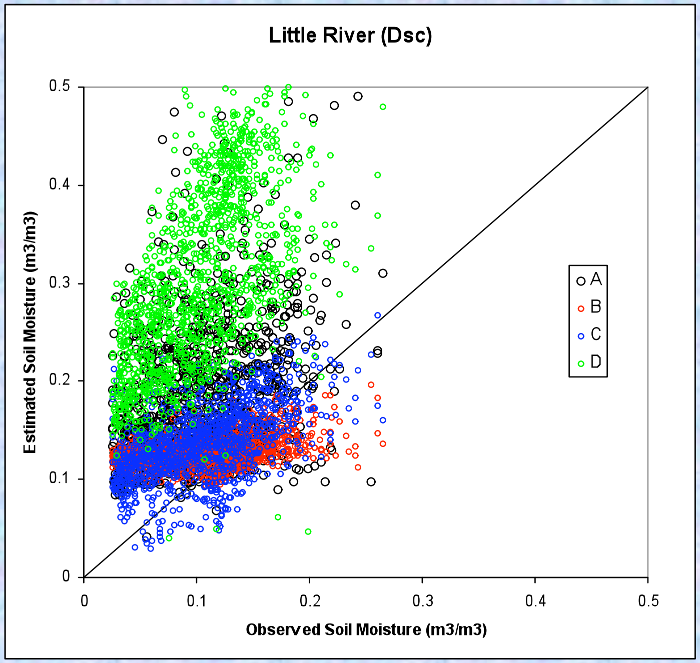
Algorithm Session Short Presentations

- (A. Freeman)*
- Soil moisture estimation using passive microwave (R. Bindlish)
- Soil temperature for L-band (T. Holmes)
- Radiometer angular response from a forest canopy (R. Lang)
- Effect of dew on L-band T_B (B. Hornbuckle)
- SMEX05 vegetation validation (L. Li)
- A bare surface algorithm for VV & HH measurements (J. Shi)
- Numerical studies of exponential surface backscattering (L. Tsang)
- Soil moisture inversion using simulated annealing (A. Tabatabaeenejad)
- Soil moisture inversion algorithm case study: Soybean (Y. Du)
- Soil moisture estimation using active microwave (R. Bindlish)
- Microwave scattering model of vegetated surfaces (X. Xu)
- Frozen soil algorithm (T. Zhang)
- Use of precipitation measurements in teh SMAP algorithms (Z. Haddad)

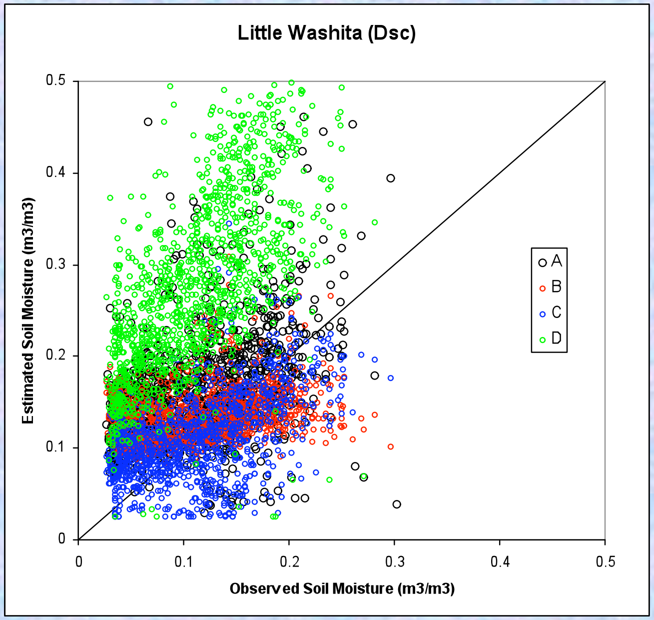
Soil moisture estimation using Passive Microwave

- Several retrieval approaches have been proposed using tau-omega model
  - Single Channel Algorithm
  - Multi-channel Algorithm
  - Polarization Ratio
  - Look-up table
  - LPRM
- Current (SMEX, AMSR-E) and future datasets (SMOS, Aquarius) can be used to evaluate these approaches
- These have been tried and evaluated using AMSR-E observations
- Each approach has its advantages and disadvantages
- Performance can be evaluated using in-situ observations from validation watersheds (Little Washita, OK; Little River, GA; Walnut Gulch, AZ; Reynolds Creek, ID)



Error Statistics for Dsc (2002-2007)

Algorithm	SEE	Bias	R	N
A	0.074	0.052	0.464	3823
B	0.063	0.044	0.330	4366
C	0.039	0.008	0.542	3747
D	0.181	0.164	0.640	3499

