Using in-situ, modeled and AMSR-E retrieved soil moisture for AMSR-E validation

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Project Goal:

To provide modeling support to the AMSR-E validation activities through a combination of soil moistures retrievals, process-based hydrological modeling, and evaluation of such retrievals.

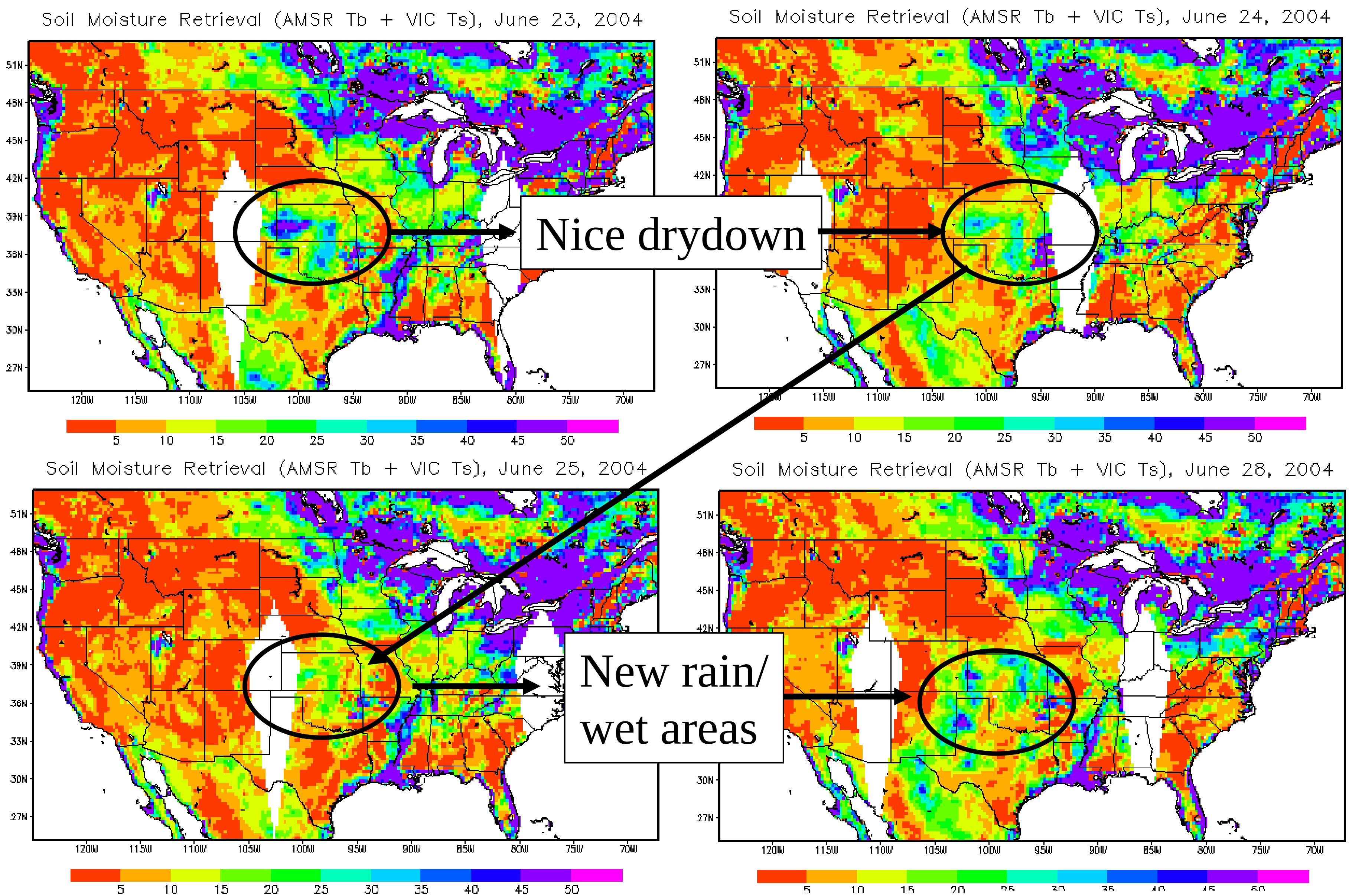
Project Activities:

1. Validation using SMEX02/03, NAME, and OK-mesonet data
2. Comparisons between AMSR-E and TMI over OK region

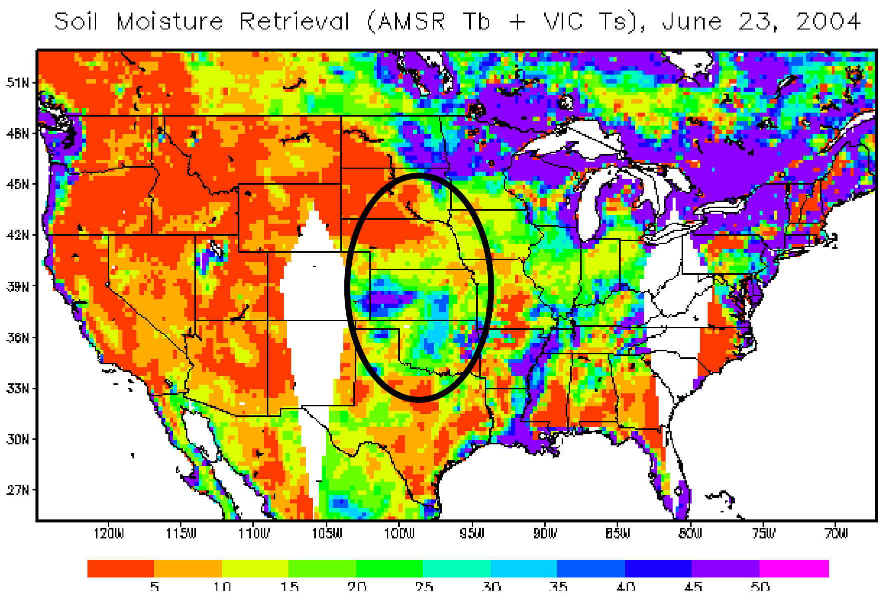
Todays Focus

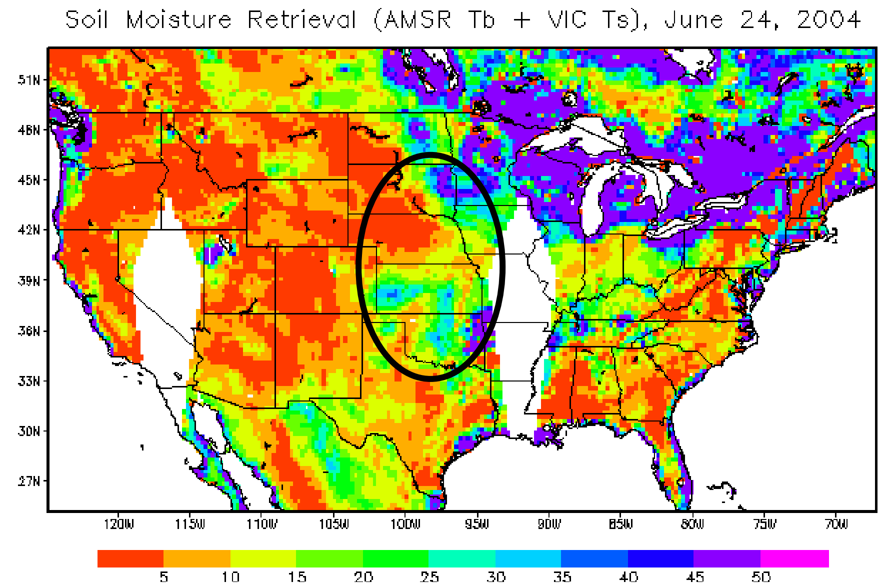
Validation of AMSR-E retrievals based on the concept of predictive skill of the retrieved data product.

