NOAA Satellites and Information
National Environmental Satellite, Data, and Information Service

STAR Center for Satellite Applications and Research
formerly ORA — Office of Research and Applications

Satellite Soil Moisture Remote Sensing and Data Assimilation: Brief History & Current Status

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OUTLINE

5. SM Data Research Plan

4. Soil Moisture Data Assimilation

3. MW Soil Moisture Retrievals

2. SM Observation Techniques

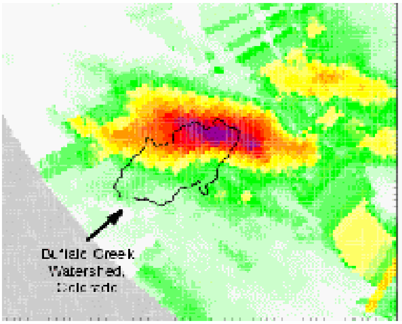
1. SM Data & Importance

Soil Moisture Data & their Values

- ***SM*** **= Water held between soil particles:**
  - *Volumetric Soil Moisture (VSM) = [m^3 H_2O]/[m^3 Soil], [%]; [-]*
  - *Gravimetric Soil Moisture (GSM) = [kg H_2O]/[kg Solid Soil], [g/g]*
  - *Soil Wetness (SW) = VSM/Porosity*
- **Soil moisture directly impacts agricultural productivity, military mobility, runoff potential/flood control/reservoir management, and for NOAA**

Soil Moisture Impacts on Weather Forecasting (1)

Observed Rainfall from intense storm in Colorado:

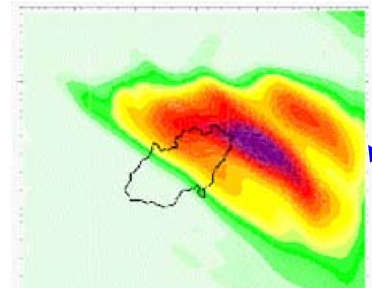


Buffalo Creek Basin

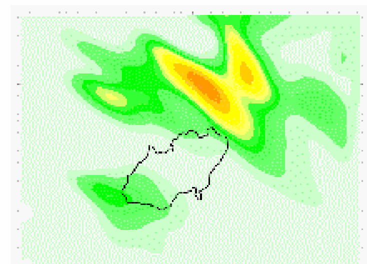
Observed Rainfall
0000Z to 0400Z 13/7/96
(Chen et al., NCAR)

24-Hours Ahead Atmospheric Model Forecasts

Model forecasts with and w/o soil moisture:



With Realistic Soil Moisture



Without Realistic Soil Moisture

Actual storm event is forecasted accurately only if soil moisture information is available.

Soil Moisture Data Will Improve Numerical Weather Prediction (NWP) Over the Continents by Accurately Initializing Land Surface States

“The experience of the last ten years at ECMWF has shown the importance of soil moisture...Soil moisture is a major player on the quality of weather parameters such as precipitation, screen-level temperature and humidity and low-level clouds."

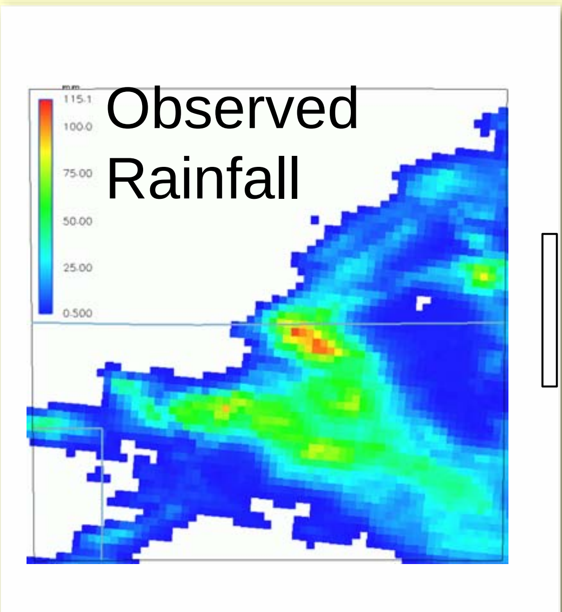
Anthony Hollingworth, ECMWF

"The strong motivation for this land data assimilation and land-monitoring space missions such as Hydros is that the land states of soil moisture, soil ice, snowpack, and vegetation exert a strong control on ...the heating and moistening of the lower atmosphere…forecast of tomorrow's heat index, precipitation, and severe thunderstorm likelihood."

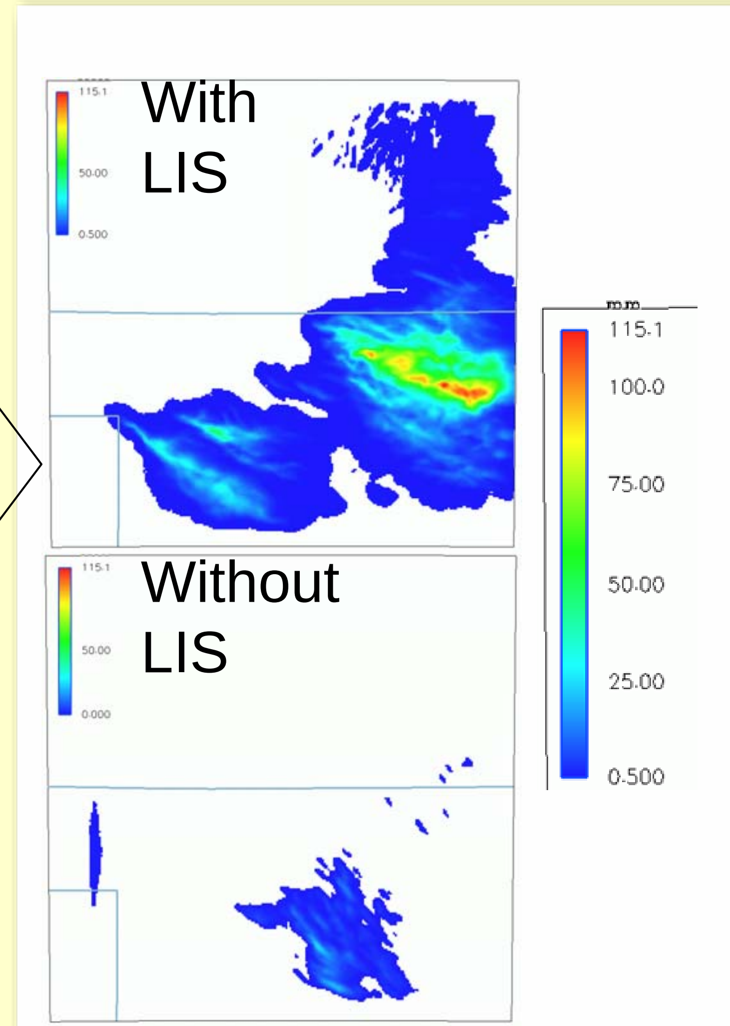
Louis Uccellini, NCEP

Soil Moisture Impacts on Weather Forecasting (2)

Soil Moisture Impact Example:
WRF/LIS simulation for IHOP June 12, 2002



12-Hours Ahead
Weather Forecasts

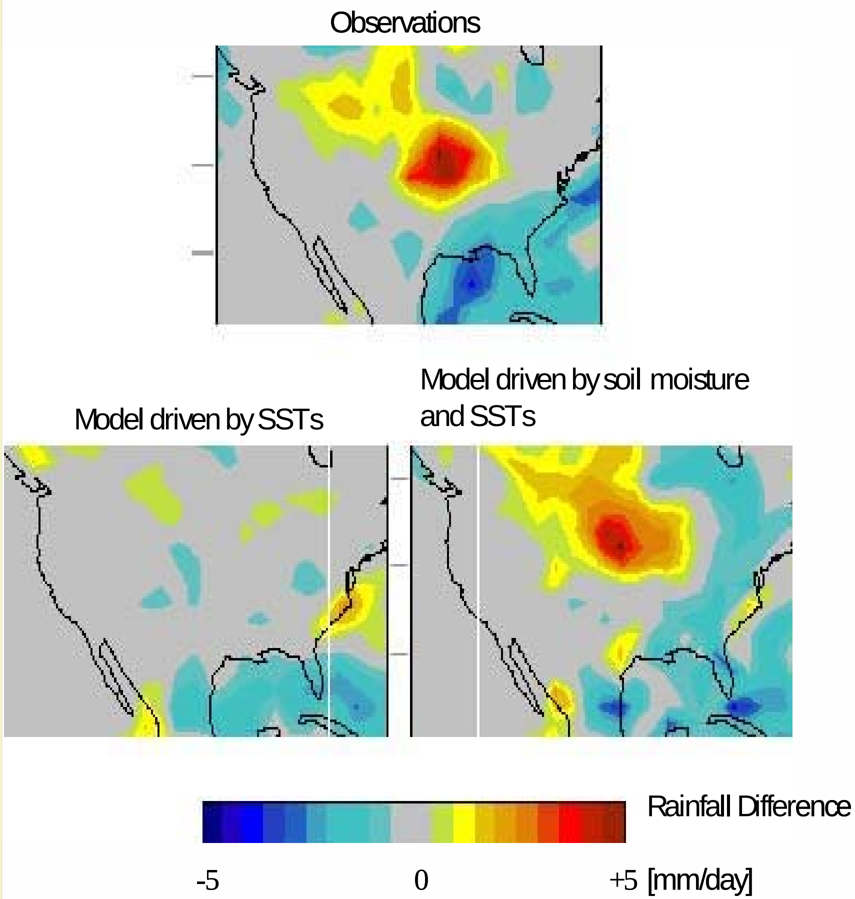


Forecast rainfall more accurate with LIS-initialized soil moisture

Peters-Lidard, et al, 2006

Soil Moisture Impacts on Seasonal Predictability

Summer 1993 Rainfall Minus Summer 1988 Rainfall



Schubert et al. (2002)

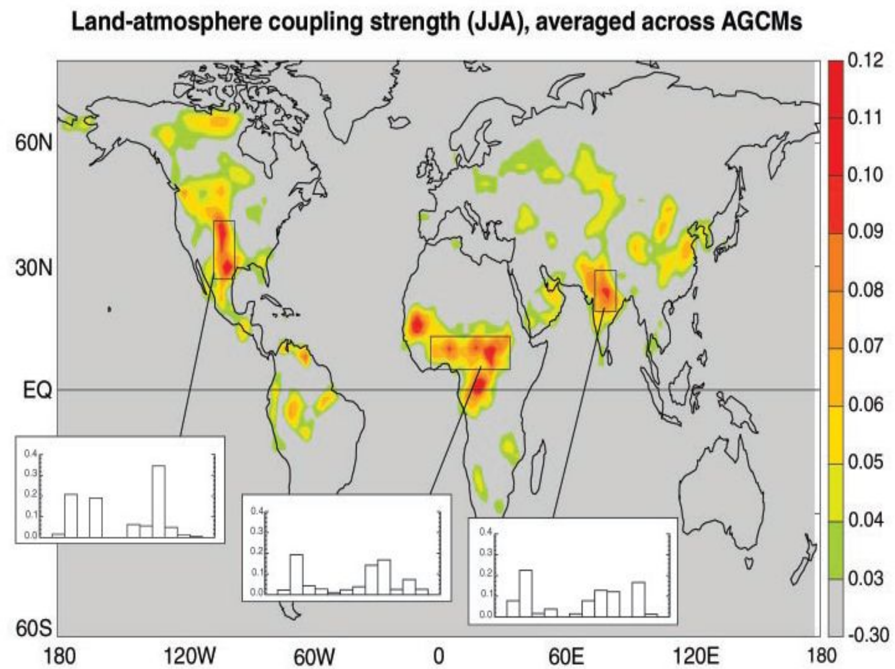
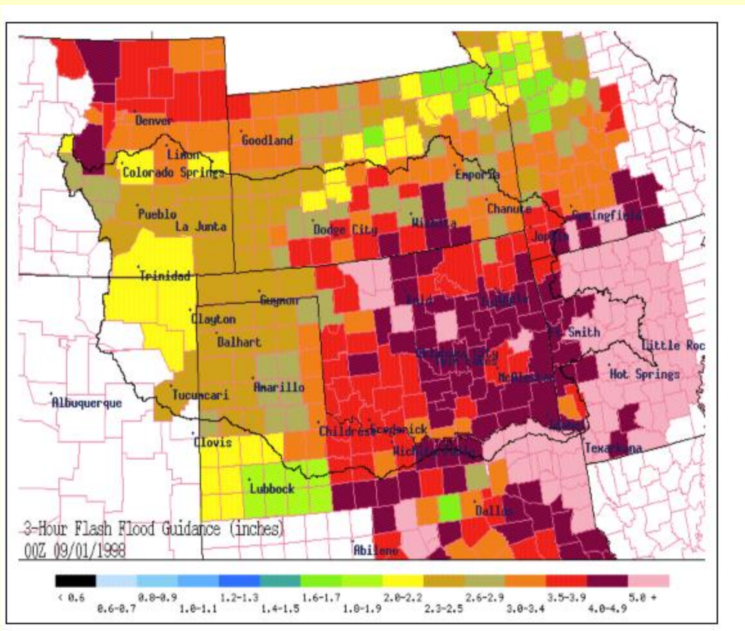


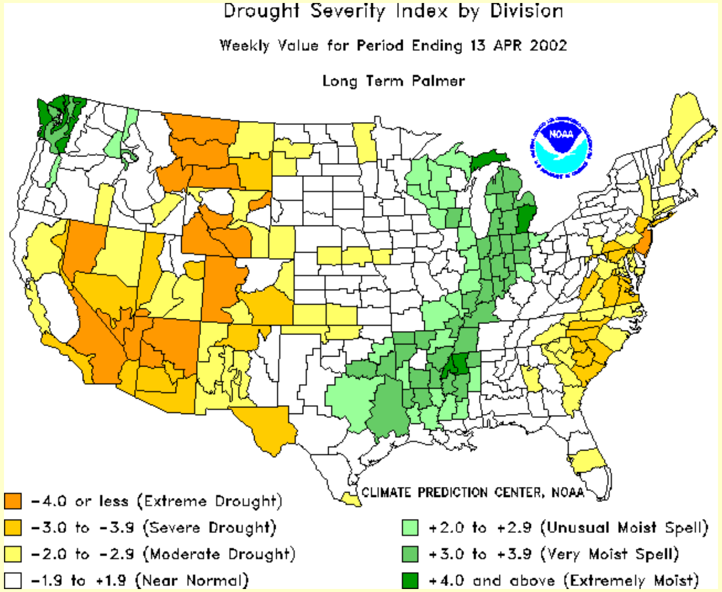
Fig. 1. The land-atmosphere coupling strength diagnostic for boreal summer (the Ω difference, dimensionless, describing the impact of soil moisture on precipitation), averaged across the 12 models participating in GLACE. (**Insets**) Areally averaged coupling strengths for the 12 individual models over the outlined, representative hotspot regions. No signal appears in southern South America or at the southern tip of Africa.

Koster et al. (2004), *Science*, 305, 1138-1140.

Soil Moisture Data for Flood & Drought Monitoring

Current NWS Operational 30 km Flash Flood Guidance (FFG) is Based on *Model* Surface Soil Moisture Deficit



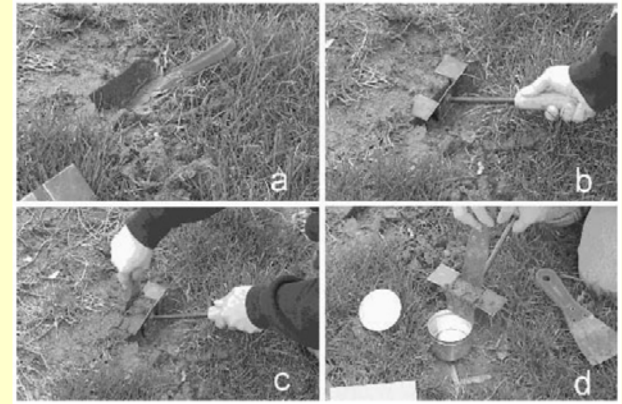


Current NOAA and National Drought Mitigation Center (NDMC) Operational Drought Index is also based on *Modeled* Soil Moisture Data.

Soil moisture Observational data will replace model or proxy SM

Soil Moisture Observation Techniques

- **Soil Sampling** ➔ Point Data Collection
  - ✓ $GSM = (W_{wet} - W_{dry})/W_{dry}$
  - ✓ BD (Bulk Density) = W_{dry}/Volume
  - ✓ VSM = GSM * BD



- **Time Domain Reflectometer (TDR):** ➔ Point Data Collection
  - ✓ Theta probe, etc

- **Microwave Radiometer/Radar:** ➔ Global/Regional Mapping
  - ✓ Ground-based: TMMR, GBMR, SLMR, etc
  - ✓ Air-borne: ESTAR, PBMR, PSR, etc
  - ✓ Satellite-borne: Skylab, SMMR, SSM/I, TMI, AMSR-E, WindSat, ESCAT, ASCAT, SMOS, Aquarius, and GPM? Hydros? MIS?

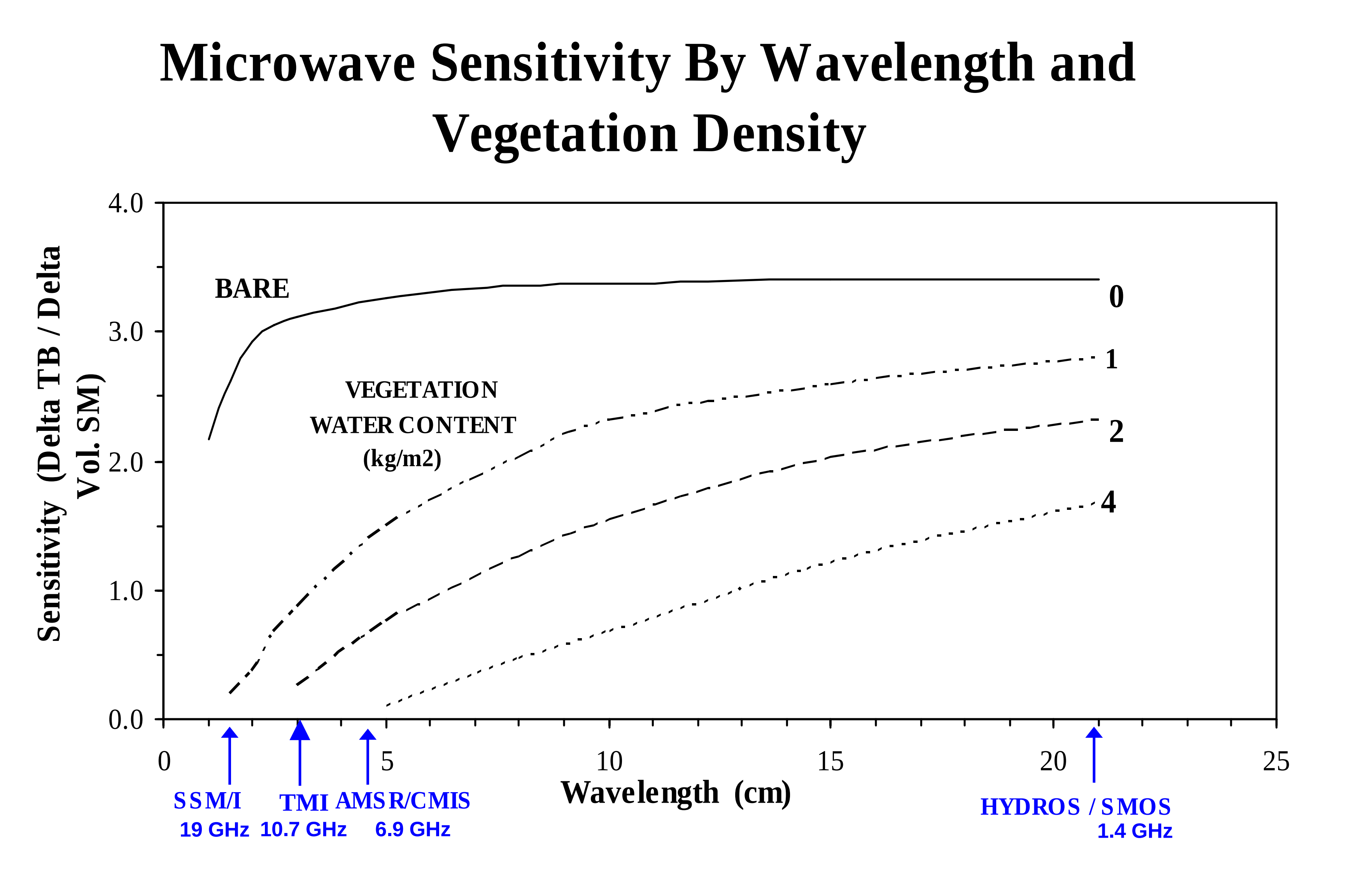
MW Soil Moisture Remote Sensing Science (1)

❖ Scientific Basis:

