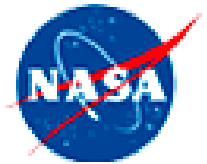
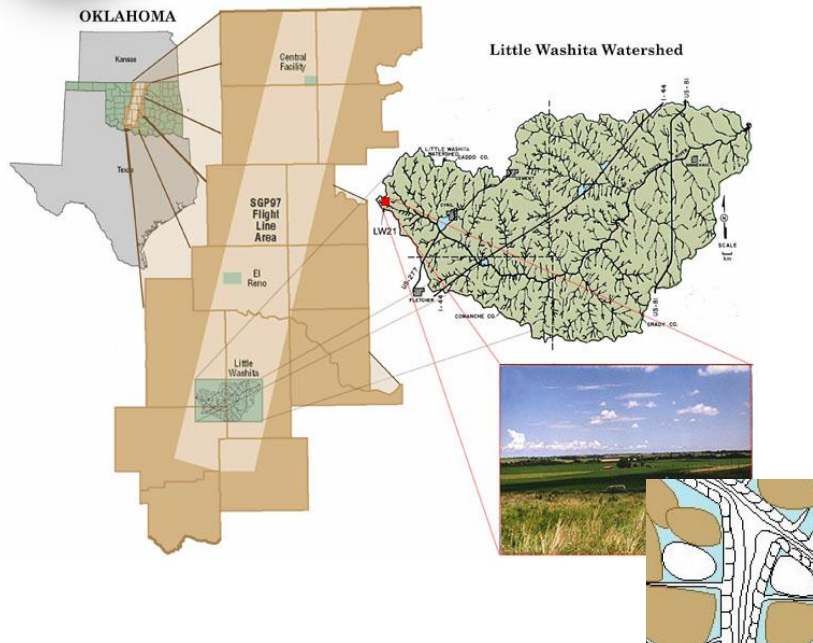




Partly supported by:



Improving Multi-Scale Root Zone Soil Water Process Representation in Land Surface Models



Binayak P. Mohanty
& Vadose Zone Group
Texas A&M University

Texas Drought Forum
Oct 22, 2012

<http://vadosezone.tamu.edu/>

Vadose Zone

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Dipankar Dwivedi



Sean Tolle



Yongchul Shin



Nandita Gaur



Taehoon Kwak



Sandeep Patil

Soil Moisture Flow Below our Feet!



Gopher Holes



Biological Pores

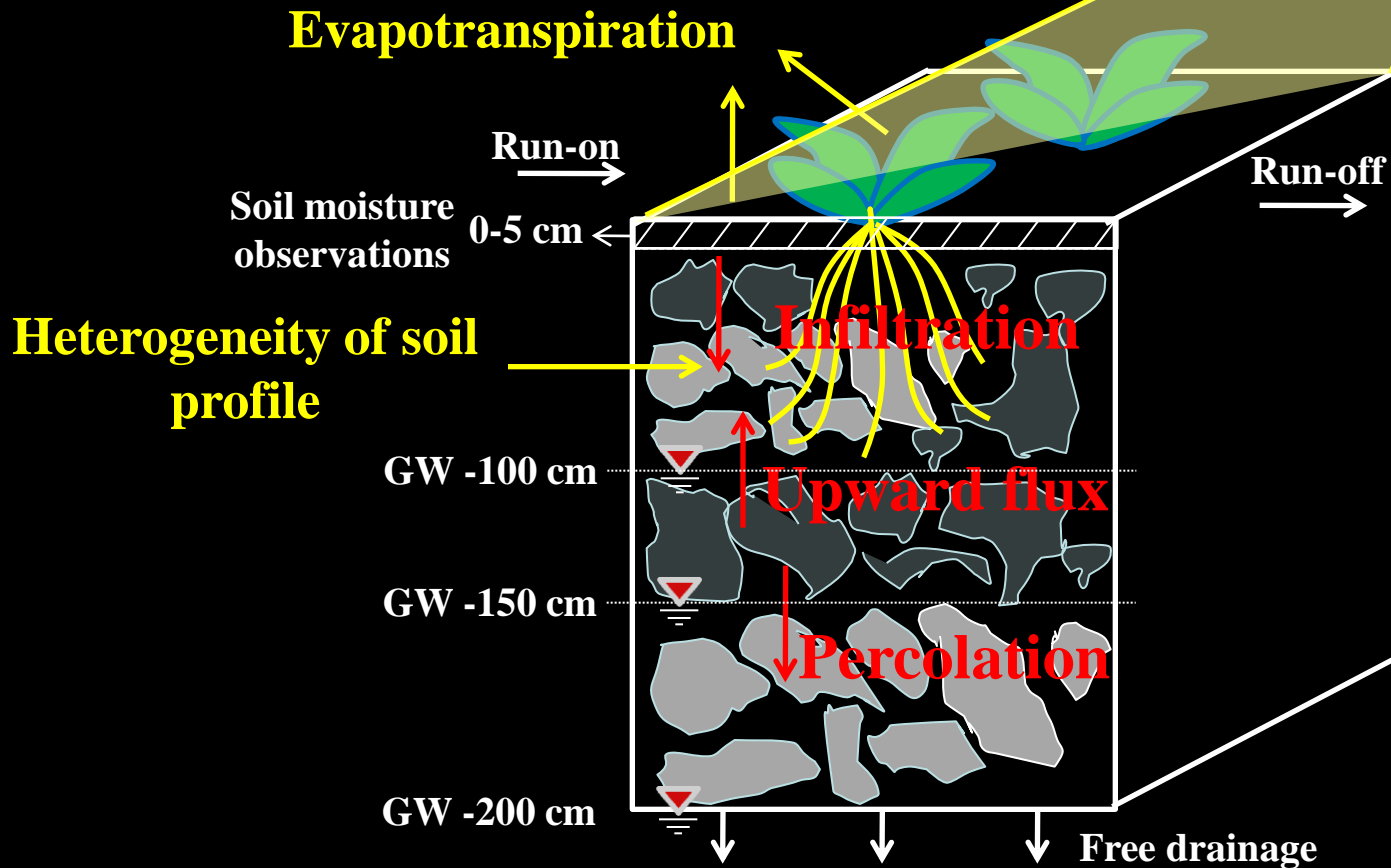
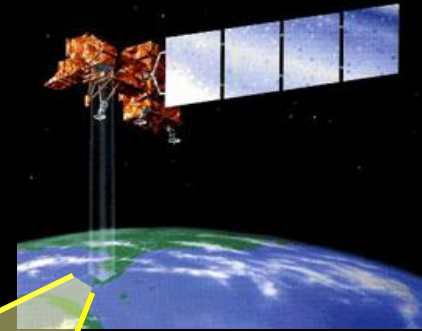


