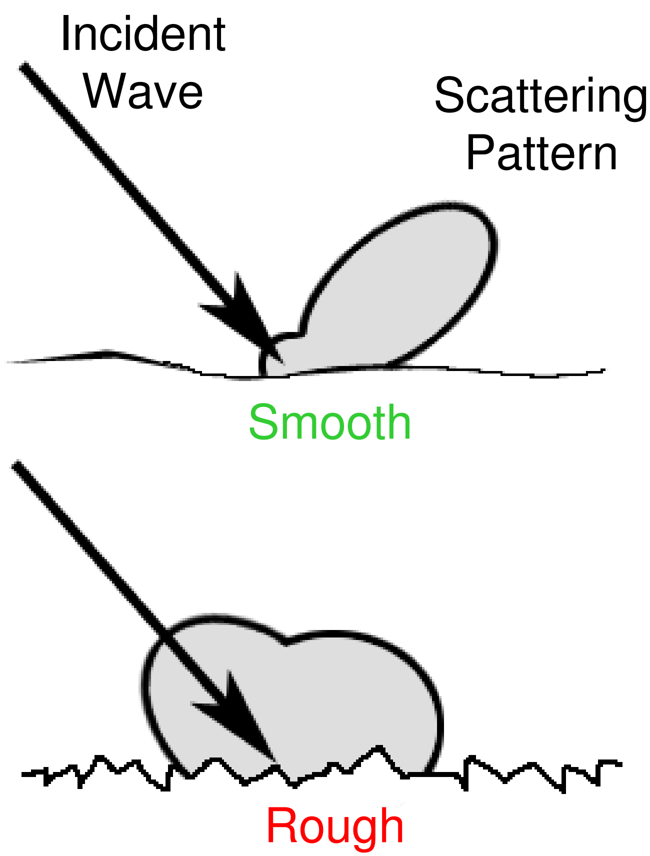
- **Radar penetrates soil up to a maximum of about 10 cm.** Penetration depends on frequency, incidence angle and soil moisture. This complicates soil moisture measurements in field as penetration depth varies due to moisture conditions.

- **Vegetation has a significant impact on radar backscatter** and as yet there are no robust models to separate vegetation from soil contributions. Therefore current applications of SAR are limited to non-vegetated targets.

Sensitivity of Active Radar to Surface Soil Parameters

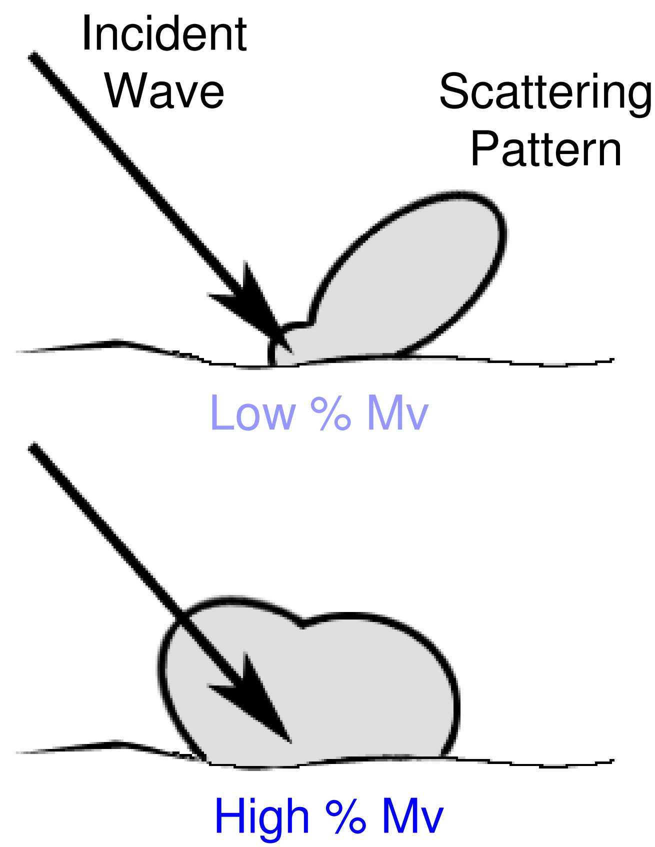
$$\sigma^o = f\,(\,\lambda,\ P,\ \theta,\ rms,\ l,\ m_v\,)$$