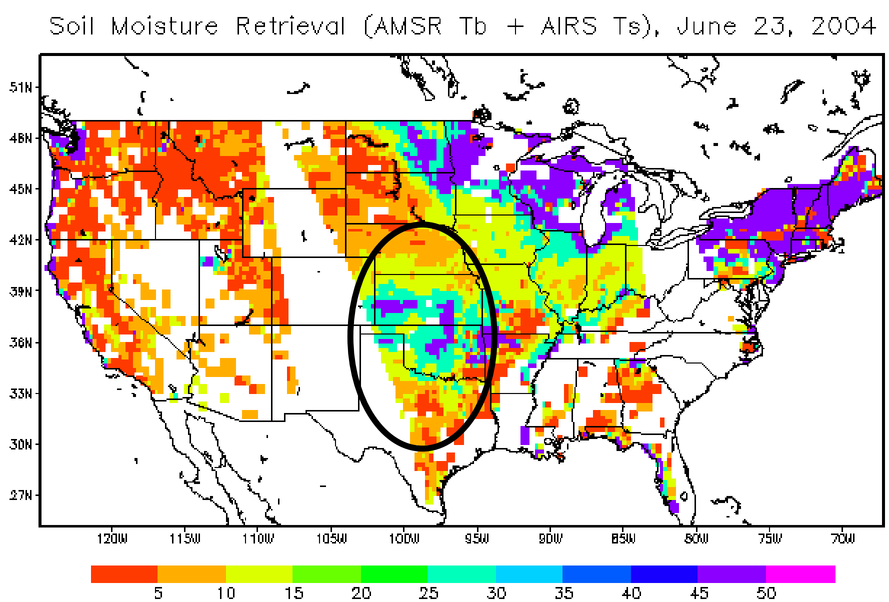
Retrievals look good; are they skillful, how can they be ‘validated’?

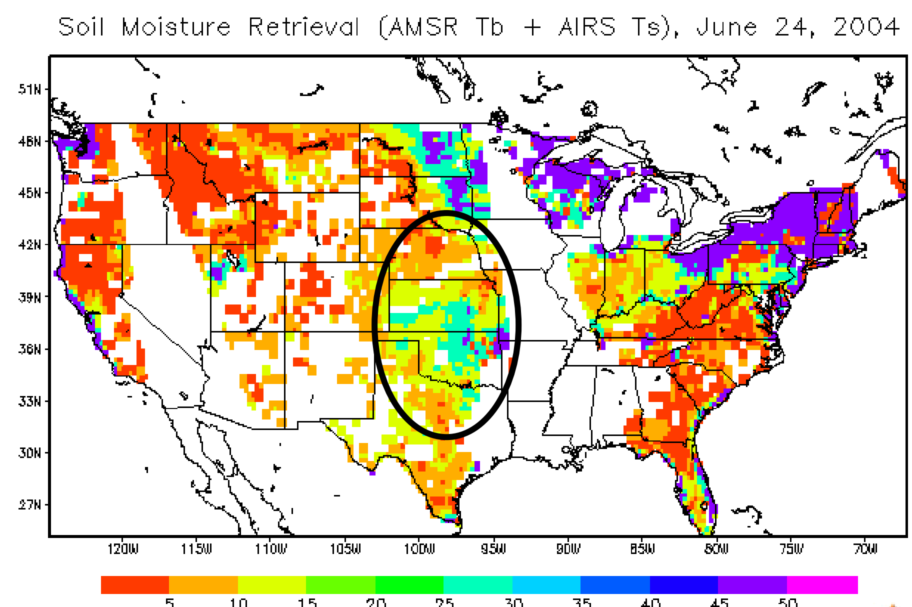


Recent LSMEM algorithm retrievals using AMSR-E and AIRS









Old Validation Paradigm:

- Obtain remotely sensed retrievals of physical variables (soil moisture, precipitation, etc.) using a retrieval algorithm.
- Compare the retrieved values to those obtained through in-situ measurements.
- If retrievals match the in-situ measurements, then sensor/algorithm is 'validated'.

Problems:
What happens when the physical variables can't be accurately measured at the sensor scale, due to spatial heterogeneity, scale mismatches, poor in-situ sensors? And, different algorithms give different results?

Examples: Soil moisture, precipitation, SWE, ET.

Examples of the ‘old’ validation approach

- Comparisons between precipitation patterns and changes in soil moisture – consistency.
- Comparisons were made to SMEX field data, 5-cm soil moisture from 30 Oklahoma mesonet data sites, and to 10-cm soil moisture from a land surface model --- they’re all different.
- Soil moisture retrievals using the Princeton (PU) Land Surface Microwave Emission Model (LSMEM) and 10.7 GHz AMSR-E brightness temperatures are compared to the NASA/AMSR-E 10.7 GHz retrievals – they’re different.