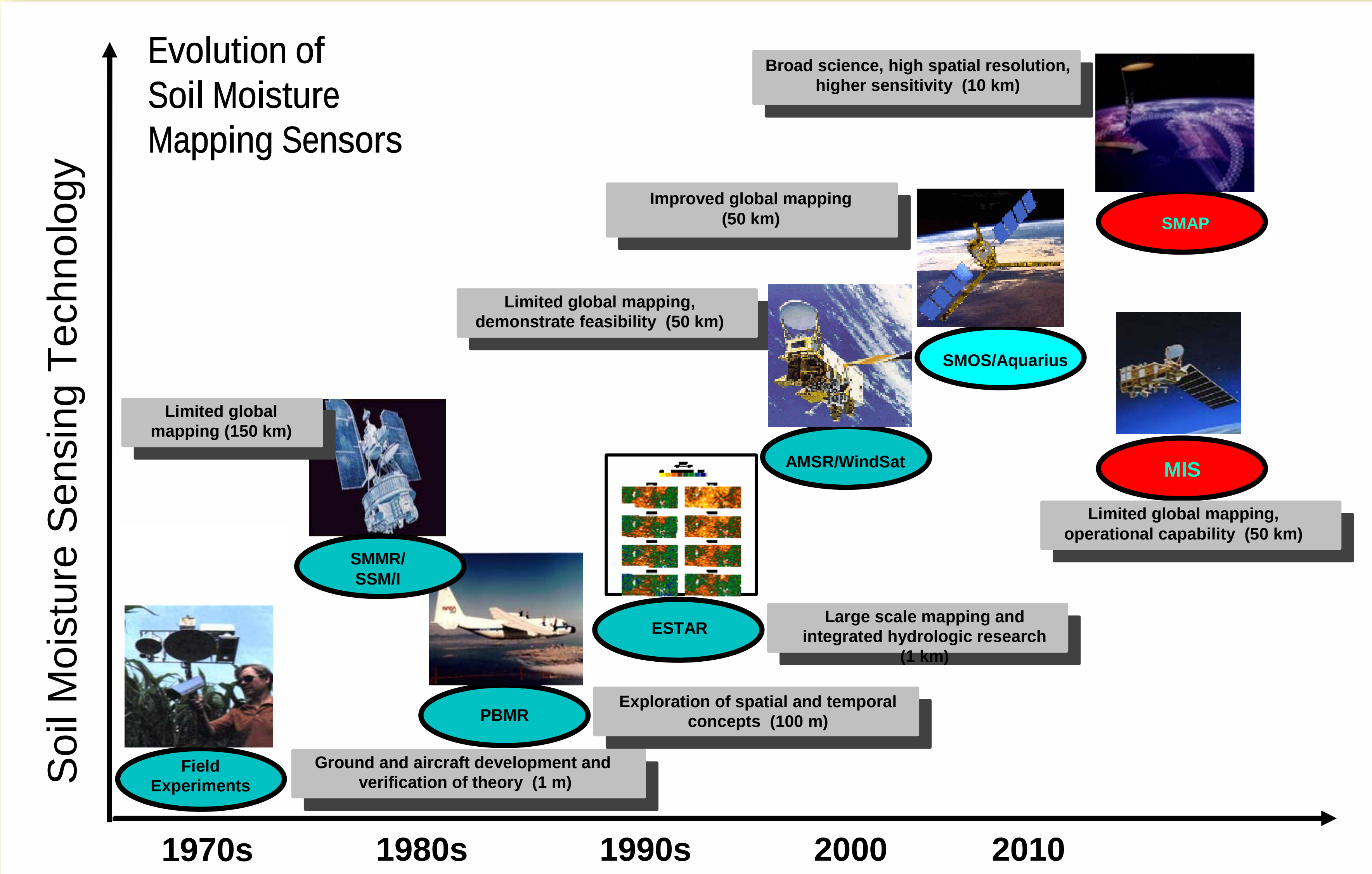
- ✓ *Dielectric constants: ε_{water} = ~ 80, ε_{dry_soil} < 4,* → *ε_{wet_soil} = 4 – 80;*
- ✓ *Fresnel equation: reflectivity <-> ε_{wet_soil}* → *σ = f(SM, etc, etc);*
- ✓ *emissivity = 1 – reflectivity,* → *T_B = g(SM, etc).*

❖ Brief Research History (Passive Radiometry):

- ✓ *1930s-1950s: MW "upward" radiometer used to measure EM energy of extraterrestrial origin.*
- ✓ *Straiton et al (1958): 1st radiometer pointing "downward" for terrestrial observations.*
- ✓ *Blinn & Quade (1973), Schmugge et al (1974, 1977), England (1975), Ulaby et al (1975), Njoku & Kong (1977), Eagleman & Lin (1976), Schmugge (1978): 1st radiometers for soil moisture remote sensing.*
- ✓ *Choudhury et al (1979), Schmugge (1980), Wang & Schmugge (1980), Dobson & Ulaby (1981), Jackson et al (1982), Mo et al (1982), Shutko et al (1982), Dobson et al (1984, 1985), Wang (1985): 1st studies accounting impacts of roughness, soil texture, vegetation canopy, skin temperature and SM itself on the SM-TB relationships.*
- ✓ *Jackson (1993), Jackson (1997), Njoku & Li (1999), Owe et al (2001), and others: development, refinement, and validation of regional or global soil moisture retrieval algorithms.*


Microwave Sensitivity By Wavelength and Vegetation Density
Sensitivity (Delta TB / Delta Vol. SM)
4.0
3.0
2.0
1.0
0.0
BARE
0
1
2
4
VEGETATION WATER CONTENT (kg/m2)
0
5
10
15
20
25
Wavelength (cm)
SSM/I
19 GHz
TMI
10.7 GHz
AMSR/CMIS
6.9 GHz
HYDROS / SMOS
1.4 GHz

MW Soil Moisture Remote Sensing Technology



Microwave Soil Moisture Sensors Details (1)

- The Scanning Multichannel Microwave Radiometer (SMMR): launched with Nimbus-7 in 1978 and stopped in 1987; was measuring TBs at 6.63, 10.69, 18.0, 21.0 and 37.0 GHz frequencies. Own et al (2001) created a SM product.
- The Special Sensor Microwave Imager (SSM/I) is a passive microwave radiometer flown aboard Defense Meteorological Satellite Program (DMSP) satellites since 1987: DMSP F-8, 10, 11,12,13,14,15. SSMI/S on F-16 follows. A Global Soil Wetness Index product has been created by Bob Kuligowski.

Frequency (GHz)	Polarization	Integration Period	3 dB Footprint Size Along-track	Cross-track
19.35	vertical	7.95 ms	69 km	43 km
19.35	horizontal	7.95 ms	69 km	43 km
22.235	vertical	7.95 ms	50 km	40 km
37.0	vertical	7.95 ms	37 km	28 km
37.0	horizontal	7.95 ms	37 km	29 km
85.5	vertical	3.89 ms	15 km	13 km
85.5	horizontal	3.89 ms	15 km	13 km

- The Tropical Rainfall Measurement Mission (TRMM) Microwave Imager (TMI) observes the 35N-35S latitude zone at five separate frequencies since 1997: 10.7, 19.4, 21.3, 37, 85.5 GHz. Bindlish & Jackson (2003) has created a global tropical area soil moisture data product.

Microwave Soil Moisture Sensors Details (2)

- **AMSR-E is Japan's Advanced Microwave Scanning Radiometer for NASA's Earth Observing System. It's onboard the Aqua satellite of EOS that was successfully launched in May 2002. A global Soil moisture has been created by Njoku et al (2003) since 2002.**

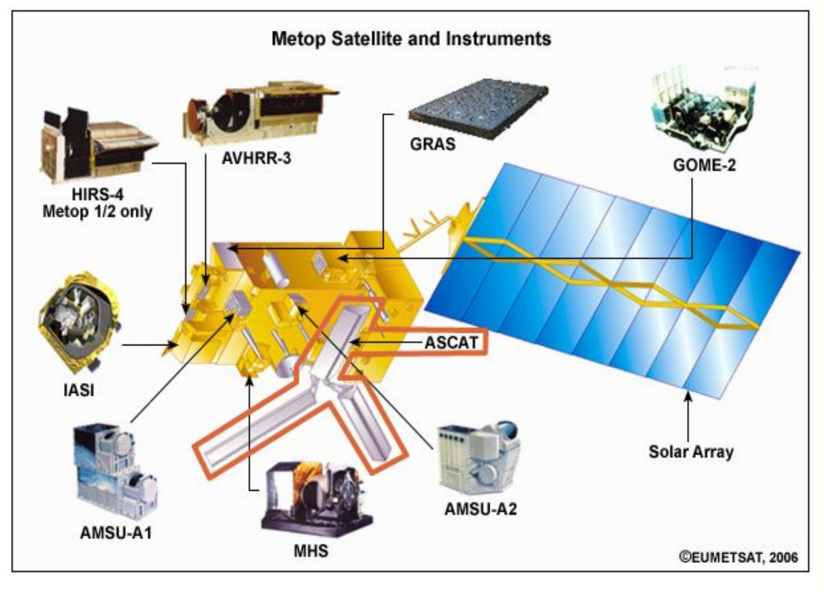
Observation Frequency	6.925 GHz	10.65 GHz	18.7 GHz	23.8 GHz	36.5 GHz	89.0 GHz	
						A	B
Spatial Resolution	50 km		25 km		15 km	5 km	
Band Width	350 MHz	100 MHz	200 MHz	400 MHz	1000 MHz	3000 MHz	
Polarization	Horizontal and Vertical						
Incident Angle	55°						54.5°
Cross polarization	less than –20 dB						
Swath Width	more than 1,450 km						

- **WindSat/Coriolis is another MW radiometer successfully launched by Naval Research Lab (NRL) primarily for ocean wind and SST in Jan. 2003. It has C- and X-band observations similar to AMSR-E and can be used to derive global soil moisture products.**

Freq, GHz	Channels	BW, MHz	EIA, deg	IFOV, km
6.8	v, h	125	53.5	40x60
10.7	v, h, ±45, lc, rc	300	49.9	25x38
18.7	v, h, ±45, lc, rc	750	55.3	16x27
23.8	v, h	500	53.0	12x20
37.0	v, h, ±45, lc, rc	2000	53.0	8x13

Microwave Soil Moisture Sensors Details (3)

- **ESCAT-1/2 are C-band (5.3GHz) scatterometer flown onboard ERS-1 (1991-1996) and ERS-2 (1995-present). ASCAT is the advanced scatterometer flown on MetOP-A since Oct. 2006. Intensive researches have been done at Vienna University of Technology in Austria to derive a global soil moisture data set from these scatterometers' observations (Wagner et al, 2003).**



- **The synthetic aperture radars (SAR) on ERS-1/2 (1991-present) and the advanced SAR (ASAR) onboard ENVISAT (2002-present) are providing high spatial resolution backscatter observations which can also be used to derive soil moisture. However, further research is needed to derive operational soil moisture data products from the radar observations.**

Microwave Soil Moisture Sensors Details (4)

- **European Space Agency (ESA) has planned a Soil Moisture and Ocean Salinity (SMOS) mission to specifically observation global soil moisture using L-band MW radiometry. The satellite will be launched in 2008.**

- **United States planned a Hydrospheric States (Hydros) mission to specifically observation global soil moisture using both L-band MW radiometer and radar, but cancelled the mission in later 2005.**

- **United States also planned the Conical Scanning Microwave Imager/ Sounder (CMIS) for NPOESS, and cancelled the instrument in 2006.**

- **NASA's decadal survey on Earth Science and Applications from Space listed a soil moisture active-passive mission (SMAP) as one of four missions recommended to NASA for year 2010-2013 time frame.**

Microwave Soil Moisture Retrievals

- <u>Evaluation of NASA's Current AMSR-E Soil Moisture Data Product</u>
- *An Alternative AMSR-E Soil Moisture Data Product from NOAA-USDA*
- *Retrieving High Resolution Soil Moisture From Hydros*

NASA's AMSR-E Soil Moisture Data Product

- ✓ *NASA's newest satellite observational data product of global land surface soil moisture.*
- ✓ *Acquired (almost) continuously since June 18, 2002.*
- ✓ *Spatial resample resolution is 25km by 25km and available for most land areas once every 2-3 days.*
- ✓ *Generated from constrained inversion method using AMSR-E 10.7 and 18.7GHz channels with footprint sizes about 21km to 38km.*

Land Surface Model Simulations from LDAS

- ✓ *NASA GSFC and partners have developed the North America Land Data Assimilation System (NLDAS) and Global Land Data Assimilation System (GLDAS) that can output soil moisture simulations of various land surface models (e.g. Mosaic, Noah, CLM, …);*
- ✓ *NLDAS Mosaic soil moisture data for the years since 1996 have been available at the website http://ldas.gsfc.nasa.gov*
- ✓ *Through the enhanced version of LDAS software system (LIS), LDAS LSMs can be run at many spatial resolution (e.g., 0.25 lat/long matching AMSR-E soil moisture data product)*
- ✓ *The NLDAS atmospheric forcing data sets (Cosgrove et al, 2003) are used to simulate soil moisture with Mosaic and Noah LSMs for this study.*

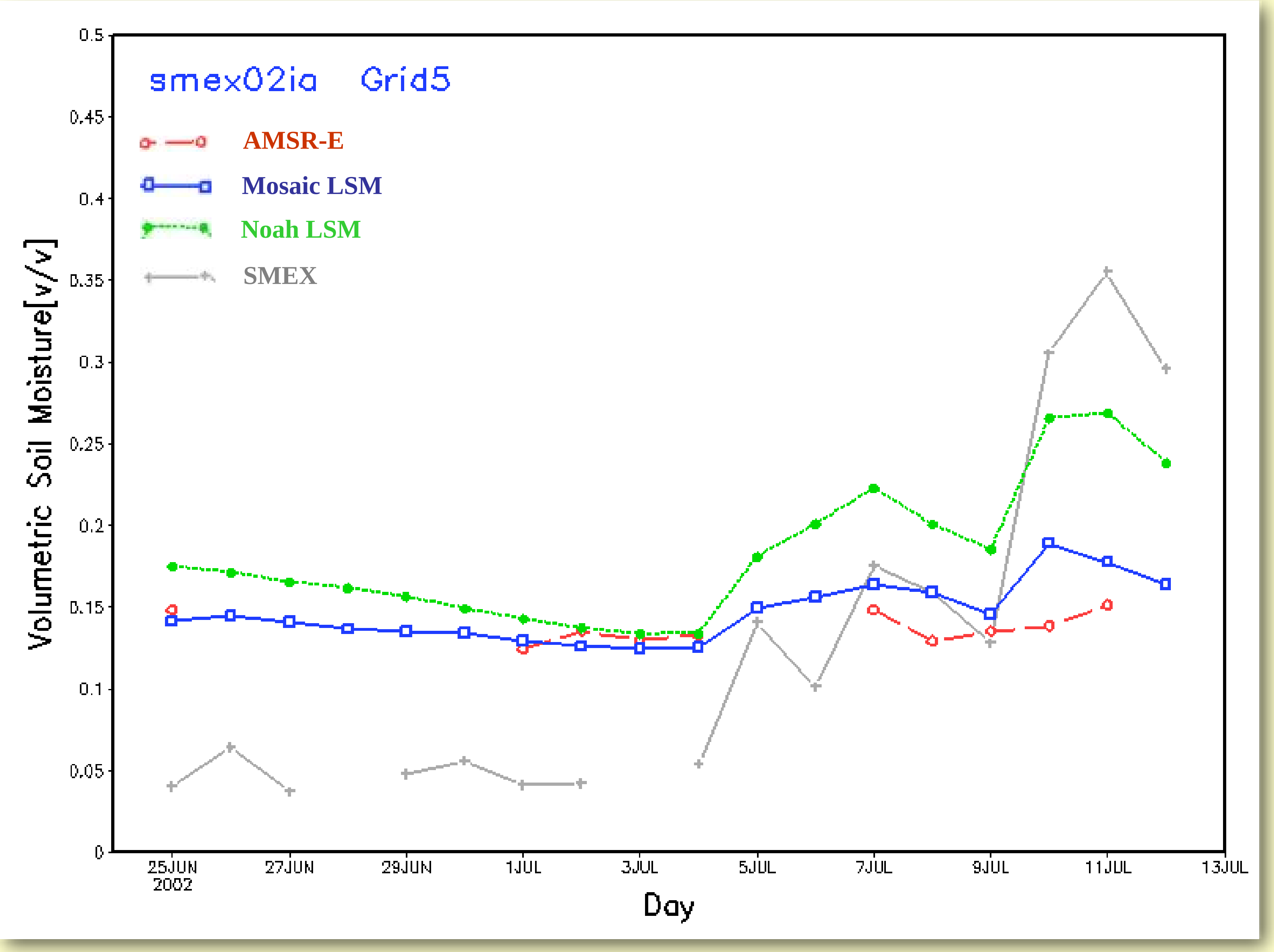
Soil Moisture Experiments (SMEX)

Name	Latit.	Long.	#site	#day	St Day	End Day
smex02ia	41.50N	94.00W	48	18	6/25	7/12
smex03ga	30.75N	84.00W	49	10	6/23	7/02
smex03on	35.75N	98.25W	36	16	7/02	7/17
smex03os	34.25N	98.50W	52	16	7/02	7/17
smex04az	31.00N	110.5W	40	24	8/03	8/26

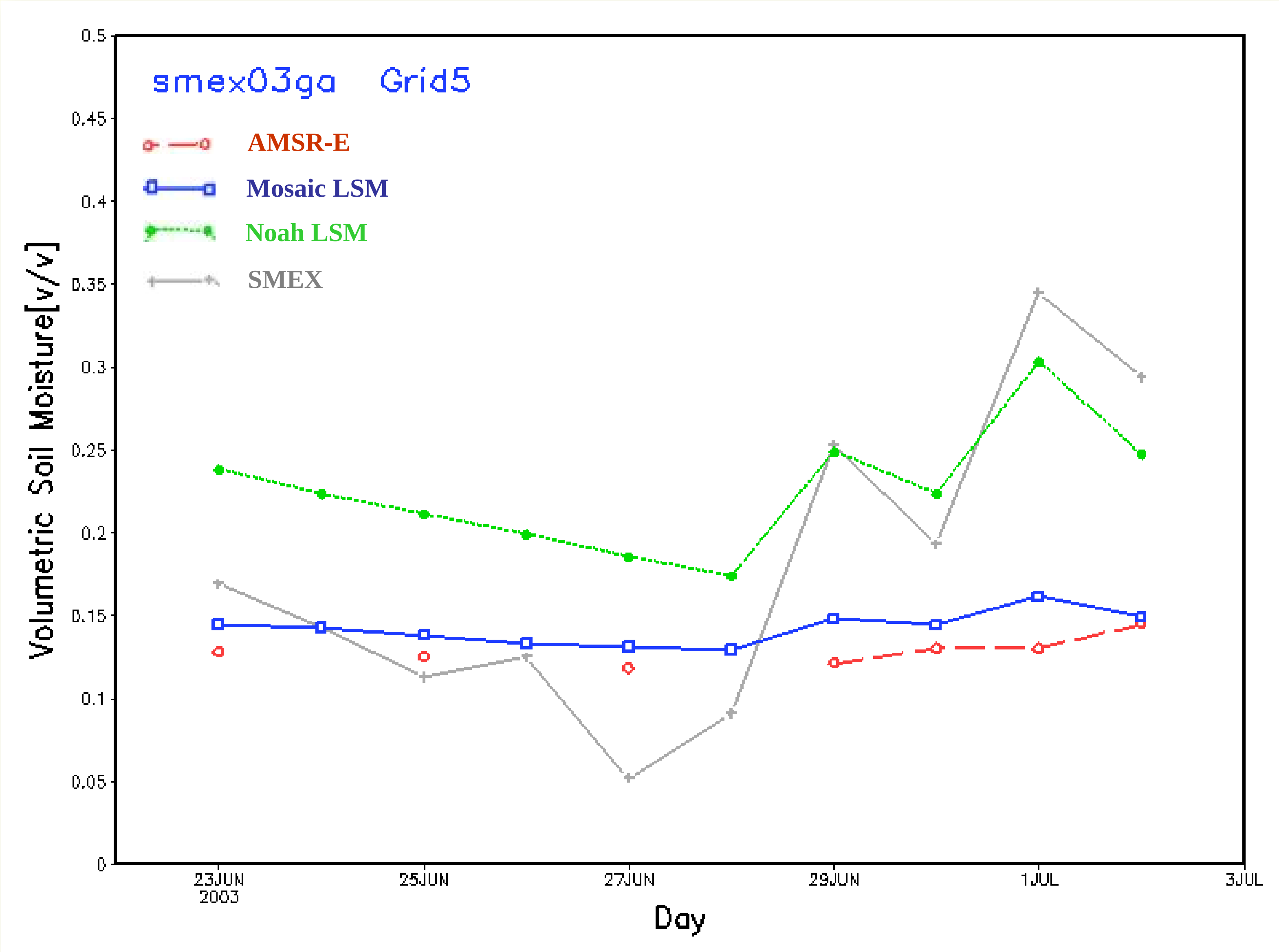
Comparison Procedure

- ✓ *Resample AMSR-E Level2 soil moisture retrievals to 0.25 degree lat/long grids matching the LDAS 0.25 degree grids;*
- ✓ *Spin up Mosaic and Noah model simulations within NLDAS domain from 1997 to 2002;*
- ✓ *Run NLDAS-Mosaic/Noah LSMs from 2002 to 2004 to cover the time periods of AMSR-E and SMEXes data time;*
- ✓ *Average the regional sampling sites of SMEXes within each 0.25 degree lat/long grids of NLDAS simulations and AMSR-E data.*