Structural Cracks



Karst Geology

■ Soil Water Flow Processes



Soil Moisture at Different Process Scales

SCALE



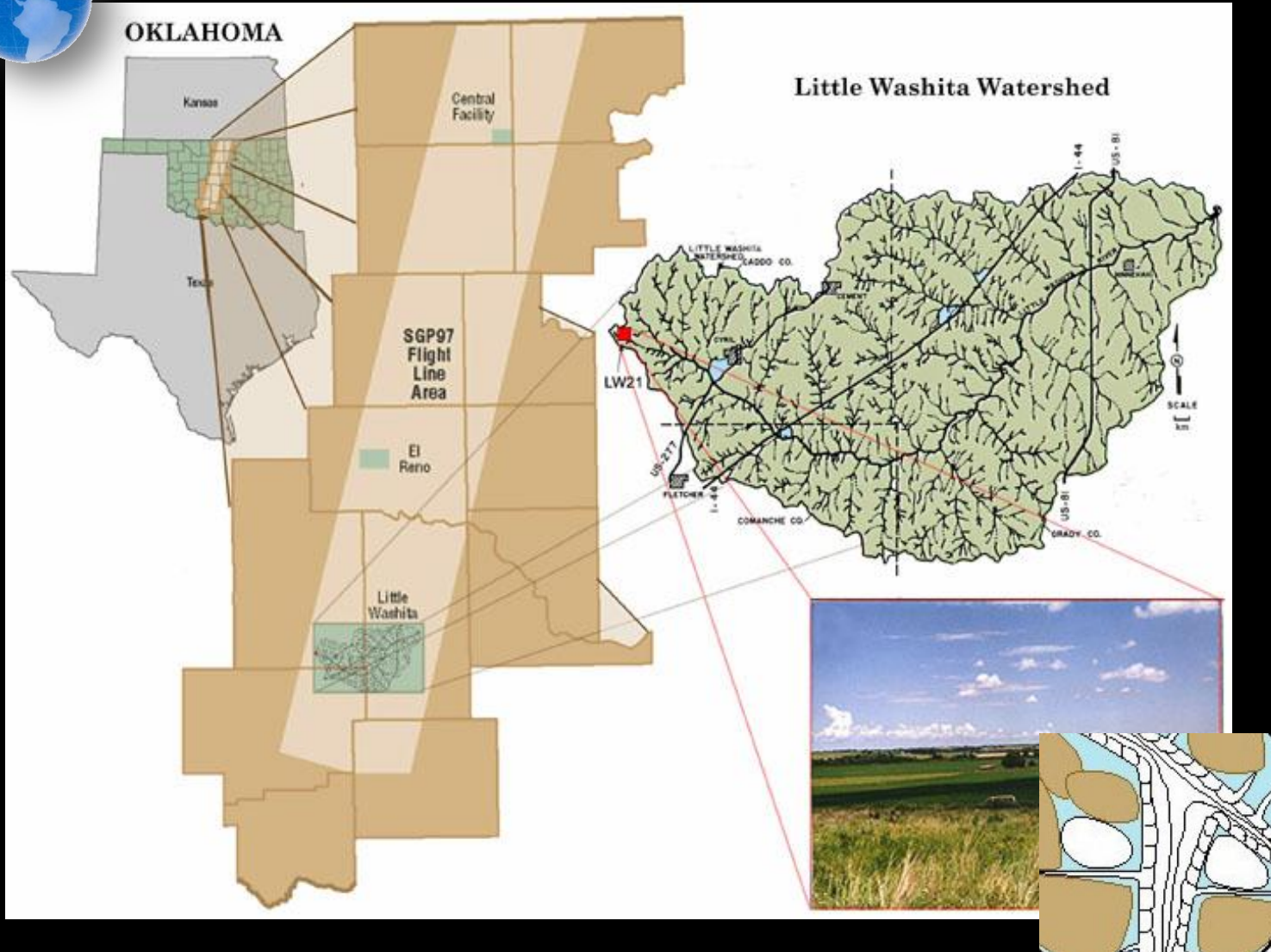
Global

Regional

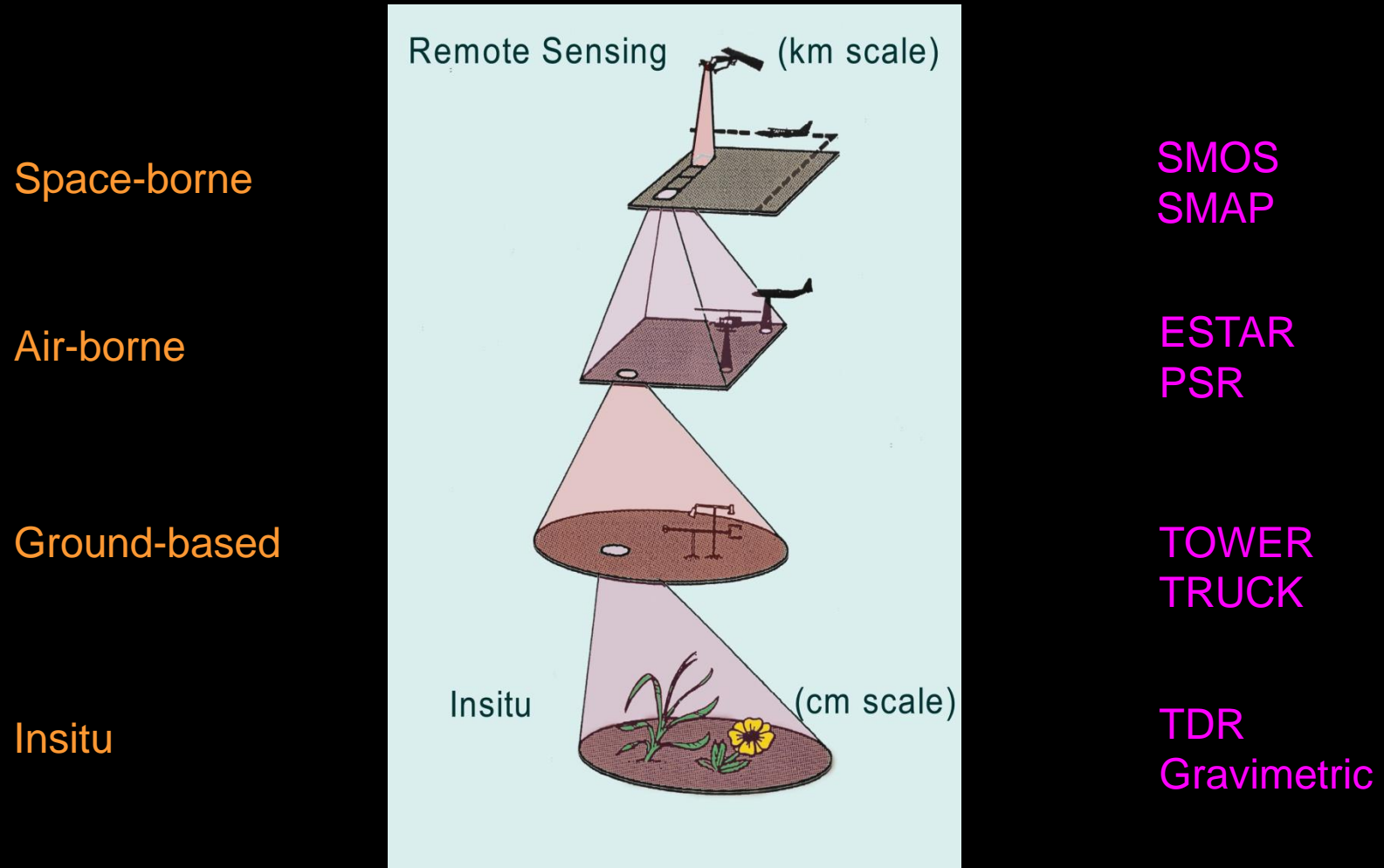
Watershed

Field

Pore

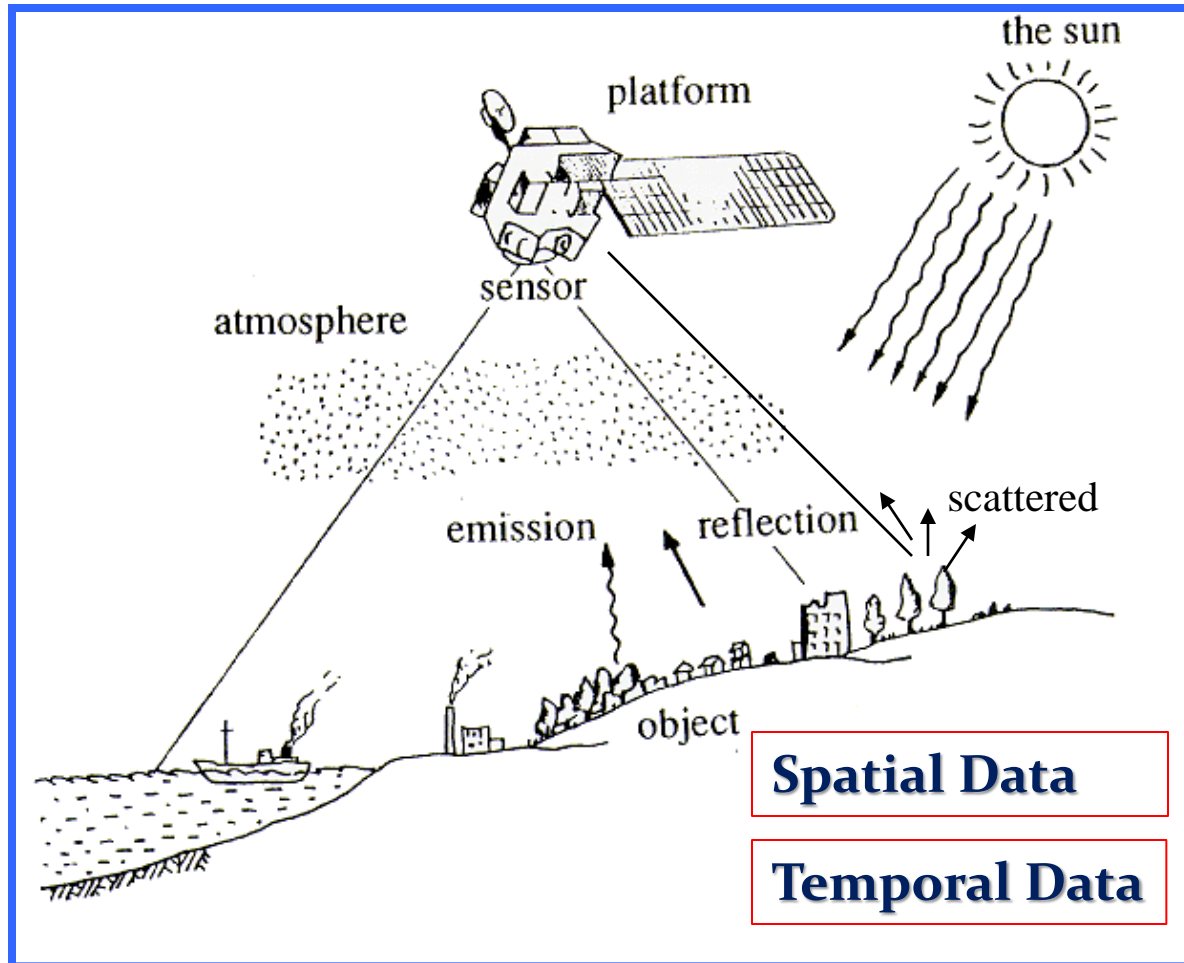


Soil Moisture / Brightness Temperature Measurement Scales

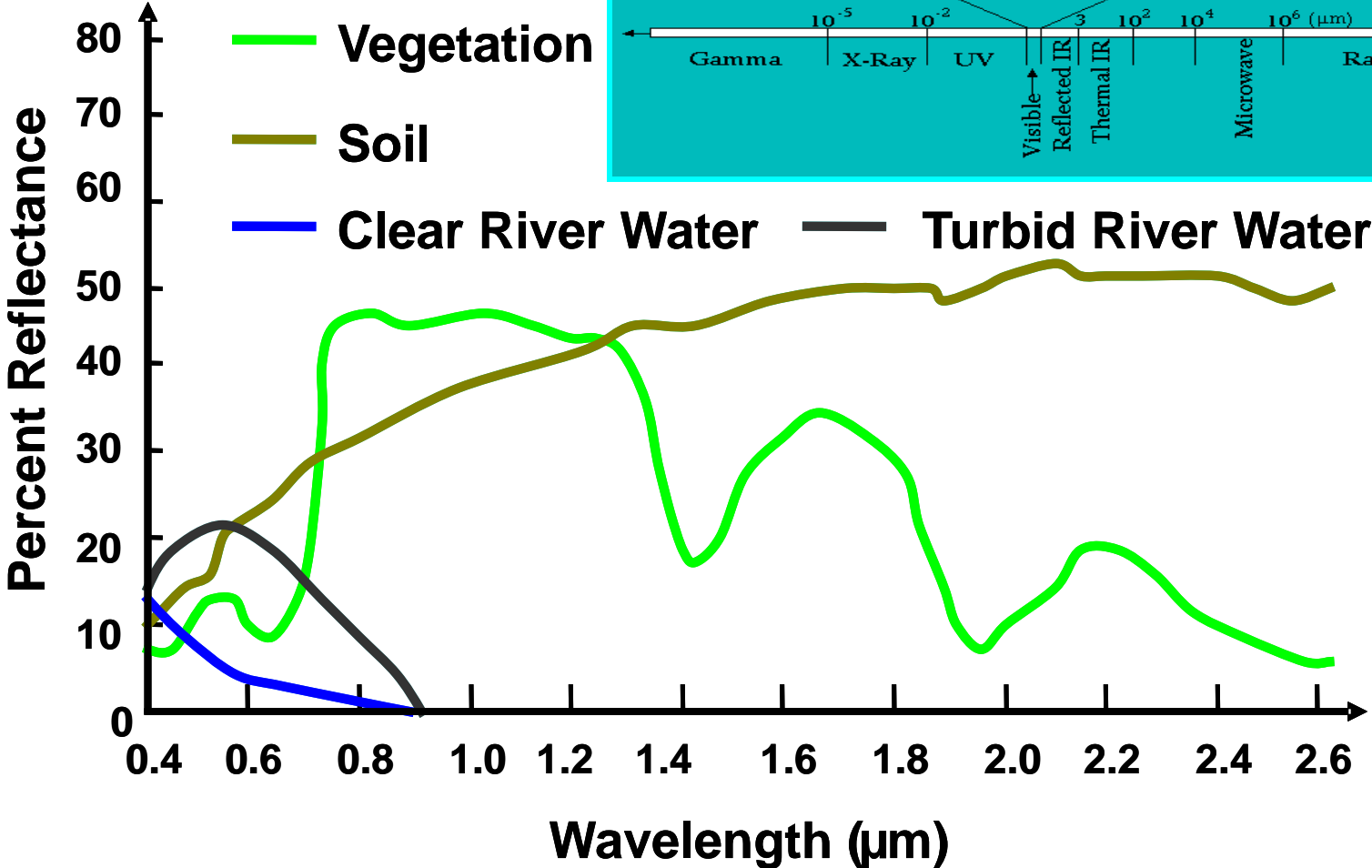
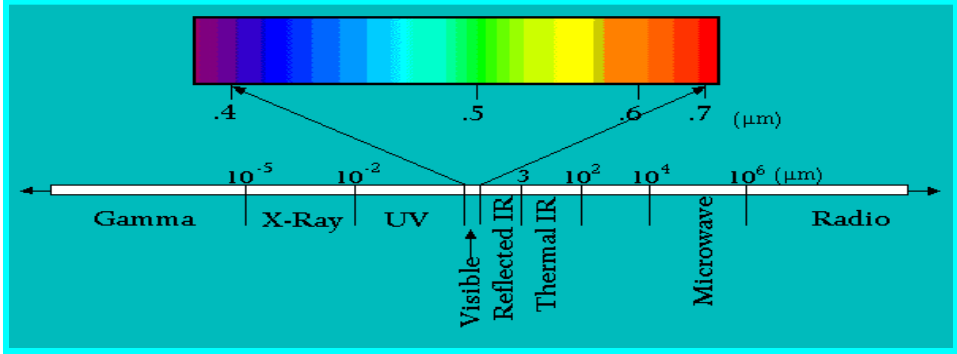


Upcoming Soil Moisture Satellite Missions
SMOS, 2010, ESA.....SMAP, 2013, NASA

Remote Sensing of Environment

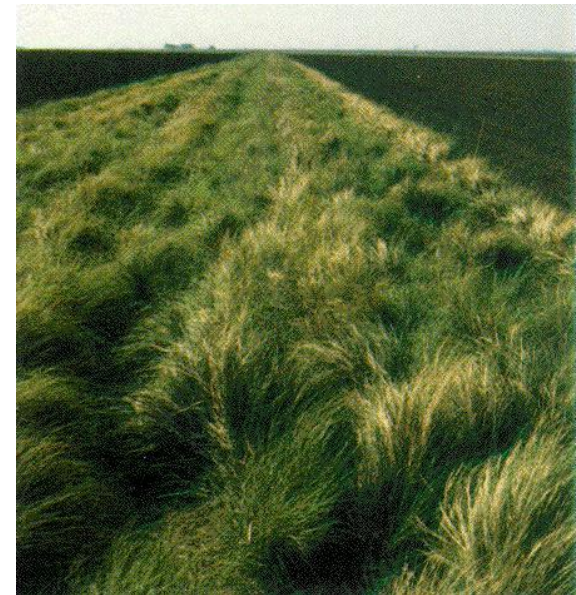


Spectral Reflectance



Remote Sensing of Soil Moisture...

- T_B for **homogenous vegetated surface**:
- $T_B = T_S \{ e_s \exp(-\tau_c) + (1-\omega)[1-\exp(-\tau_c)][1+r_s \exp(-\tau_c)] \}$
- $\tau_c = bw_c / \cos\theta$
 - soil and vegetation T_S are assumed to be equal
 - τ_c vegetation opacity
 - ω vegetation single scattering albedo
 - b coefficient depends of frequency and vegetation type
 - w_c vegetation water content
 - θ incidence angle
 - e_s emissivity of soil



Remote Sensing of Soil Moisture...