Rainfall and Retrieved PU/AMSR soil moisture patterns

June 26

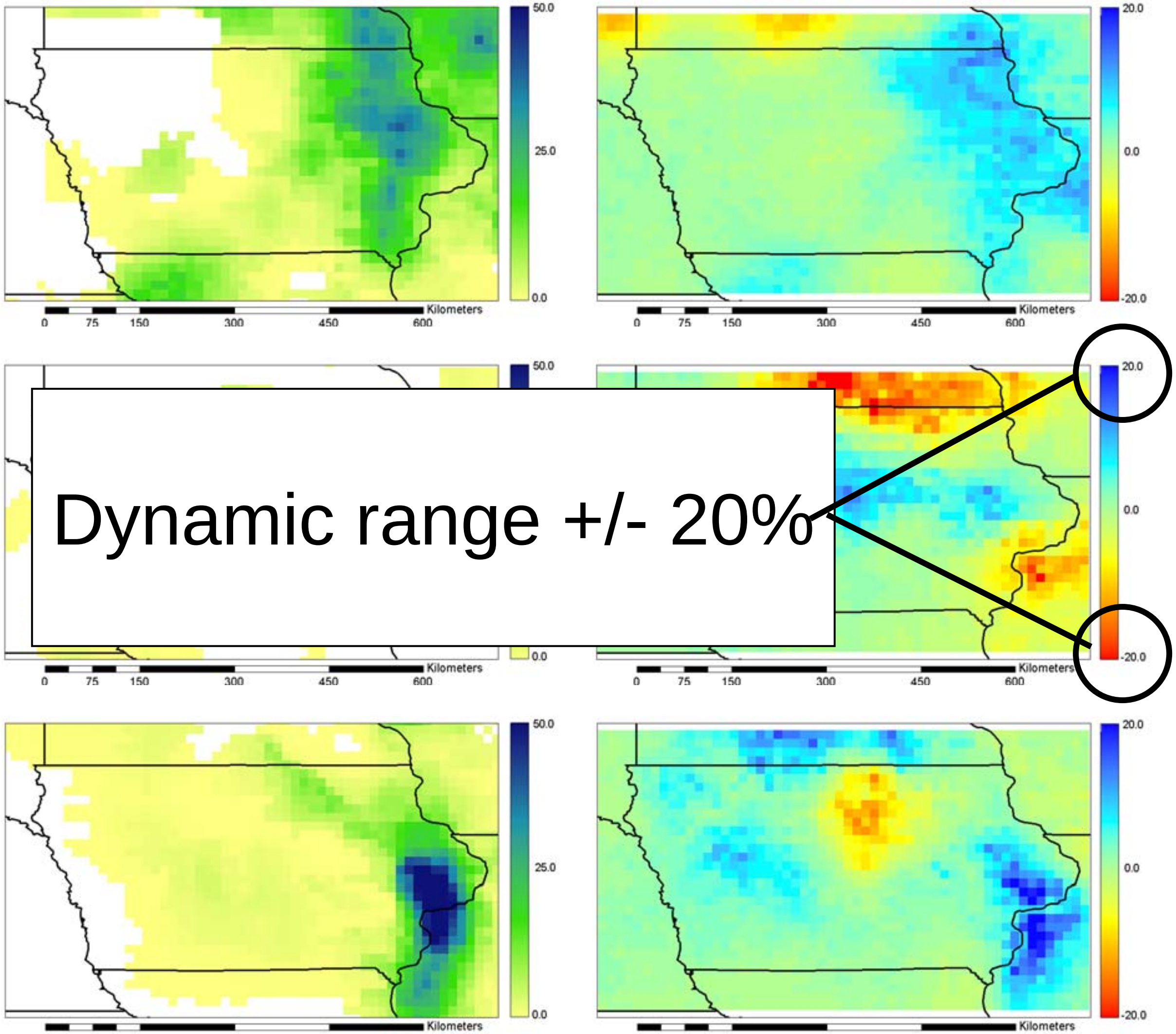
June 27 - 25

July 5

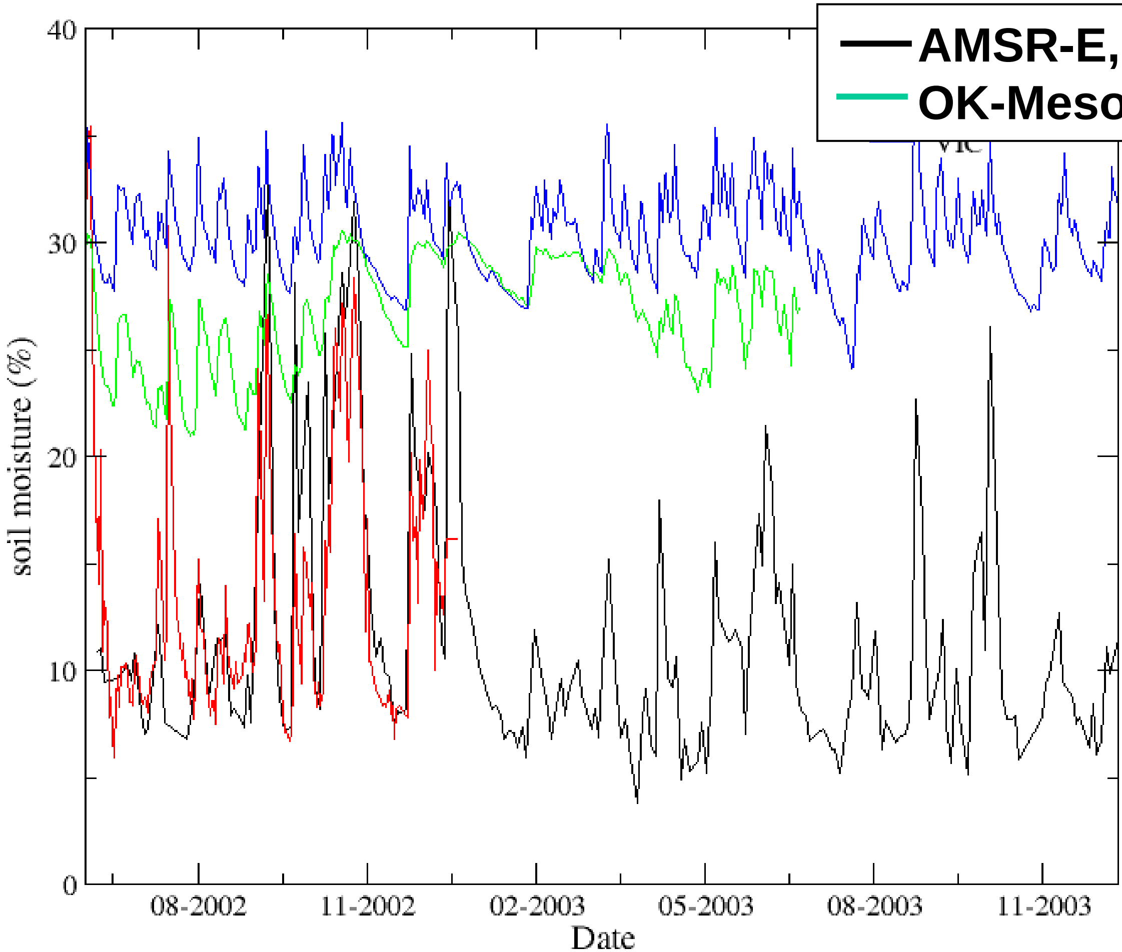
July 6 – 4

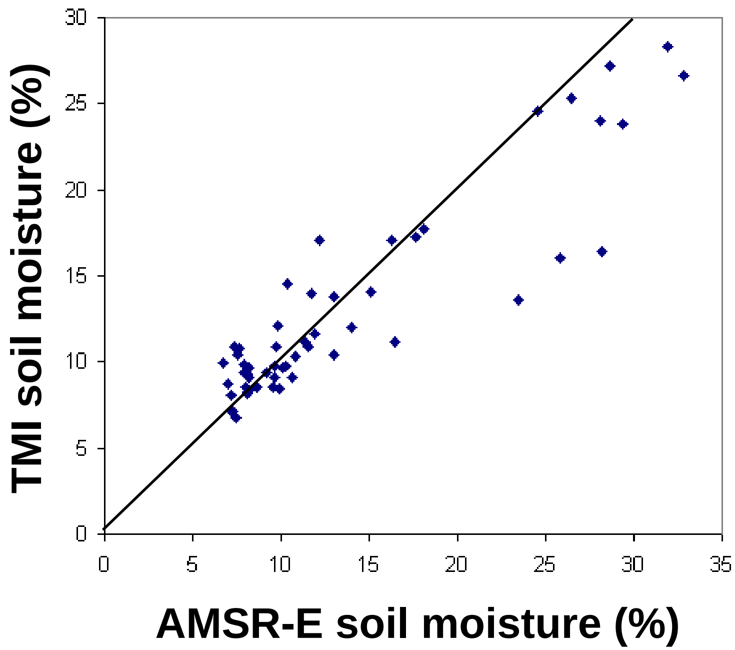
July 19

July 20 – 18



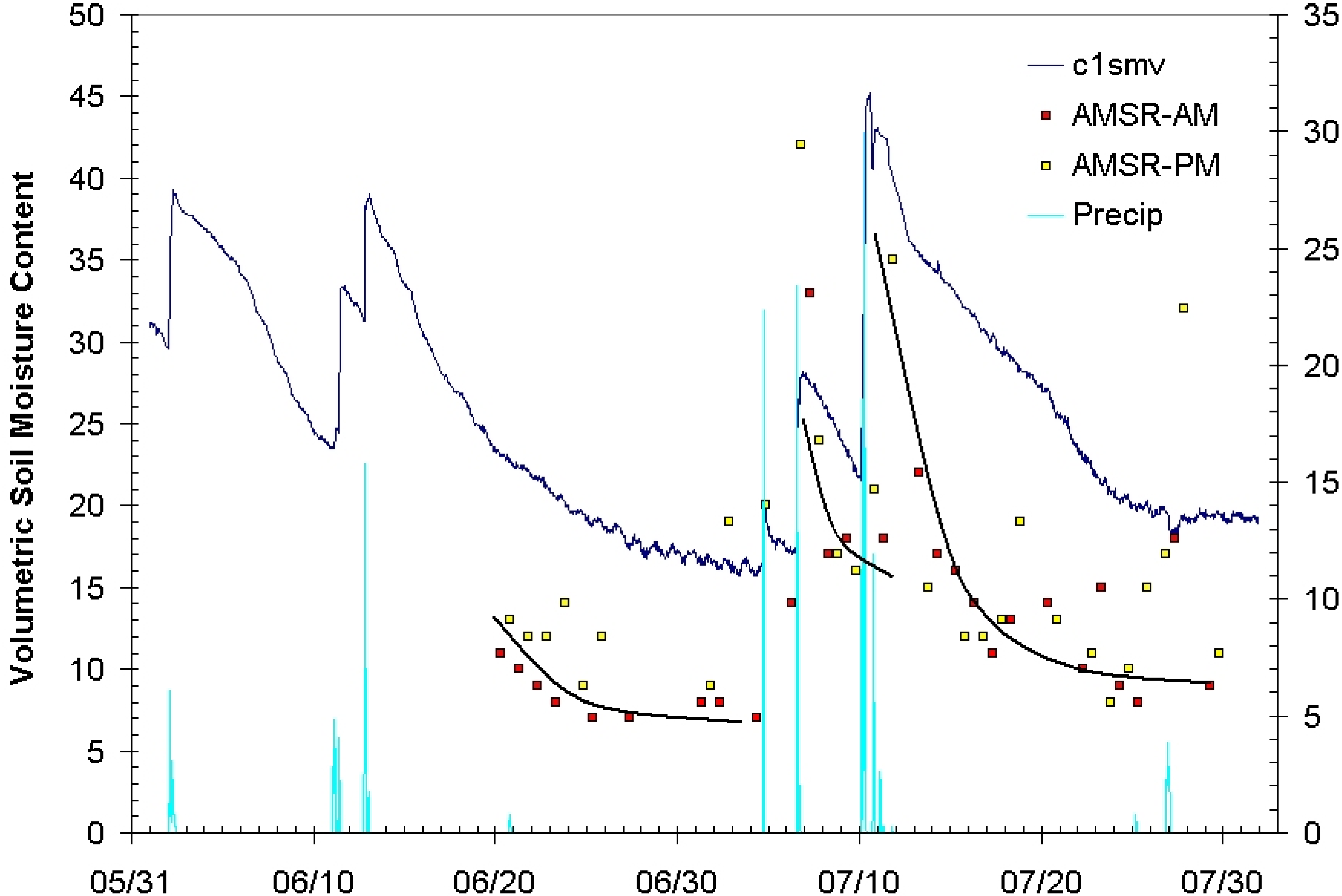