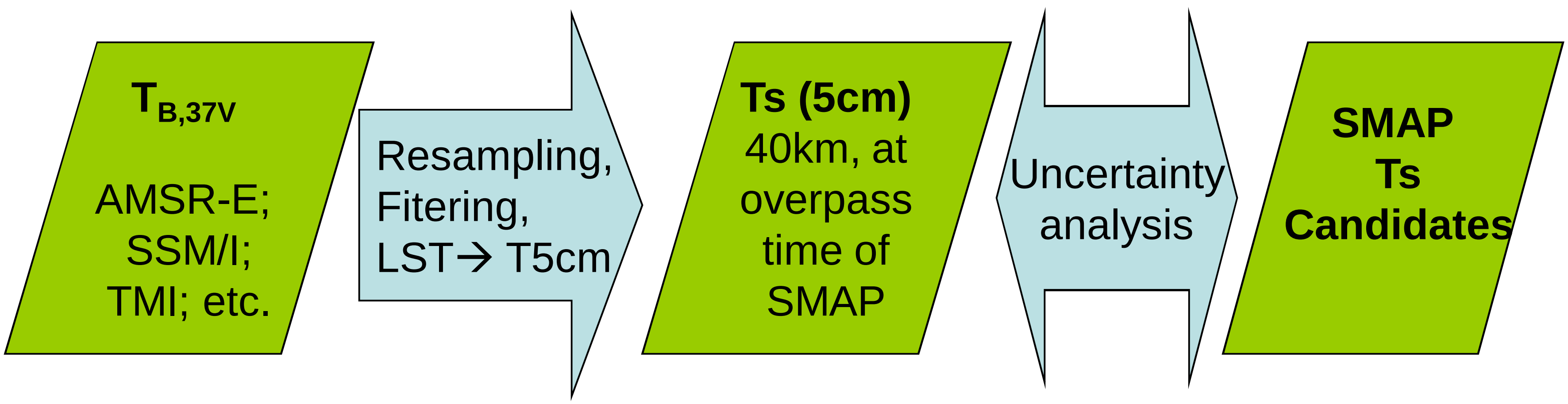


R. Bindlish

Soil Temperature for L-band

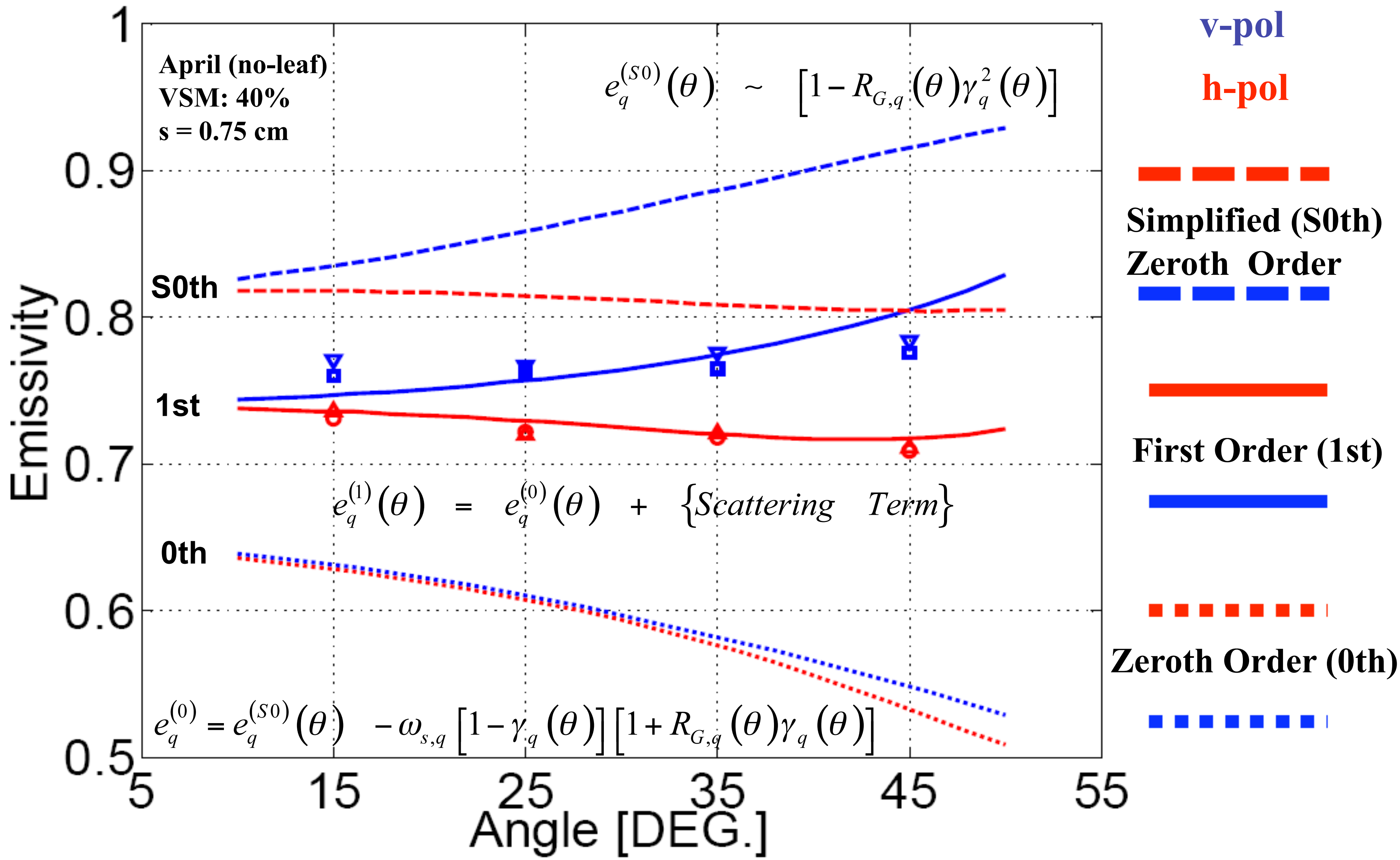
Thomas Holmes, USDA ARS Hydrology and Remote Sensing Lab

- SCA and LPRM soil moisture retrievals have successfully used Ka-band ($T_{B,37V}$) derived soil temperature.
- Can Ka-band be used to analyze potential ancillary soil temperature data for SMAP?



- Is ancillary T for SMAP available for study?

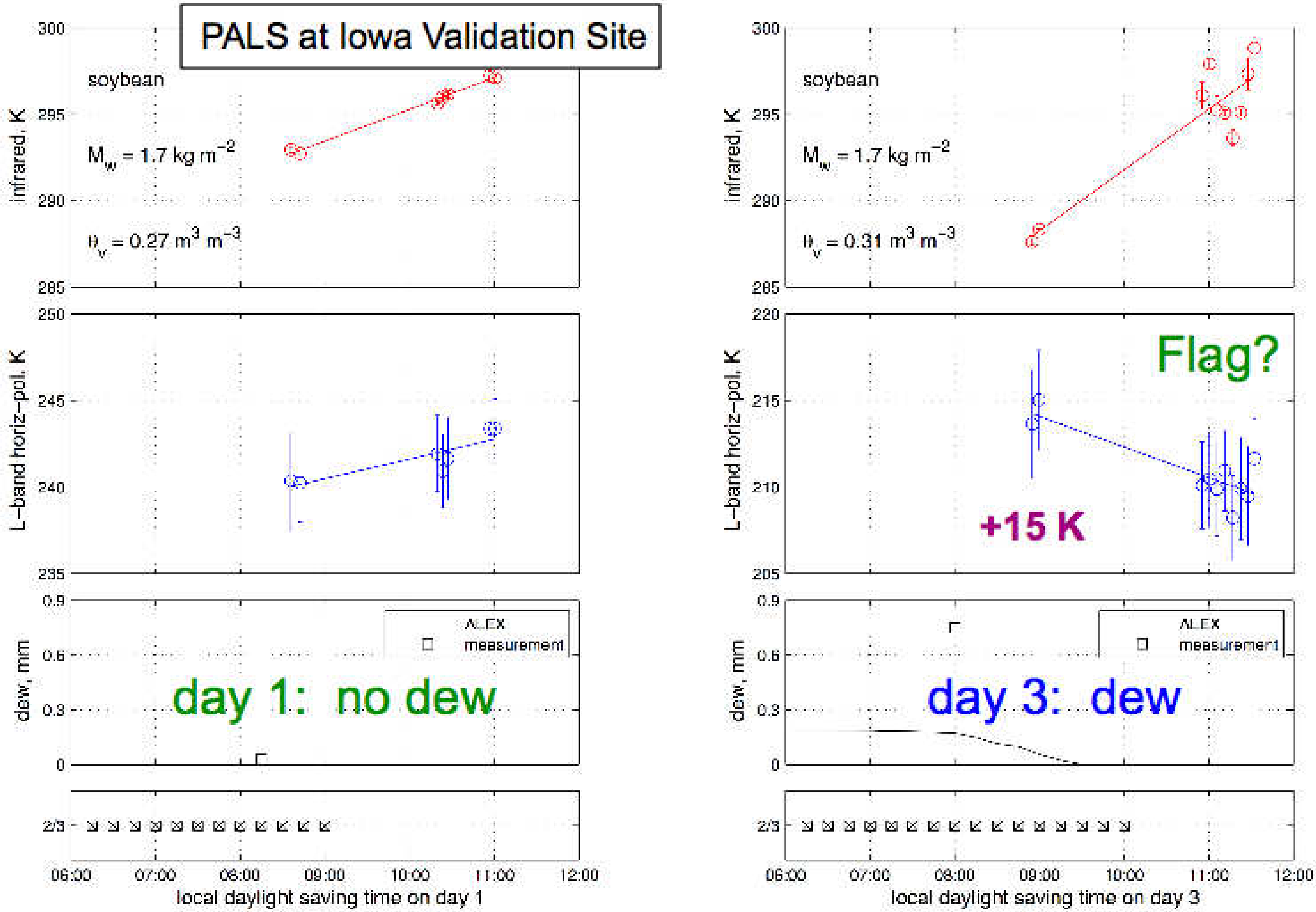
Radiometer Angular Response from a Forest Canopy (Models vs Data)



R. Lang, George Washington University

IOWA STATE UNIVERSITY

Hornbuckle et al., Effect of dew on L-band T_B.