- Reflectivity of a **rough soil surface**:

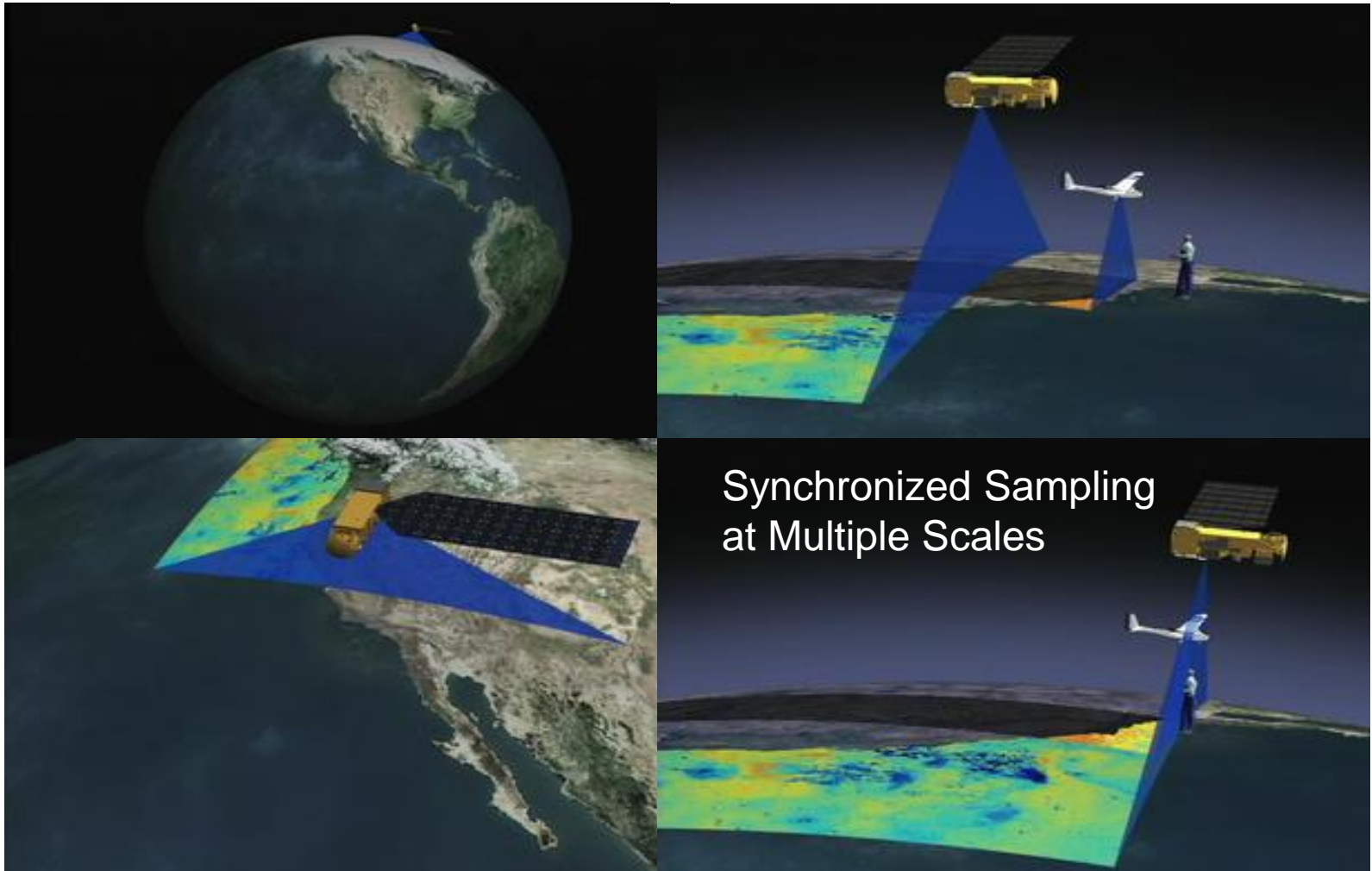
- $r_s = [(1-Q)r_o + Qr_o] \exp(-h)$

- Q, h are roughness parameter

- r_o reflectivity of a smooth surface



Remote Sensing Cal/Val Studies for Soil Moisture

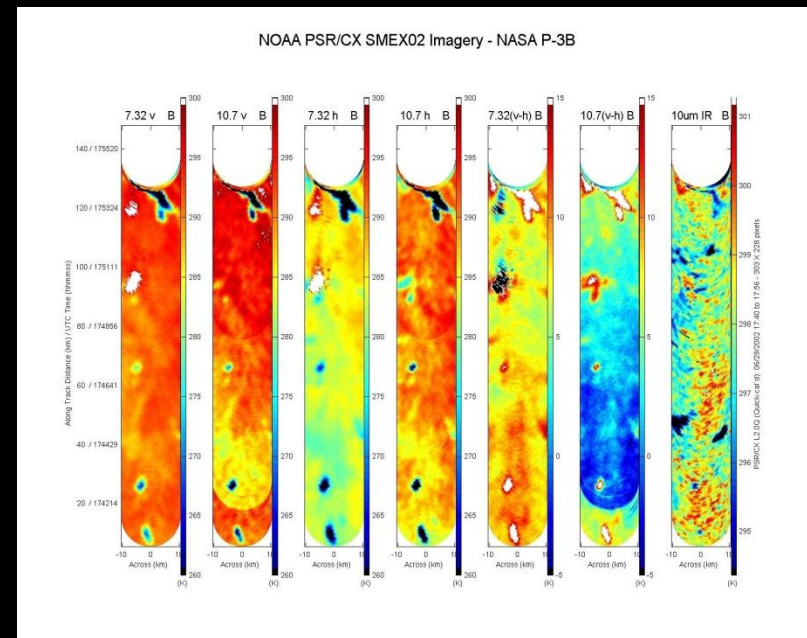
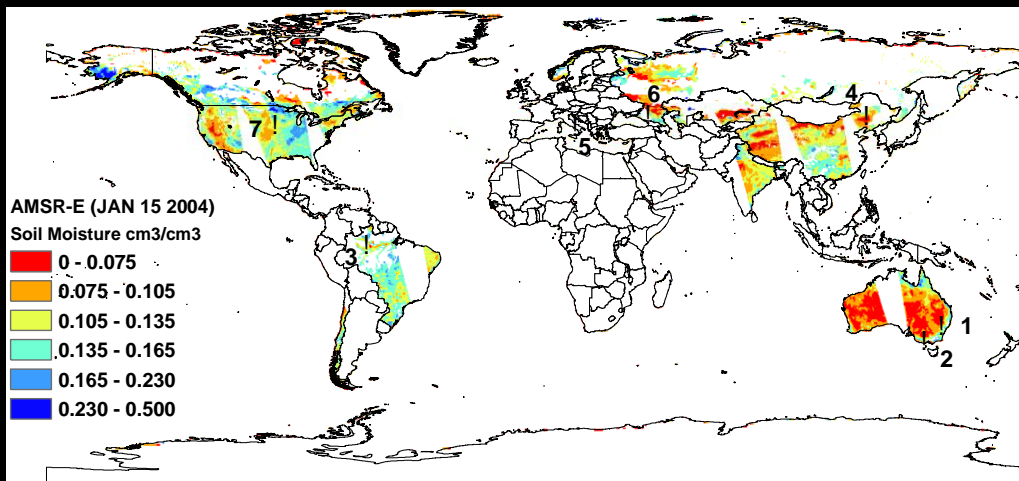
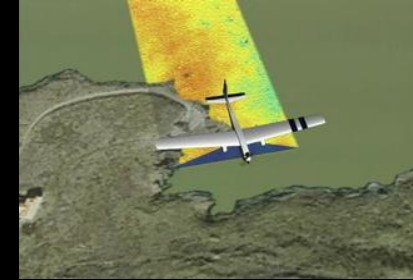