Backscatter versus Soil Roughness



for identical λ, P, θ, Mv

Backscatter versus Soil Moisture



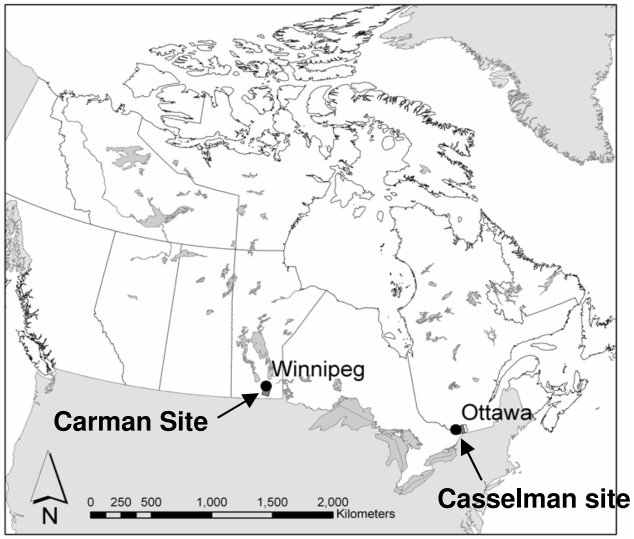
for identical λ, P, θ, rms

Methods for Soil Moisture Estimation

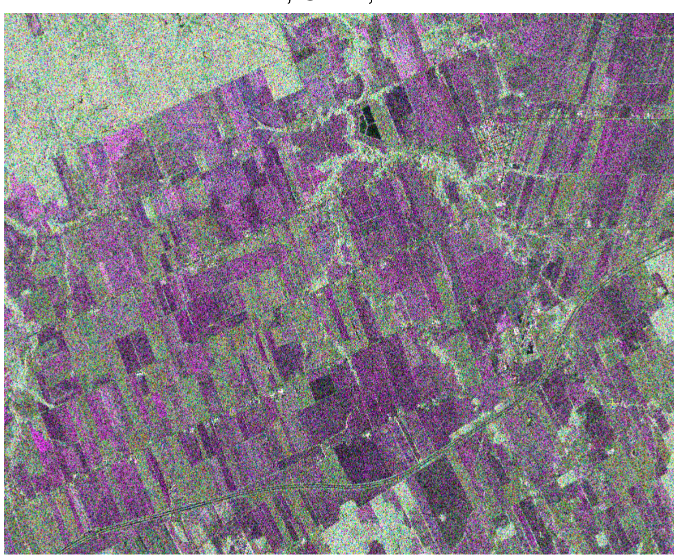
- Empirical models
- Change detection
  - Assumes that soil moisture changes over time but that roughness changes are small
  - Relies on good relative calibration and images must all be acquired using the exact same radar configuration (only moisture changes)
  - Provides only relative changes, unless change is calibrated with ground data
- Semi-empirical models (i.e. Dubois and Oh)
  - More robust than empirical, but coefficients may not always be valid under new circumstances
  - Relatively easy to invert
  - Most require multi-polarized or multi-angle data to resolve soil moisture and surface roughness contributions
- Physical scattering models (i.e. IEM)
  - Well suited for investigating backscatter responses as a function of radar configuration or for exploring the sensitivity of backscatter to target characteristics
  - Complex and difficult to invert
- Neural Networks
  - Requires extensive training data
  - NN developed with one set of training data not applicable to other data sets

  (must be re-trained)

RADARSAT-2 Data Over Ontario and Manitoba



May 5, 2008 (RSAT-2 FQ19)
R-HH, G-VH, B-VV



- Spring 2008 Casselman (ON):
May 5 (FQ19), 16 (FQ11) & 23 (FQ16)

- Spring 2008 Carman (MB):
April 23 (FQ11), May 10 (FQ15) &17 (FQ11)

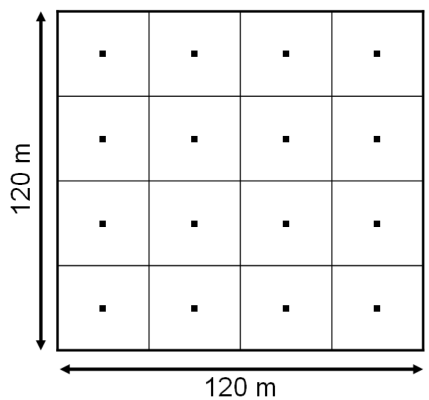
- *In situ* soil moisture using ThetaProbe
    - > 2100 measurements over 44 fields per acquisition (ON)
    - > 2400 measurements over 39 fields per acquisition (MB)

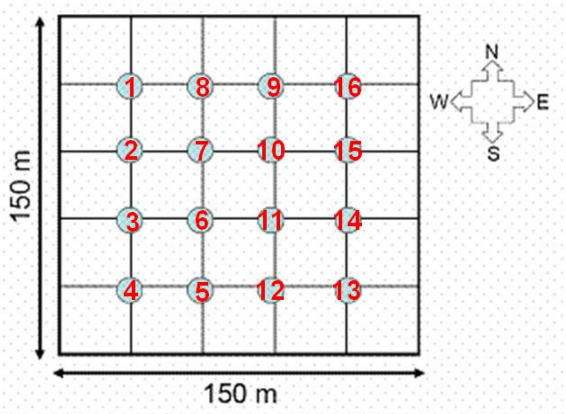
- roughness measured using 1-metre pin board

- experiment represents application of SAR modeling under “realistic” conditions – untilled and tilled conditions

Soil Moisture Sampling Design

• site uniformity: roughness, residue cover, tillage implementation, soil type, slope
• 16 sample site with 3 replicates (total of 48 readings per site)