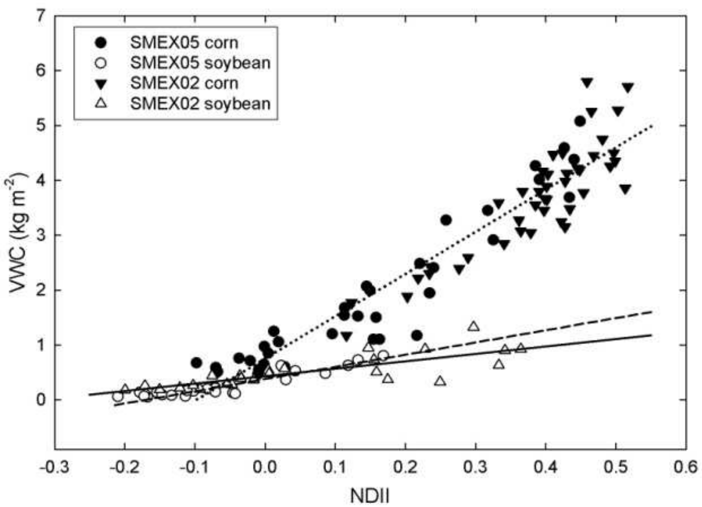
SMEX05 Vegetation Validation

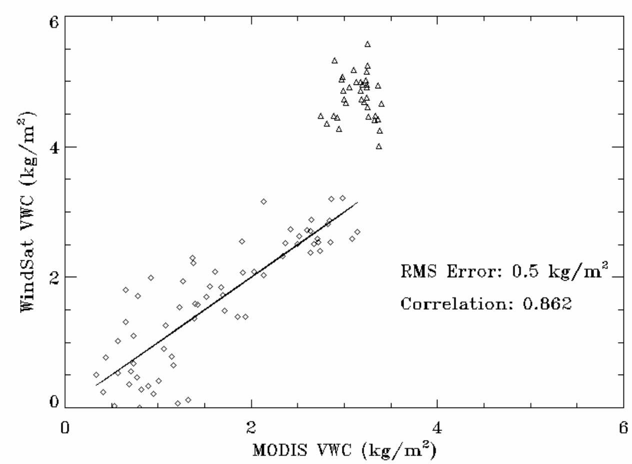
E.R. Hunt, Jr./USDA, L. Li/NRL, T. Yilmaz/GMU

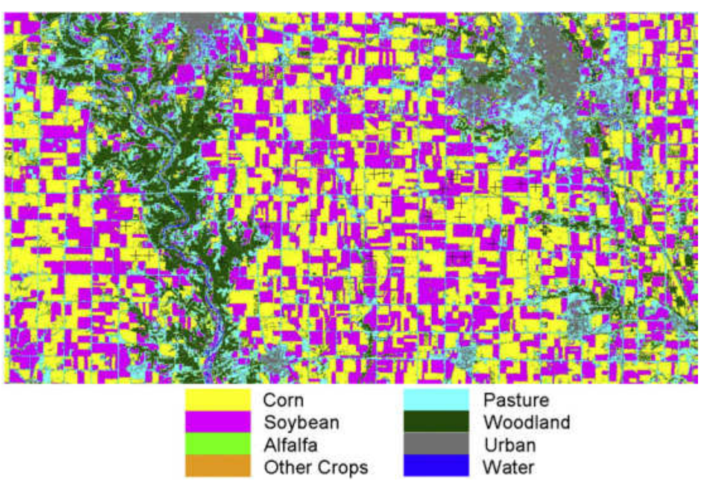
The Normalized Difference Infrared Index (NDII) is linearly related to canopy water (EWT):

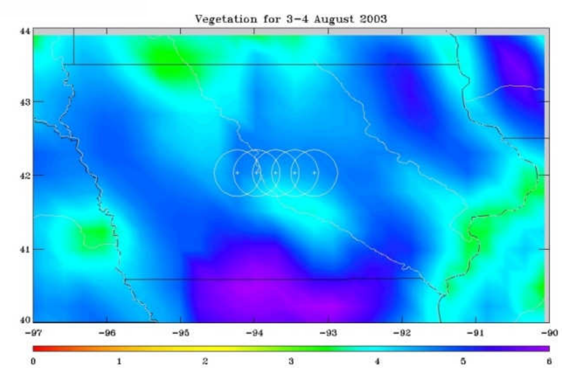
$$NDII = (R_{0.85}-R_{1.65})/(R_{0.85}+R_{1.65})$$

Assuming linear allometric relationships, the VWC is then linearly related to EWT and NDII









A Bare Surface Algorithm for VV&HH measurements

Basic Inversion Concept

$$\sigma_{pp}(\theta) = R_{pp}(\varepsilon_r, \theta) \cdot Sr_{pp}(s, l, \theta)$$

$$R_{pp} = |\alpha_{pp}|^2$$ **L-band**

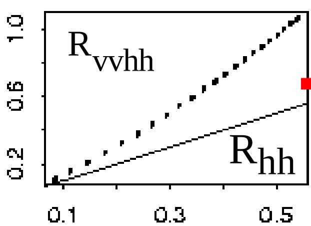
Two functions: 1) R_{pp}-polarization magnitudes and 2) Sr_{pp}-roughness

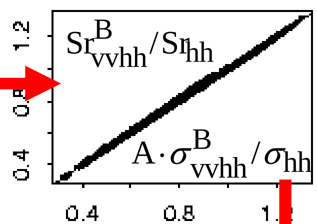
Technical Concept:

1) **Most reliable relation: $R_{vv}=f(R_{hh})$**
2) **Inversion requires $Sr_{vv} \approx f(Sr_{hh})$**
3) **How to reduce speckle effect?**

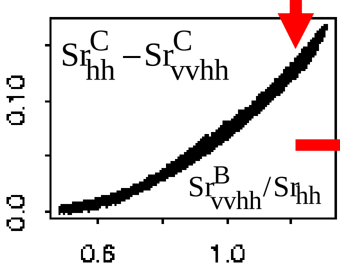
Based on $R_{hh} = A \cdot R_{vvhh}^B$ **A,B,C,D,E,F are coefficients**

$$A \cdot \sigma_{vvhh}^B / \sigma_{hh} = Sr_{vvhh}^B / Sr_{hh} = Sr_{index}$$





$$\log\left(Sr_{hh}^C - Sr_{vvhh}^C\right) = D + E \cdot \log(Sr_{index}) + F \cdot Sr_{index}$$



Major Problems

1) **High variability of roughness impacts at different polarizations**
2) **Independent speckle effect**

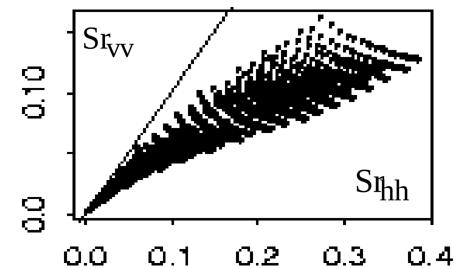
Algorithm Development

1) **Numerical simulation for a wide range database by AIEM to develop the algorithm**
2) **Using σ_{vvhh} and one of σ_{hh} or σ_{vv} to reduce speckle effect**
3) **Develop the roughness index and the relationship of roughness parameters at different polarization**
4) **Validation with the field experimental data**