Soil Moisture Remote Sensing

Space-Borne
NASA: AMSR-E on AQUA



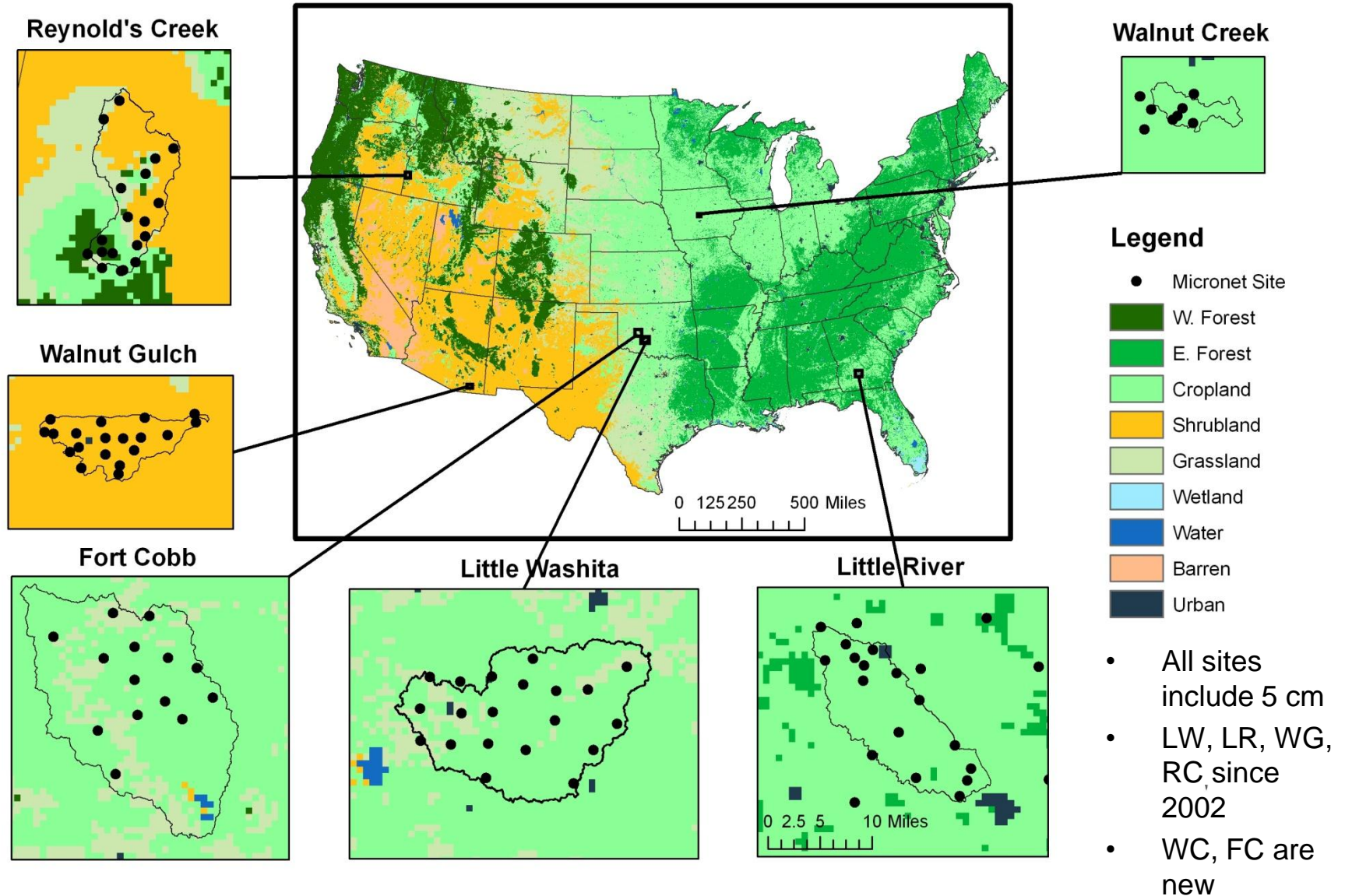
Air-Borne
NOAA: PSR



Spatio-Temporal Data in Iowa

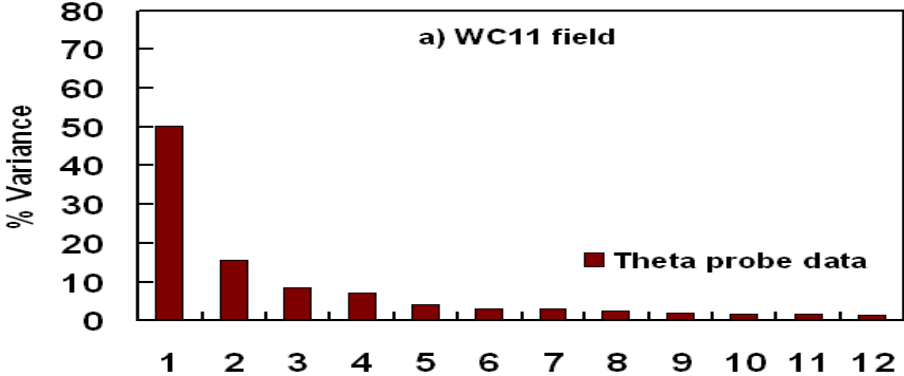
Global Coverage every 1.5 days

U.S. Watershed Soil Moisture Validation Sites

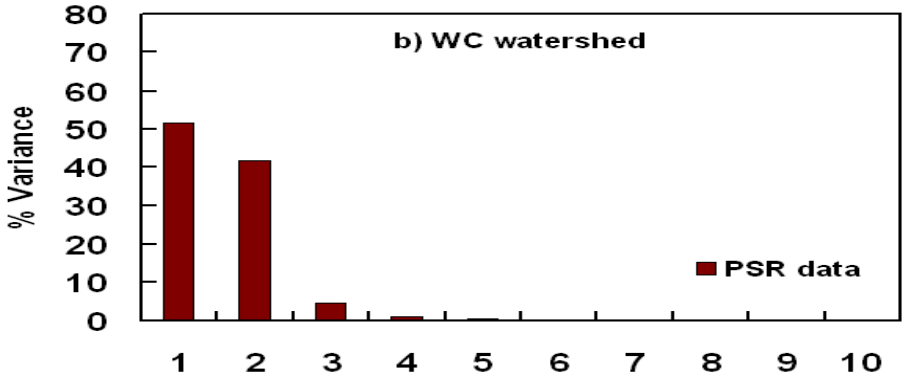


EOF Analyses Across Scales in Iowa During SMEX02

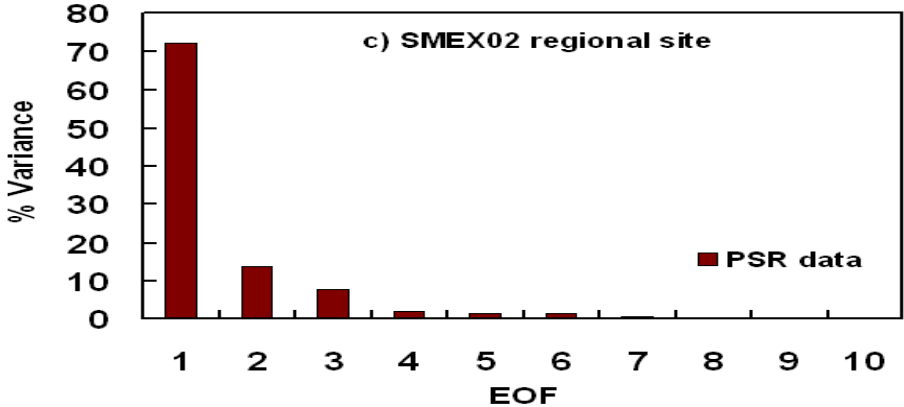
Field-scale



Watershed-scale



Regional-scale

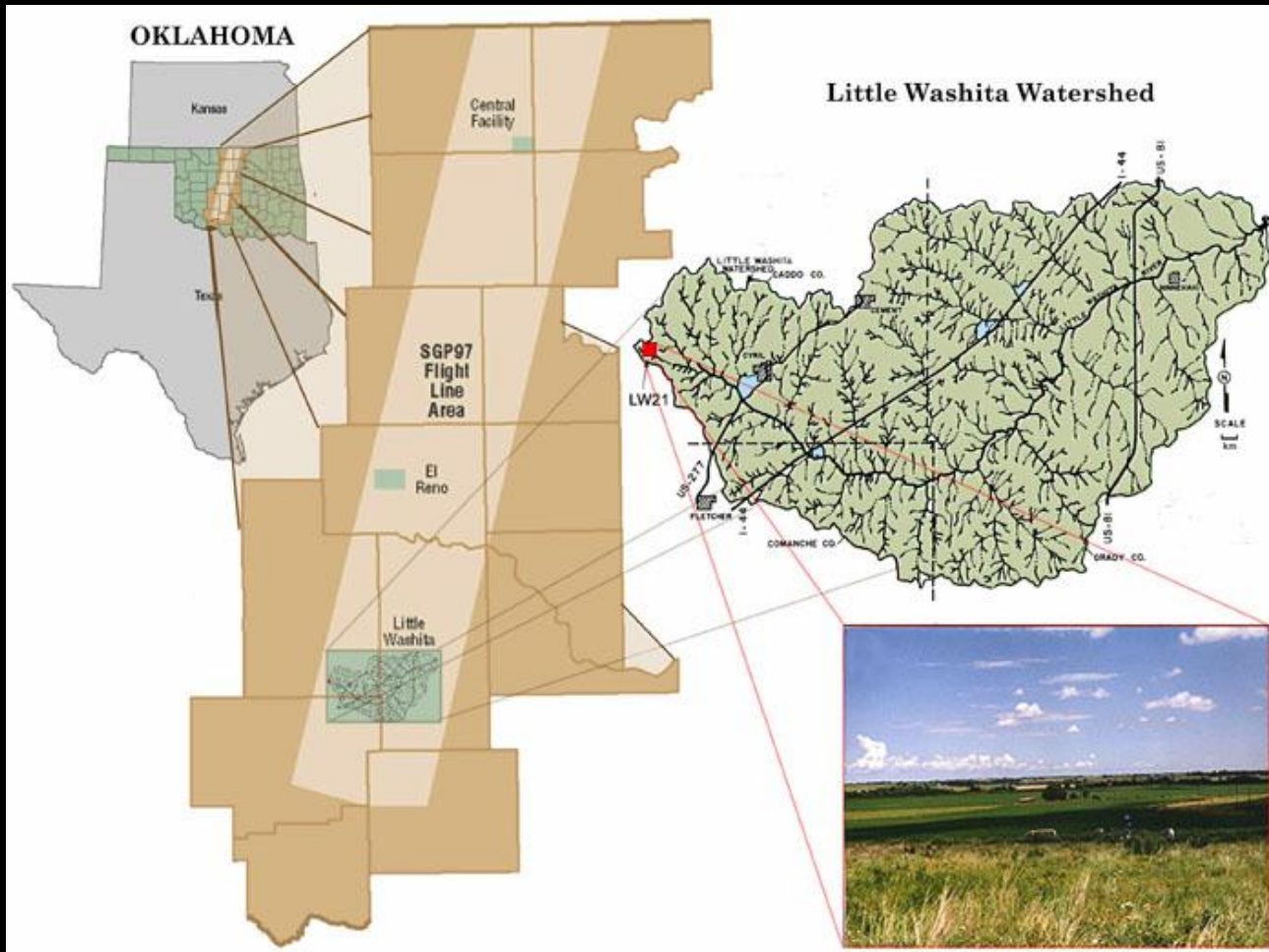


Soil Moisture Dominant Physical Controls at Different Spatial Scales

Region

Watershed

Field



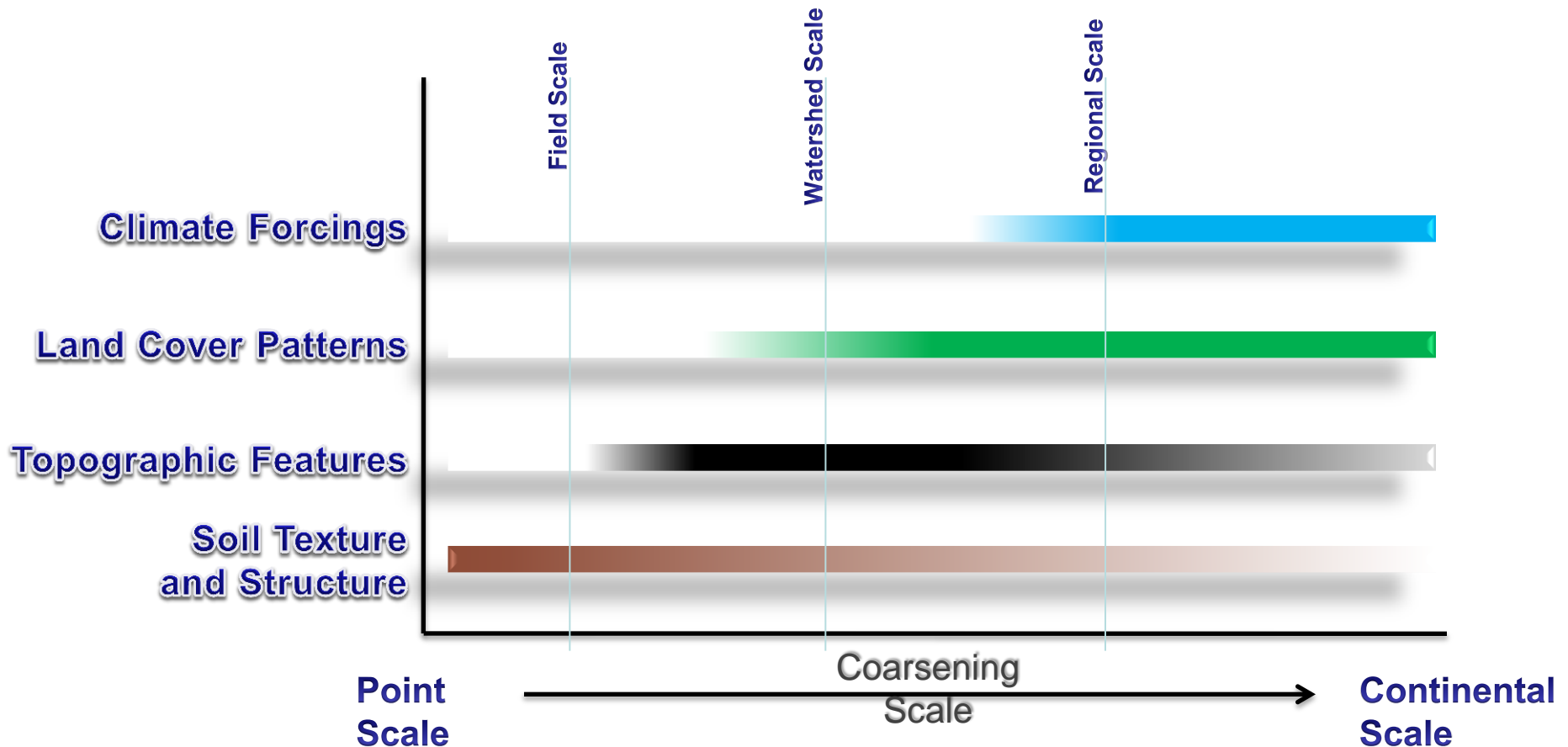
Vegetation/
Precipitation

Topography

Soil

Hypothesis

- Soil moisture variability is dominated by



Modeling Soil Moisture

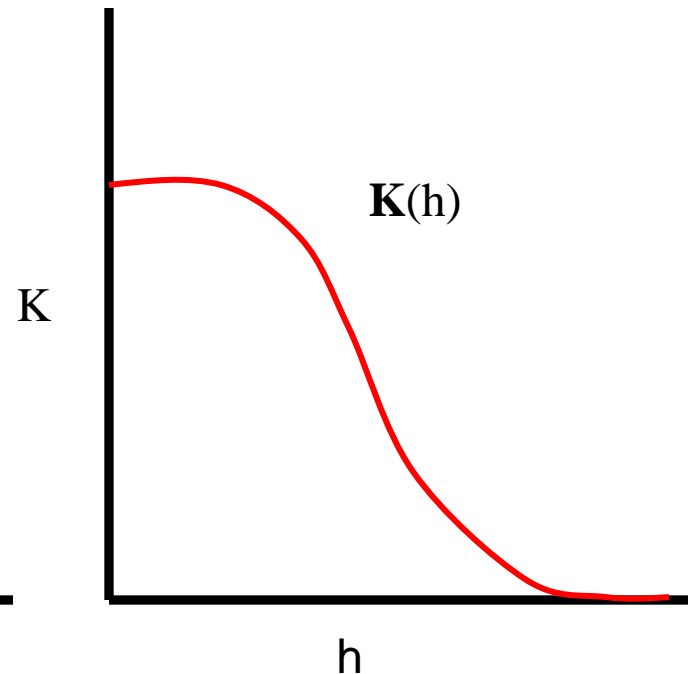
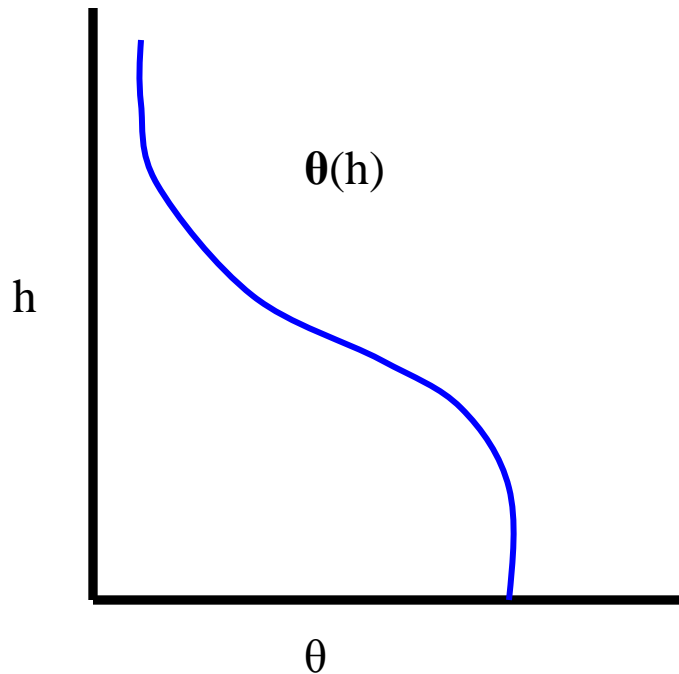
- Importance of modeling – **RS of soil moisture only limited to near-surface soil layers**
- 1D Flow equation: (**Assumption: work at any scale!!**)