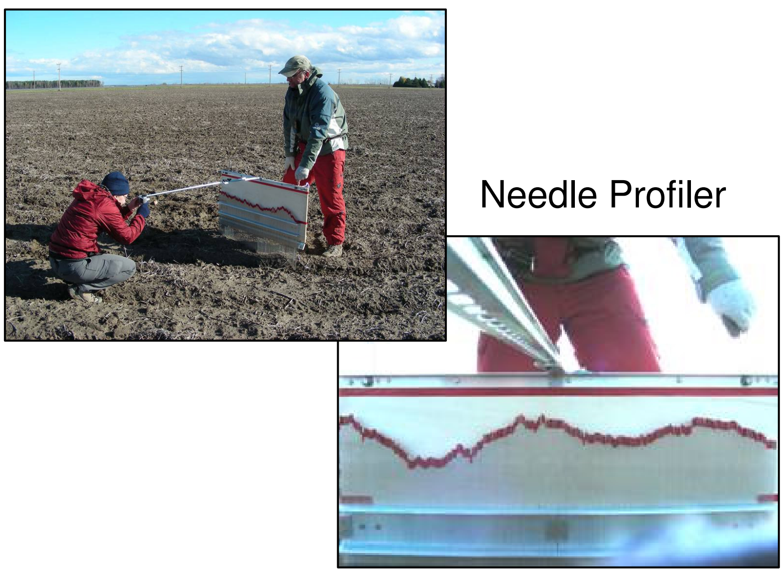


Casselman
•4 x 4 pixels (120 x 120m);
• 3.6 acres
• ~64 radar samples

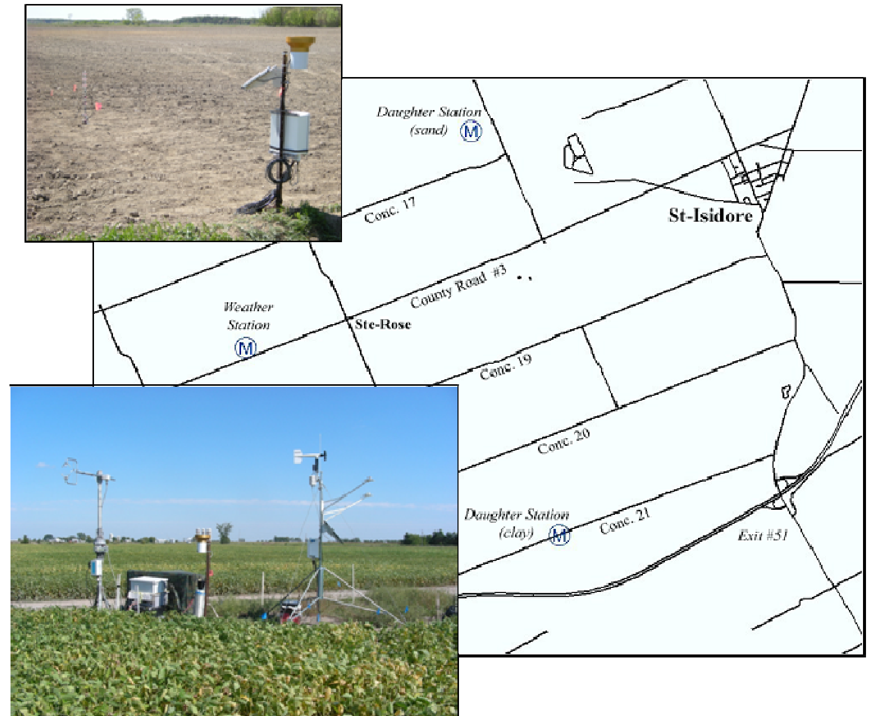
Carman
• 5 x 5 pixels (150 x 150m);
• 5.6 acres
• ~100 radar samples