Algorithm

$$Sr_{hh}^C - Sr_{vvhh}^C = \left(\frac{\sigma_{hh}}{R_{hh}}\right)^c - \left(\frac{\sigma_{vvhh}}{R_{vvhh}}\right)^c$$

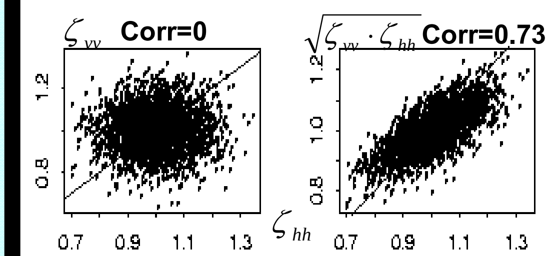
With a technique to select solution in multi-solution cases



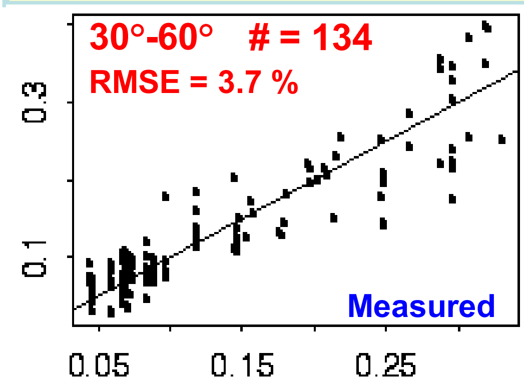
$$\sigma_{vvhh} = \sqrt{\sigma_{vv} \cdot \sigma_{hh}}$$

$$R_{vvhh} = \sqrt{R_{vv} \cdot R_{hh}} \quad Sr_{vvhh} = \sqrt{Sr_{vv} \cdot Sr_{hh}}$$

Speckle Noise Impact k_p=0.1



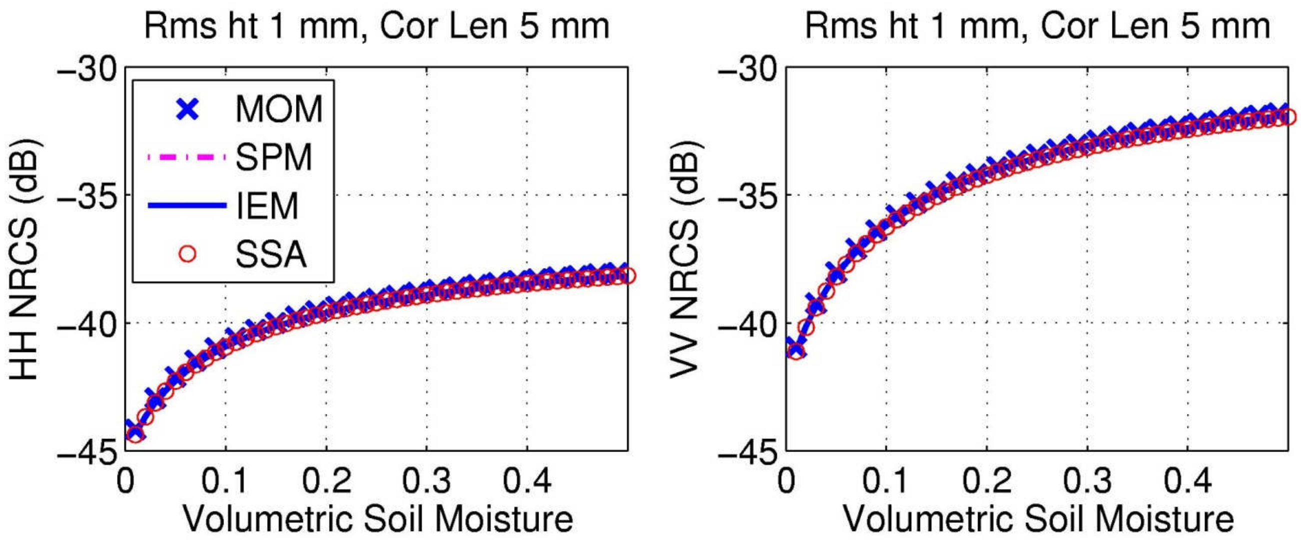
Validation from Umich's ground experiment data (Oh et al., 2004)



J. Shi, UCSB

Numerical Studies of Exponential Surface Backscattering

- It is common to use an exponential correlation function model for soil surfaces
  - Two parameters: rms height and correlation length
- Radar ATBD members are conducting a study using MOM (mostly 2-D, some 3-D surfaces) for 1.26 GHz, 40 degrees backscatter [Johnson, Moghaddam, Shi, Tsang]
  - Comparing with SPM, AIEM, SSA, and other theories
  - Tabling results for rms height 0.1, 0.5:0.5:3 cm and L=[5 10 20]xheight
- Still compiling results – to date, IEM and SSA yield very similar predictions, some evidence of overprediction of MOM VV NRCS for rougher surfaces
- Only part of the soil moisture retrieval but we have the tools at hand to do this now



L. Tsang, U. Washington

3D and 2D Comparisons for Backscattering Coefficients and Emissivities of Bare Soil Surfaces

Parameters for 3D cases

	freq (GHz)	θ_i	Correlation Length(cm)	RMS Height(cm)	ε_{soil}
Case1	1.5	40	8.4	1.12	15.34+ 3.66i
Case2	1.26	40	10.0	2.0	10.14+ 0.82i

Emissivities for 3D case1

	V	H	V-H	Comments
MoM	0.7674	0.5966	0.1708	RWG (Zhou et al., 2004) Energy conserve 1.0074 for v, 0.9967 for h ,UW
AIEM	0.7474	0.5914	0.1560	(Chen et al., 2003)
Modified AIEM	0.7416	0.5919	0.1497	(Wu et al., 2008)
SPM	0.7487	0.5742	0.1745	(Tsang et al, 2001)
Smooth	0.7367	0.5439	0.1928	

Backscattering coefficients for 3D case1

	VV	HH	VV-HH	Comments
MoM	-11.98	-15.00	3.02	Pulse (Li et al. 2005),UW
MoM	-10.70	-15.92	5.22	RWG (Zhou et al., 2004),UW, more accurate than pulse
AIEM	-12.44	-14.35	1.91	(Chen et al., 2003)
Modified AIEM	-11.31	-15.72	4.41	(Wu et al., 2008)
SPM	-9.48	-14.95	5.47	(Tsang et al, 2001)
Dubois	-13.39	-15.96	2.57	(Dubois et al.,1995)
Experimental	-9.1	-14.2	5.1	Michigan data (Oh et al.1992)

Parameters for 3D case 2

	freq (GHz)	θ_i	Correlation Length(cm)	RMS Height(cm)	ε_{soil}
Case2	1.26	40	10.0	2.0	10.14+ 0.82i

Backscattering coefficients for 3D case2

	VV	HH	VV-HH	Comments
MoM	-9.72	-13.99	4.27	RWG(Zhou et al., 2004),UW
AIEM	-11.46	-11.39	-0.07	Chen et al., 2003
Modified AIEM	-9.94	-12.95	3.01	Wu et al., 2008
SPM	-7.39	-12.36	4.97	(Tsang et al., 2001)
Dubois	-12.83	-14.19	1.36	(Dubois et al.,1995)