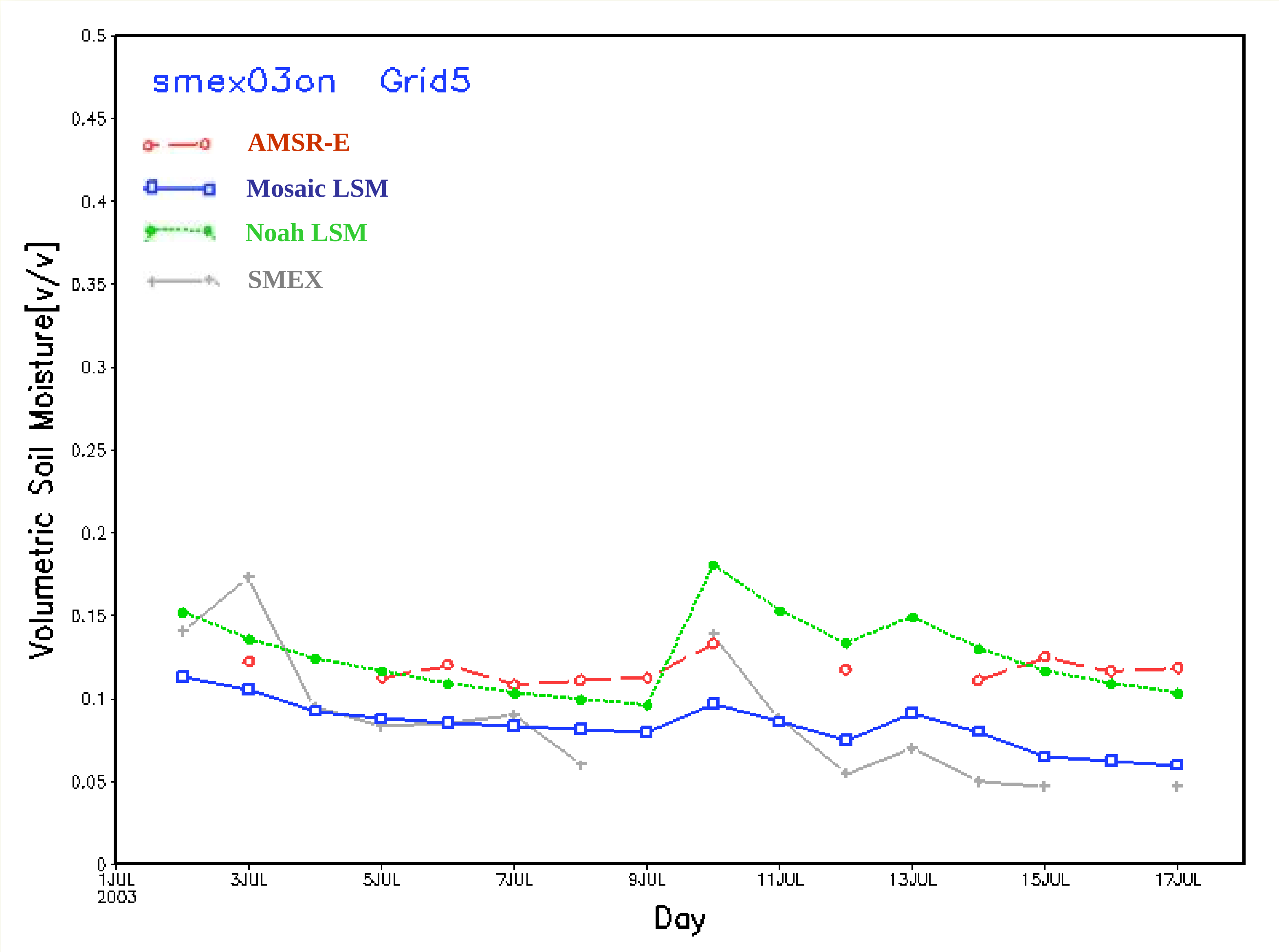
Daily (18Z) Soil Moisture Variations



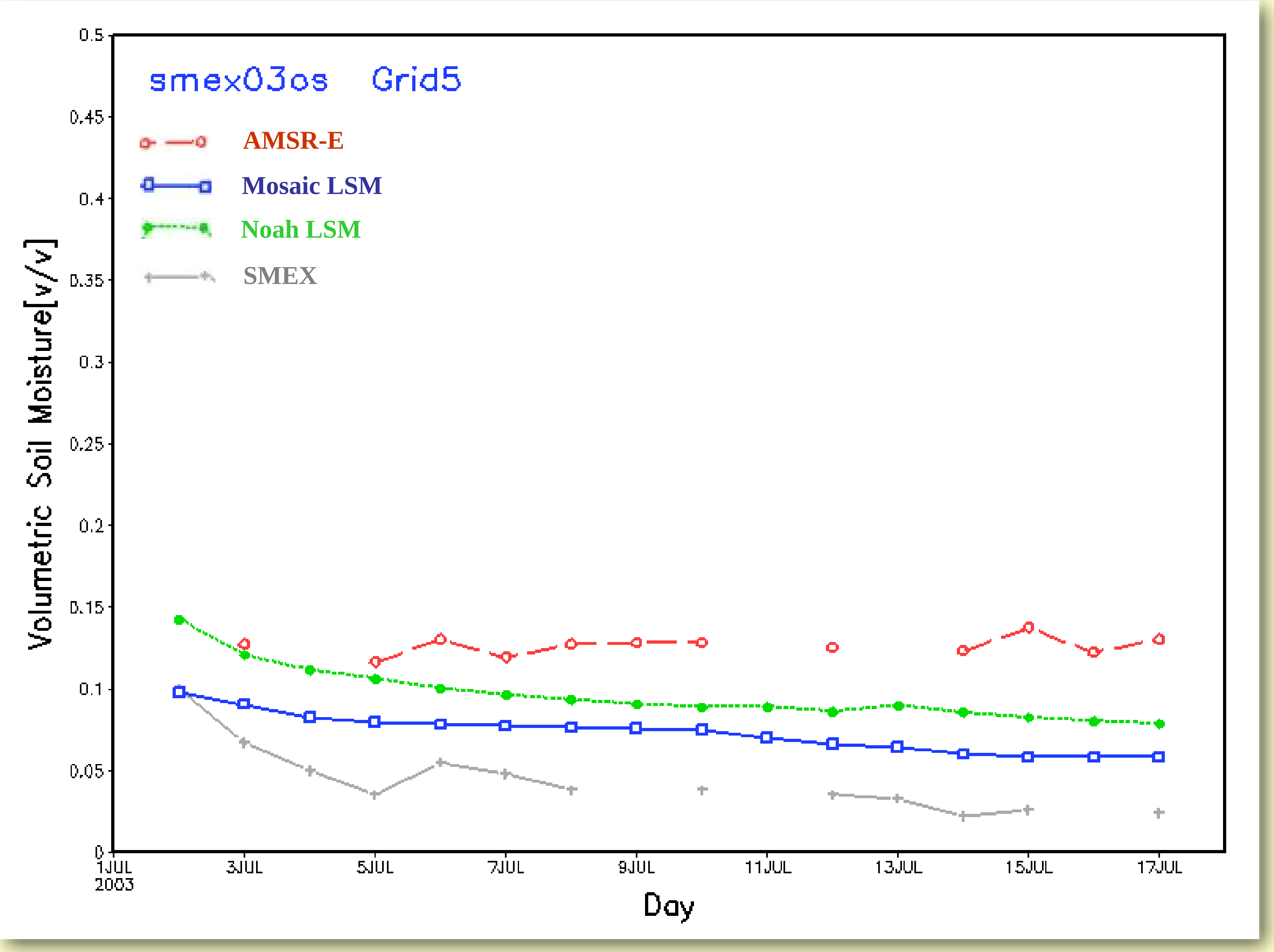
Daily (18Z) Soil Moisture Variations



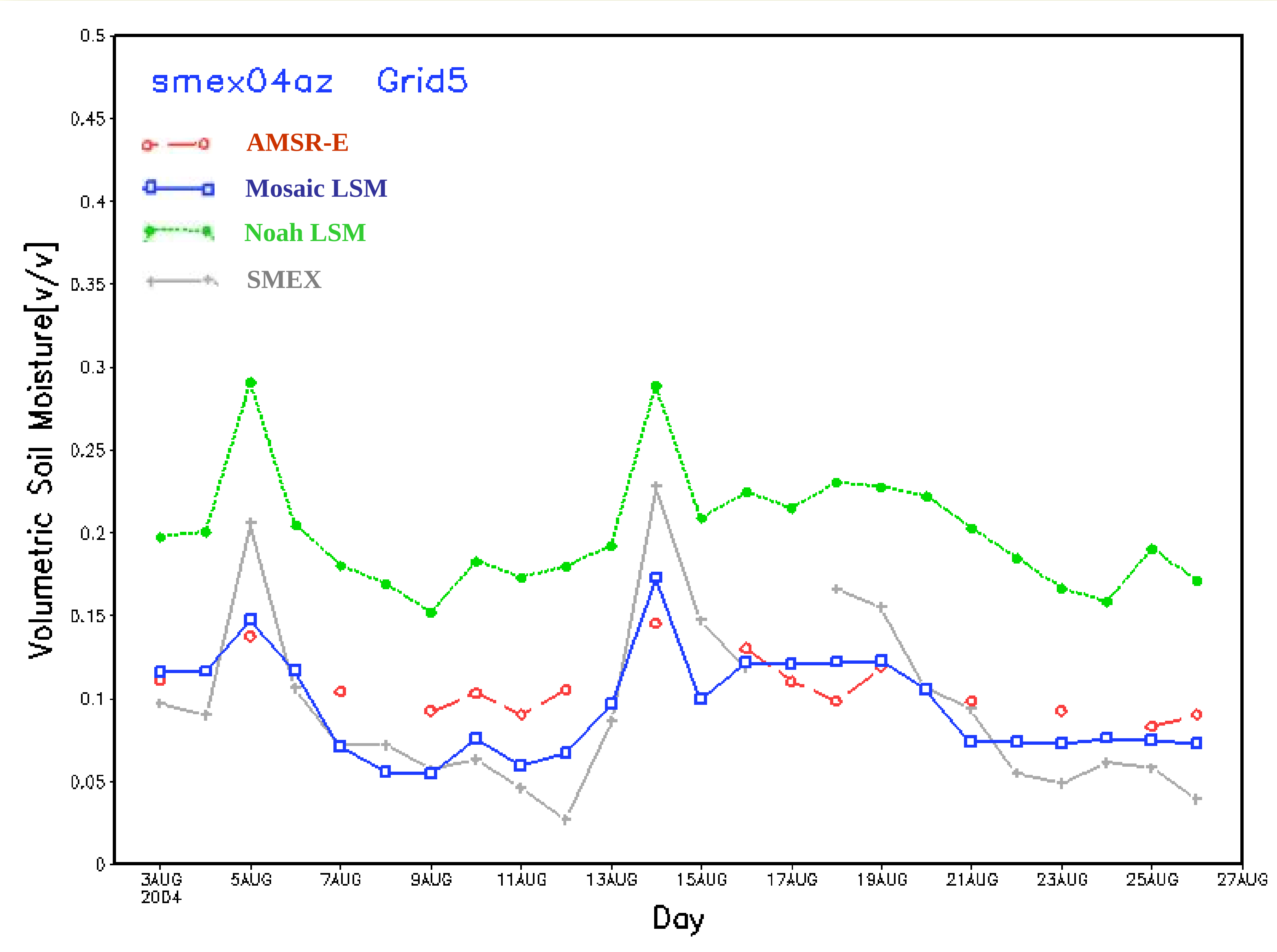
Daily (18Z) Soil Moisture Variations



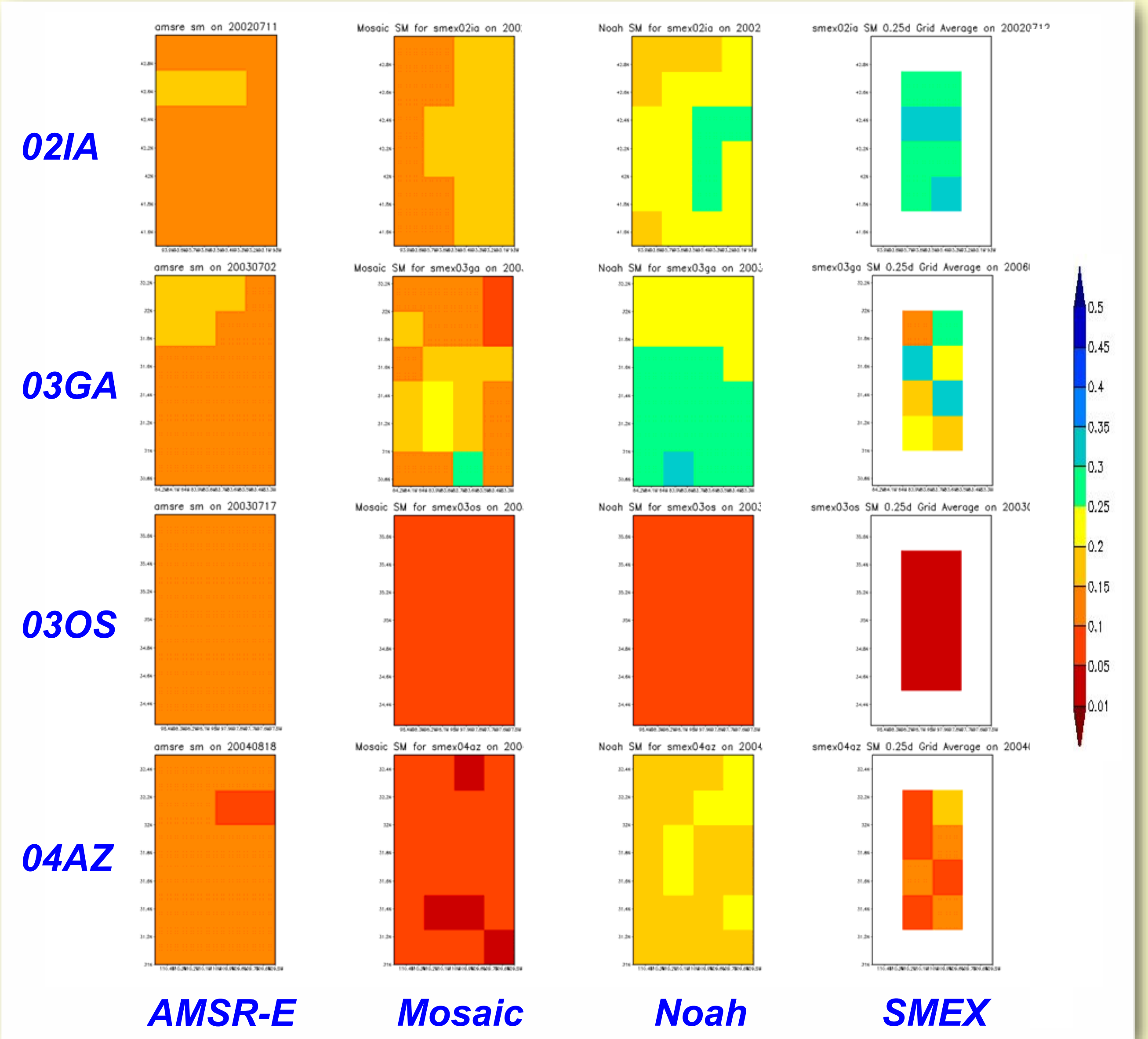
Daily (18Z) Soil Moisture Variations



Daily (18Z) Soil Moisture Variations



SM Spatial Pattern Comparison



SM Data Characteristics:

✓ AMSR-E:
1. Global MW obs;
2. Good time cover;
3. Too flat?

✓ Mosaic & Noah:
1. Good space cover;
2. Too low/high?

✓ Field Obs:
1. Too sparse?
2. Too tedious?

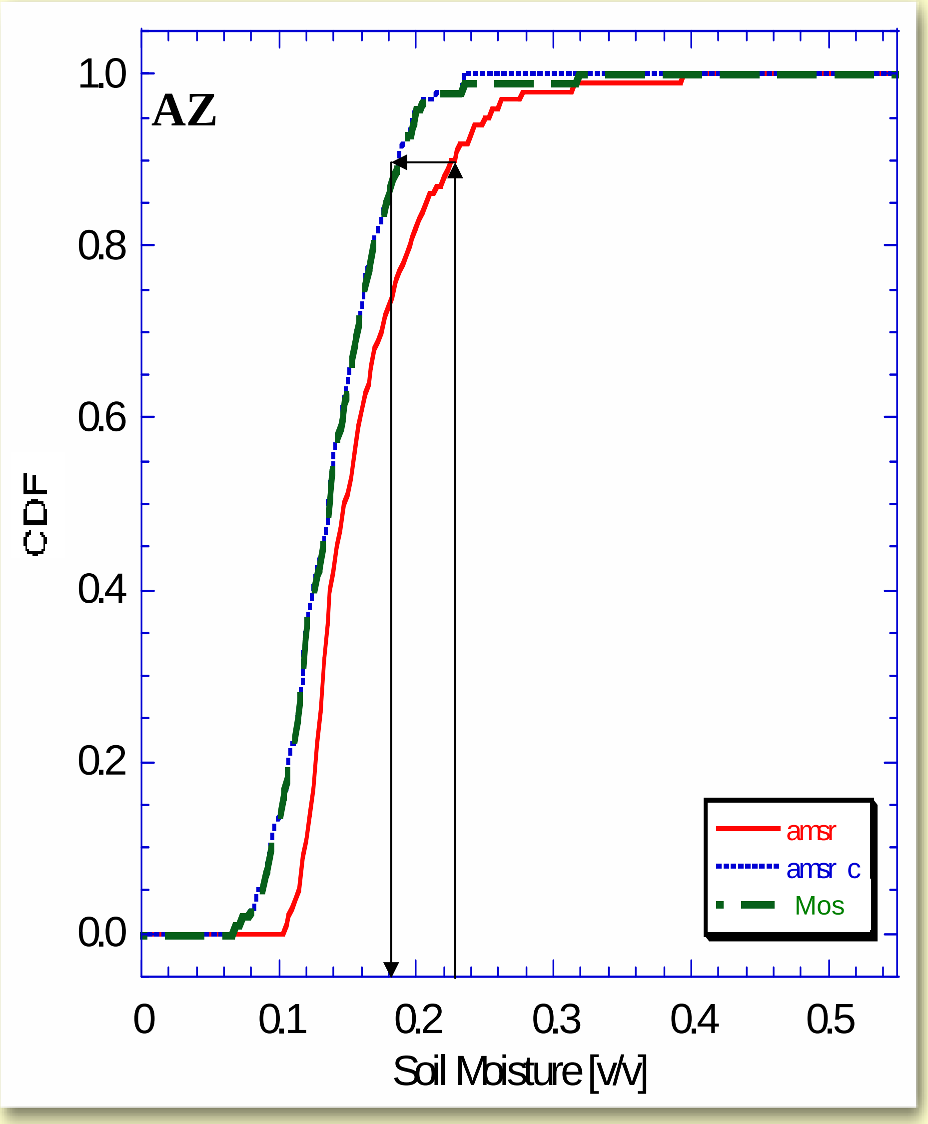
CDF Matching of AMSR-E SM to LSM Simulations

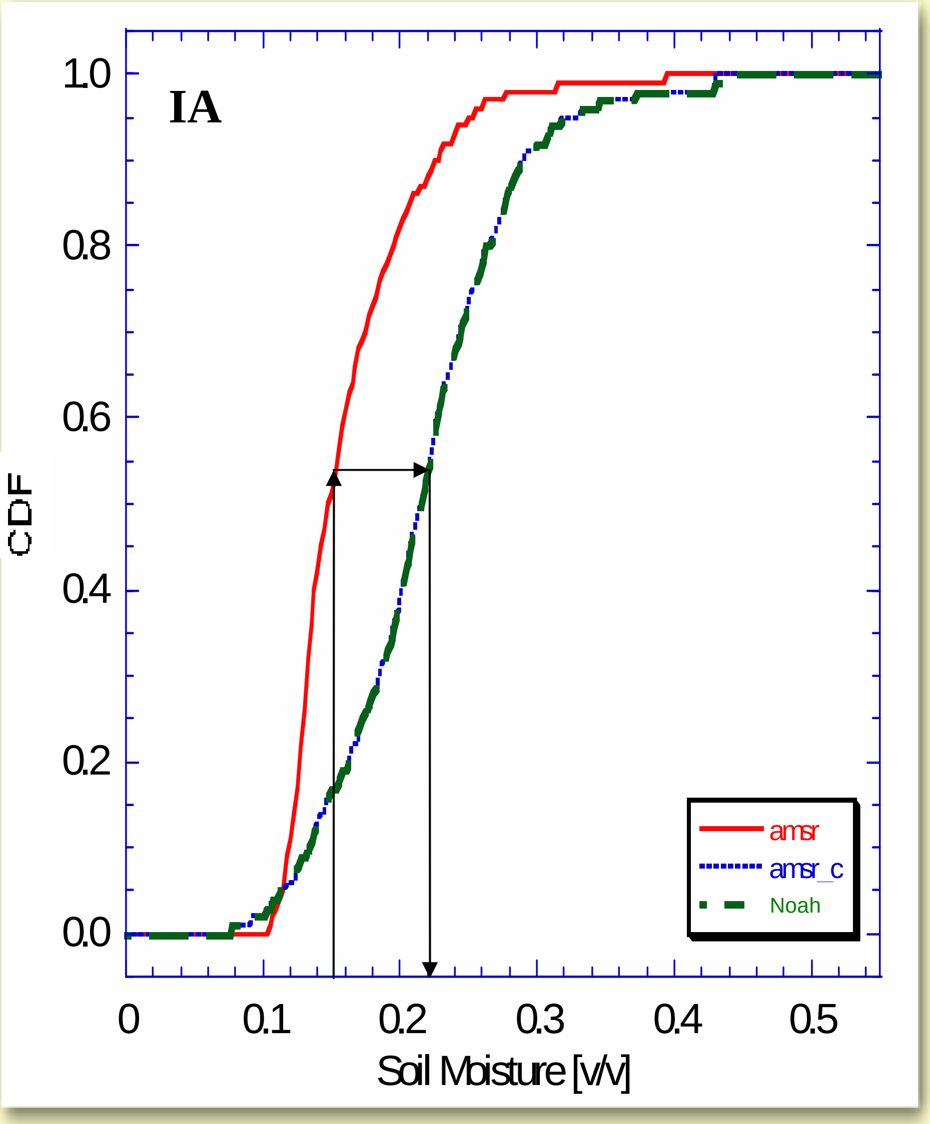
- ✓ *Purpose: LSM simulations can have full time and space coverage, but accuracy is uncertain; AMSR-E retrievals are patchy, biased and variations damped. Data assimilation can combine them, but their scales need to be matched for DA methods such as EnKF;*

- ✓ *The cumulative distribution function matching method used in Reichle & Koster (2004) can scale the AMSR-E retrievals to the simulations of LSMs to be used for assimilation;*