Ground Data Collection

Theta Probes

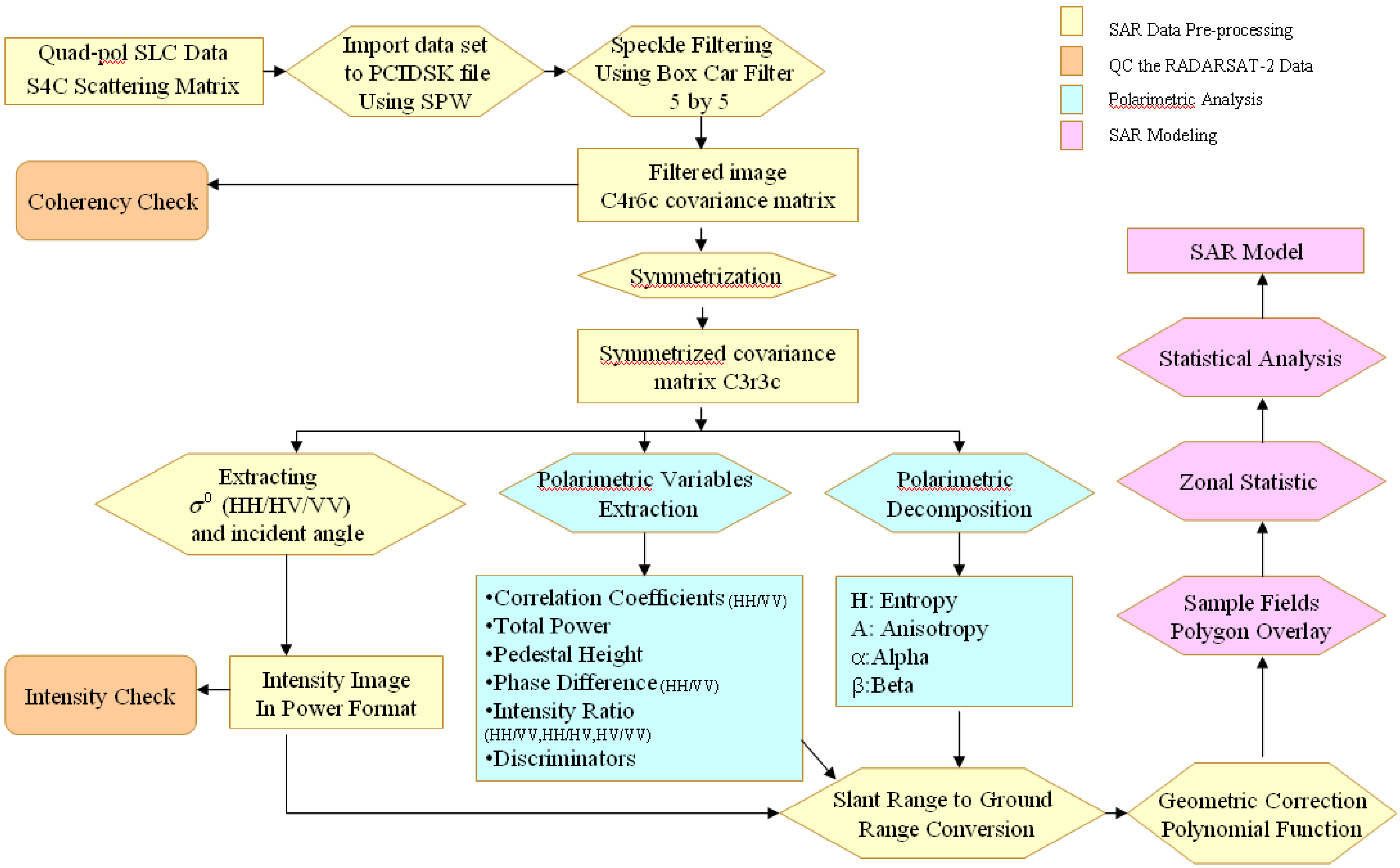


Needle Profiler



Weather and Daughter Stations

Processing Chain



RADARSAT-2 Quality Check

• Mean backscatter (HH, HV and VV) from targets were compared to backscatter statistics (at the same incidence angle) published by Ulaby and Dobson. For all three targets (water, forest, bare soil), mean backscatter from the image was within 1 dB of published backscatter values.

• Backscatter values were extracted for pixels along a transect drawn across the range of the RADARSAT-2 images. 99% of the pixels along this transect had backscatter values above the noise floor (as specified with the RADARSAT-2 product). Specifically for water, forest and bare soil targets, all backscatter values for all polarizations were well above the noise floor.

• For flat bare soil targets, HH and VV backscatter was highly correlated above the noise floor.

• For bare soil and forest targets, the cross-polarization phase (HH-HV and VV-VH) appeared noise-like.

• No artifacts were observed in the HV-VH coherency (in either magnitude or phase).

Study site	Acquisition date	Incidence angle (deg)	Target	Mean HH		Mean HV		Mean VV	
				RSAT-2	Ulaby and Dobson (1989)	RSAT-2	Ulaby and Dobson (1989)	RSAT-2	Ulaby and Dobson (1989)
Casselman	May 23, 2008	35 - 37	Forest	-10.6	-11.1	-16.5	-17.3	-10.8	-11.2
			Bare Fields	-13.4	-12.2	-23.9	-23.2	-11.9	-12.0
			Urban areas	-8.5	-8.2	-14.4	--	-9.4	--
Carman	May 16, 2008	30 - 32	Forest	-10.5	-11.6	-16.7	-16.5	-12.3	-11.1
			Bare Fields	-11.9	-10.7	-23.8	-21.5	-11.7	-10.5
			Urban areas	-8.23	-8.0	-15.68	--	-9.35	--

Forward Modelling and RADARSAT-2

Dataset	Pol.	Dubois			Corrected Dubois			Oh			Corrected Oh		
		RMSE (dB)	MAE (dB)	IA	RMSE (dB)	MAE (dB)	IA	RMSE (dB)	MAE (dB)	IA	RMSE (dB)	MAE (dB)	IA
Casselman	HH	4.23	3.53	0.42	2.57	2.10	0.42	4.96	4.63	0.40	1.82	1.52	0.50
	VV	3.36	2.85	0.48	2.21	1.86	0.49	5.18	4.86	0.40	1.79	1.53	0.50
Carman	HH	5.48	4.93	0.47	2.82	2.22	064	5.91	5.36	0.46	2.75	2.14	0.59
	VV	4.3	3.75	0.50	2.6	2.00	0.60	6.37	5.84	0.42	2.89	2.29	0.52
All	HH	4.95	4.30	0.46	2.71	2.16	0.59	5.42	4.97	0.44	2.30	1.81	0.60
	VV	3.83	3.21	0.53	2.44	1.95	0.62	5.76	5. 31	0.42	2.36	1.88	0.56

- Forward modelling revealed a significant bias in radar backscatter
    - Bias observed with all models, suggesting models may not be primary source of error
    - May be due to approach to soil moisture and roughness field measurements

- Applied Correction Factors (errors within 1dB would be considered within calibration error)

Correction Factor for HH: 3.5 dB (Dubois) and 5.0 dB (Oh)
Correction Factor for VV: 2.0 dB (Dubois) and 5.0 dB (Oh)
•correction fit both Ottawa and MB data

Model Inversion Results

RMSE and MAE statistics for Oh model for 2008

Polarization	Casselman		Carman		Both Sites	
	RMSE (%)	MAE (%)	RMSE (%)	MAE (%)	RMSE (%)	MAE (%)
HH-VV	8.02	6.82	7.73	6.32	8.64	7.35
HH-HV	**7.56**	**6.12**	**7.70**	**6.57**	**8.13**	**6.63**
VV-HV	8.30	7.04	7.85	6.25	8.12	6.70
HH-VV-HV	8.87	7.56	7.86	6.63	8.41	7.13