PU/AMSR-E X-Band Soil Moisture Comparisons with PU/TMI X-Band Soil Moisture





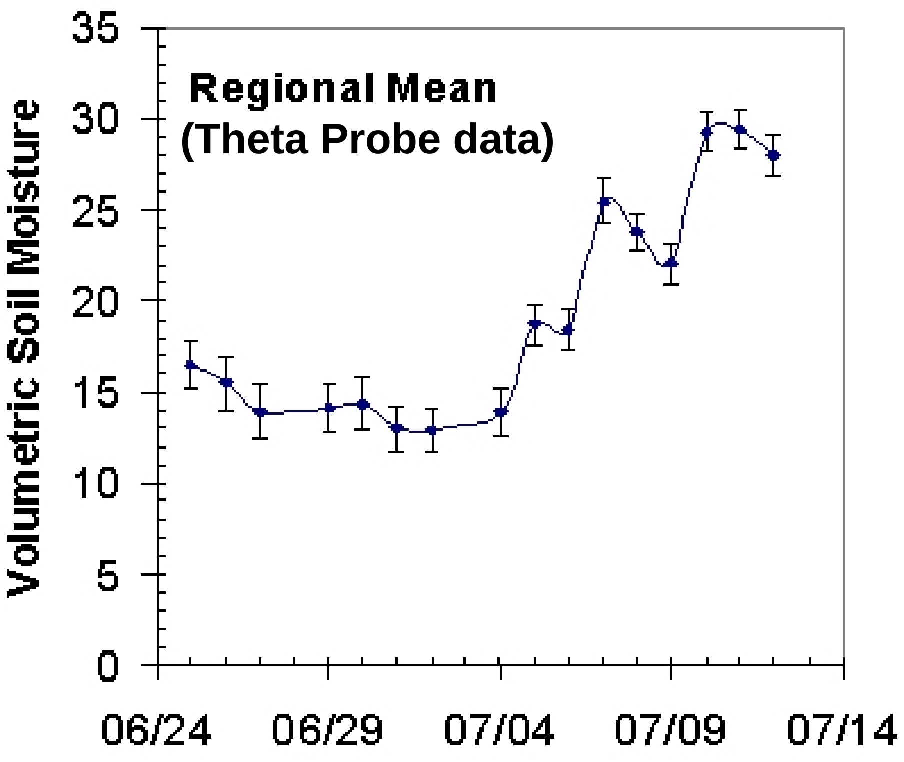
Lesson: Retrievals consistent across sensors, but different from *in-situ*

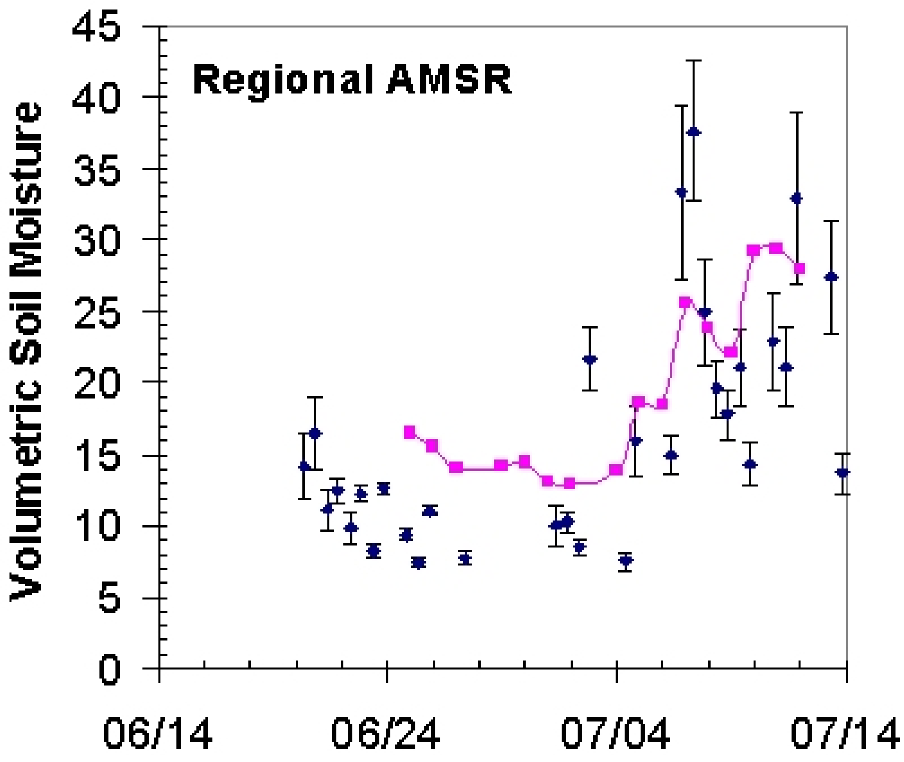
SMEX02: PU/AMSR-E X-Band Soil Moisture Comparison with the ARS SCAN Soil Moisture Monitoring Site