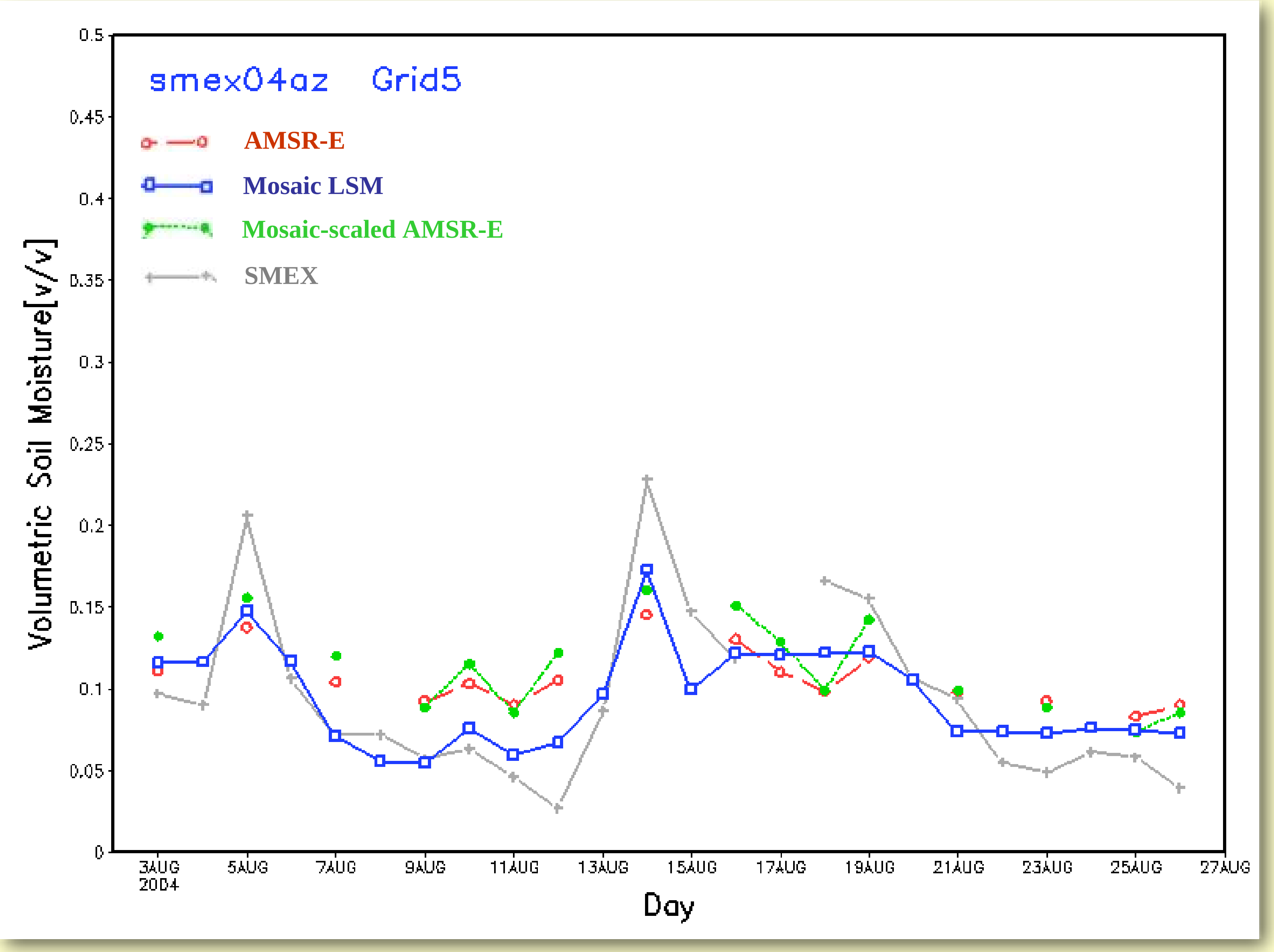
- ✓ *How will the scaled AMSR-E data be compared with the model simulations?*

CDFs for SMEX Sites

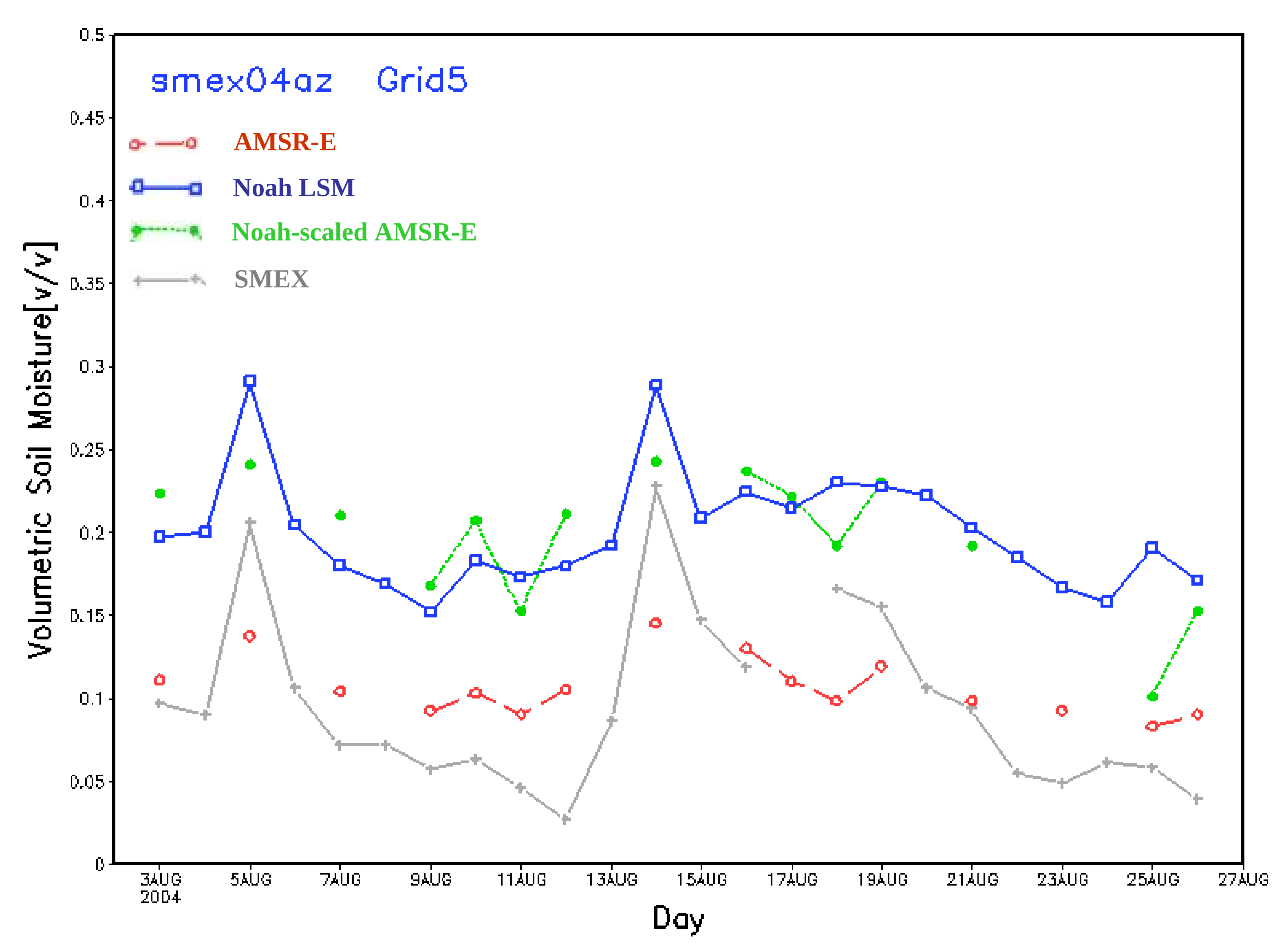




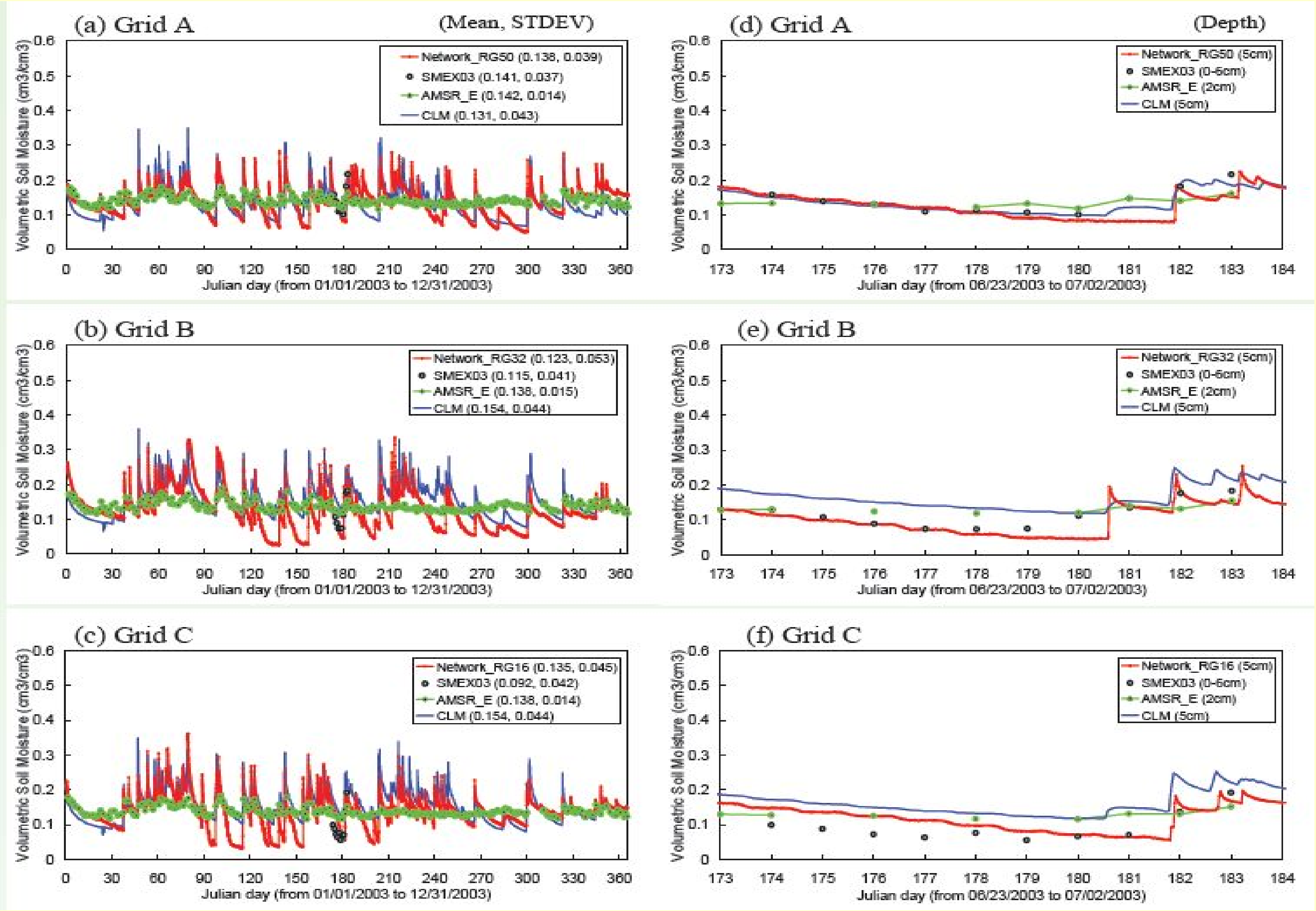
Scaled AMSR-E SM vs Model Simulations



Scaled AMSR-E SM vs Model Simulations

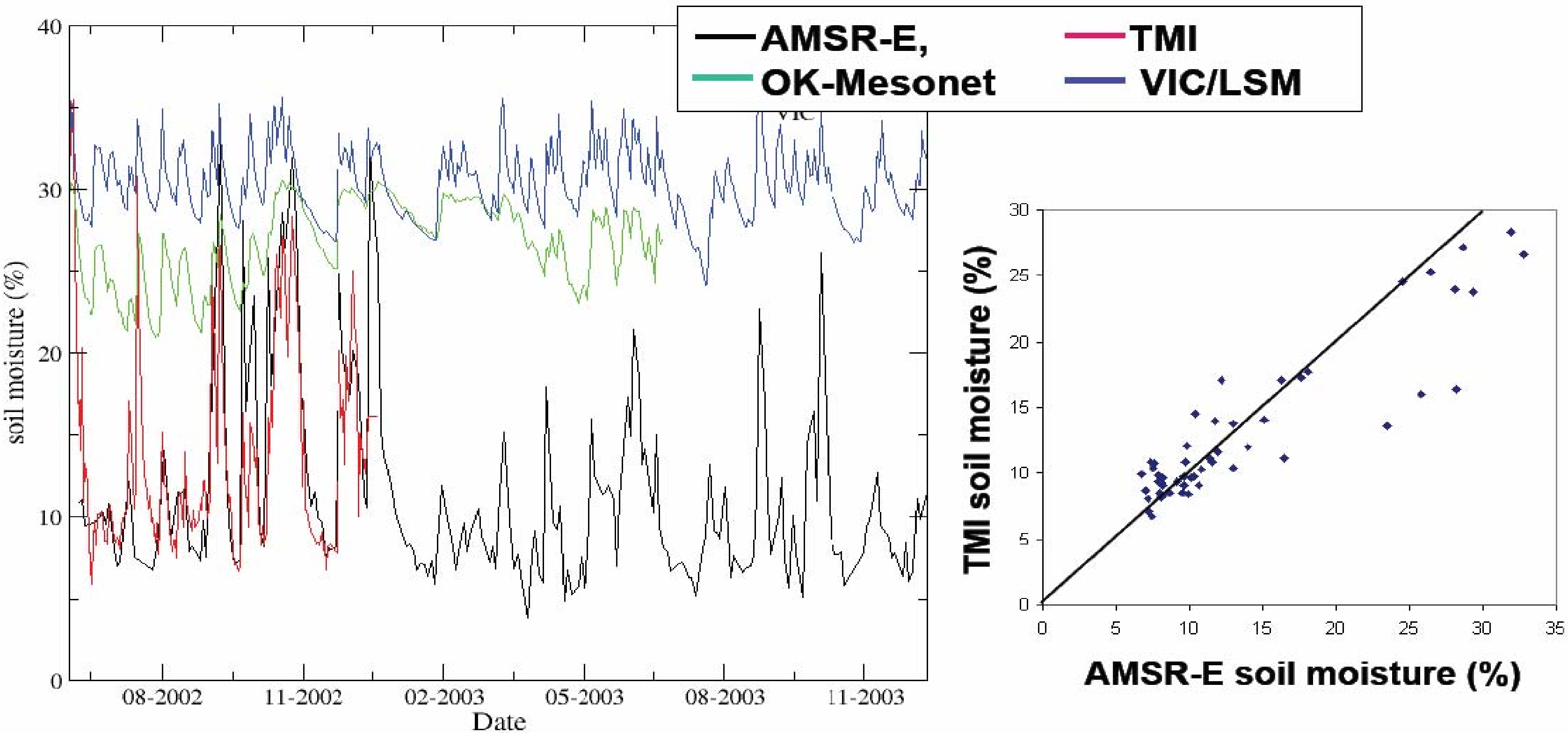


UNH's Comparison Results (Choi & Jacobs, 2006)



PU's Comparison Results (McCabe et al, 2004)

PU/AMSR-E X-Band Soil Moisture Comparisons with PU/TMI X-Band Soil Moisture

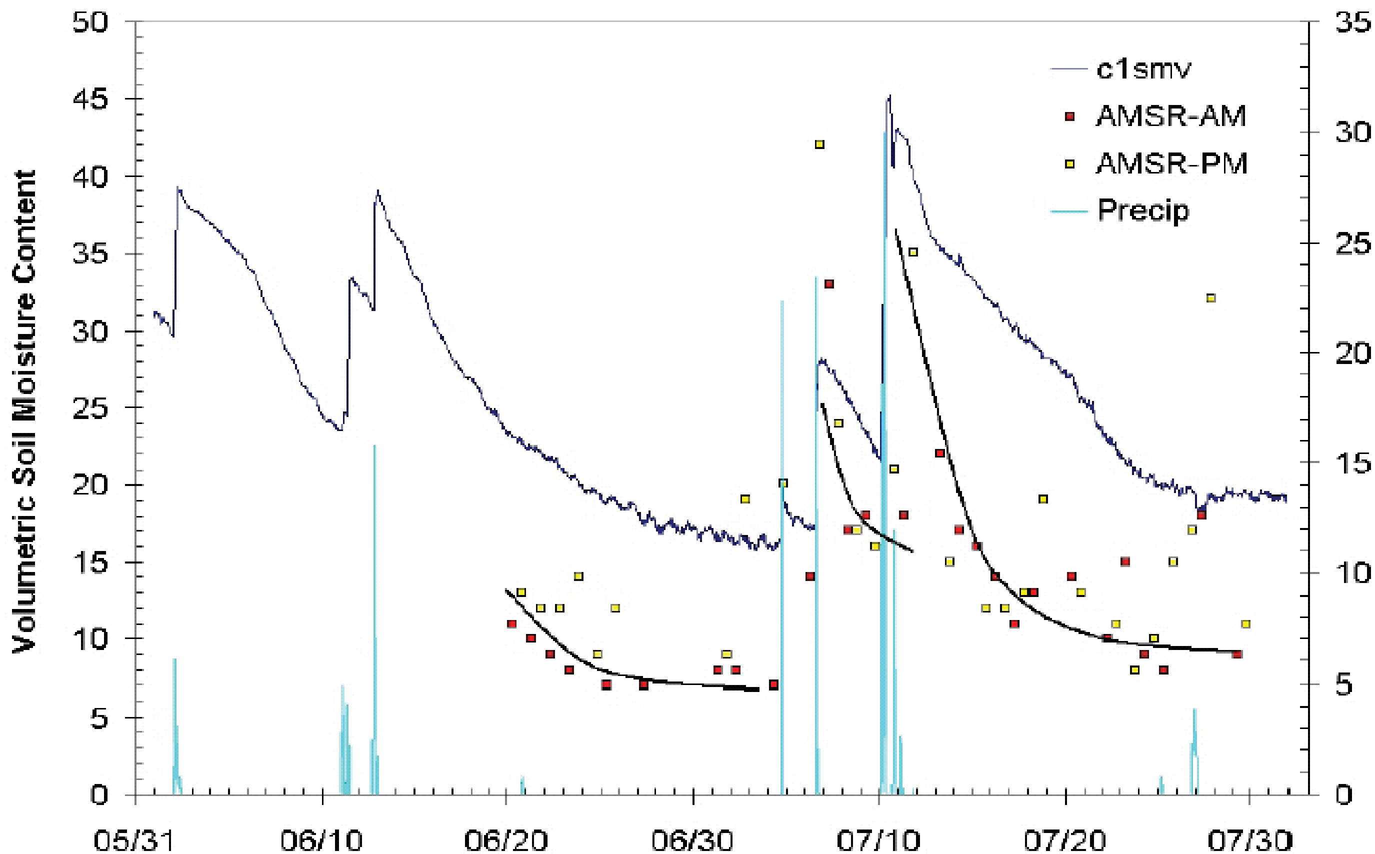


Lesson: Retrievals consistent across sensors, but different from *in-situ*

Princeton University

PU's Comparison Results (McCabe et al, 2004)

SMEX02: PU/AMSR-E X-Band Soil Moisture Comparison with the ARS SCAN Soil Moisture Monitoring Site



Princeton University

Summary on NASA's AMSR-E SM Product Evaluation

- ✓ ***AMSR-E soil moisture retrievals, Mosaic and Noah LSM simulations are compared with SMEXes field measurements at the 0.25 degree grid scale;***

- ✓ ***AMSR-E soil moisture retrievals mostly followed the soil moisture dynamic trends of either model simulations or field measurements;***

- ✓ ***But AMSR-E soil moisture retrievals are generally too wet for dry surfaces and too dry for wet surfaces;***

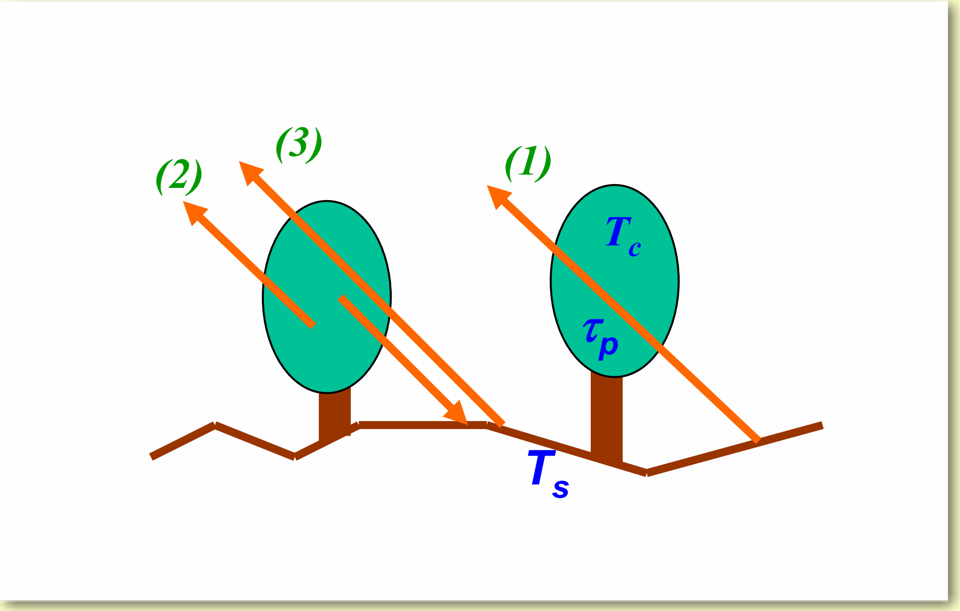
- ✓ ***The current utilization of AMSR-E soil moisture retrievals is to assimilate them into a LSM after matching their CDFs;***

- ✓ ***Further work is needed to improve the AMSR-E retrievals.***

Microwave Soil Moisture Retrievals

- Evaluation of NASA's Current AMSR-E Soil Moisture Data Product
- ***An Alternative AMSR-E Soil Moisture Data Product from NOAA-USDA***
- Retrieving High Resolution Soil Moisture From Hydros

$$T_{Bp} = T_s\, e_{r,p} \exp(-\tau_p/\cos\theta) + \qquad (1)$$
$$T_c\,(1-\omega_p)\,[1-\exp(-\tau_p/\cos\theta)] + \qquad (2)$$
$$T_c\,(1-\omega_p)\,[1-\exp(-\tau_p/\cos\theta)]\, R_{r,p} \exp(-\tau_p/\cos\theta)] \qquad (3)$$