RMSE and MAE statistics for Dubois model for 2008

Polarization	Casselman		Carman		Both Sites	
	RMSE (%)	MAE (%)	RMSE (%)	MAE (%)	RMSE (%)	MAE (%)
HH-VV	6.21	5.18	9.61	8.13	8.66	7.21

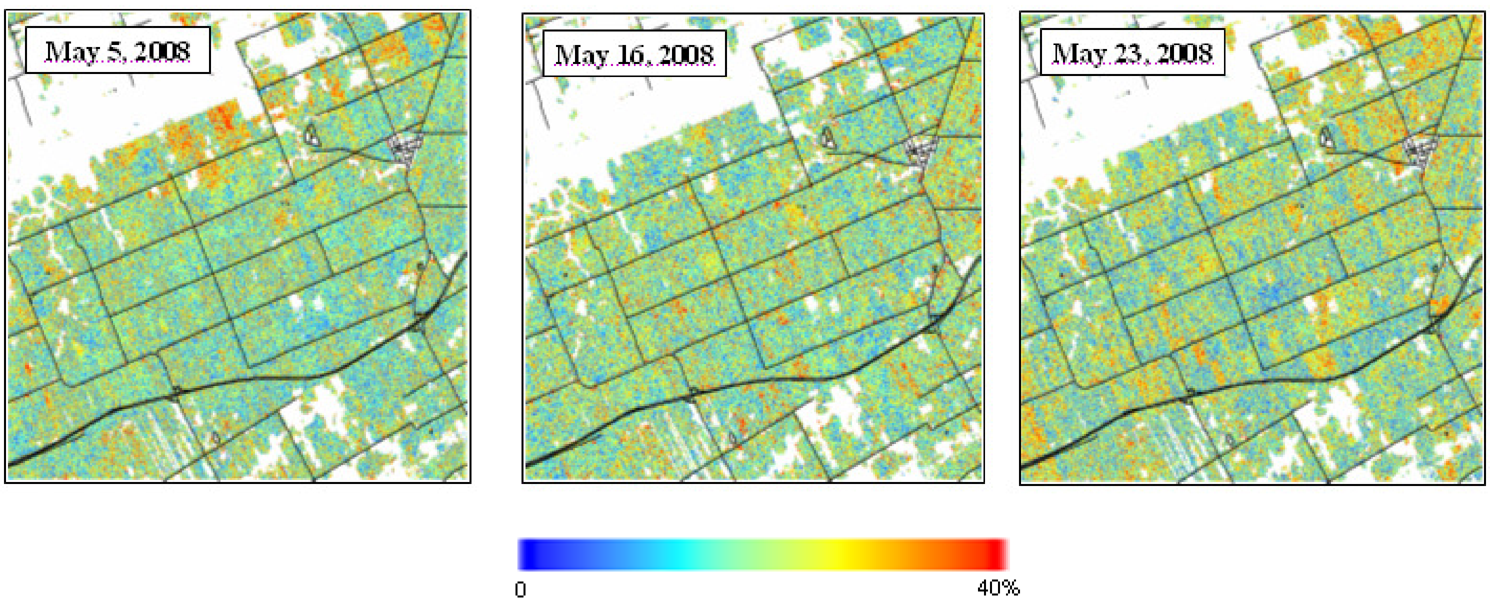
- ✓ Root Mean Square Error: $$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2}$$
- ✓ Mean Absolute Error: $$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|P_i - O_i\right|$$

Soil Moisture Maps Combining Dubois and Oh Model Estimates

Radar Models	Authors	ks	kl	θ°	Mv (%)	*f* (GHz)
Standard Dubois	Dubois et al., 1995	≤ 2.5	NA	≥ 30°	≤ 35%	1.5 to 11.0
Oh	Oh et al., 1992	> 0.1 < 6.0	> 2.6 < 19.7	> 20°	> 9% < 31%	1.5 to 9.5