$$\frac{\partial \theta(h)}{\partial t} = C(h) \frac{\partial h}{\partial t} = \frac{\partial \left[K(h) \left(\frac{\partial h}{\partial z} + 1 \right) \right]}{\partial z} - S(h)$$

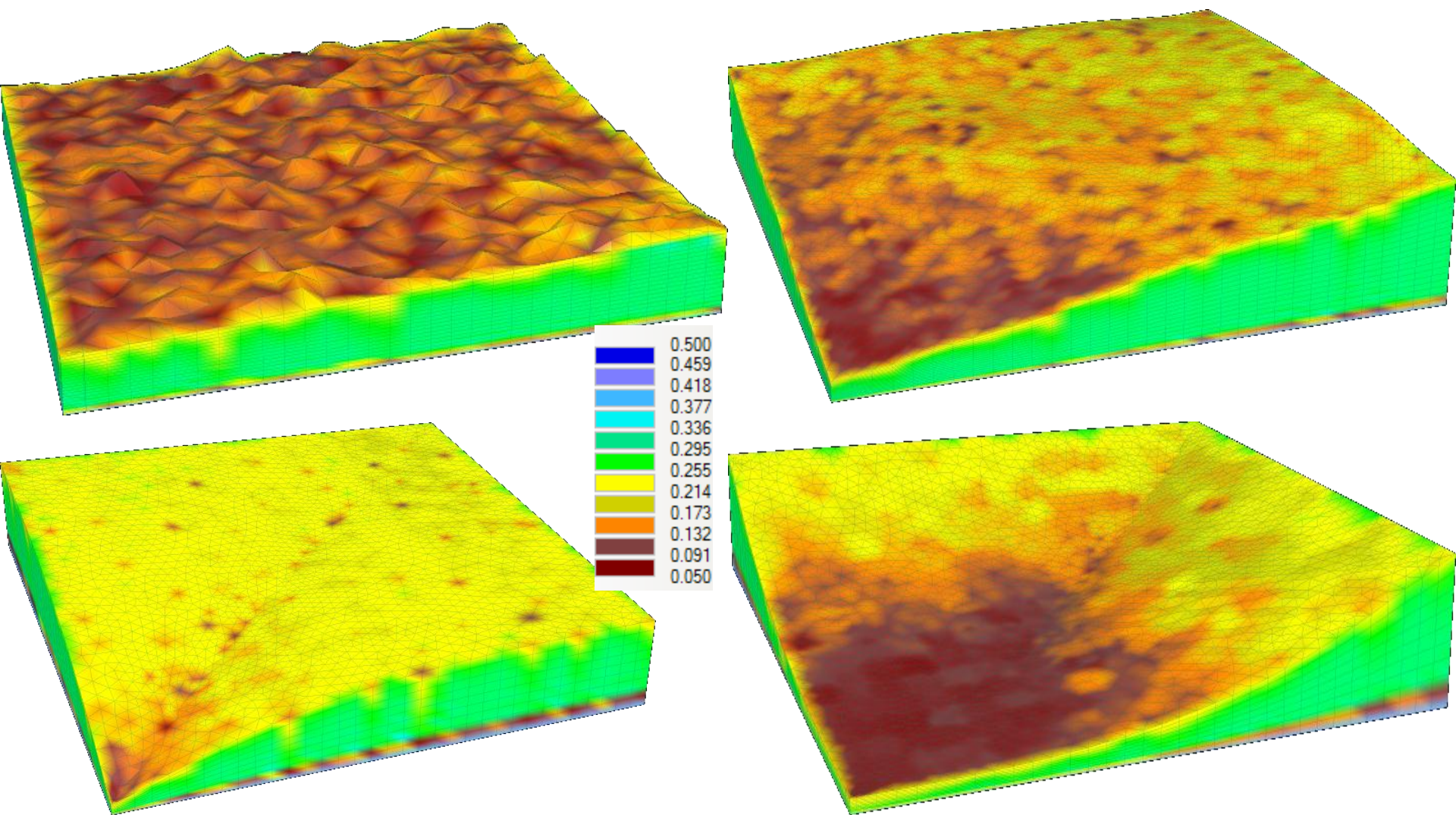
$$S(h) = \alpha_w(h) \frac{T_{\text{pot}}}{|z_r|}$$

Soil Hydraulic Properties

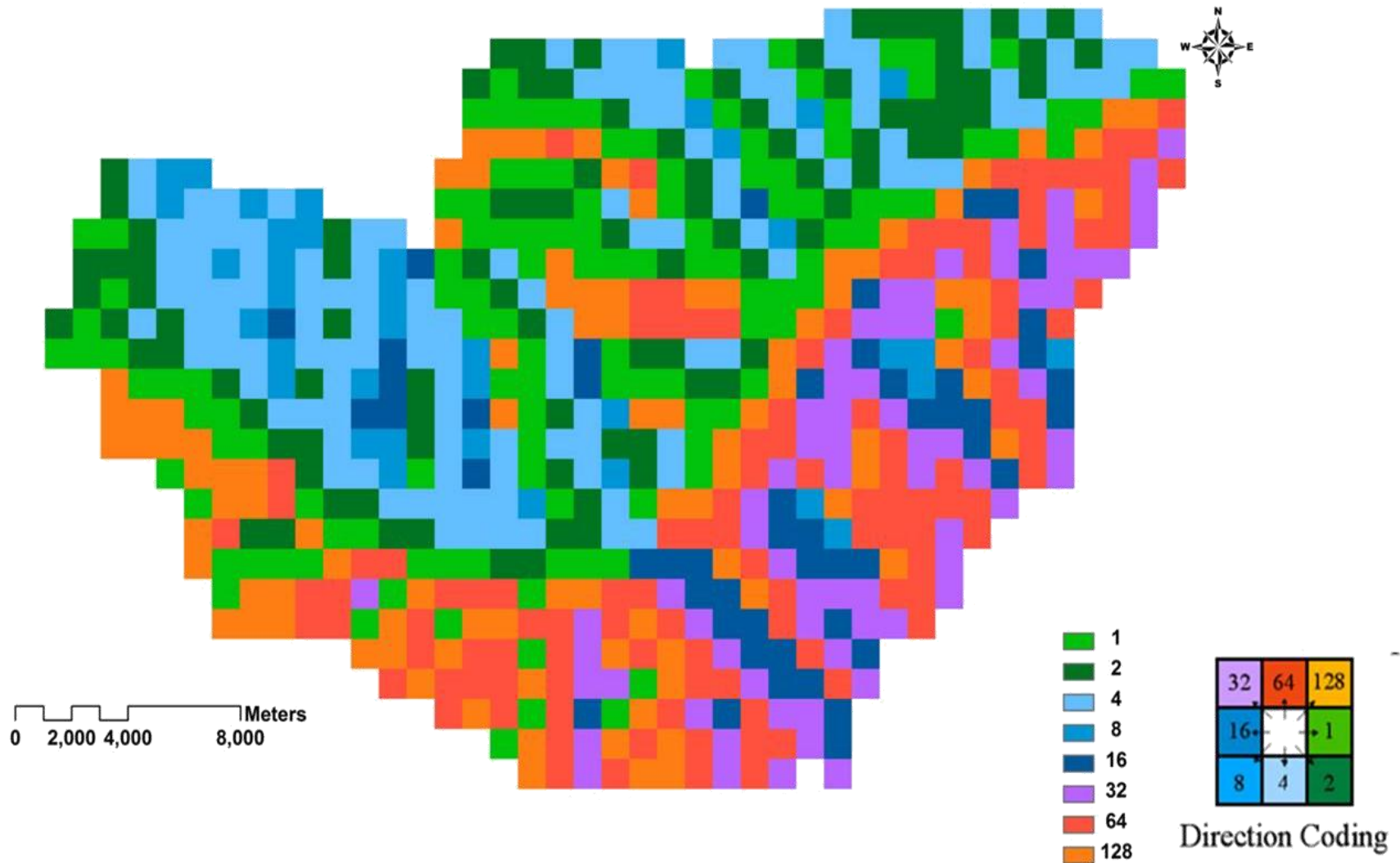
- Soil-moisture retention property, $\theta(h)$
- Soil hydraulic conductivity property, $K(h)$



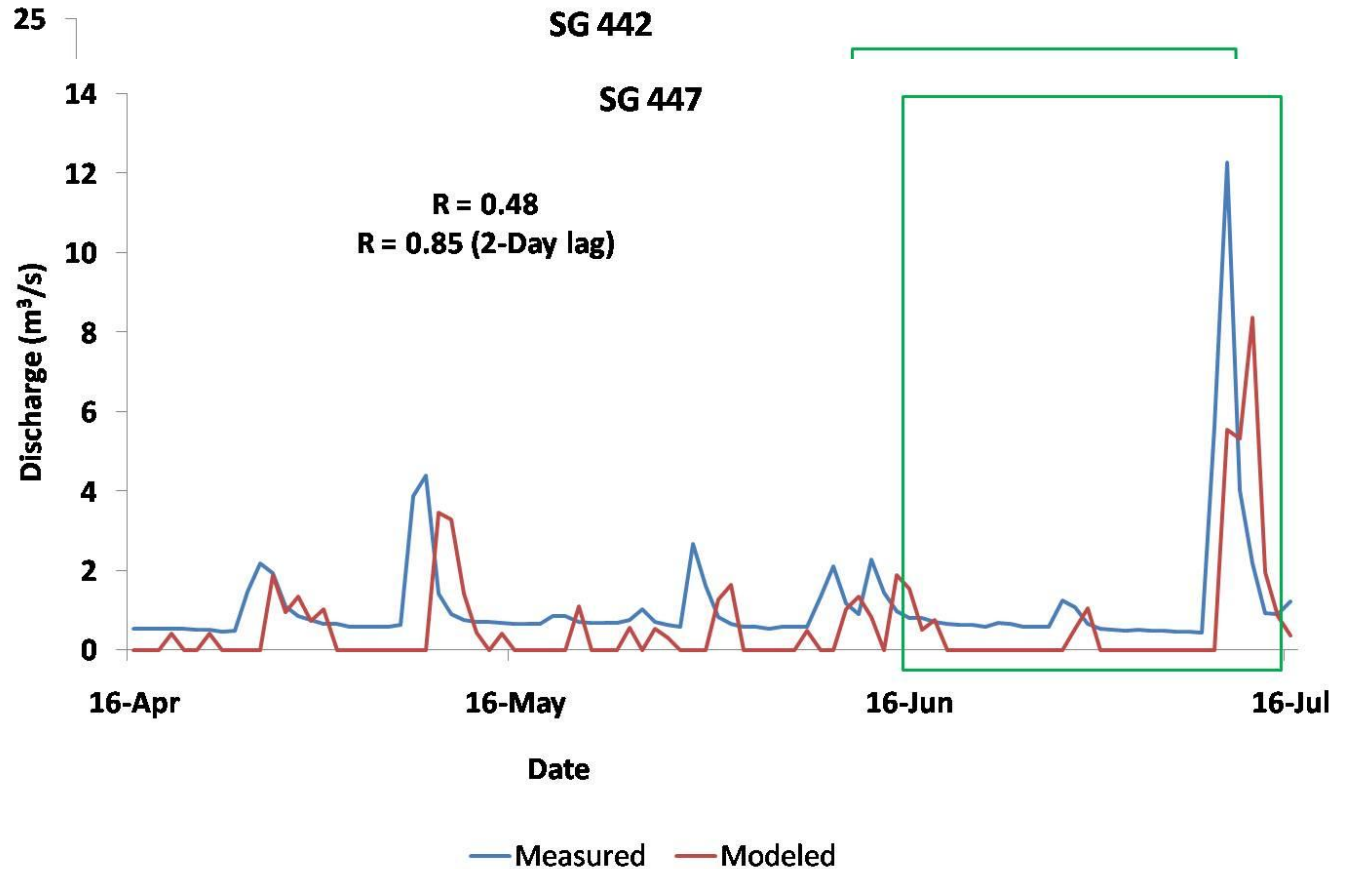
Modeled Soil Moisture States under Different Topographic Configurations