NASA's AMSR-E SM Baseline Retrieval Algorithm:

$$\min\{ \chi^2 = \sum_{i=1}^{6} \left(\frac{T_{B,i}^{obs} - T_{B,i}^{cmp}}{\sigma_i} \right)^2 \}$$

$$T_{B,i}^{cmp} = T_{skin} \{e_{r,p} \exp(-\tau_i/\cos\theta) + (1 - \omega) [1 - \exp(-\tau_i/\cos\theta)] [1 + R_{r,i} \exp(-\tau_i/\cos\theta)]\}$$

$$\tau_i = b * VWC$$

$$R_{r,i} = R_s \exp(h \cos^2\theta)$$

$R_s = f(\varepsilon)$ -- Fresnel Equation

$\varepsilon = g(SM)$ -- Mixing model

$$T_{B,i}^{obs} = T_{B06h}, T_{B06v}, T_{B10h}, T_{B10v}, T_{B18h}, T_{B18v}$$

MW Emission Model and SM Retrieval Algorithms (3)

An Alternative AMSR-E SM Retrieval Algorithm – Single Channel Retrieval (SCR):

$$T_{B10h} = T_s\,[1 - R_r \exp(-2\tau/\cos\theta)]$$

$$R_r = R_s \exp(h \cos^2\theta)$$

$$R_s = f(\varepsilon) \quad \text{-- Fresnel Equation}$$

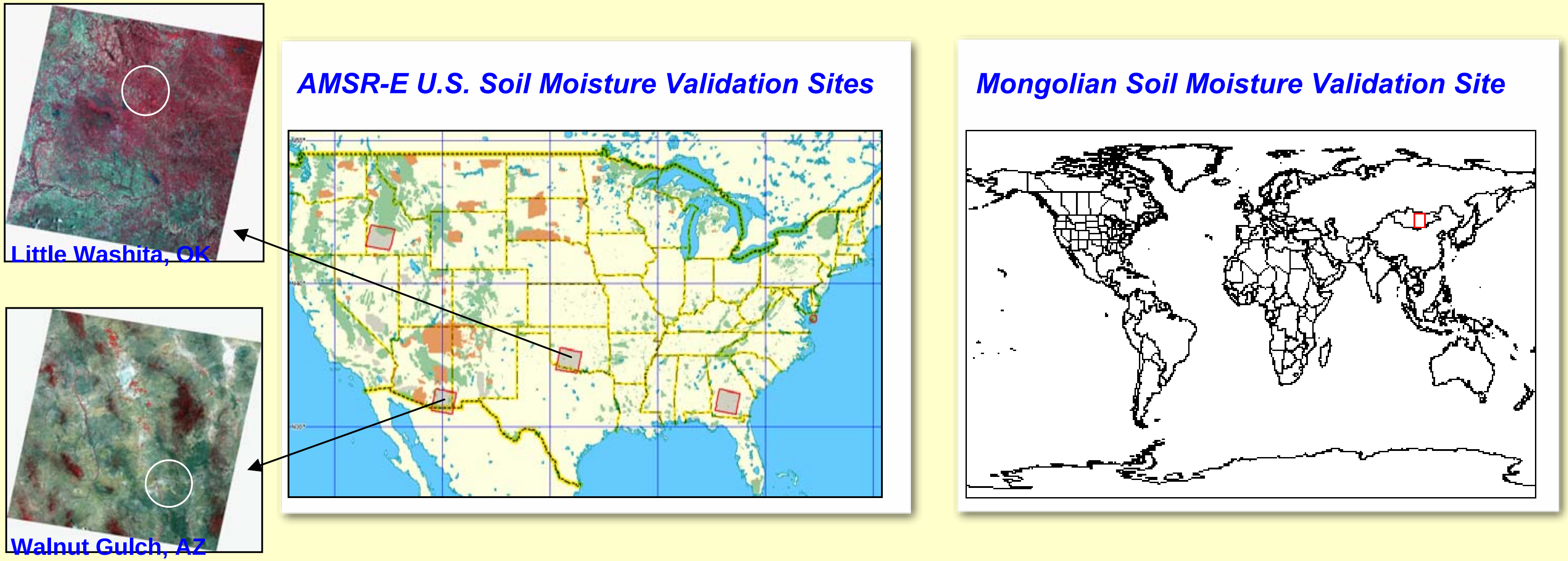
$$\varepsilon = g(SM) \quad \text{-- Mixing model}$$

$$T_s = reg_1(T_{B37v}) \text{ or } T_s^{LSM}$$

$$\tau = b * VWC$$

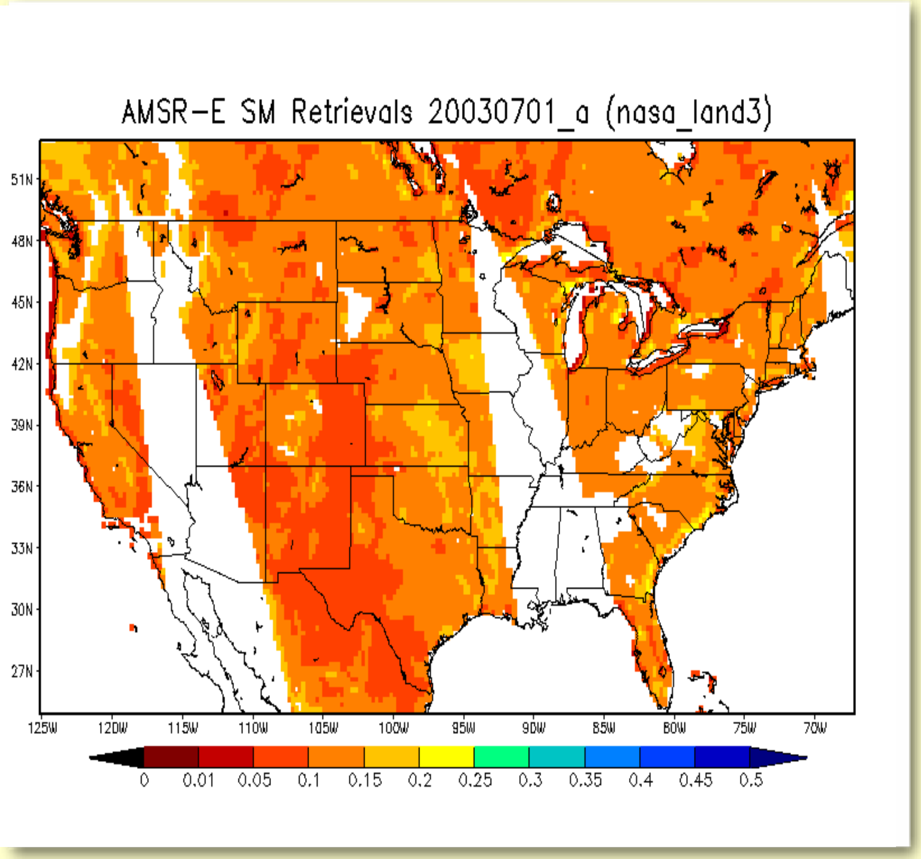
$$VWC = reg_2(NDVI)$$

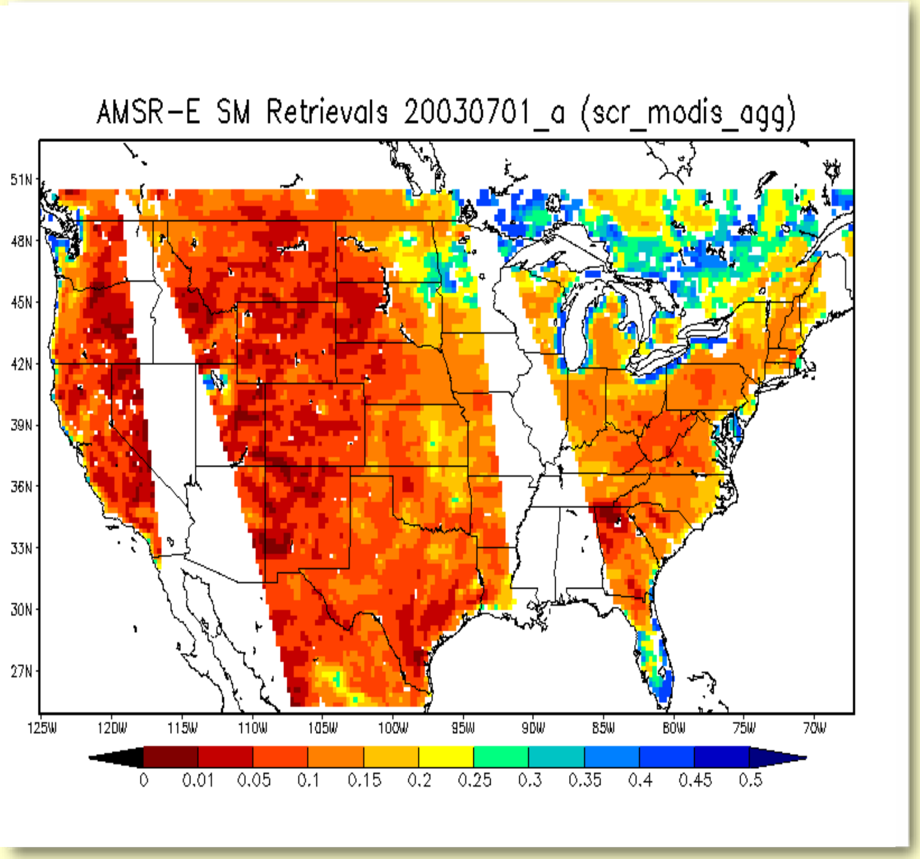
- ✓ *The SCR algorithm is adopted to take advantage of optical VWC observations.*
- ✓ *Use only AMSR-E TB10h as primary input and AMSR-E TB37v and MODIS/AVHRR NDVI as ancillary input.*
- ✓ *To be Tested against field data from two sites of USDA's ground observation network and one site in Mongolia for the year 2003.*



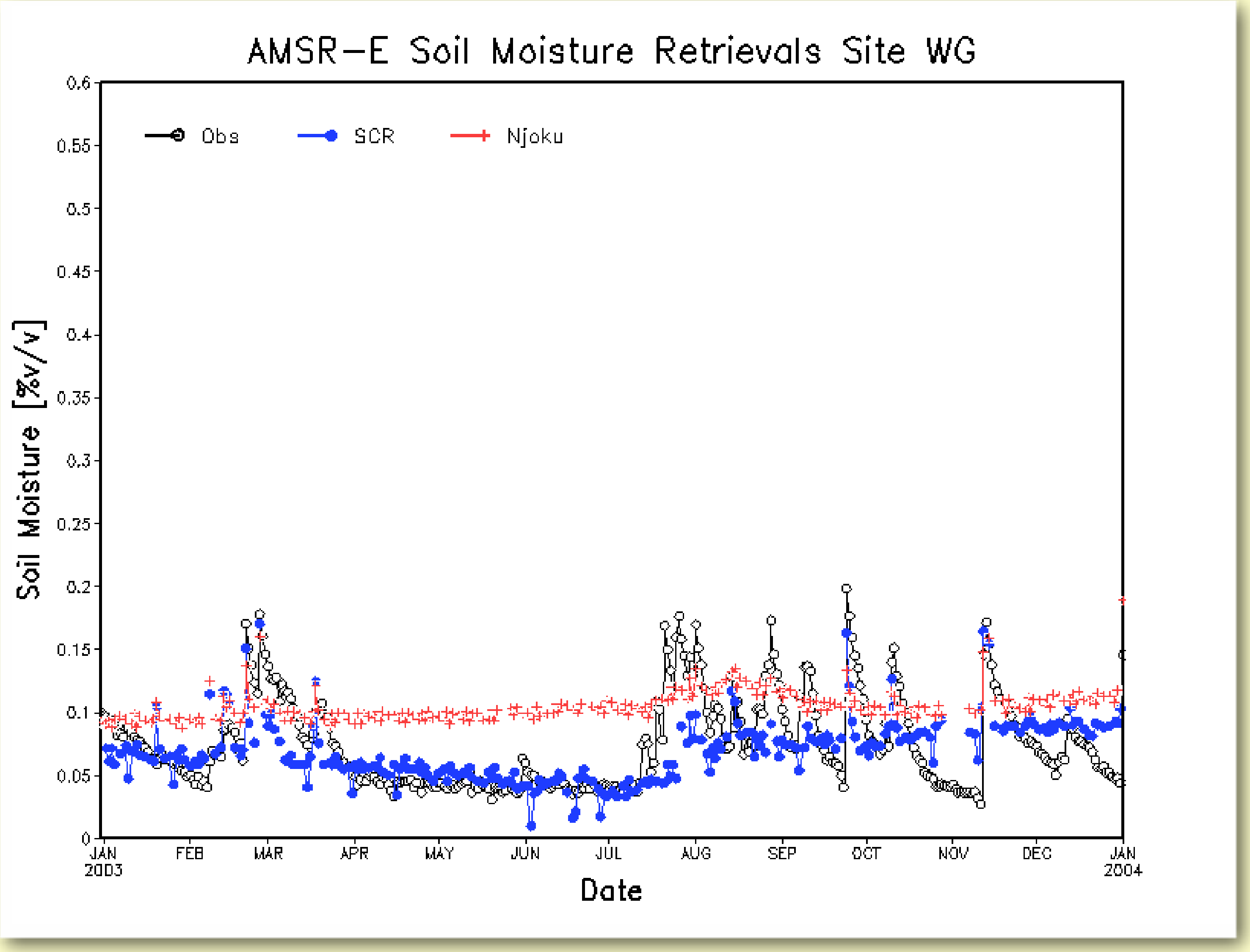
Experimental Alternative AMSR-E SM Product (2)

Spatial Map

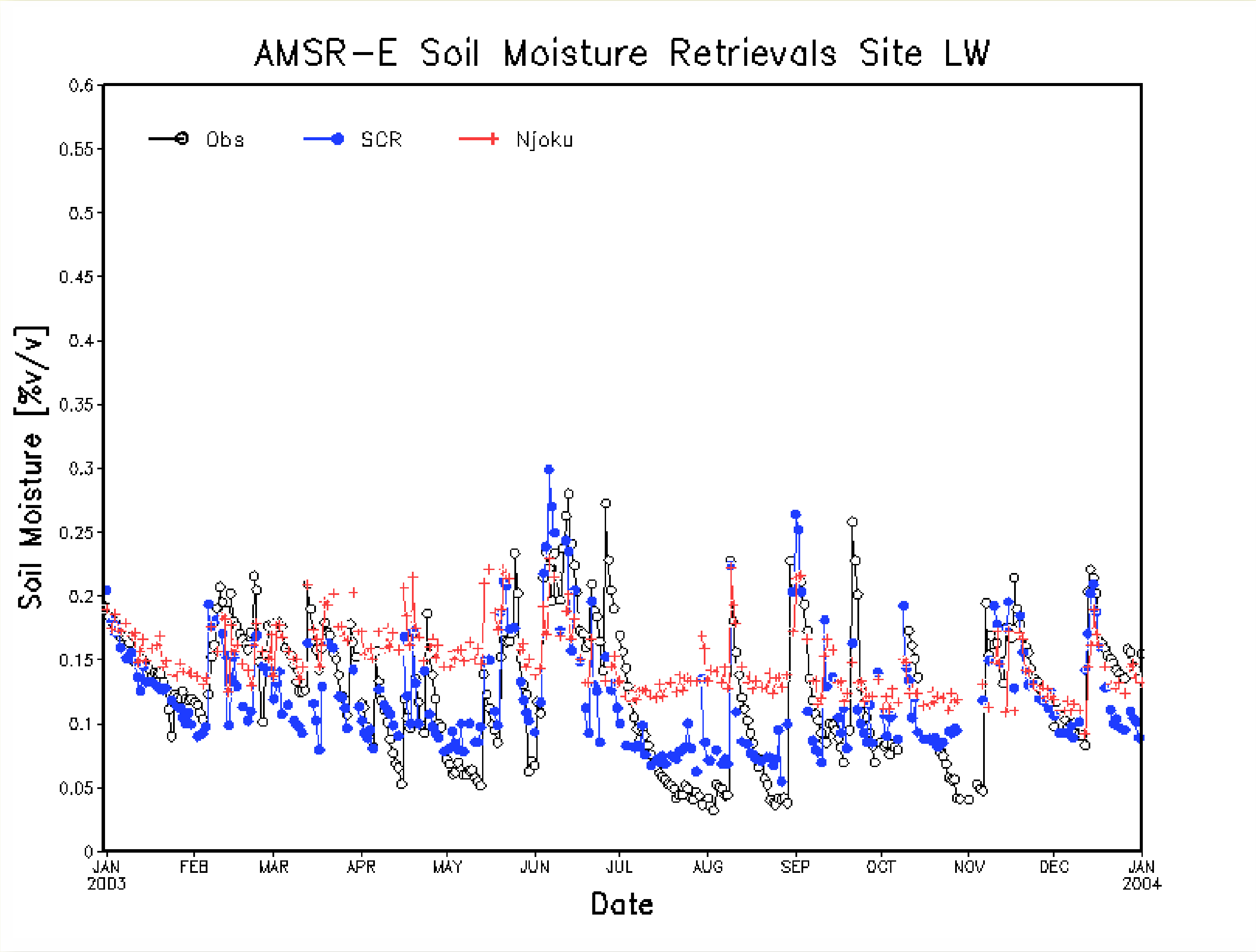




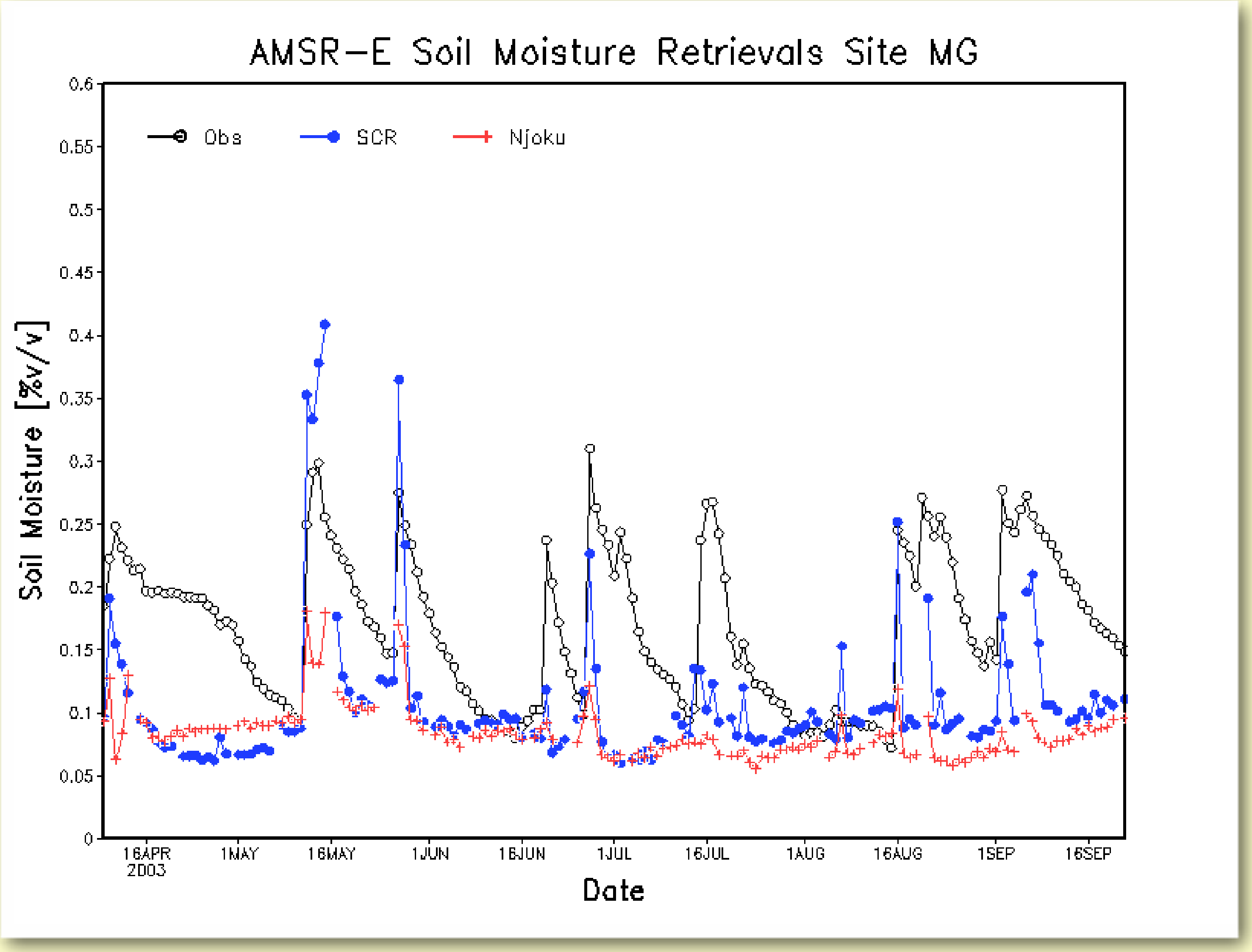
Experimental Alternative AMSR-E SM Product (3)



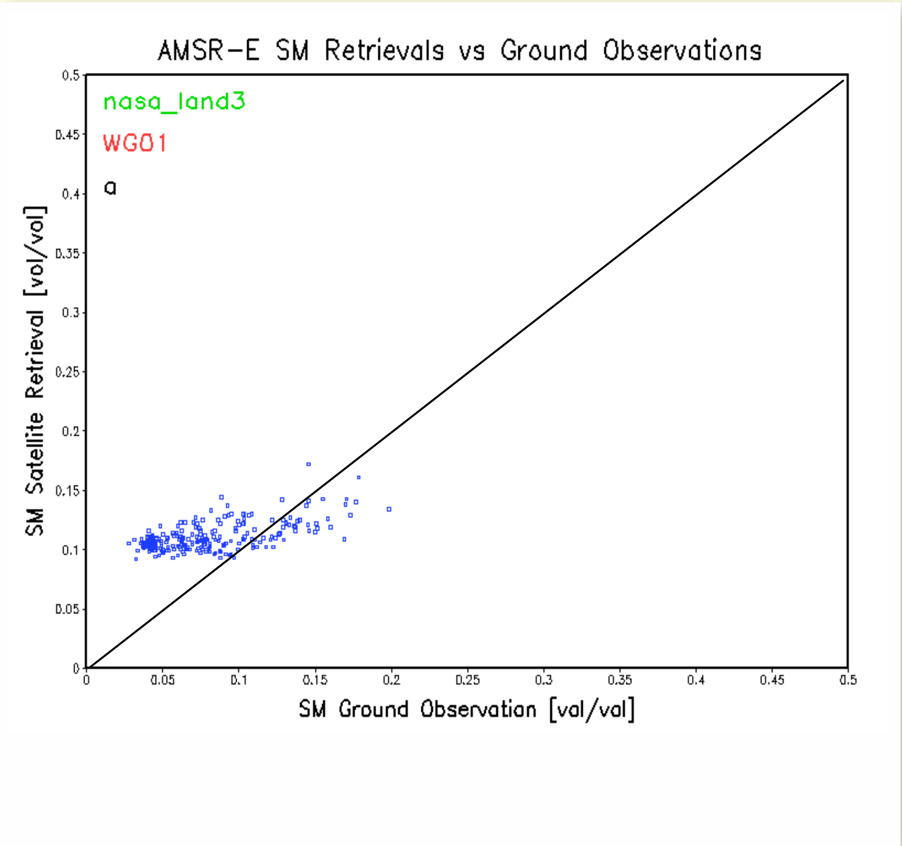
Experimental Alternative AMSR-E SM Product (4)