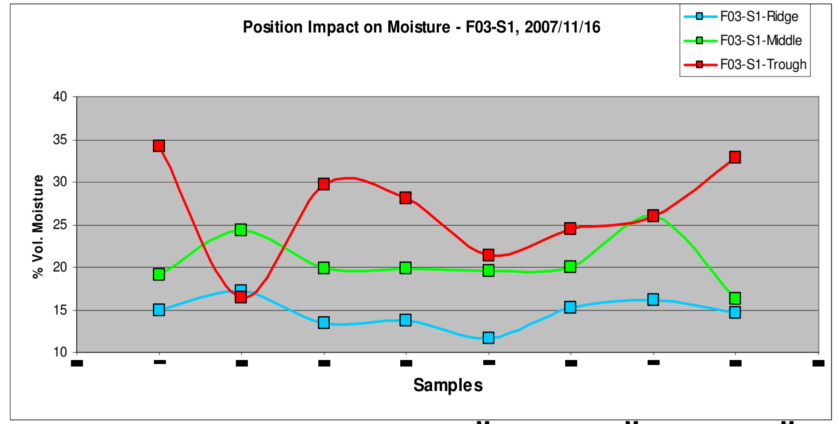
$k = 2\pi/\lambda$

Validity ranges of models

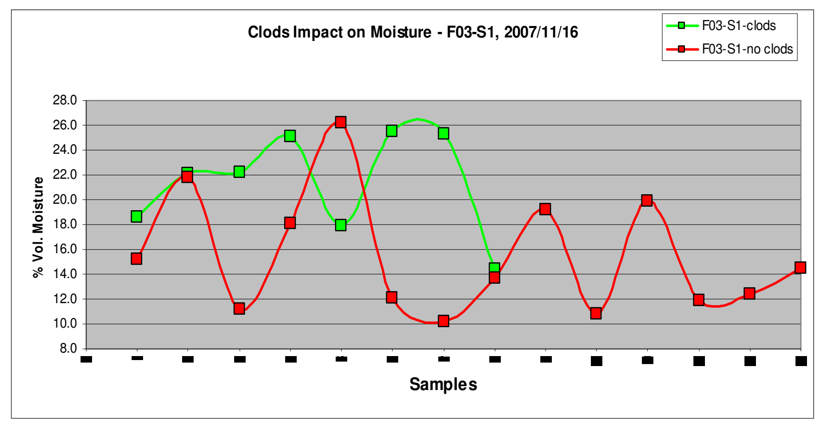


Field Measured Soil Moisture

- Approx. 1% error in precision for ThetaProbe
- Approx. 4% error in conversion of the dielectric to volumetric soil moisture
- Non-coincident collection of *in situ* and satellite data
- Mismatches between measurement depths and microwave penetration depths
- Spatial variability in soil moisture across a sampling area due to
  - soil texture, organic matter, soil structure and topography
  - tillage structure activities.