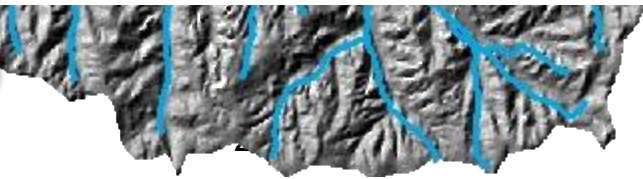
Flow Routing at Watershed Scale



Stream Flow Comparison



SG447



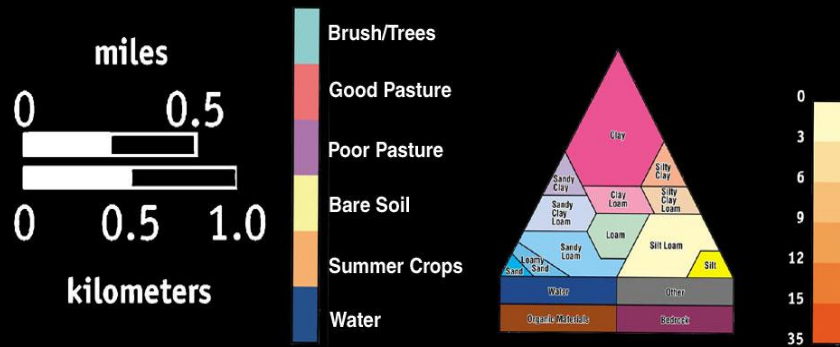
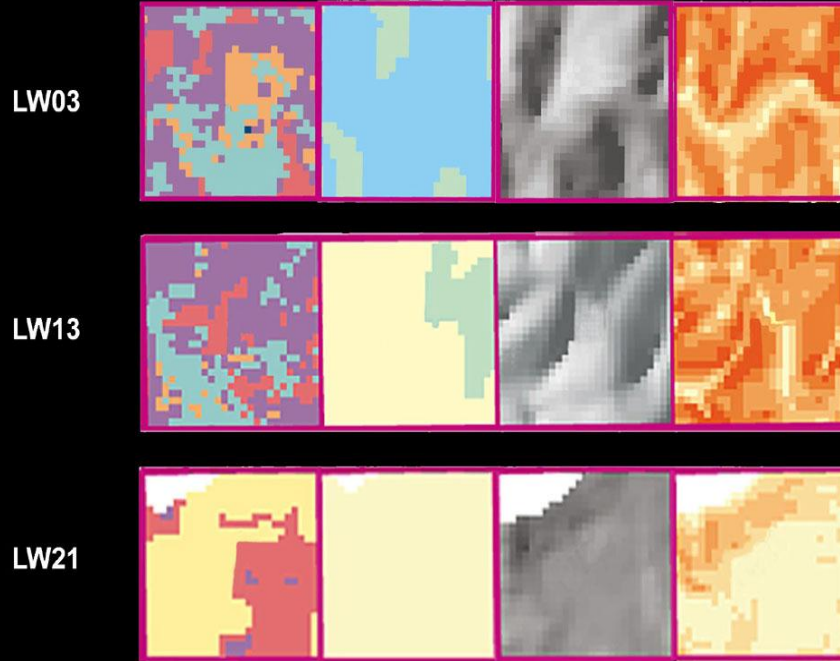
Motivation

- To address the connections between the environmental factors and “effective” soil hydraulic parameters at various scales across the land surface
- To develop scaling (downscaling and upscaling) algorithms, data assimilation, inverse model, and incorporation of stochastic evolutionary schemes

Limitation: What is Pixel-Scale Parameter!?

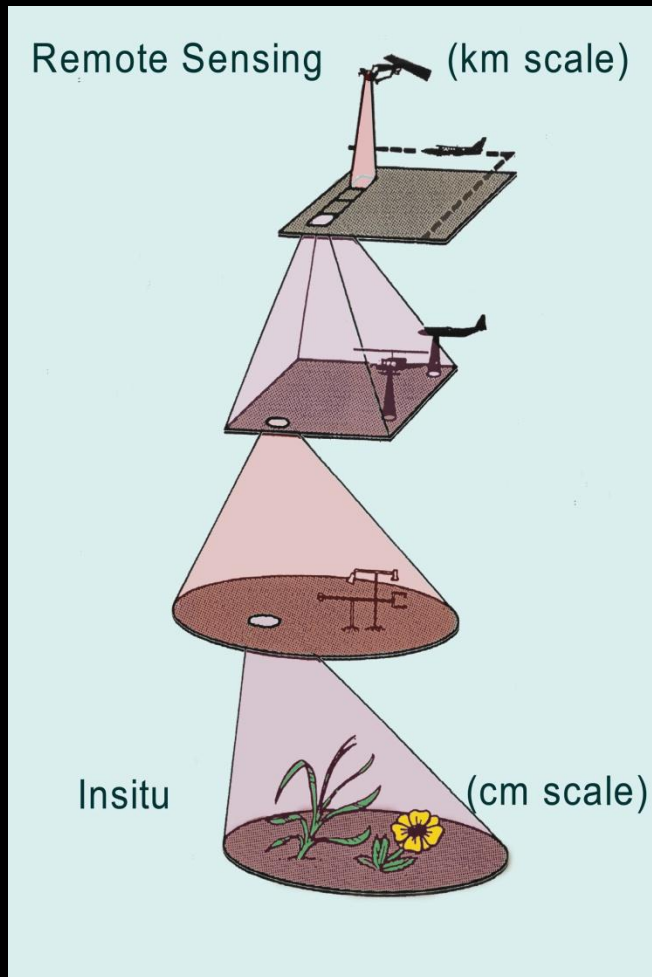
Vegetation Soil Slope

Vegetation Soil Texture Hillshade Percent Slope



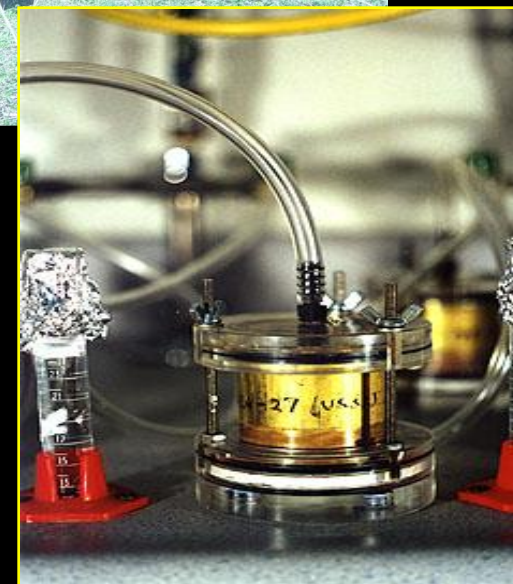
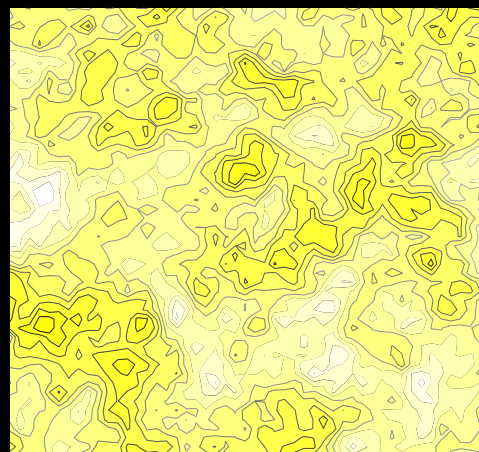
Top-down versus Bottom-up Approach

New Study



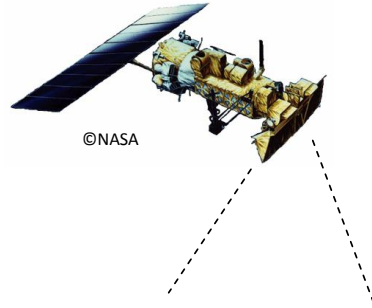
Hydraulic Property Estimation
Across the Pixel :
Top- Down Approach

Traditional Soil Physics

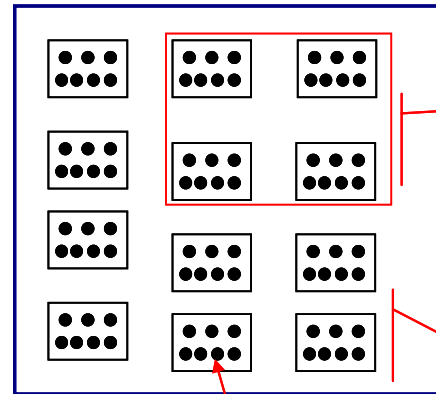


Hydraulic Property Measurement
Across the Pixel :
Bottom- Up Approach

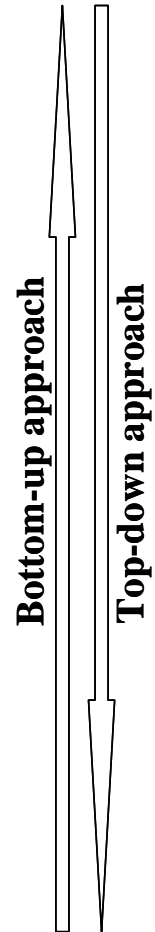
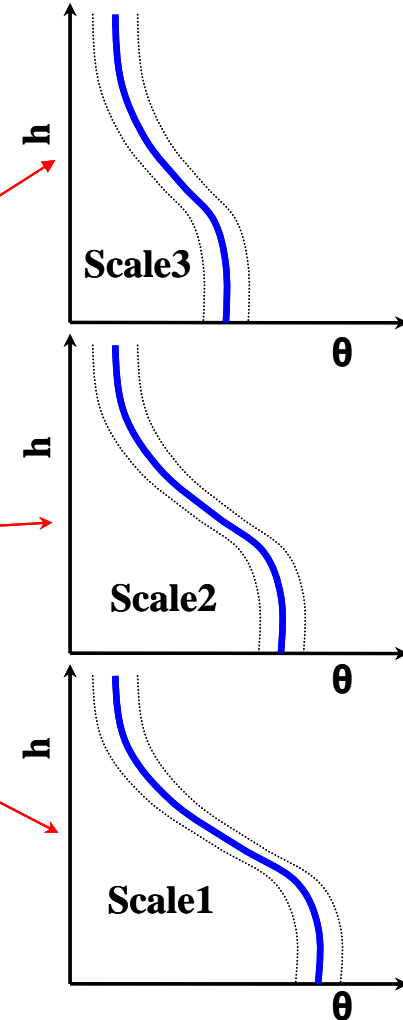
Soil Hydraulic Function Scaling Hypothesis