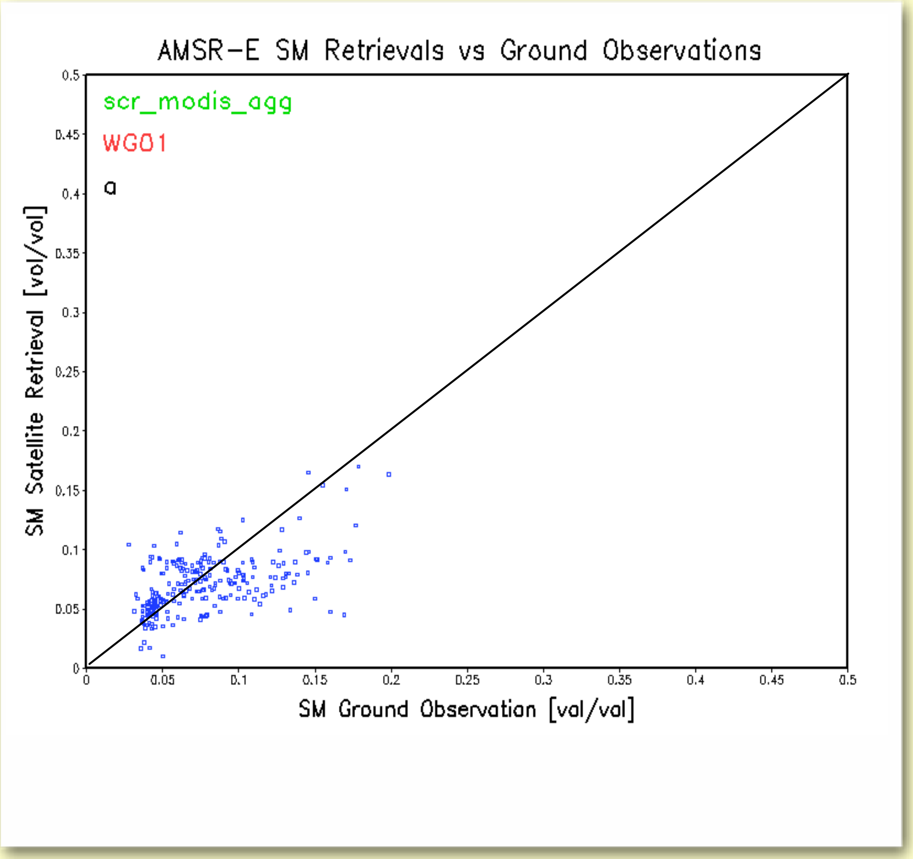


Experimental Alternative AMSR-E SM Product (5)



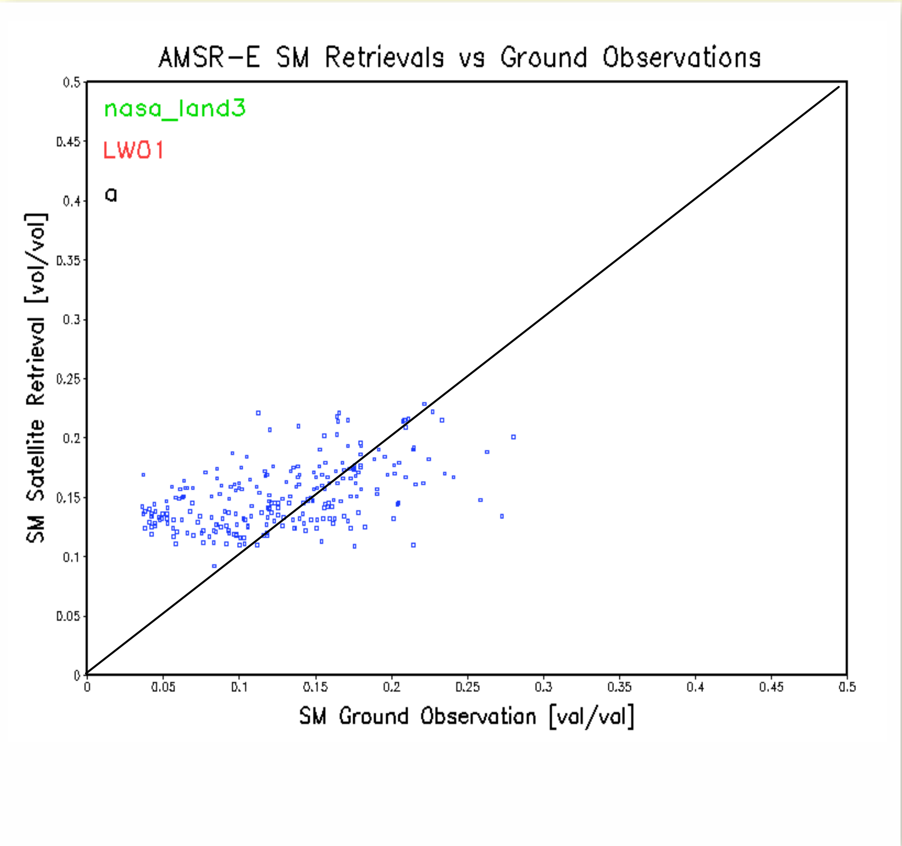
Scatter Plot

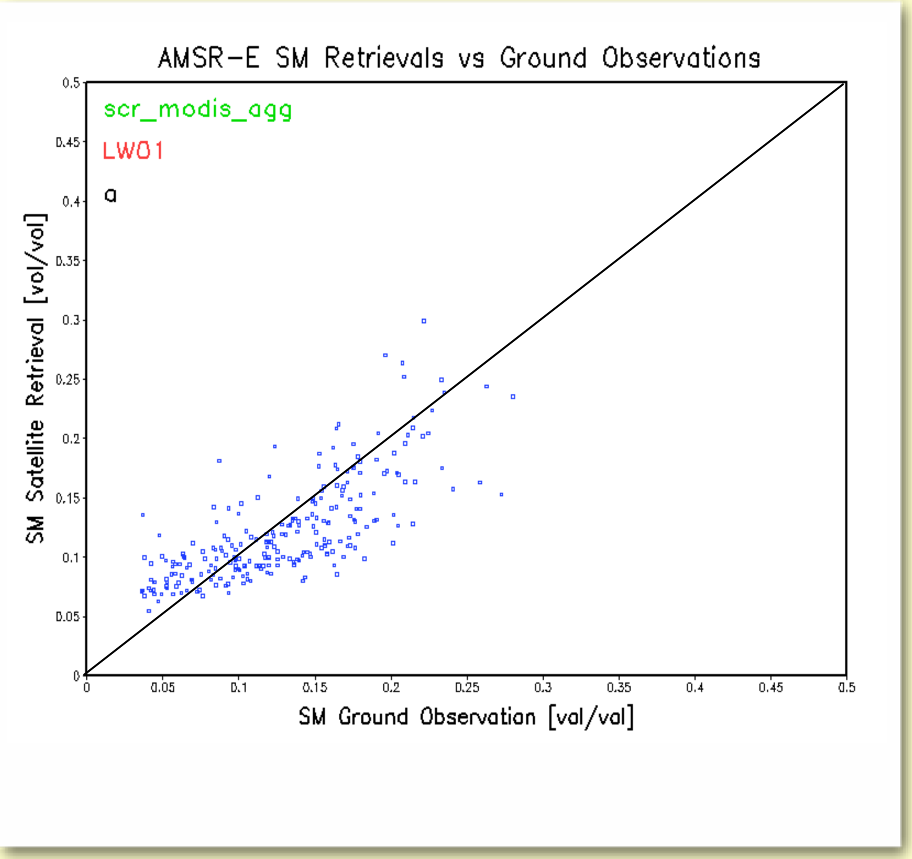




Experimental Alternative AMSR-E SM Product (7)

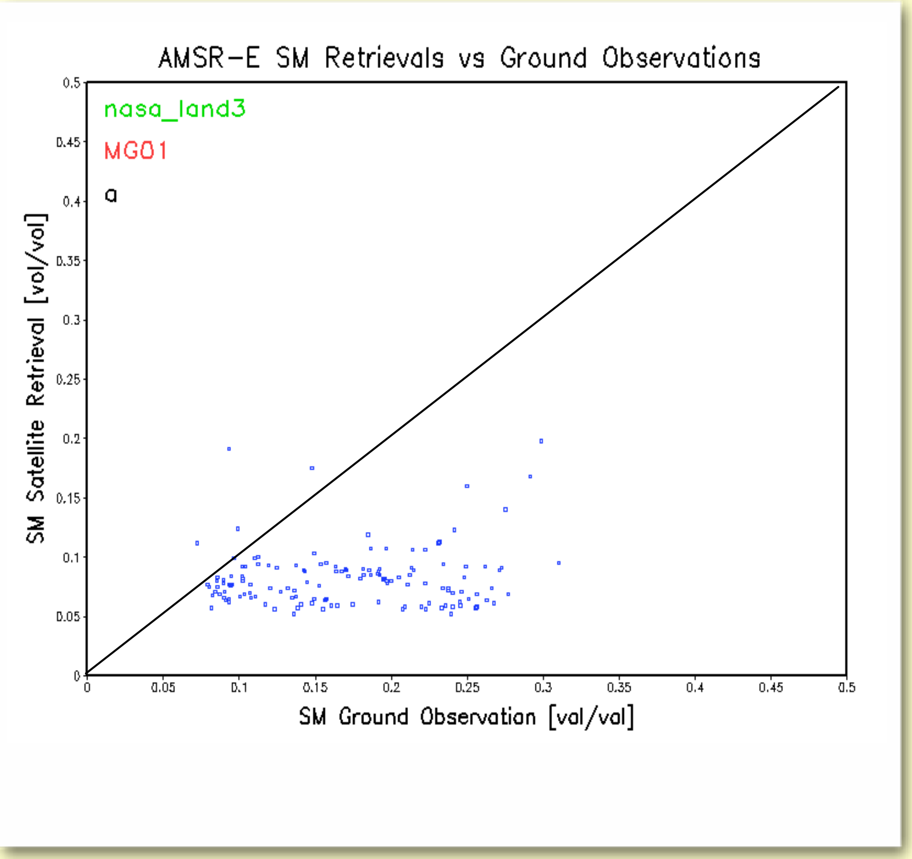
Scatter Plot

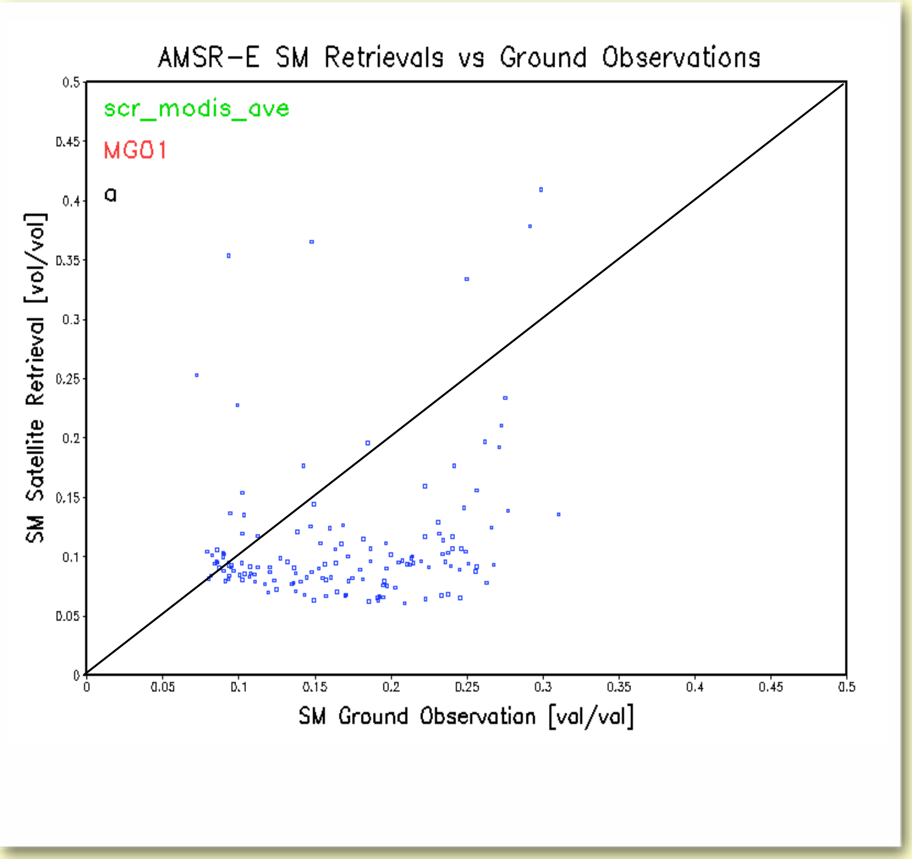




Experimental Alternative AMSR-E SM Product (8)

Scatter Plot





Experimental Alternative AMSR-E SM Product (9)

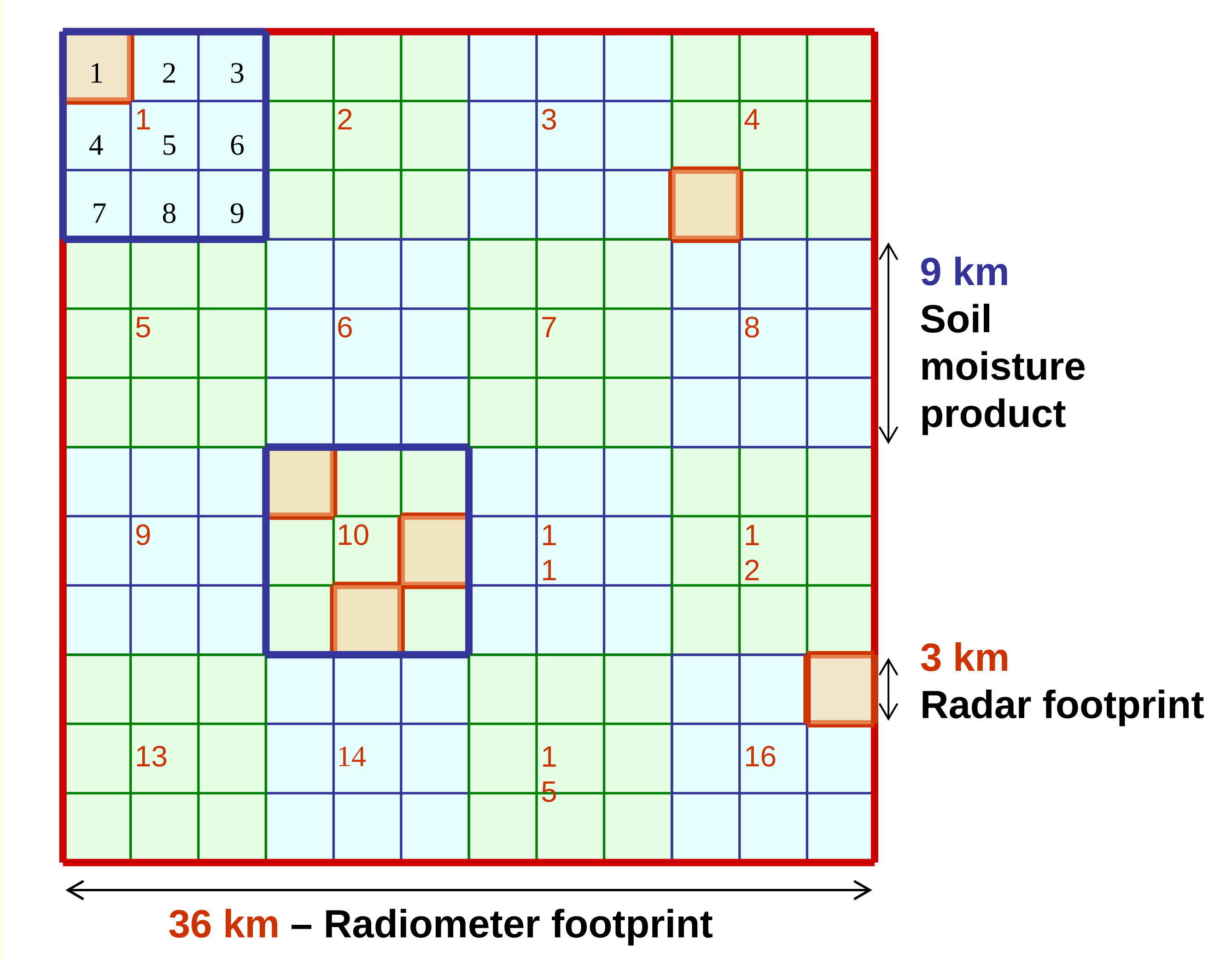
Error Statistics

Site	Alg	RMSE	Bias	R	Slope
WG01	NASA	3.1%	3.2%	0.626	0.201
	SCR	3.0%	-0.7%	0.564	0.379
LW01	NASA	4.6%	2.4%	0.508	0.255
	SCR	3.6%	-0.7%	0.756	0.601
MG01	NASA	7.7%	-3.8%	0.089	0.025
	SCR	6.4%	-4.1%	0.583	0.460

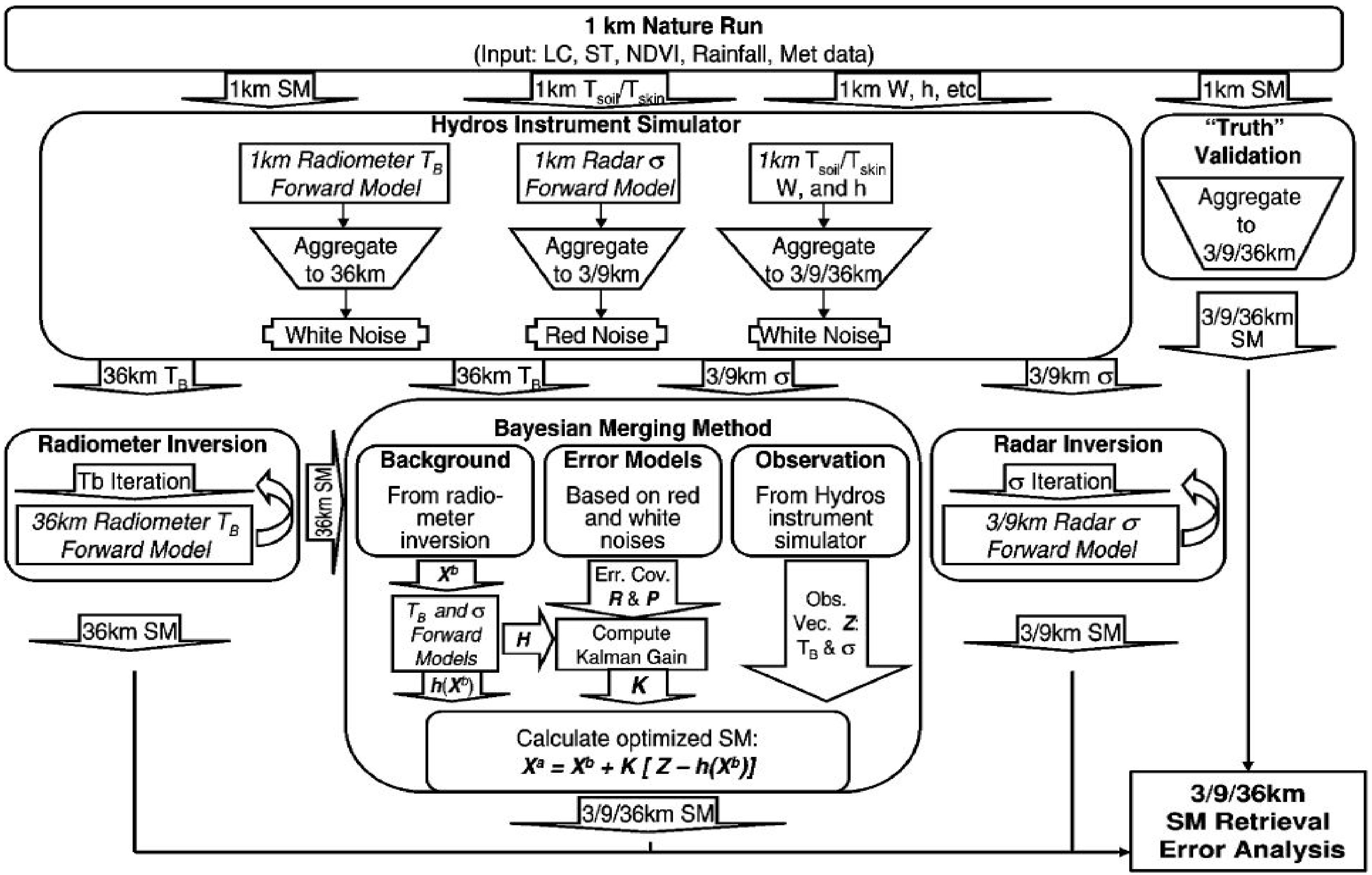
Microwave Soil Moisture Retrievals

- *Evaluation of NASA's Current AMSR-E Soil Moisture Data Product*
- *An Alternative AMSR-E Soil Moisture Data Product from NOAA-USDA*
- ***Retrieving High Resolution Soil Moisture From Hydros***