Emissivities for 3D case2

	V	H	V-H	Comments
MoM	0.8736	0.7395	0.1341	RWG (Zhou etal 2004), Energy conserve 0.0141 for h, 0.0199 for v,UW
AIEM	0.8330	0.7119	0.1211	(Chen et al., 2003)
Modified AIEM	0.8270	0.7132	0.1138	(Wu et al., 2008)
SPM	0.8356	0.6940	0.1416	Tsang et al., 2001
Smooth surface	0.7450	0.5525	0.1925	

2D Results of Backscattering and Emissivities

Parameters for 2D case 1

	freq (GHz)	θ_i	Correlation Length(cm)	RMS Height(cm)	ε_{soil}
Case1	1.26	40	30.0	3.0	12.274 + 1.016i

Emissivities for 2D case

	V	H	V-H	Comments
MoM	0.7795	0.5921	0.1874	Rooftop Energy conserve : 0.9971 for v, 0.9993 for h, UW
AIEM	0.7449	0.5999	0.1450	Peng Xu, Wuhan U
SPM	0.7985	0.6038	0.1947	
Smooth	0.7369	0.5441	0.1928	

Backscattering coefficients for 2D case

	VV	HH	VV-HH	Comments
MoM	-9.11	-12.59	3.48	Rooftop,UW
MoM	-8.83	-11.91	3.08	Joel Johnson, OSU
AIEM	-9.78	-11.61	1.83	Peng Xu, Wuhan U
AIEM	-10.63	-11.60	0.97	J.C.Shi,UCSB
IEM	-8.28	-11.75	3.47	Joel Johnson, OSU
SPM	-7.56	-12.76	5.20	

More 2D and 3D results are in forthcoming team report.

Parameters for 2D case 2

	freq (GHz)	θ_i	Correlation Length(cm)	RMS Height(cm)	ε_{soil}
Case2	1.50	40	8.4	1.12	15.34 + 3.66i

Backscattering coefficients for 2D case

	VV	HH	VV-HH	Comments
MoM	-10.62	-15.05	4.43	Rooftop UW
AIEM	-11.01	-15.32	4.31	Peng Xu, Wuhan U
IEM	-9.70	-14.84	5.14	Joel Johnson, OSU
SPM	-9.36	-14.84	5.47	
EBCM	-8.95	-13.96	5.01	Michigan

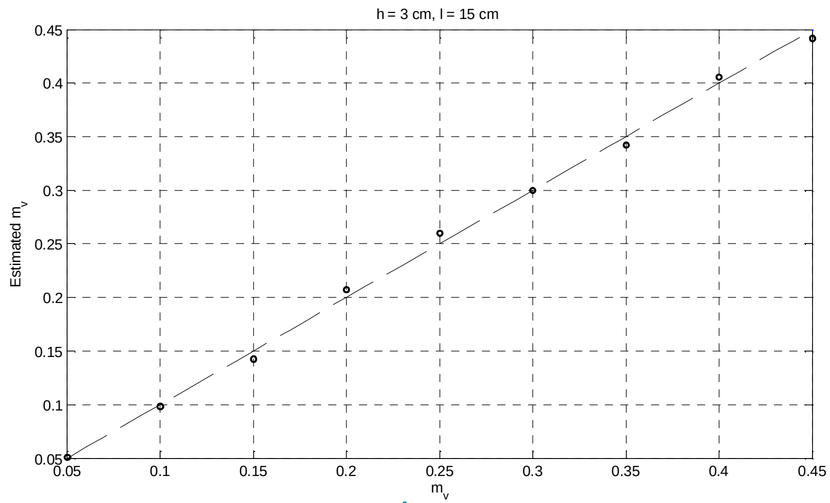
Emissivities for 2D case

	V	H	V-H	Comments
MOM	0.7795	0.5921	0.1874	Rooftop Energy conservation: 0.9971 for v, 0.9993 for h,UW
AIEM	0.7449	0.5999	0.1450	Peng Xu, Wuhan U
SPM	0.7985	0.6038	0.1947	
Flat	0.7369	0.5441	0.1928	

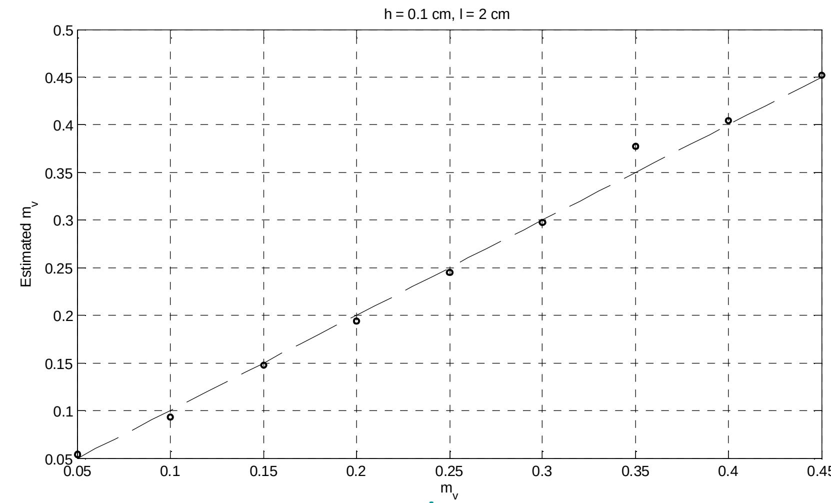
More 2D and 3D results are in forthcoming team report.

Soil Moisture Inversion using Simulated Annealing

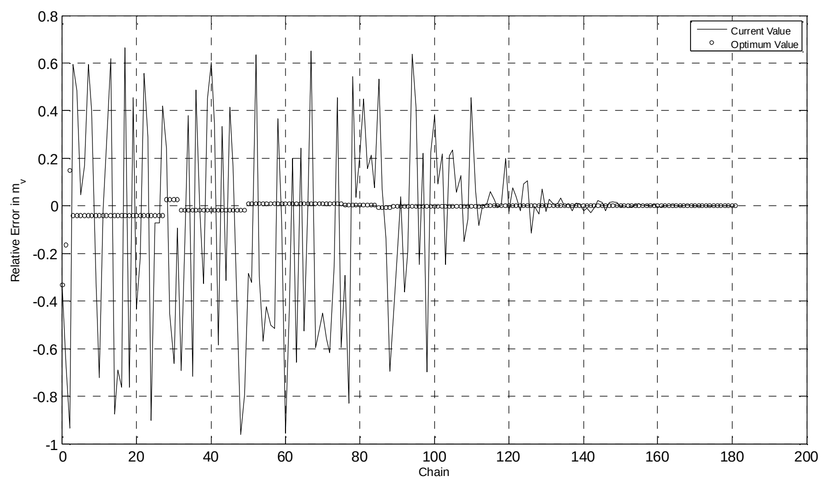
Alireza Tabatabaeenejad and Mahta Moghaddam



Estimated vs. true m_v (rougher surface)



Estimated vs. true m_v (smoother surface)