RS
footprint scale



Point scale



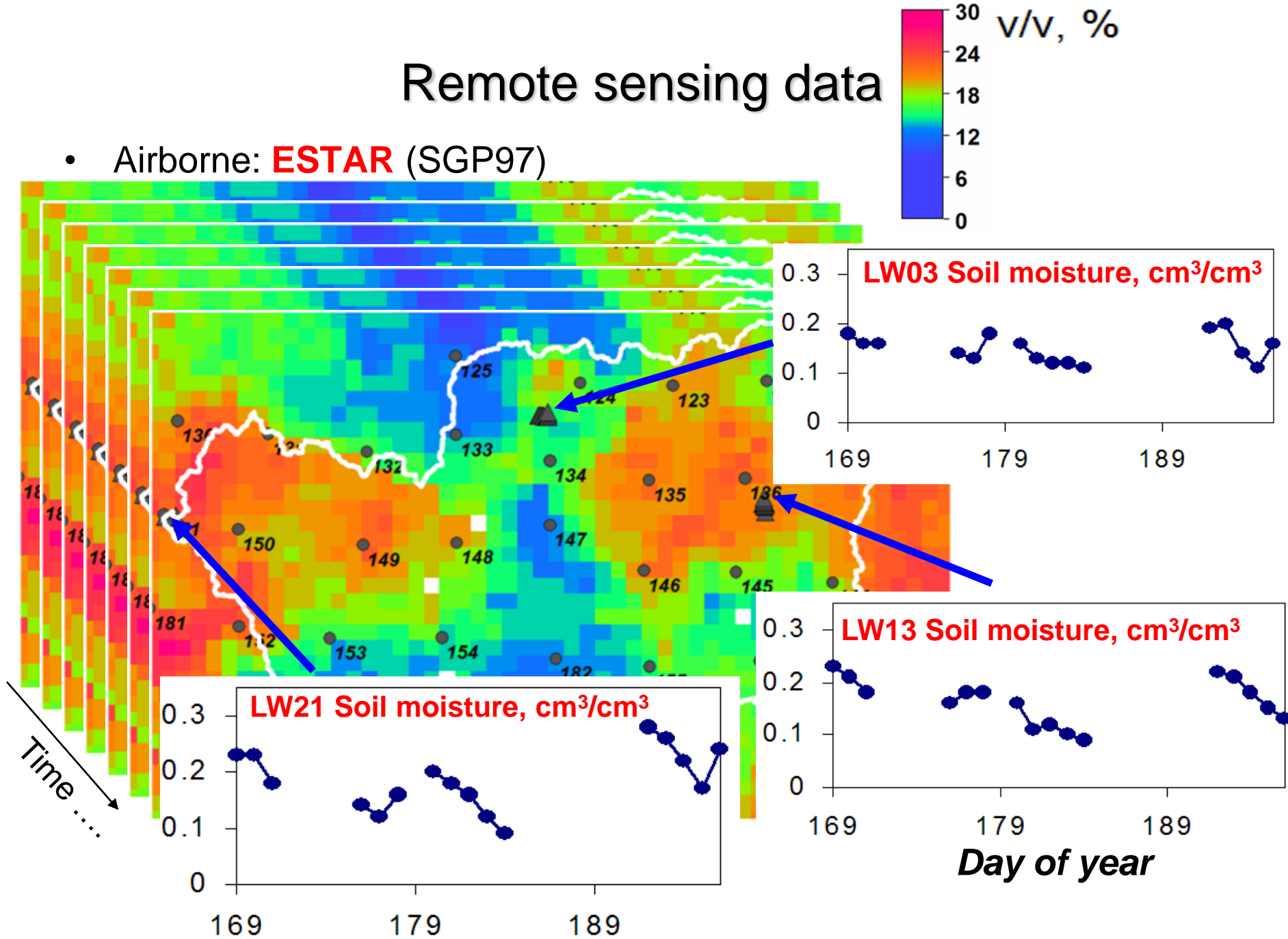
Using the information content of the soil moisture data collected at that particular SCALE, we can estimate the scale dependent soil hydraulic properties

$$S_e = \frac{\theta(h) - \theta_{res}}{\theta_{sat} - \theta_{res}} = \left[\frac{1}{1 + |\alpha h|^n} \right]^m$$

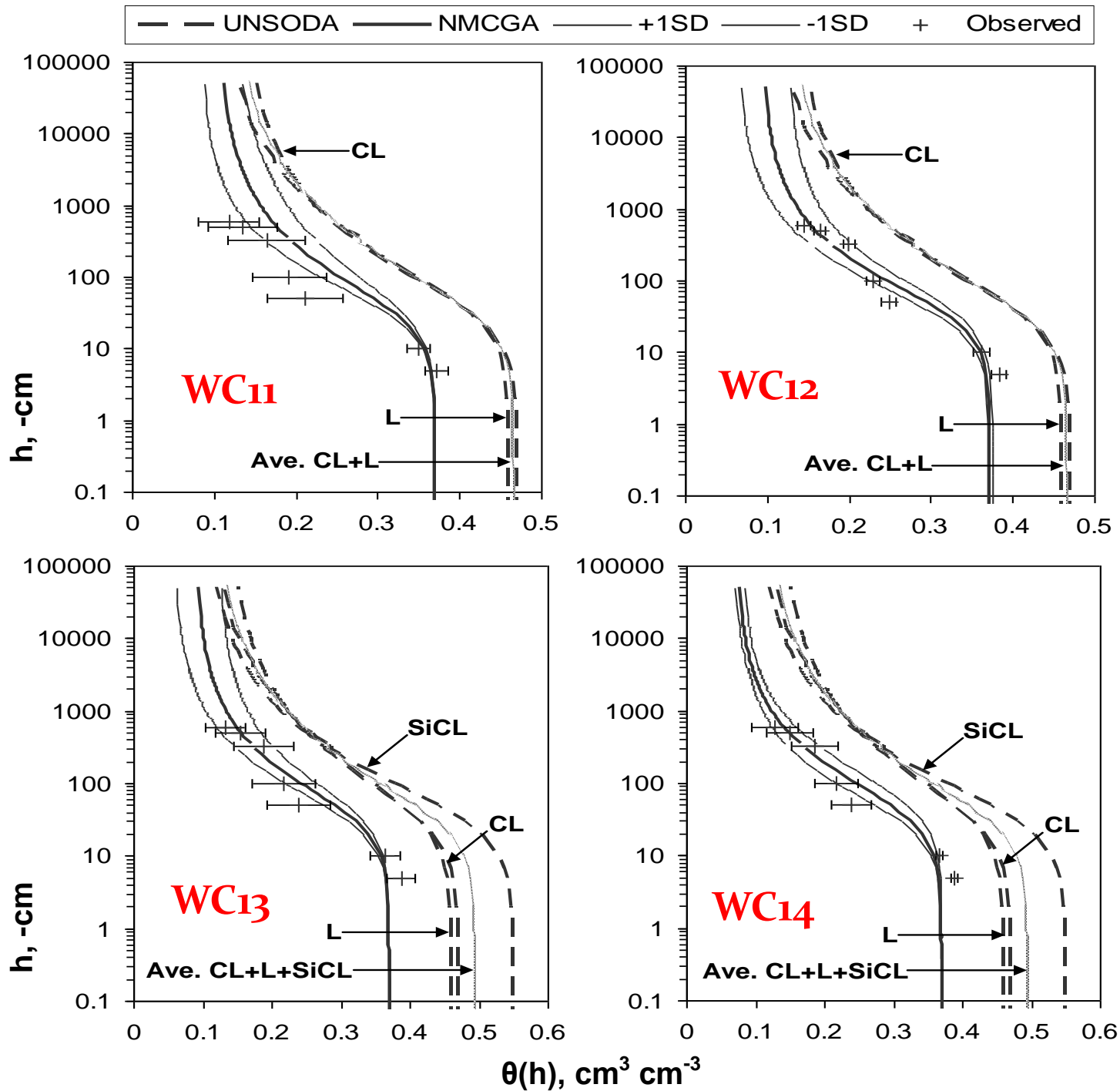
$$K(h) = K_{sat} S_e^\lambda \left[1 - \left(1 - S_e^{1/m} \right)^m \right]^2$$

Remote sensing data

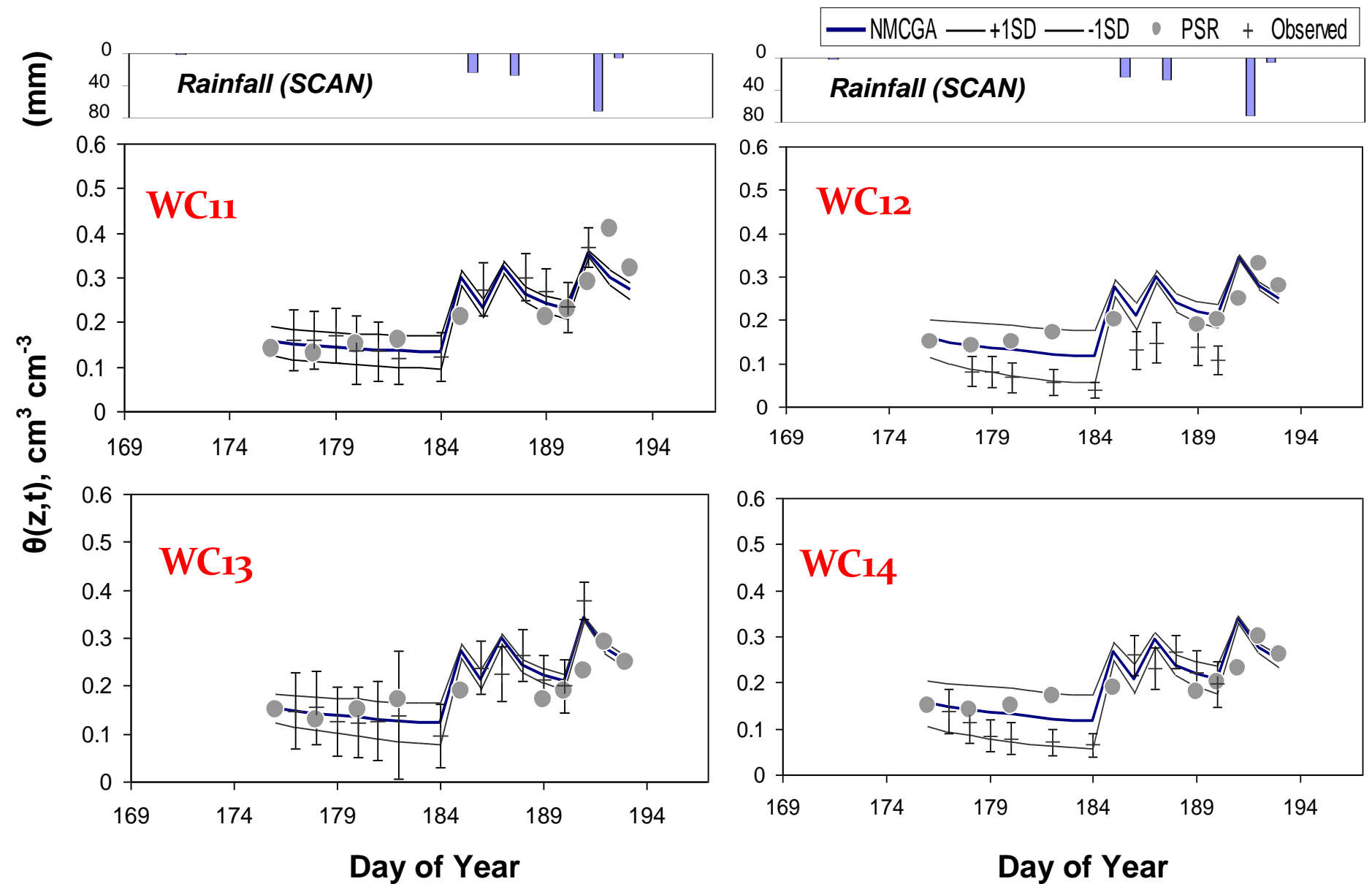
- Airborne: **ESTAR** (SGP97)



Air-borne RS scale (Polarimetric Scanning Radiometer: PSR)