Princeton University

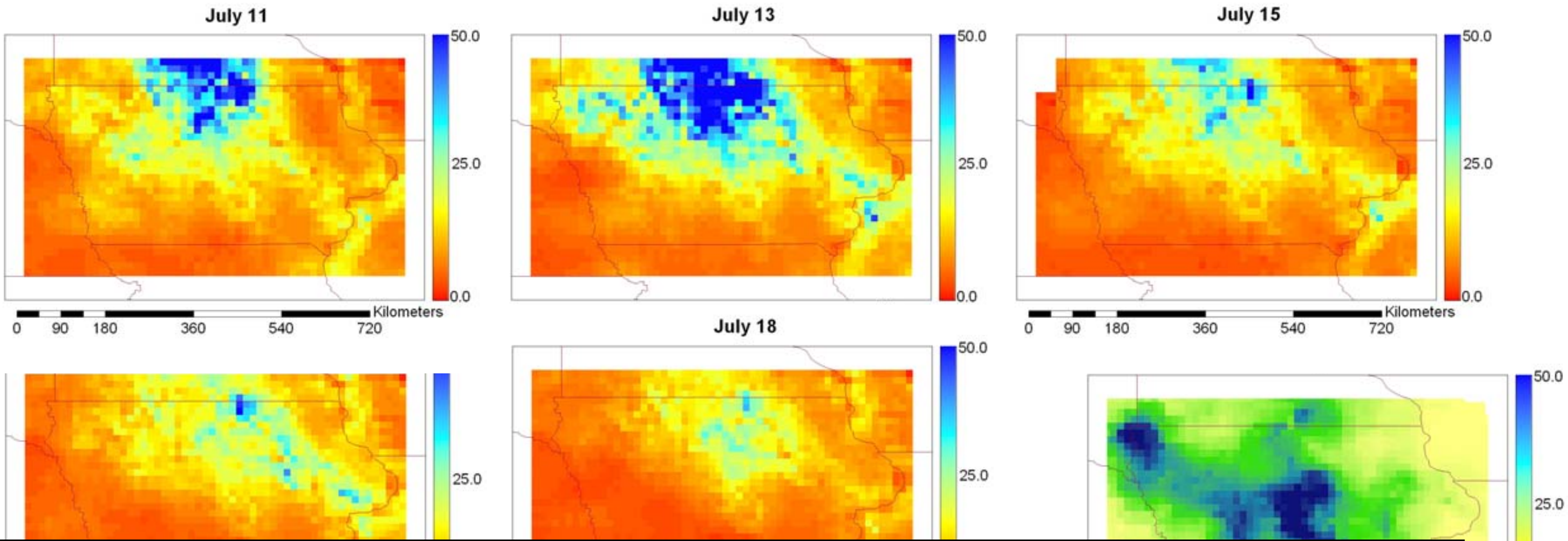
SMEX02: PU/AMSR-E X-Band Soil Moisture Comparison with the Field Theta Probe Measurements





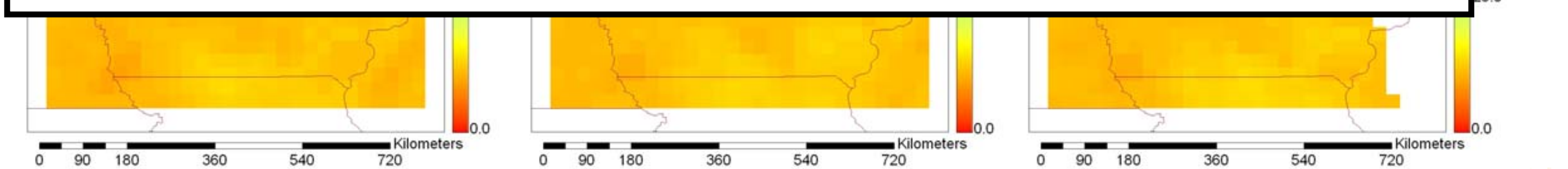
(Notice how PU/AMSR-E has more realistic variability after rain events)

PU/
AMSR

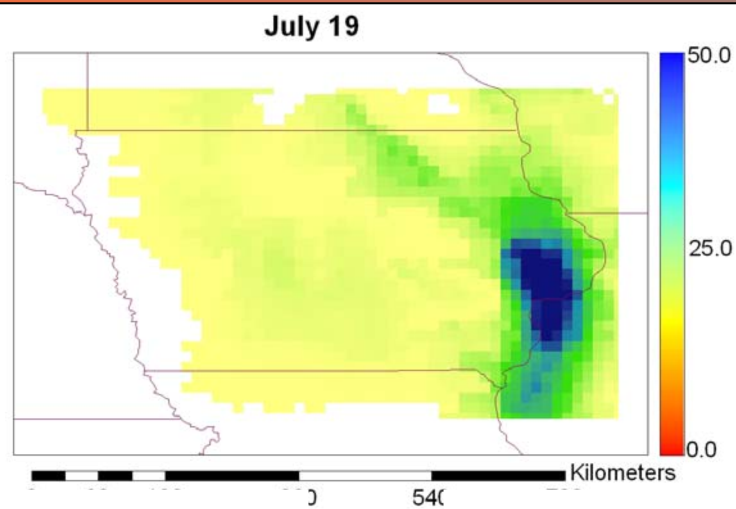


NASA/
AMSR

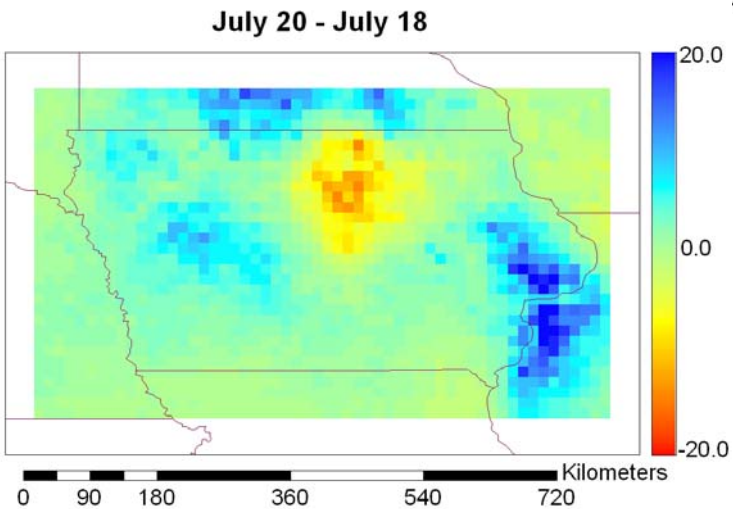
NASA/AMSR-E has significantly reduced dynamic range when compared to PU/AMSR-E. Because of scale effects IT IS IMPOSSIBLE TO RESOLVE (VALIDATE) WHICH IS CORRECT. Therefore we must consider statistical consistency between satellite and in-situ observations.



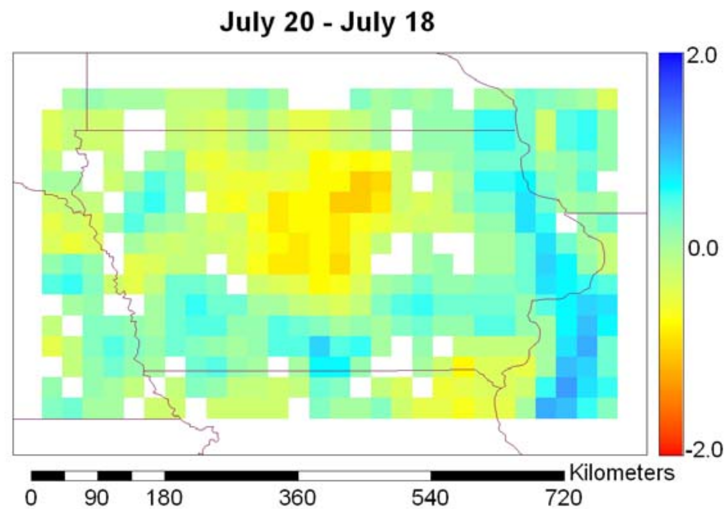
Looking at soil moisture differences between pre- and post-rain days



Rainfall (mm)