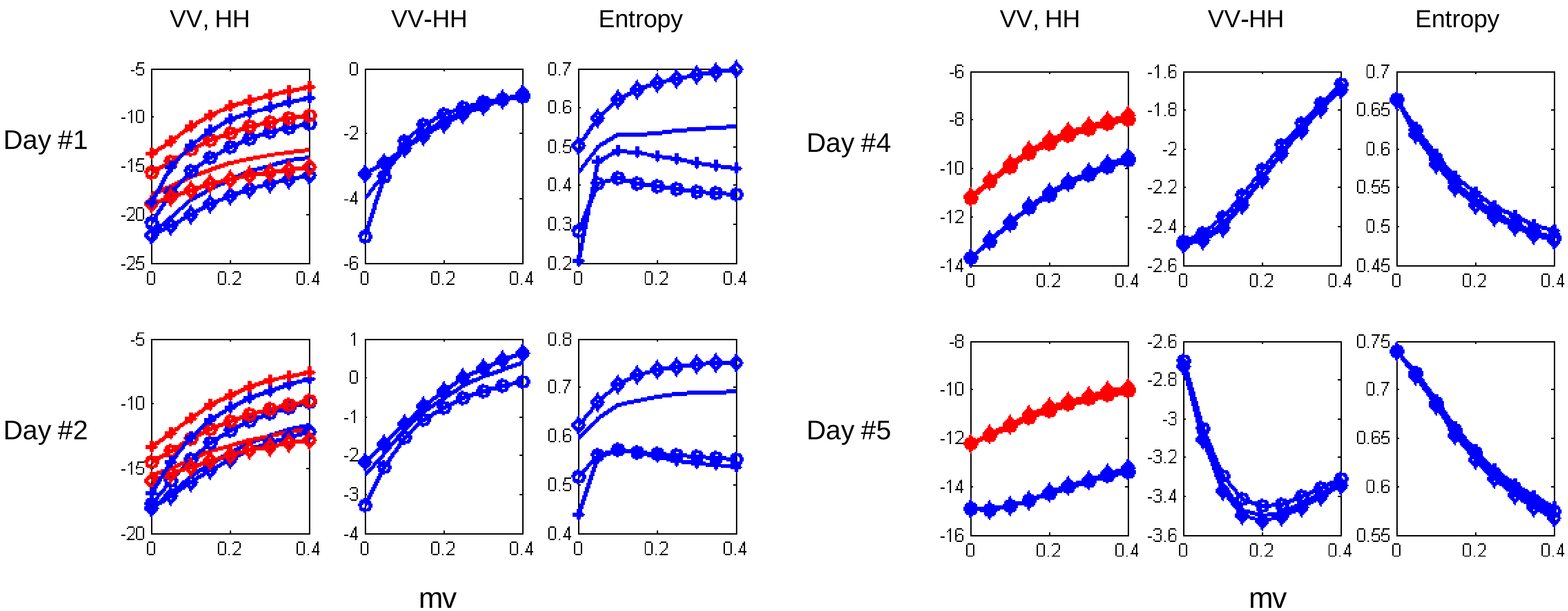


Estimated m_v: convergence of SA (m_v=0.3, rough case)

1. Simulated Annealing is a powerful, but slow, tool for accurately estimating surface soil moisture.
2. The method has a good noise response.
3. The forward model used to demonstrate is first-order SPM. More accurate forward models can be used.

Soil Moisture Inversion Algorithm Case Study: Soybean

Yang Du[1] and Leung Tsang[2]
[1] Zhejiang Univ., China
[2] The Univ. of Washington, USA



Feature extraction numerical study

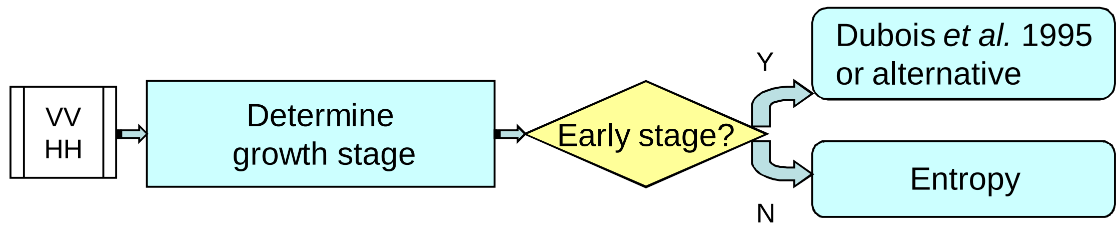
Goals:

- To identify features sensitive to mv while insensitive to roughness.
- To investigate the impact of vegetation growth stage.

Setup:

- Ground truth taken from Yueh *et al.* (1992).
- rms height takes values {0.7, 1, 1.5, 2} times original value.
- Direct surface contribution via EAIEM (Du,2008)

Proposed inversion algorithm



Soil moisture estimation using Active Microwave

Radar Obs σ^o

↓

Water Cloud model

$$\sigma^o = \sigma^o_{veg} + \sigma^o_{veg+soil} + \tau^2 \sigma^o_{soil}$$

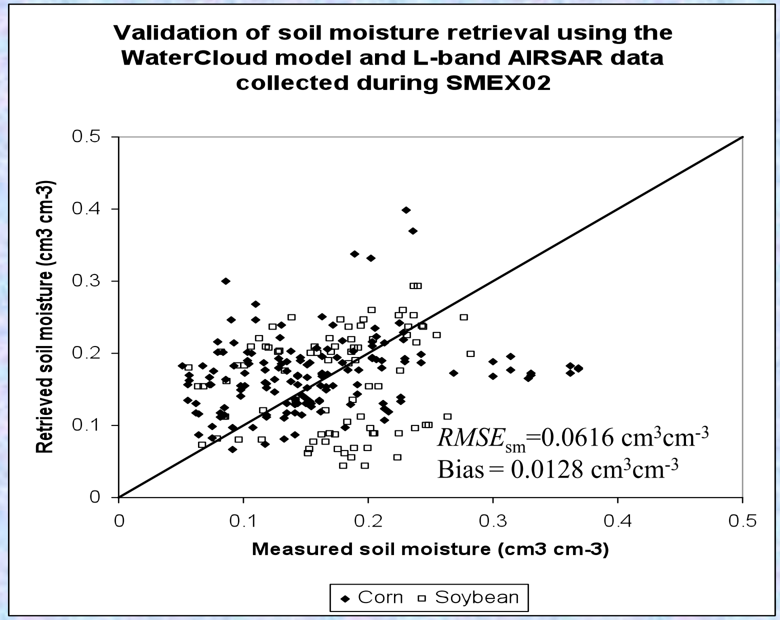
↓

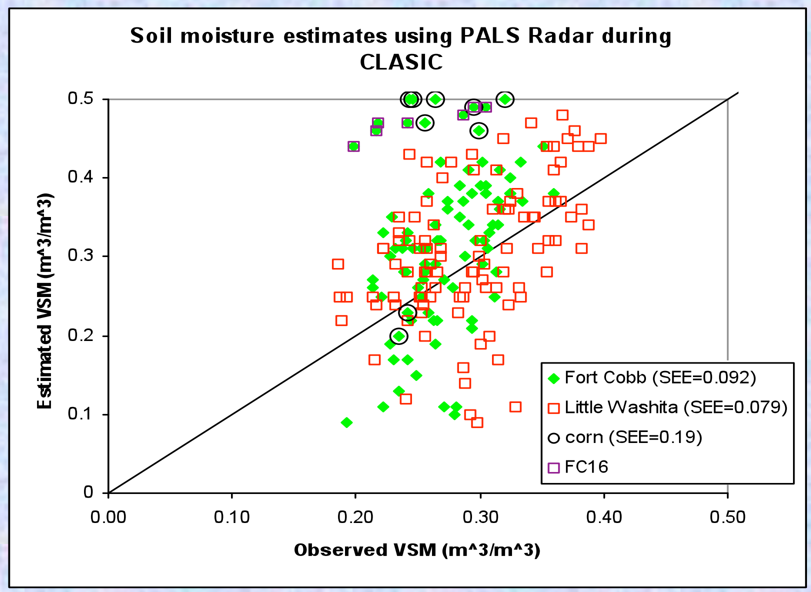
Vegetation Parameterization
(Eom and Fung, 1984)