Hydros Sensor Model in the OSSE

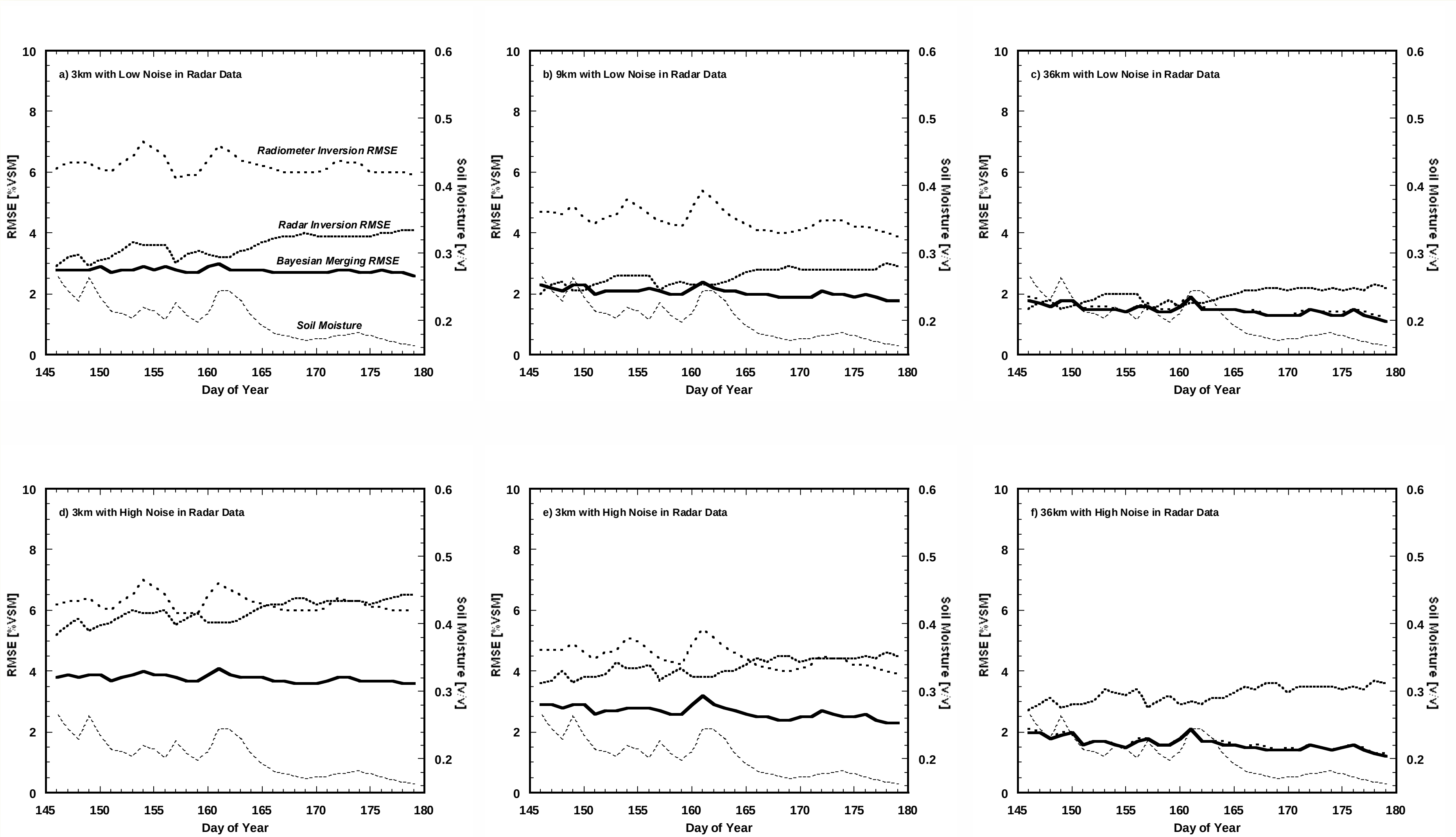


Retrieving High Resolution Soil Moisture from Hydros

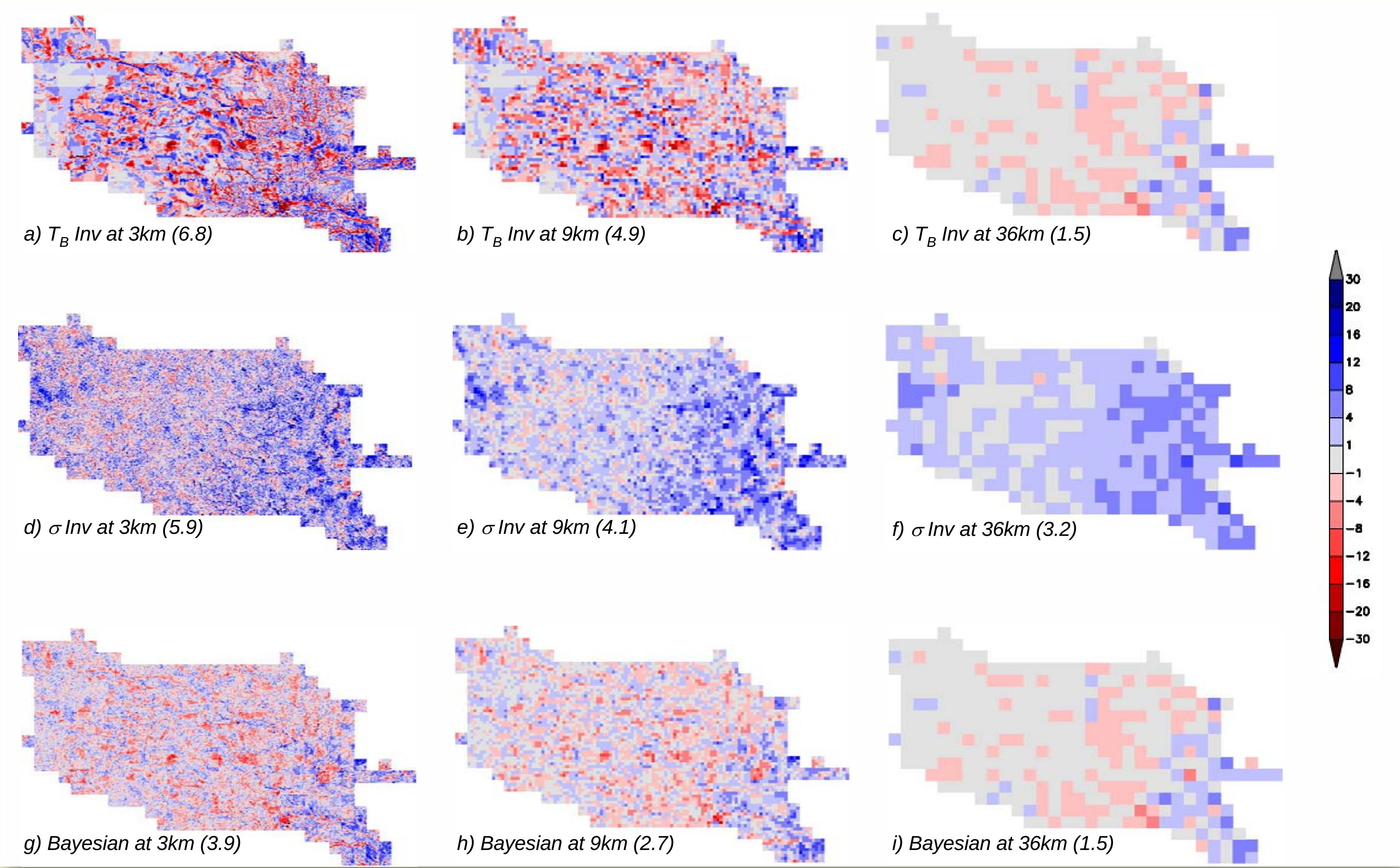


X. Zhan, P. Houser, J. Walker & W. Crow. 2006. IEEE TGRS 44(6):1534-1544

Retrieval Error Comparison



Retrieving High Resolution Soil Moisture from Hydros



Soil Moisture Data Assimilation

❖ **EnKF, LIS and Soil Moisture Data Assimilation**

Brief History of Kalman Filter Data Assimilation

- **Swerling (1958), Kalman (1960):** *Kalman Filter(KF) - a recursive solution for the discrete-data linear filtering problem. Applied in NASA's Apollo navigation computer in 1960.*
- **Schmidt (~1960):** *Applied Extended KF (EKF) to non-linear systems.*
- **Evensen (1992):** *Applied EKF for oceanic sequential data assimilation and found closure problem for error covariance propagation in EKF.*
- **Evensen(1994):** *Applied Monte Carl method for error covariance estimation in KF that lead to the Ensemble Kalman Filter (EnKF) for sequential data assimilation.*
- **Entekhabi (1994):** *Applied EKF to estimate soil temperature and moisture profile from surface observations.*
- **Walker & Houser (2001):** *Applied EKF to assimilate surface soil Moisture for providing GCM soil moisture initialization data fields.*
- **Reichle et al (2002):** *Applied EnKF for soil moisture estimation.*
- **Crow & Wood (2003):** *Used EnKF to assimilate TB observations.*
- **Zhan et al (2002), Kumar et al (2006), Zhan et al (2006):** *Implemented EKF & EnKF in LDAS/LIS for operational land data assimilation.*

Land Information System and EnKF

- ***Land Information System (LIS) is a package of computer programs of the Land Data Assimilation Systems (LDAS) enhanced with object-oriented programming technology;***

- ***LIS executes major land surface models (Noah, Mosaic, CLM, etc.) with unified input land surface parameter and meteorological forcing fields and standardized outputs;***

- ***Ensemble Kalman Filter (EnKF) is the mostly used sequential data assimilation algorithm in hydrological research;***

- ***EnKF is implemented in such a way that any observations of any LSM state variables can be assimilated into the LSM without much modification to the computer code.***

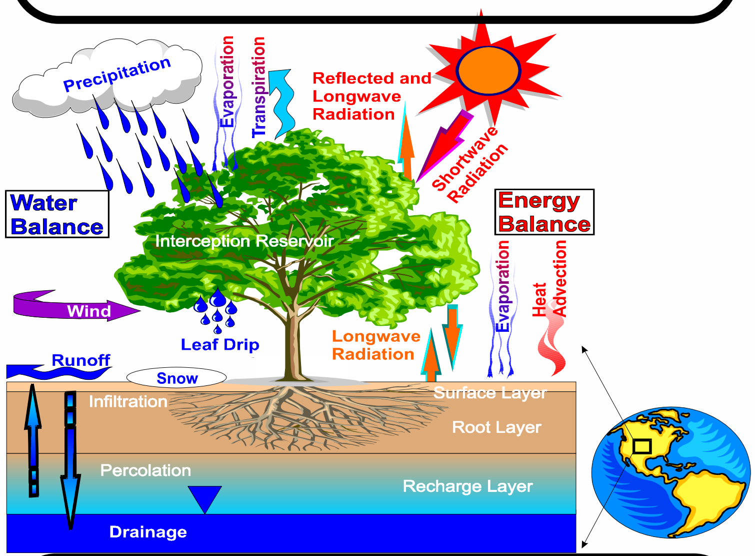
Land Data Assimilation Systems (LDAS)

Inputs

- Topography, Soils
- Land Cover, Vegetation Properties
- Meteorology
- Snow Soil Moisture Temperature

Physics

Land Surface Models



Data Assimilation Modules

Outputs

- Soil Moisture & Temperature
- Evaporation
- Runoff
- Snowpack Properties

Applications

- Weather/ Climate
- Water Resources
- Homeland Security
- Military Ops
- Natural Hazards

Implementation of Kalman Filters in LIS

Domain Init: read card, define grids, allocate mem, tile spec, etc.

LSM Init: tile allocate, LSM comp registration, etc.

Base & Obs Forcing Init: standardize format, mem, etc.

DA Init: algorithm/data registration, etc.

LSM Setup: wire forcing & input, static param, output struct, et.

Read Restart: LSM state variable initial value, etc.

Tick Time

Done

Read Base and Obs Forcings

Transfer Grid Forcings to Tiles

Run LSM on Tiles

Write LSM Output

Write Restart

X. Zhan, W. Crow, S. Kumar, P. Houser, & C. Peters-Lidard. 2006. AGU Spring Meeting, Baltimore, MD

Data Assimilation Setups in lis.crd File

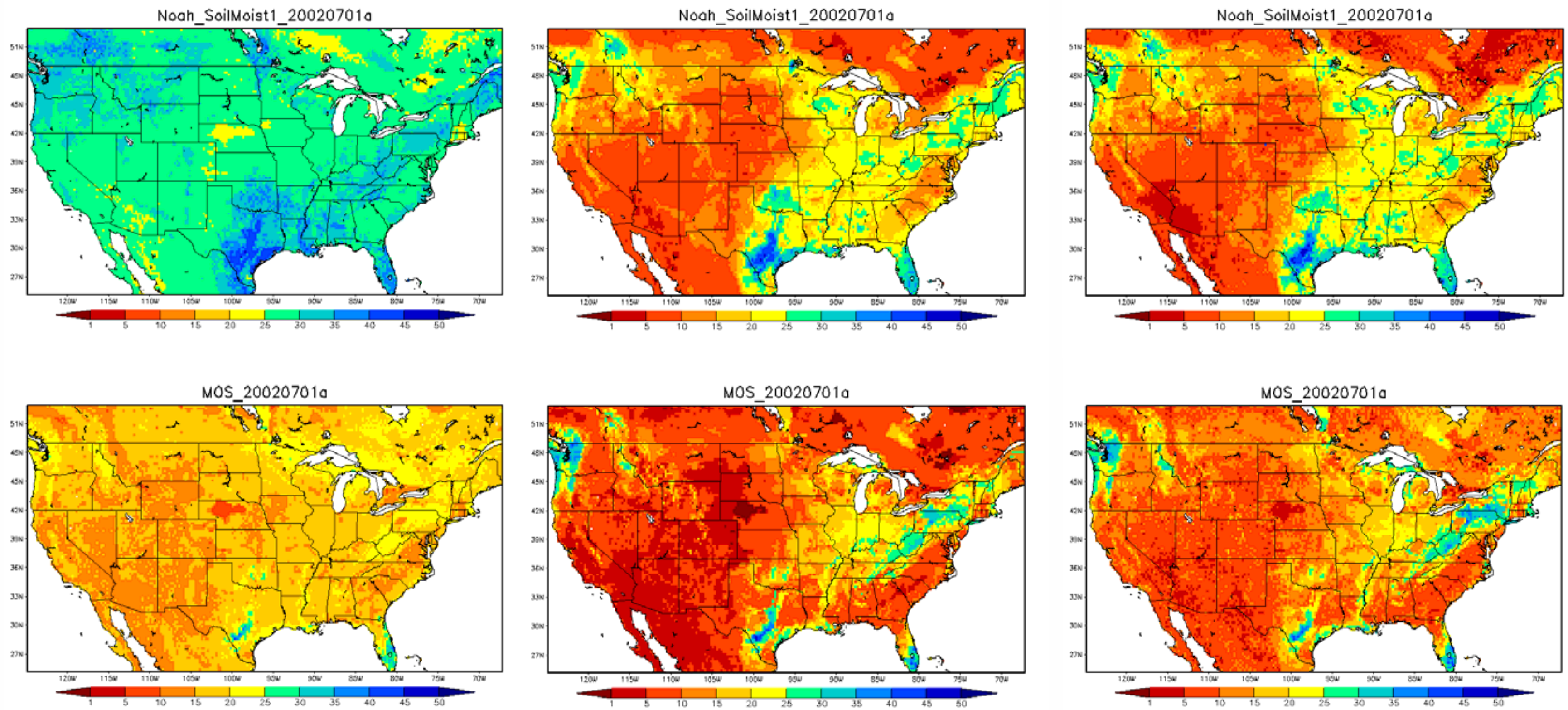
```
&data_assimilation
LIS%a%DAALG = 3  ! 0-no,1-di,2-ekf,3-enkf da method
LIS%a%DAOBS = 2  ! 0-no,1-tmi_sm,2-syn_sm,3-amsre_sm, …
LIS%a%DAVAR = 1  ! 0-no,1-sm,2-ts,
LIS%a%NSTV  = 16 ! # of LSM state variables
LIS%a%NDAV  = 4  ! # of prog model vars to be assimilated
LIS%a%NENS  = 10  ! number of ensemble members for EnKF
LIS%a%RENSEM= 0  ! write ensember data into files (0-n,1-y)
LIS%a%fvlfn = "./data/perturb/f_mos.dat"  ! forc perturb’ns
LIS%a%svlfn = "./data/perturb/s_mos.dat"  ! stat perturb’ns
/

&soil_moisture_da
smobsdir  = "./data/NOAHSoilMoist1_NLDAS" ! data location
nob      = 1      ! # of obs vars (e.g. surface sm)
oer      = 0.01   ! obs error rate
Mer      = 0.03   ! Mdl error rate
/
```

EnKF Assimilation of Synthetic SM Data in LIS

Test LIS-KF with Synthetic SM Data

Noah

Mosaic



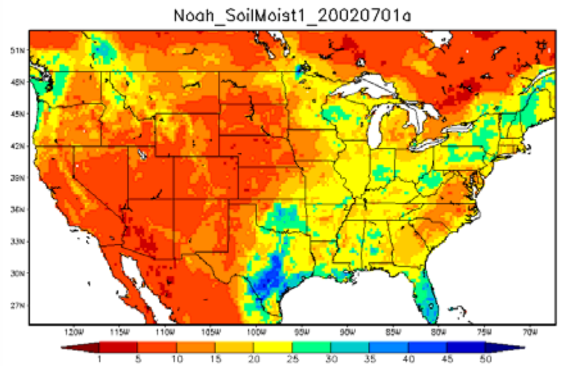
LSM Run | **Synthetic Obs** | **EnKF Assimilation**

X. Zhan, W. Crow, S. Kumar, P. Houser, & C. Peters-Lidard. 2006. AGU Spring Meeting, Baltimore, MD

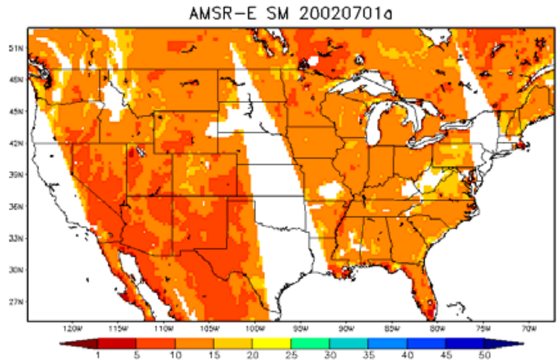
EnKF Assimilation of AMSR-E SM Data in LIS