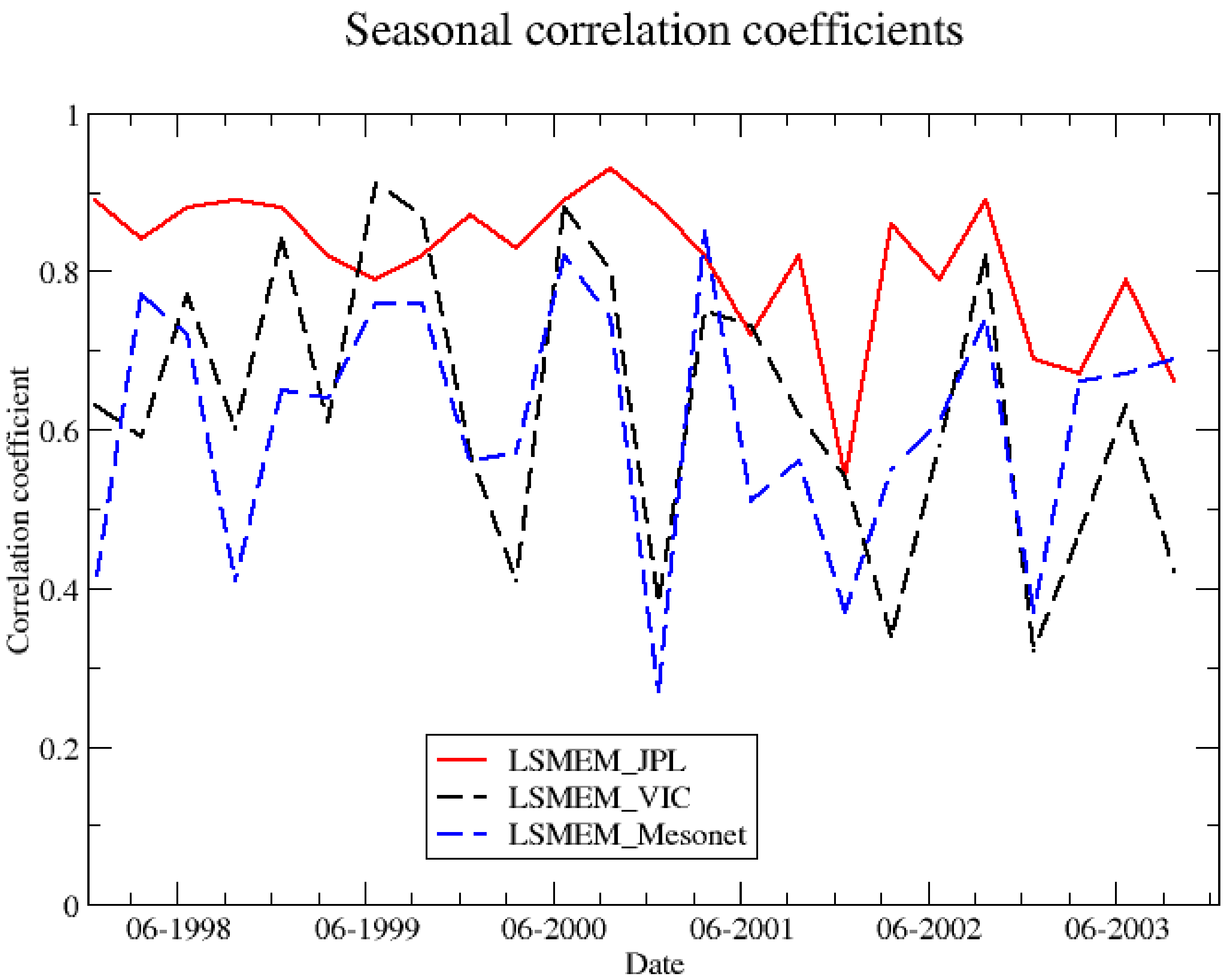


PU/AMSR-E differences % soil moisture



NASA/AMSR-E differences – reduced range

Statistical consistency between LSM and retrieved soil moistures



The new validation paradigm for land surface parameters

The reality that retrieved soil moistures have different mean values and dynamic ranges implies that new, innovative statistical approaches are needed for validation, based on "statistical consistency" and "predictive skill" of the retrieved variable.

This has significant implications for estimating retrieval errors and the use of remote sensing in assimilation.

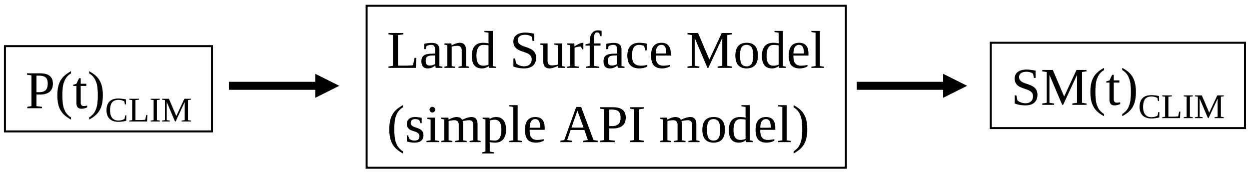
How to compute the predictive skill of soil moisture?

- Determine how much information soil moisture provides to a land surface model when the soil moisture is assimilated.
- One approach was proposed by Wade Crow "A novel method for quantifying value in remotely-sensed soil moisture retrievals" *JHM* (in press) – will be used here.
- A second approach is through a Bayesian posterior distributions, updated via soil moisture observations/retrievals.

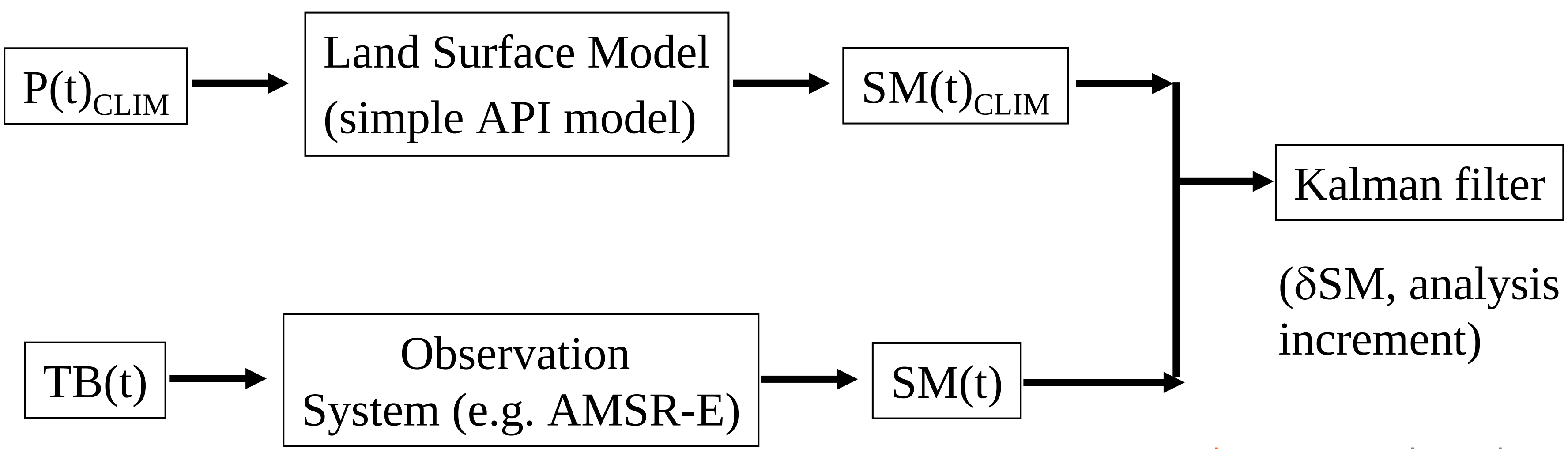
How to compute the predictive skill of soil moisture?

Steps:

1: Predict soil moisture using a precipitation climatology, obtained by shuffling the historical record (Crow used GPCP precipitation).