↓

Scattering Model
(Dubois et al, 1985)

- Soil Moisture estimates better for areas with low to moderate vegetation
- Extreme field conditions led to higher retrieval error
- Introducing a simple vegetation parameterization can improve radar soil moisture estimation





R. Bindlish

UNIVERSITY of WASHINGTON
COLLEGE of ENGINEERING

Microwave Scattering Model of Vegetated Surfaces

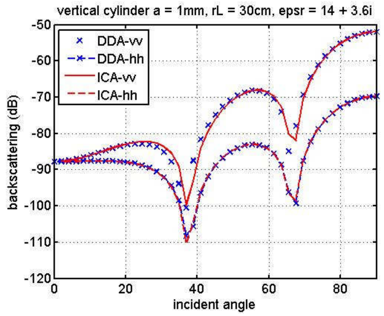
Electrical Engineering

Xiaolan Xu, Leung Tsang, University of Washington

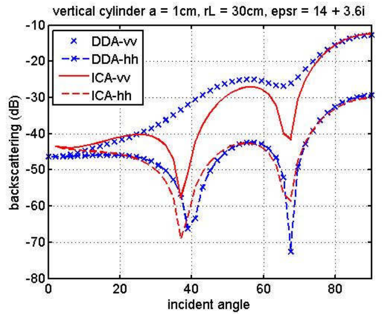
Single Cylinder Scattering

1. Infinite Cylinder Approximation
   - Quasi-static approach
   - Volume integration approach
2. Discrete Dipole Approximation

Case 1: small radius (1mm)



Case 2: large radius (10mm)



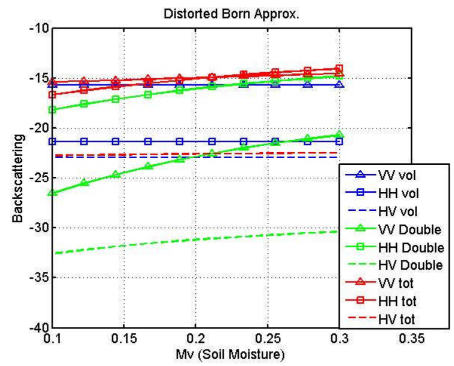
Energy Conservation Check (case 2)

	Infinite Cylinder Approx.			Discrete Dipole Approx.	
Incident wave polarization	v	h		v	h
Scattering coef.	7.16e-3	3.32e-4		4.69e-3	2.95e-4
Absorption coef.	7.01e-3	3.86e-4		4.00e-3	2.06e-4
Extinction coef.	1.42e-2	7.18e-4		8.96e-3	5.01e-4
Optical theorem	1.48e-2	8.64e-4		8.95e-3	5.01e-4
error with Opt Thm	4.6%	16.7%		0.12%	0.048%

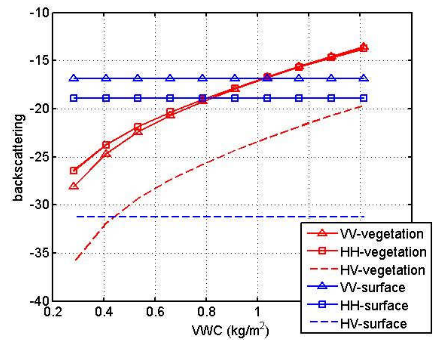
Vegetation Layer of Cylinders

1. Vector Radiative Transfer Theory (First order)
2. Distorted Born Approx.

Sensitivity to soil moisture



Sensitivity to VWC



Model Comparison

F=1.26GHz, a = 2mm,L = 50cm, Hlayer = 50cm, n0 = 900/m^3

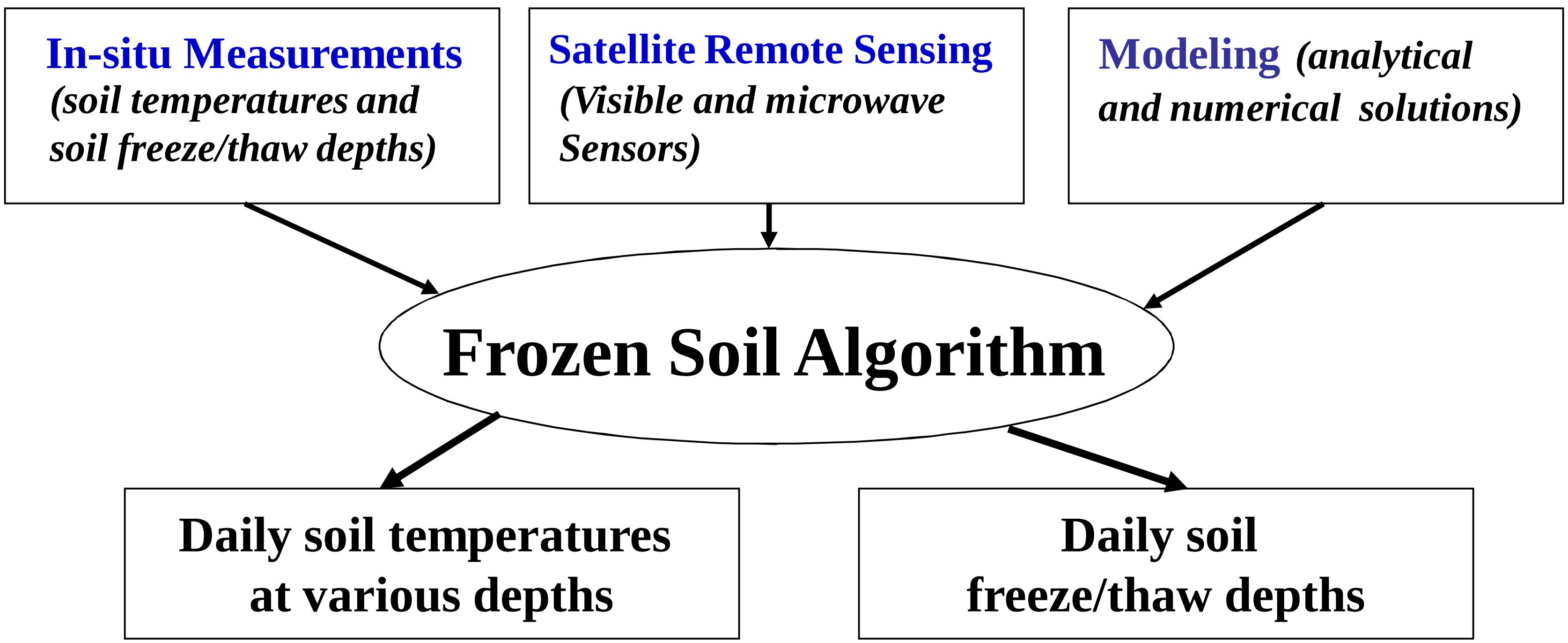
Backscattering (dB)	Vector Radiative Transfer Theory	Distorted Born Approx.	Caltech Model by Van Zyl and Motofumi
volume-VV	-15.7	-15.7	-15.8
volume-HH	-21.4	-21.4	-20.0
volume-HV	-23.0	-23.0	-23.4
DB-VV	-26.0	-23.0	-18.8
DB-HH	-19.2	-16.1	-13.9
DB-HV	-25.4	-31.4	-29.9