Test LIS-KF with AMSR-E SM Data

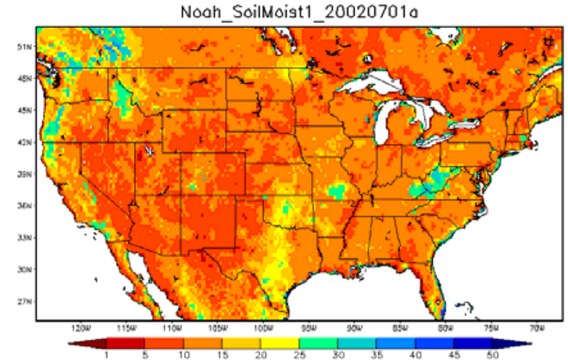
Noah LSM Run



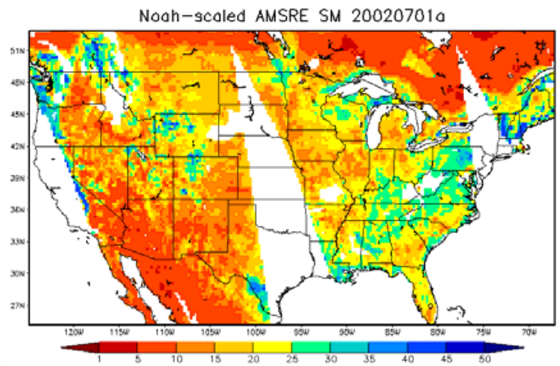
AMSR-E SM



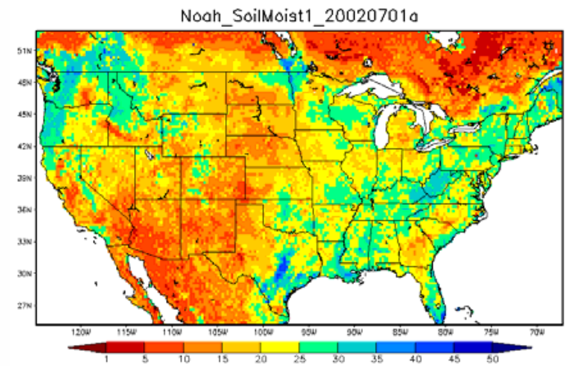
EnKF Assimilation



Scaled AMSR-E

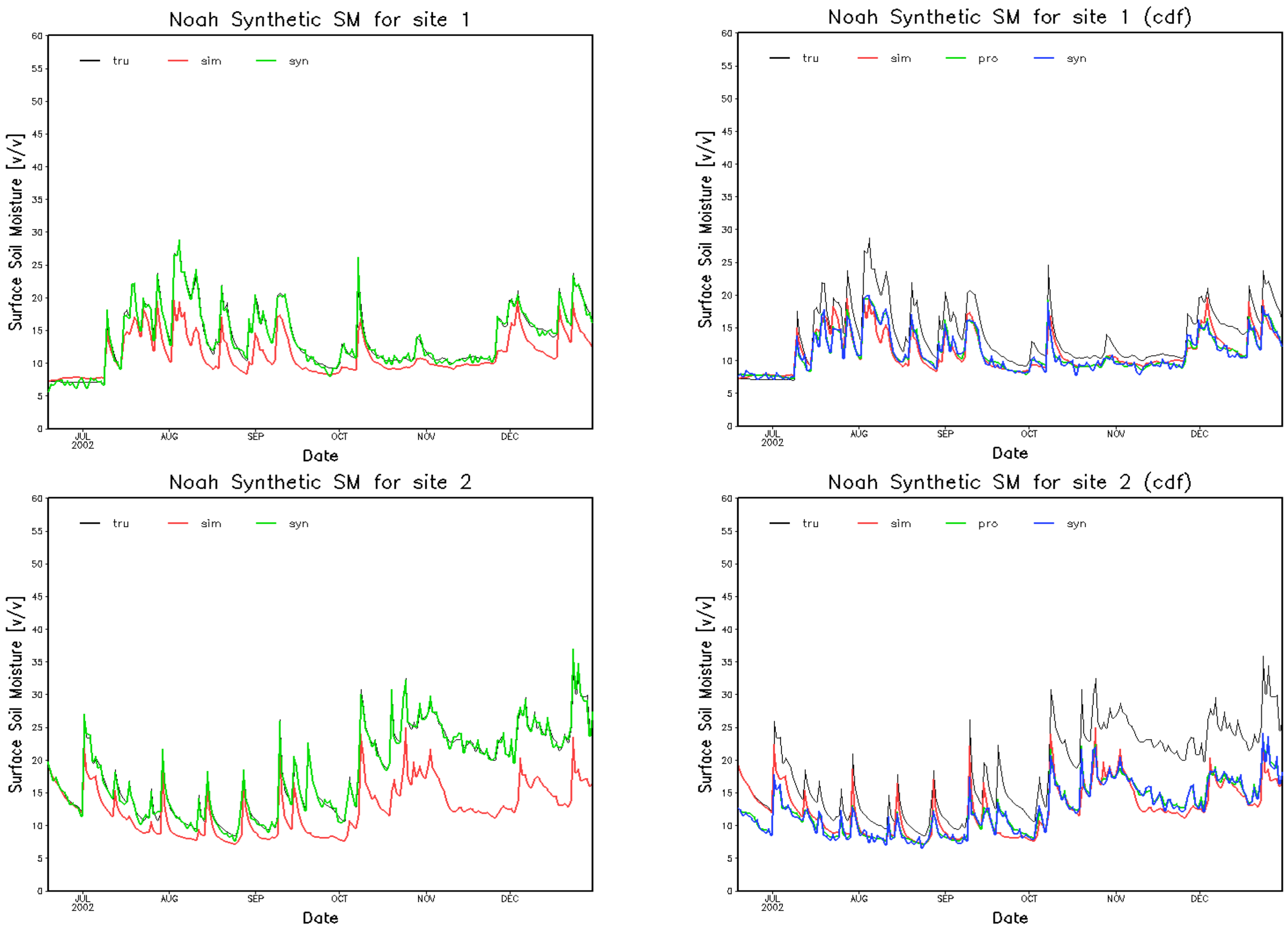


EnKF Assimilation



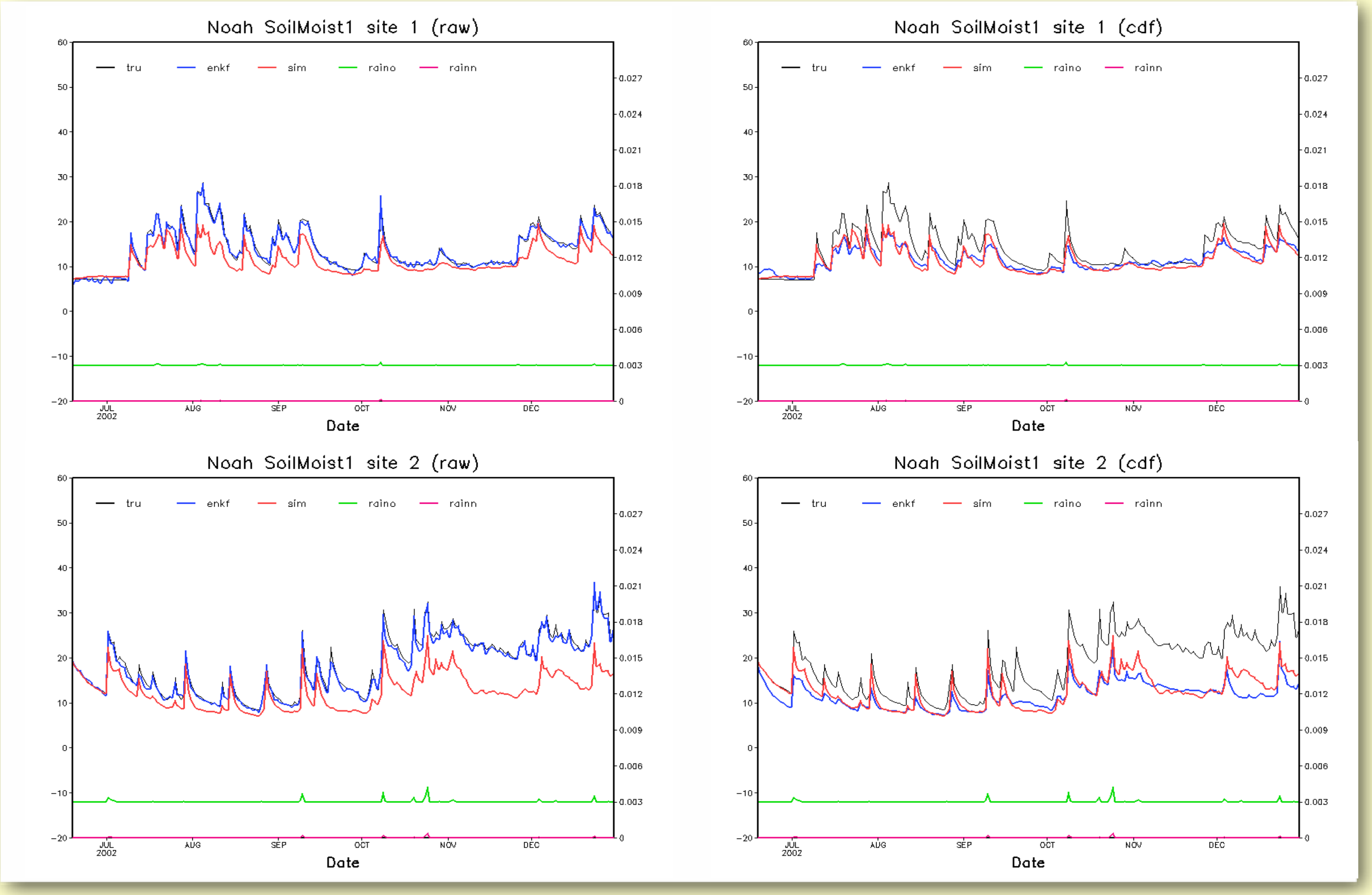
X. Zhan, W. Crow, S. Kumar, P. Houser, & C. Peters-Lidard. 2006. AGU Spring Meeting, Baltimore, MD

CDF Matching Impact with Synthetic SM Data



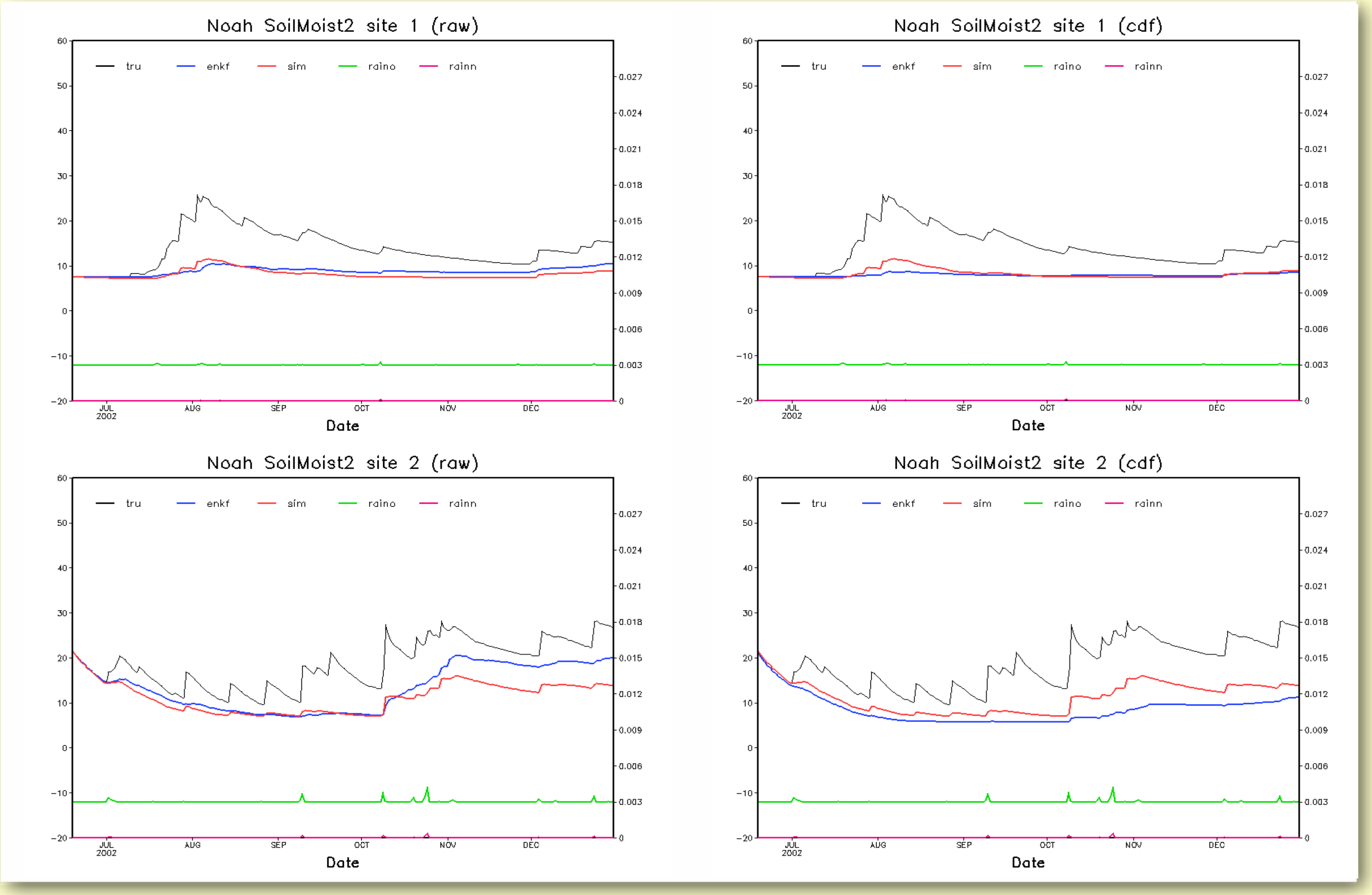
Zhan, X., et al. 2007. AMS Annual Meeting, San Antonio, TX

CDF Matching Impact on EnKF DA (1)



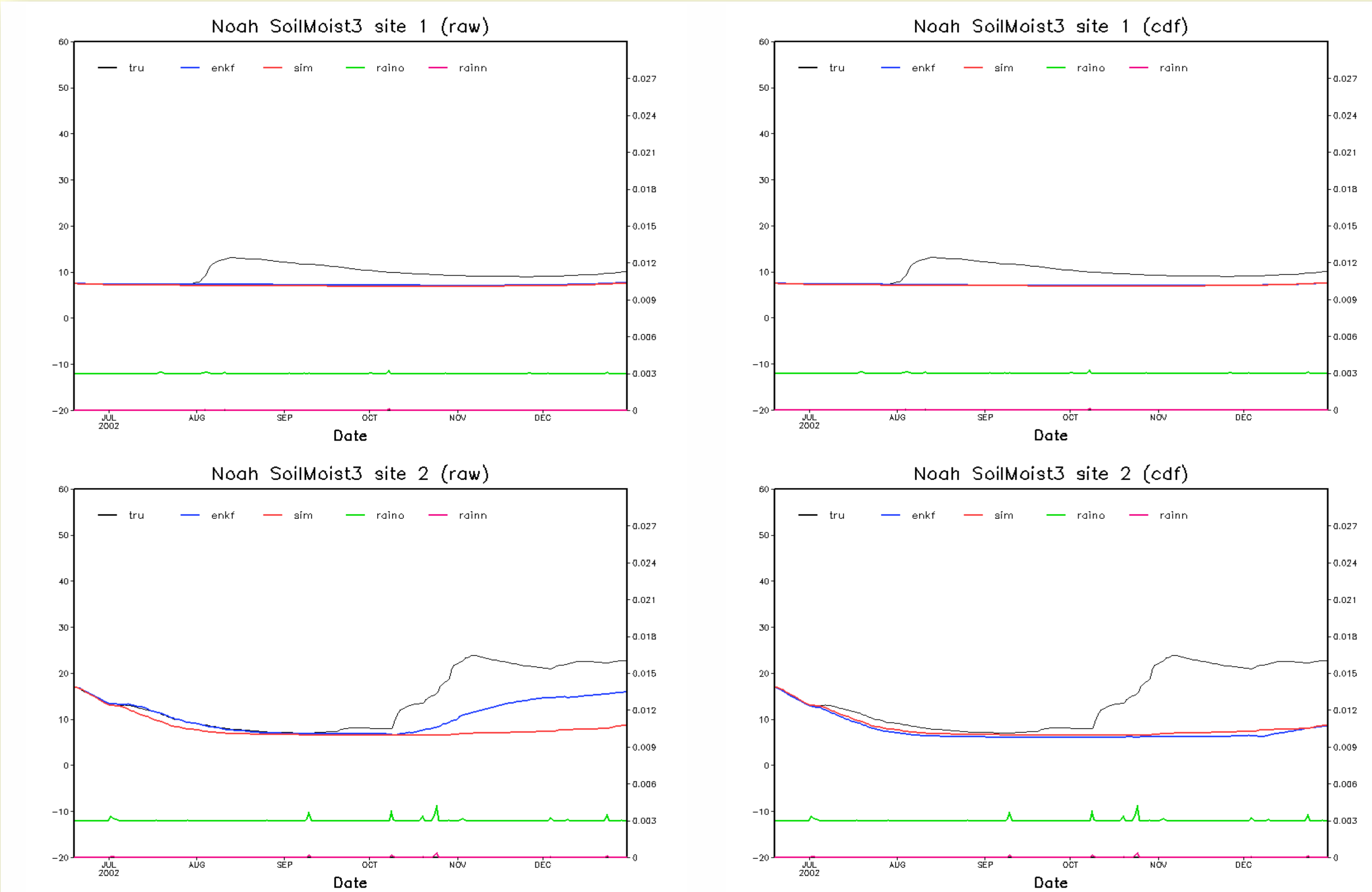
Impact of Obs Data Preprocessing on EnKF DA

CDF Matching Impact on EnKF DA (2)

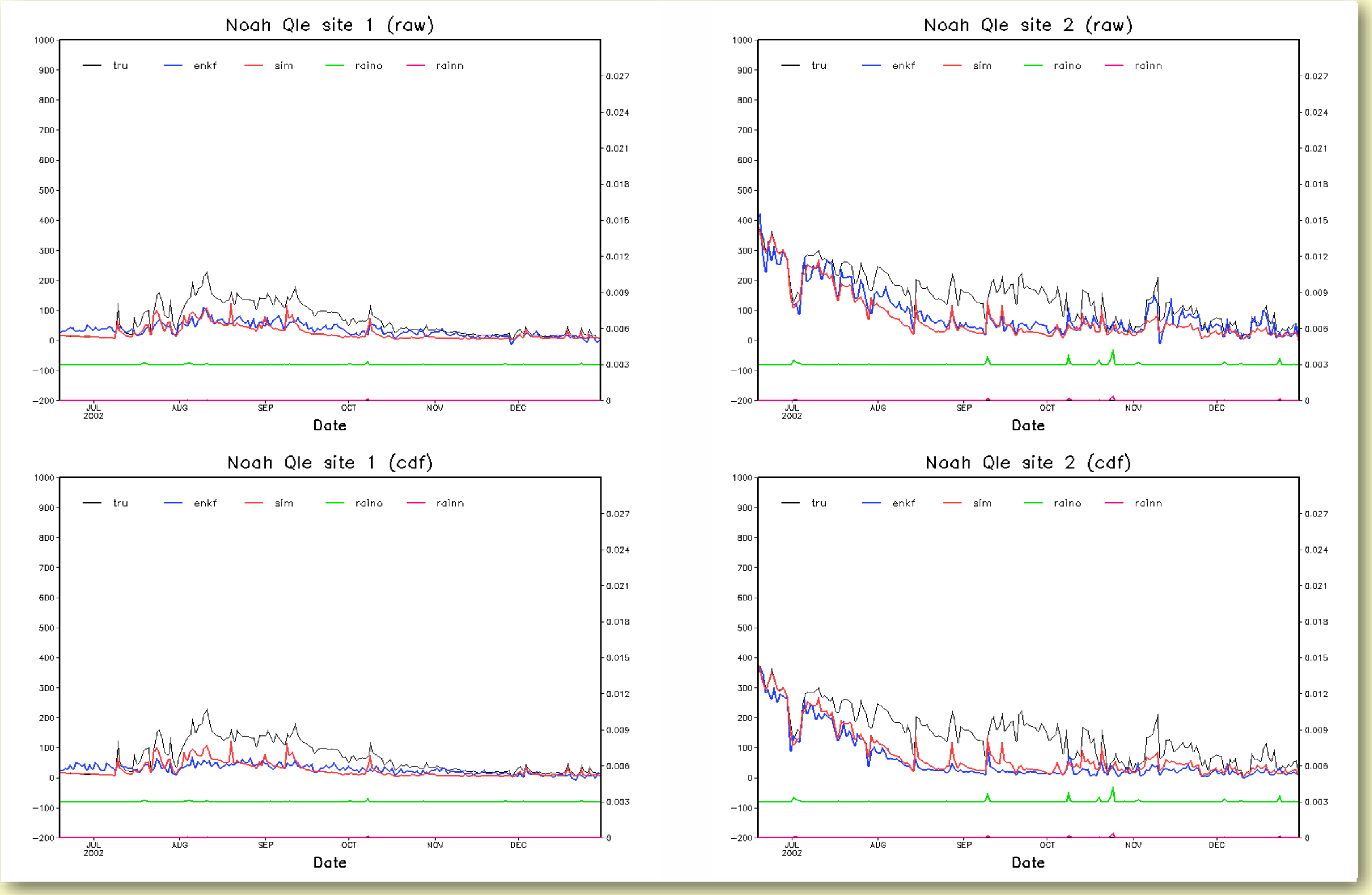


Impact of Obs Data Preprocessing on EnKF DA

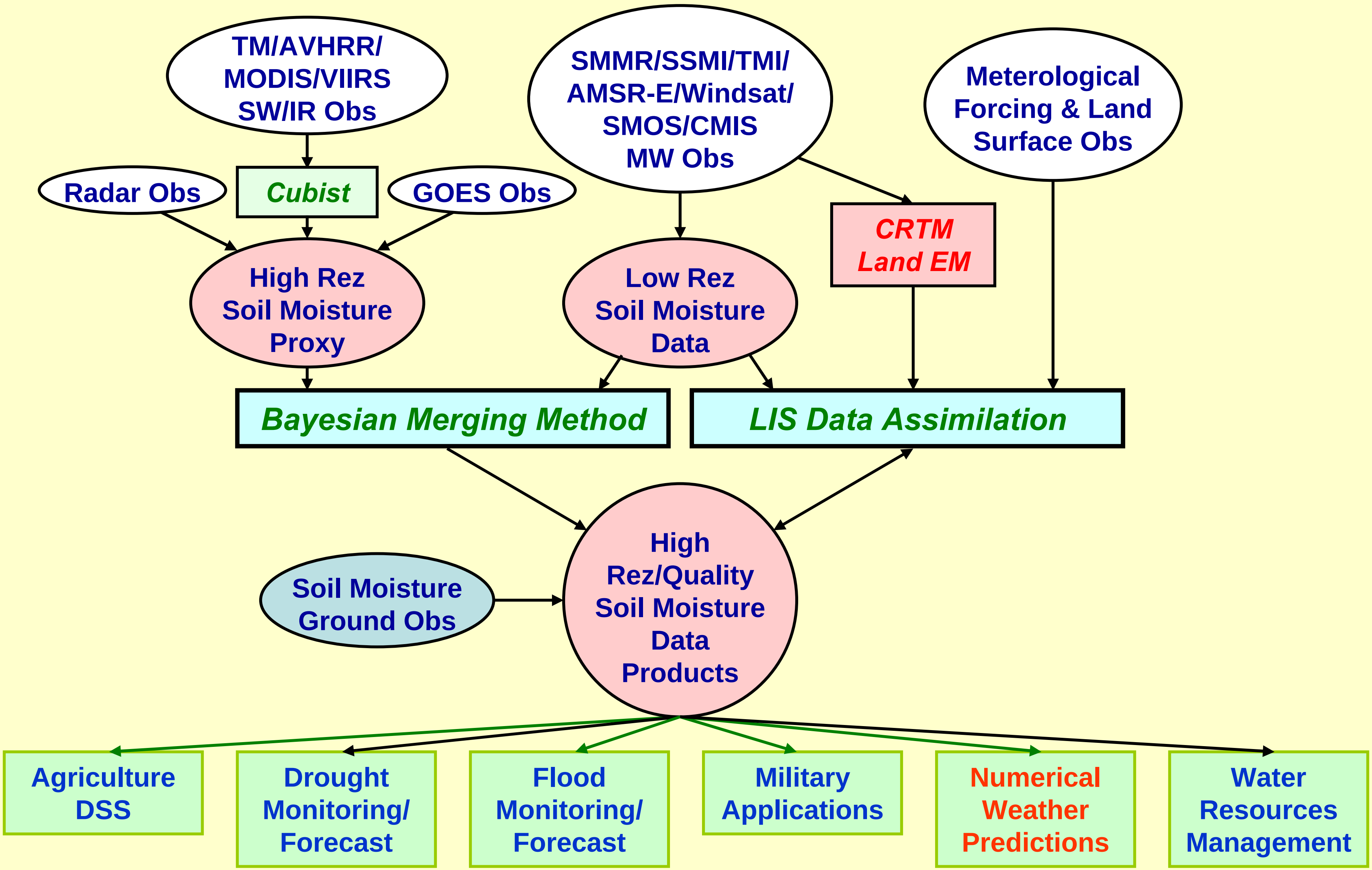
CDF Matching Impact on EnKF DA (3)



CDF Matching Impact on EnKF DA (4)



SM Data Research Plan



SUMMARY

1. SM Data & Importance
2. SM Observation Techniques
3. MW Soil Moisture Retrievals
4. Soil Moisture Data Assimilation
5. SM Data Research Plan

Many research opportunities exist to improve accuracy and resolution of soil moisture data products and to broad their applications.


The END