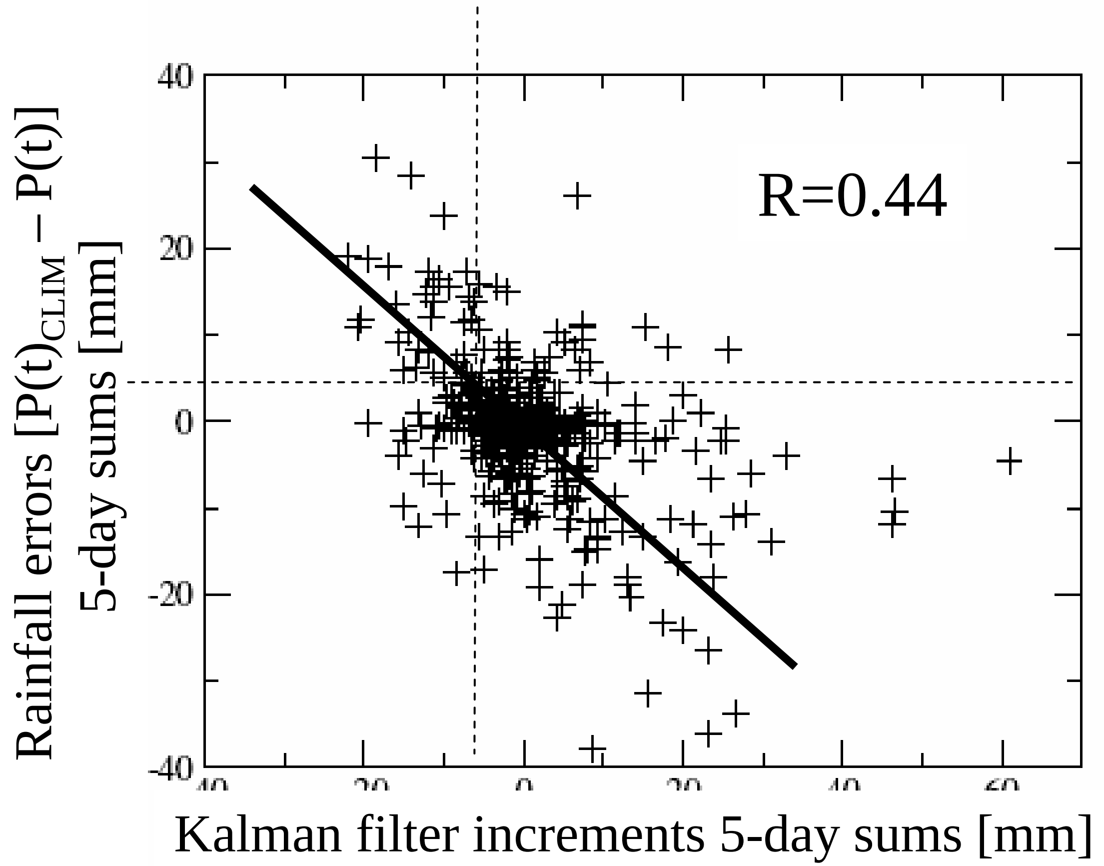


2: Use a soil moisture 'observation' to update the $SM(t)_{CLIM}$ via data assimilation (e.g. Kalman filtering).

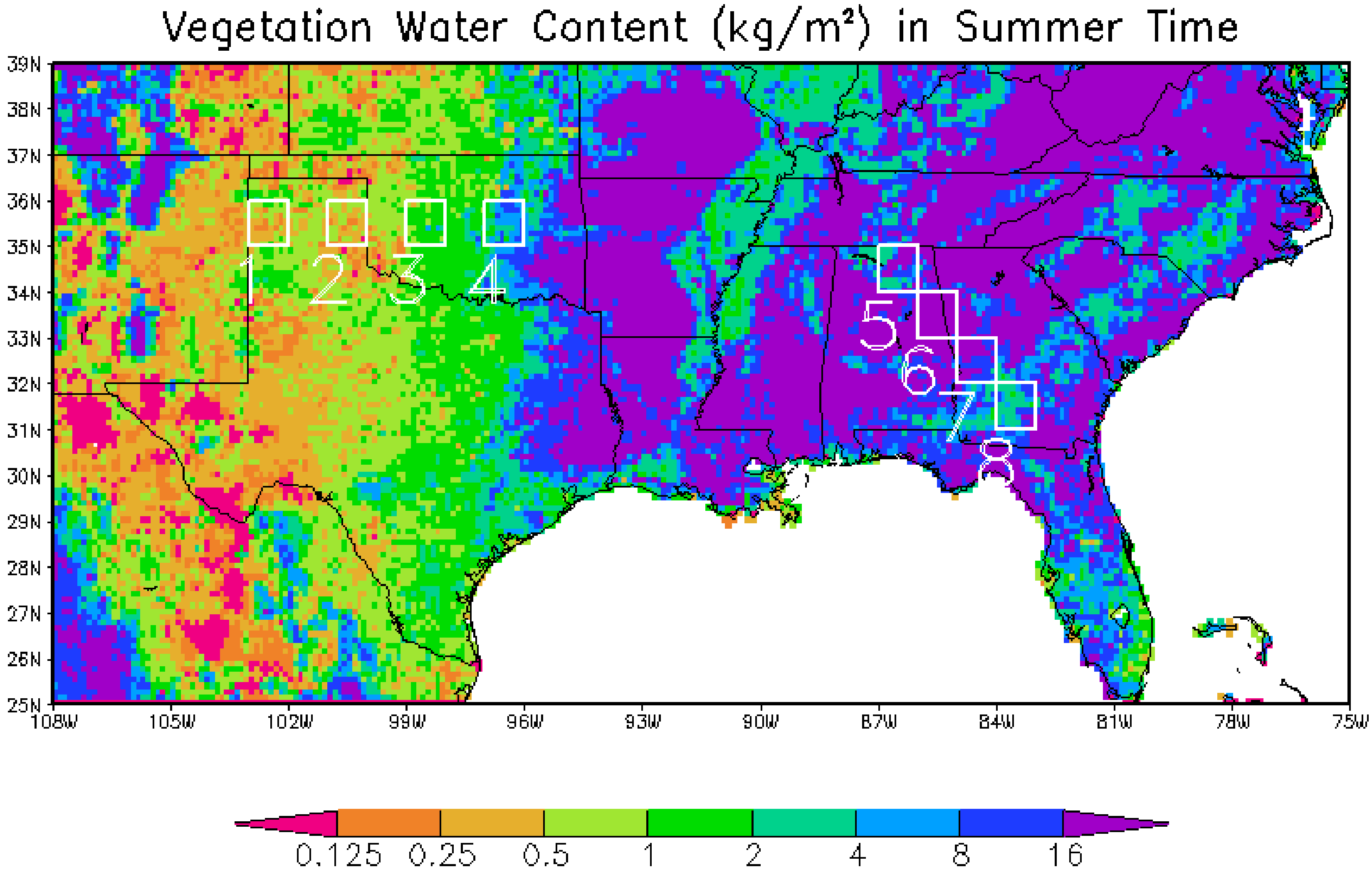


Compare the rainfall error $[P(t)_{CLIM} – P(t)]$ with the soil moisture analysis increment $\delta SM(t)$ from the Kalman filter. If the observation system has predictive skill, then they should be highly correlated.