Total effect of the vegetation layer

	Vector Radiative Transfer Theory	Distorted Born Approx.	Caltech Model by Van Zyl and Motofumi
Total-VV	-15.3	-15.0	-14.0
Total-HH	-17.3	-15.1	-13.0
Total-HV	-21.2	-22.6	-22.5

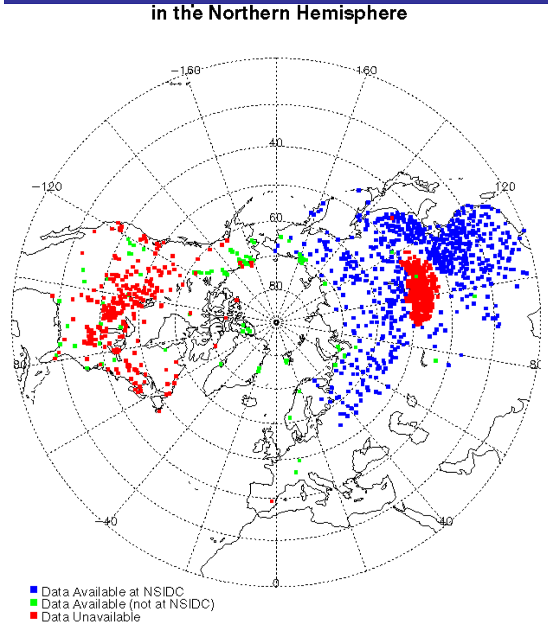
Frozen Soil Algorithm

Objective: ***To produce blended daily soil temperatures at various depths and daily soil freeze/thaw depths at regional and global scales.***

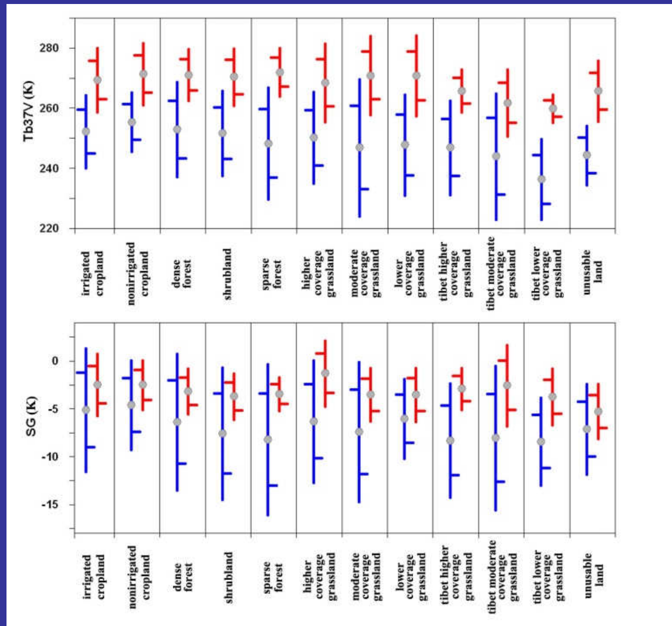


Tingjun Zhang, NSIDC

In-situ Data

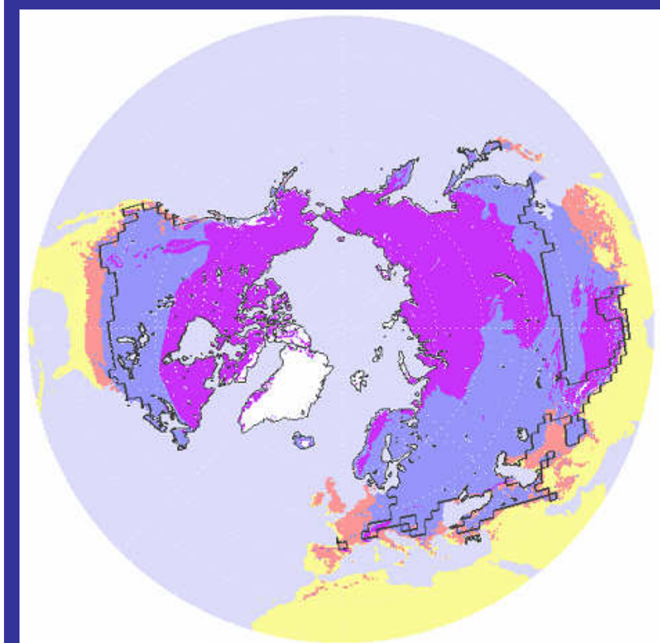


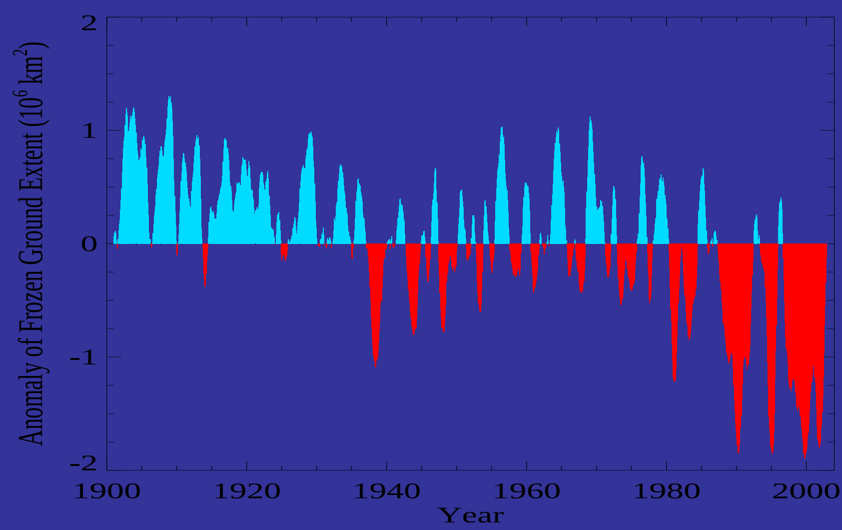
Remote Sensing



Modeling

Conductive heat transfer with phase change, including: **(i) seasonal snow cover and peat layer, (ii) variable physical and thermal properties, (iii) heat flux lower boundary, (iv) primarily driven by air temperature or surface energy balance if available.**





Comments from Ziad Haddad (JPL)

Use of Precipitation measurements in the SMAP algorithms:

TRMM-3B42, GPCP, CMAP, CMORPH, PERSIANN, SCAMPR, NRL-blend, RSS …

- quantify how current High Resolution Precipitation Products correlate with soil moisture
  * identify different estimators that can be derived from HRPP, such as "surface accumulation" or "area-time integral",
  * quantify the correlation of different estimators at t-minus-delta with delta(soil-moisture),
  * reconcile with a water balance model that forecasts what would be expected

- quantify the effect of different measures of uncertainty in the available precipitation products on the soil moisture estimation
  * effect of detection/false-alarm issues (discrimination between clouds and precip)
  * effect of conditional spatial covariance matrix (given rain) at what scale
  * how do these affect SMAP algorithms (e.g. at what level of uncertainty would precip "info" be useless)