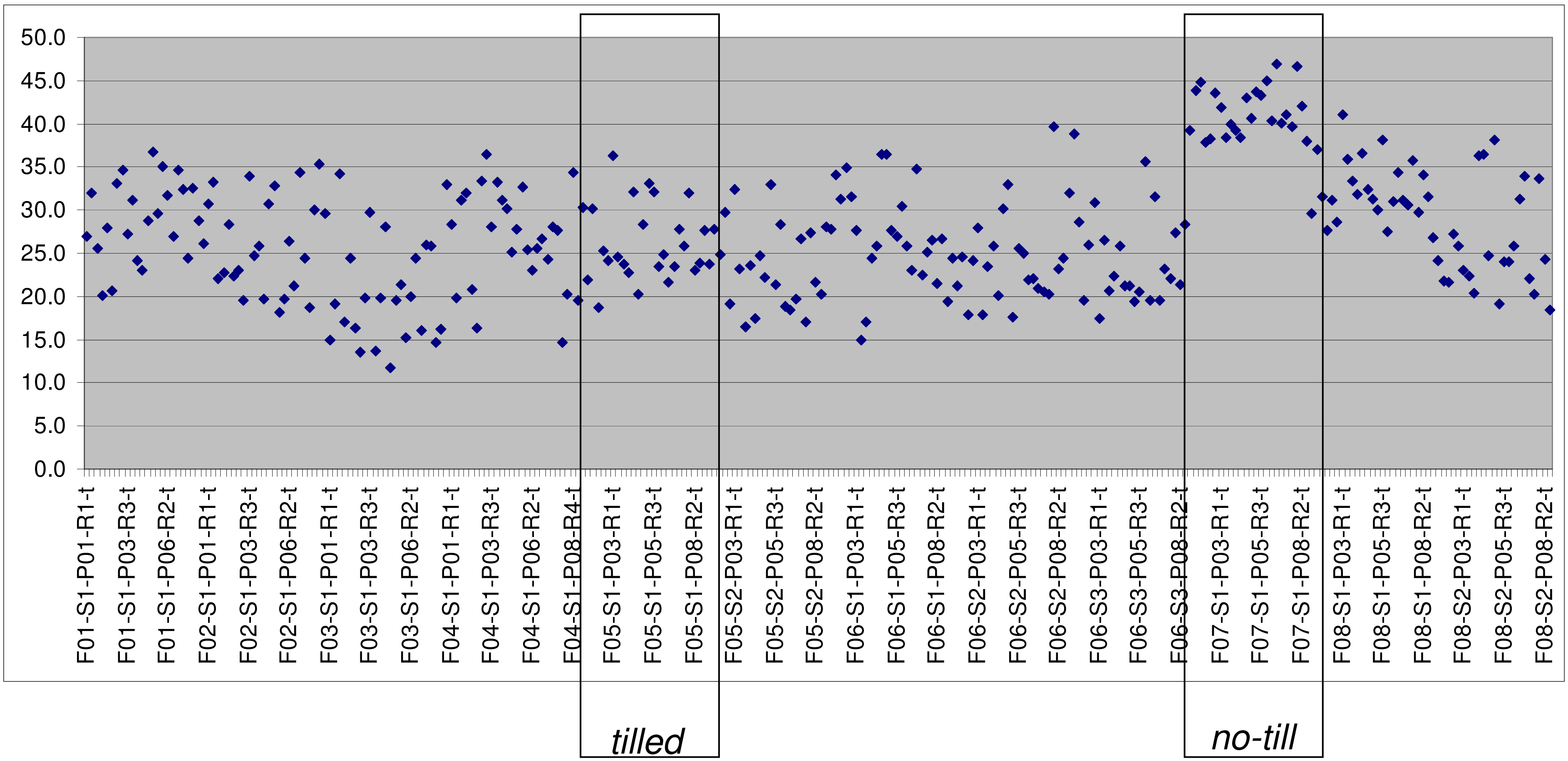


Mean Ridge	Mean Middle	Mean Trough
14.6	20.6	26.6

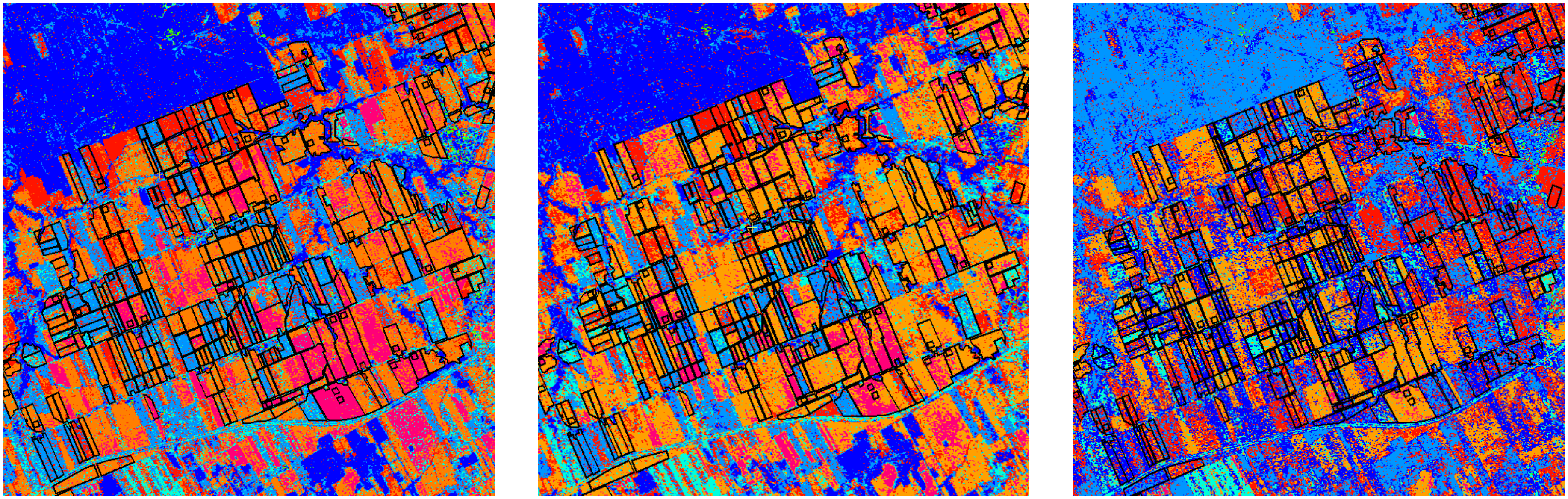


Mean Clods	Mean No clods
21.4	15.5

Within Site and Between Site Variances in Soil Moisture (Fall 2007)

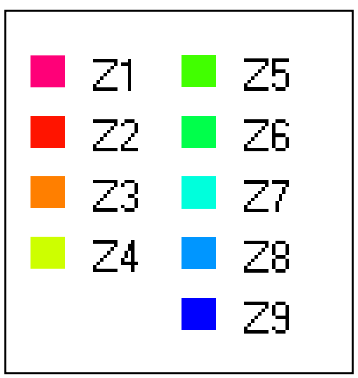


Application of Soil Moisture Estimates with Help of Polarimetric Decomposition



May 5, 2008 May 23, 2008 May 16, 2008

Unsupervised classification product based on Freeman-Durden decomposition



Classes 1 to 3 correspond to **surface scattering.**
Classes 4 to 6 correspond to the **double-bounce scattering.**
Classes 7 to 9 correspond to the **volume scattering.**

Isolating Surface Scattering for Soil Moisture Estimation Using Freeman-Durden Decomposition