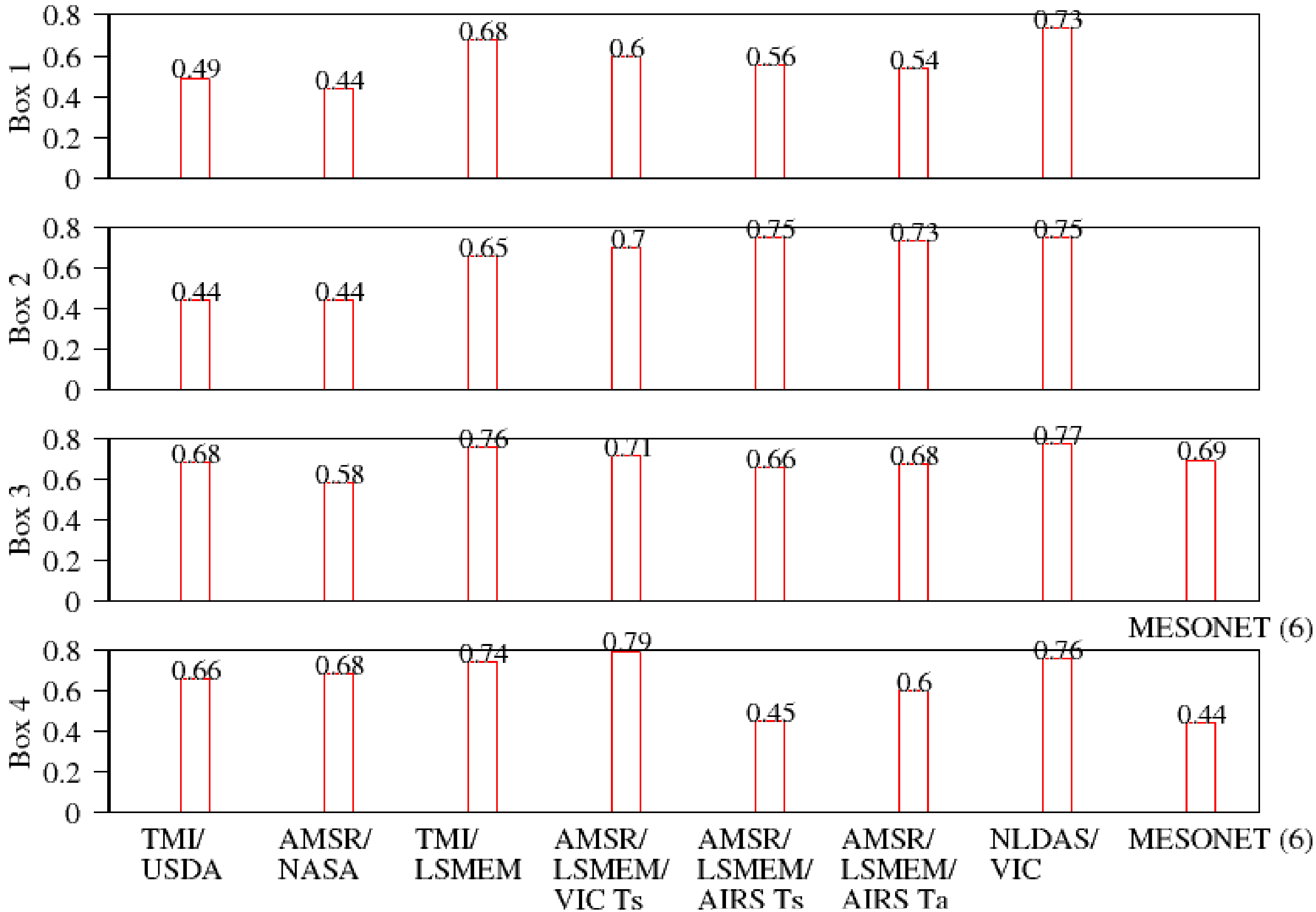
The approach does not require in-situ observations to determine skill.



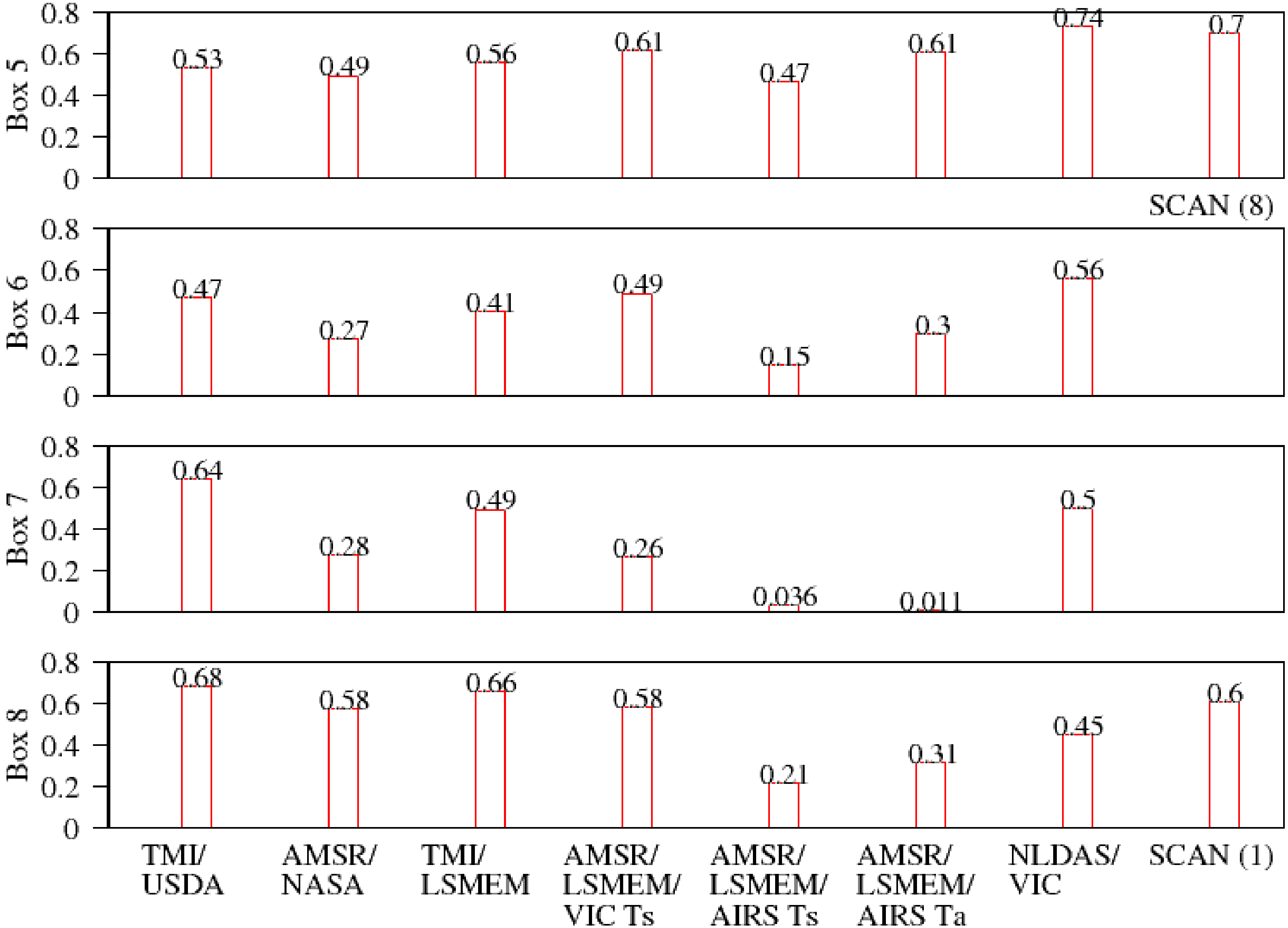
Validation 1 x 1 degree boxes, with a range of vegetation densities



AMSR-E comparisons over the Southern Great Plains boxes, with in-situ and modeled soil moisture



AMSR-E comparisons over the South-east, with in-situ and modeled soil moisture



Summary

1. Since soil moisture is a higher level land data product (level-4), generated with inputs from other lower level products, its accuracy and precision are largely dependent on these inputs. As a result, the uncertainties from all upstream inputs and the algorithm itself can introduce uncertainties to AMSR-E SM.
2. Due to spatial variability in SM and uncertainty in the in-situ measurements (‘validation data’), direct comparisons offer limited insights into product skill based on direct comparisons.
3. Based on statistical evaluations and the concept of ‘predictive skill’, AMSR-E derived SM is equal to in-situ observations, LSM predictions based on high quality forcings. Some algorithms are