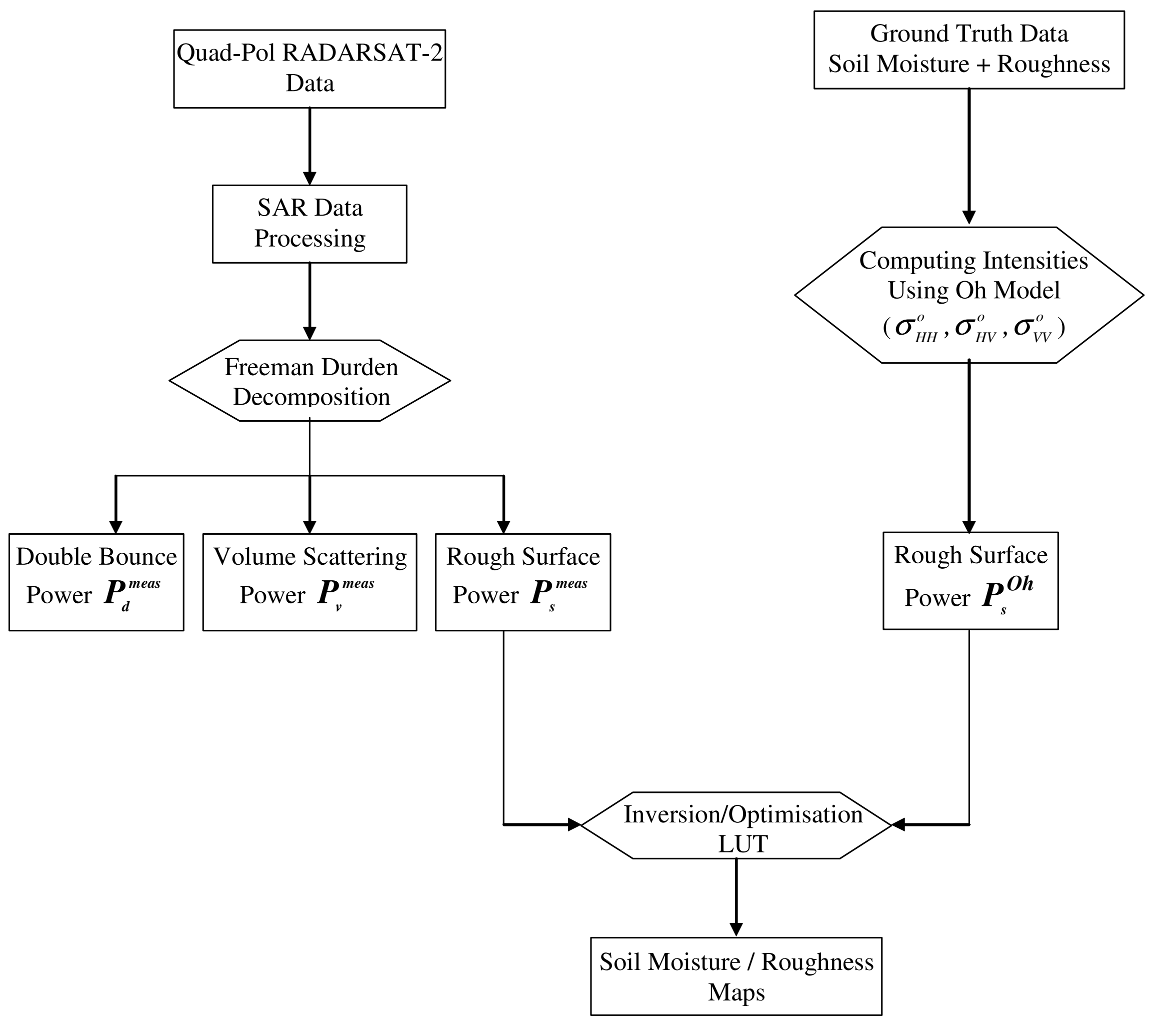
Total Power

$$P_{tot} = P_s + P_d + P_v = |S_{HH}|^2 + 2\,|S_{HV}|^2 + |S_{VV}|^2$$
$$= \sigma^o_{HH} + 2\,\sigma^o_{HV} + \sigma^o_{VV}$$

Surface **Double bounce** **Volume scattering**

- adjust backscatter model estimations using only surface interaction component
- Dubois can't provide a formulation of the cross-pol backscatter coefficient (σ_{HV})
- use of Oh semi-empirical backscatter model

Processing and Analysis Chain



Results from Oh Model Inversion – Casselman and Carman

Inversion Approach	Polarization	RMSE (%)	MAE (%)
Multi-polarization	HH-VV	8.64	7.35
	HH-HV	8.13	6.63
	VV-HV	8.12	6.70
	HH-VV-HV	8.41	7.13
Polarimetry based	Total power	8.37	6.95
	Surface Power	7.70	6.31

- ✓ Root Mean Square Error: $$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2}$$
- ✓ Mean Absolute Error: $$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|P_i - O_i\right|$$

Conclusions

- Dubois and Oh models provide soil moisture estimates that when compared to *in situ* measurements have rms errors of 6-9%.

- Future data collection is needed to evaluate repeatability of results. Repeat passes will permit easier assessment of errors for relative moisture estimation.

- Decomposition can be useful in application of soil moisture models

- Errors in ground measurements need to be evaluated

Next Steps

Will Do:

• Mask volume and double bounce dominant scatters while performing the backscatter model validation. Use Cloude-Pottier decomposition in combination with unsupervised classifier.

• Acquire additional quad-pol data in a same incidence angle configuration. Are these results repeatable?

• Assuming repeatable results, develop plan to pilot methods over sub-watershed of Red River Watershed (under AAFC SAGES project)

Would like to Do:

• Finish development of laser profiler to characterize “off-nadir” roughness view

• Conduct field campaign to assess errors in the *in situ* (Theta Probe) measurements (from SAR perspective) (What is the “truth” as we “validate” model estimates??)

• Combine these soil moisture models with vegetation model (being assessed under another AAFC GRIP project).

• Test these models with L-Band data (How do we get access to enough L-Band data?)

RADARSAT-2 and TerraSAR Acquisitions over Casselman for Fall 2009

Sensor	Field work campaign	Image Date	Start Time	Pass Type	Beam Mode	Status
RADARSAT-2	1	Sept. 14	6:58 AM	ASC	S6	**Cancelled**
		Sept. 15	7:09 AM	DES	FQ16	**Received**
		Sept. 18	6:42 PM	ASC	FQ5	**Received**
		Sept. 21	6:54 PM	ASC	FQ19	**Cancelled**
	2	Oct. 8	6:58 AM	ASC	S6	**Cancelled**
		Oct. 9	7:09 AM	DES	FQ16	**Programmed**
		Oct. 12	6:42 PM	ASC	FQ5	**Programmed**
		Oct. 15	6:54 PM	ASC	FQ19	**Programmed**
	3	Nov. 1	5:58 AM	ASC	S6	**Programmed**
		Nov. 2	6:09 AM	DES	FQ16	**Programmed**
		Nov. 5	5:42 PM	ASC	FQ5	**Programmed**
		Nov. 8	5:54 PM	ASC	FQ19	**Programmed**
TerraSAR-X	1	Sept. 21	6:52 PM	ASC	stripNear_014R	**Programmed**
	2	Oct. 13	6:52 PM	ASC	stripNear_014R	**Programmed**
	3	Nov. 4	5:52 PM	ASC	stripNear_014R	**Programmed**