Simulated vs. Observed Soil moisture



Objectives

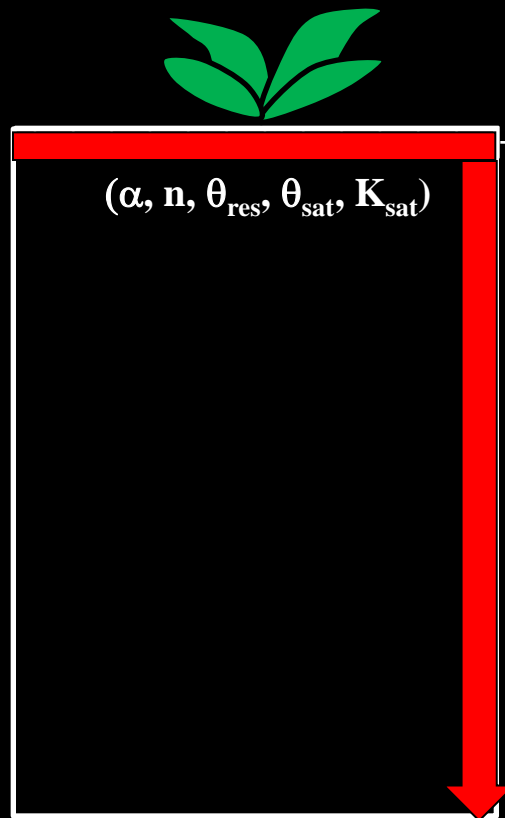
- To explore the scale dependency for certain soil hydraulic parameters used in LSMs:
saturated hydraulic conductivity, residual and saturation soil water contents, and van Genuchten parameters
- To develop suitable mathematical approaches for downscaling and upscaling hydraulic parameters in complex terrains. This proposed approaches would honor both vertical and horizontal fluxes

Research Approach

- Near-surface soil moisture assimilation scheme based on inverse model
- Physically-based (Richard's equation) hydrological models (Soil Water Atmosphere Plant-SWAP, Community Land Model-CLM, and Noah land surface model-Noah LSM)
 - SWAP: Mualem-van Genuchten (MVG) parameters
 - CLM: Clapp and Hornberger empirical equation
 - Noah LSM: Clapp and Hornberger empirical equation

Comparison of Layer-Specific and Near-Surface Assimilation approaches

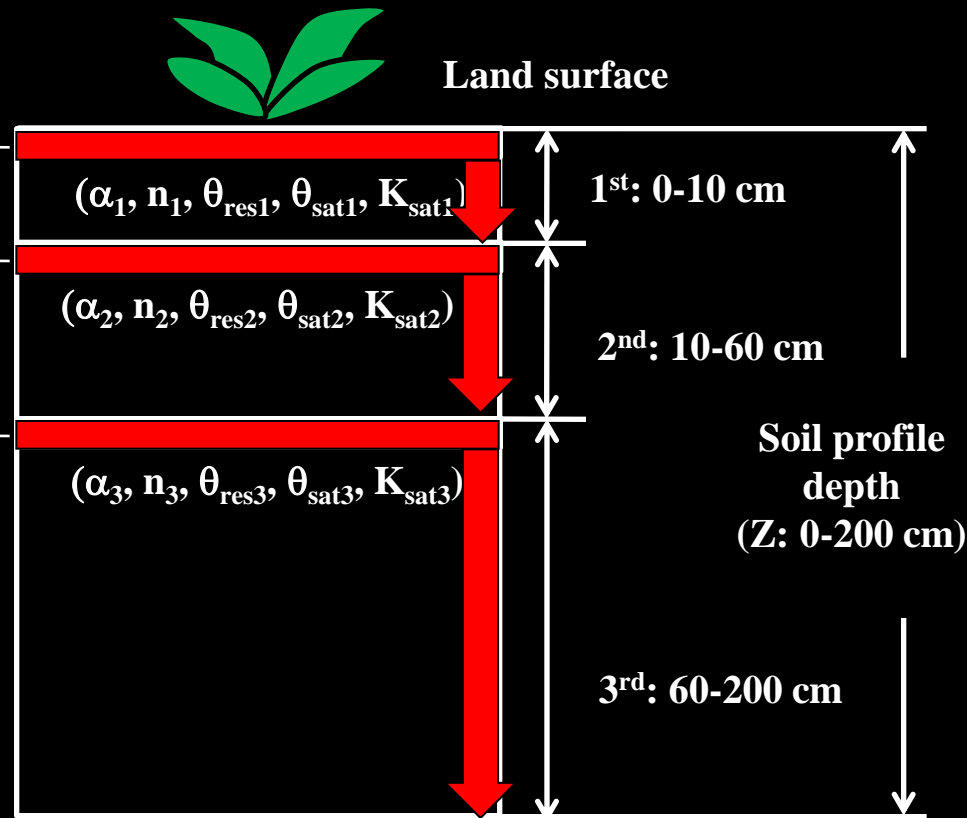
Near-surface



Layer-specific

Soil moisture Observations

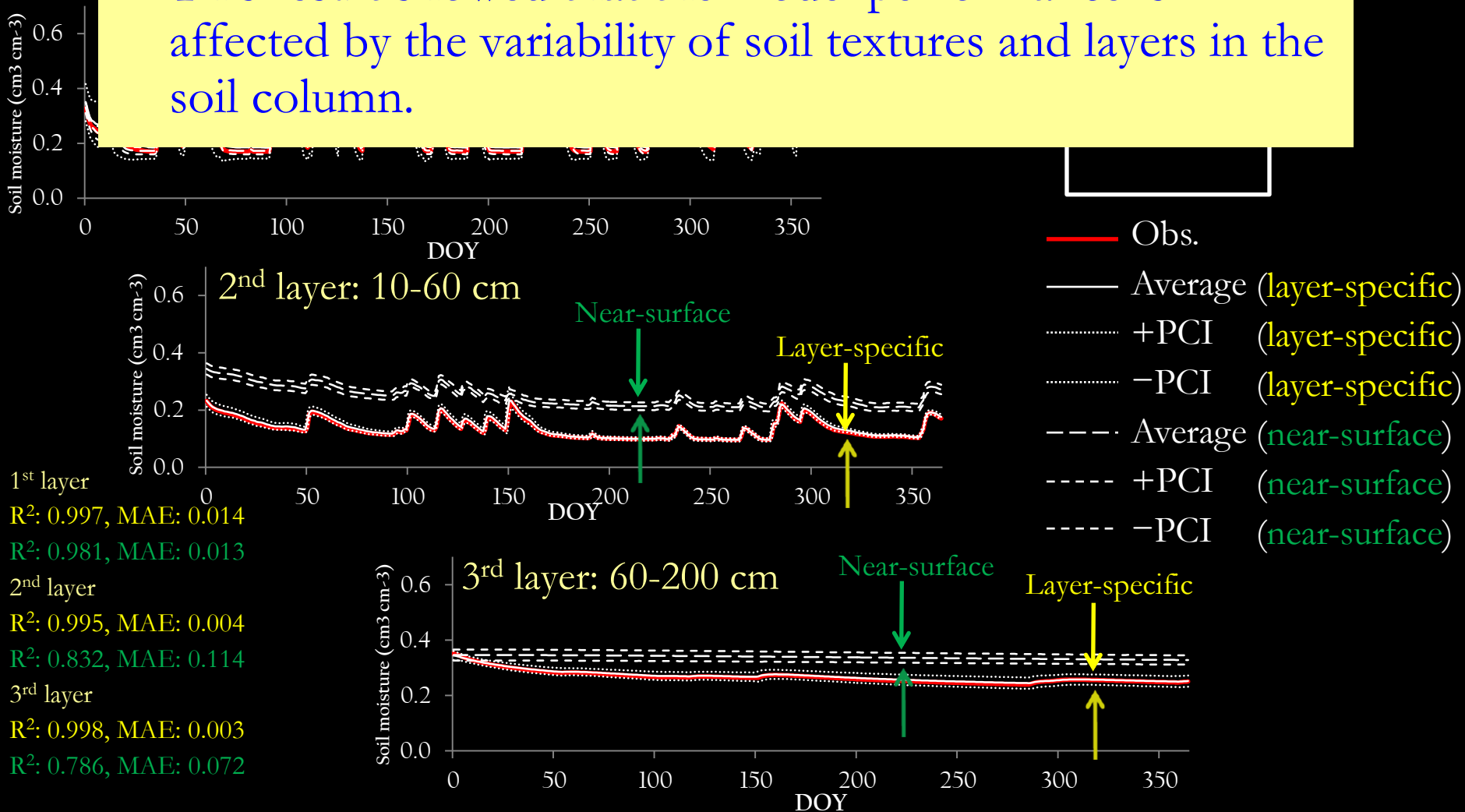
$(\theta_{obsj=1})$ 0-5 cm ←
 $(\theta_{obsj=2})$ 10-15 cm ←
 $(\theta_{obsj=3})$ 60-70 cm ←



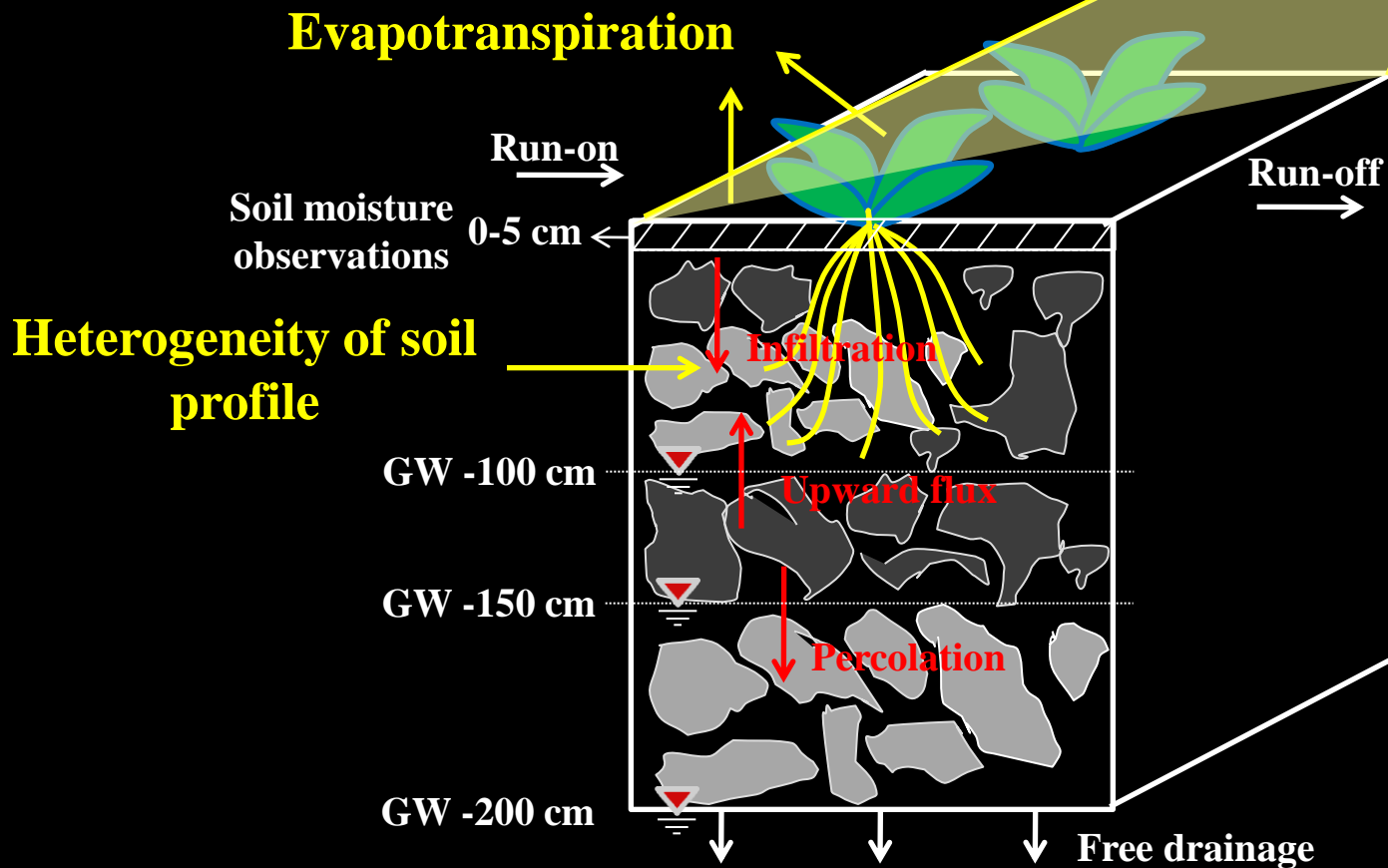
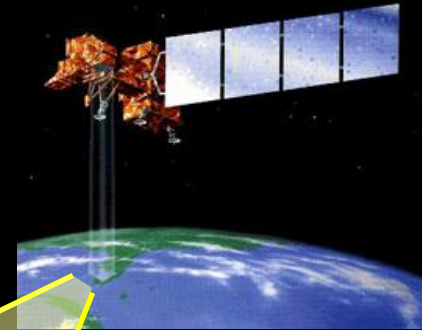
Results

Case 1: Comparison of layer-specific/near-surface approach

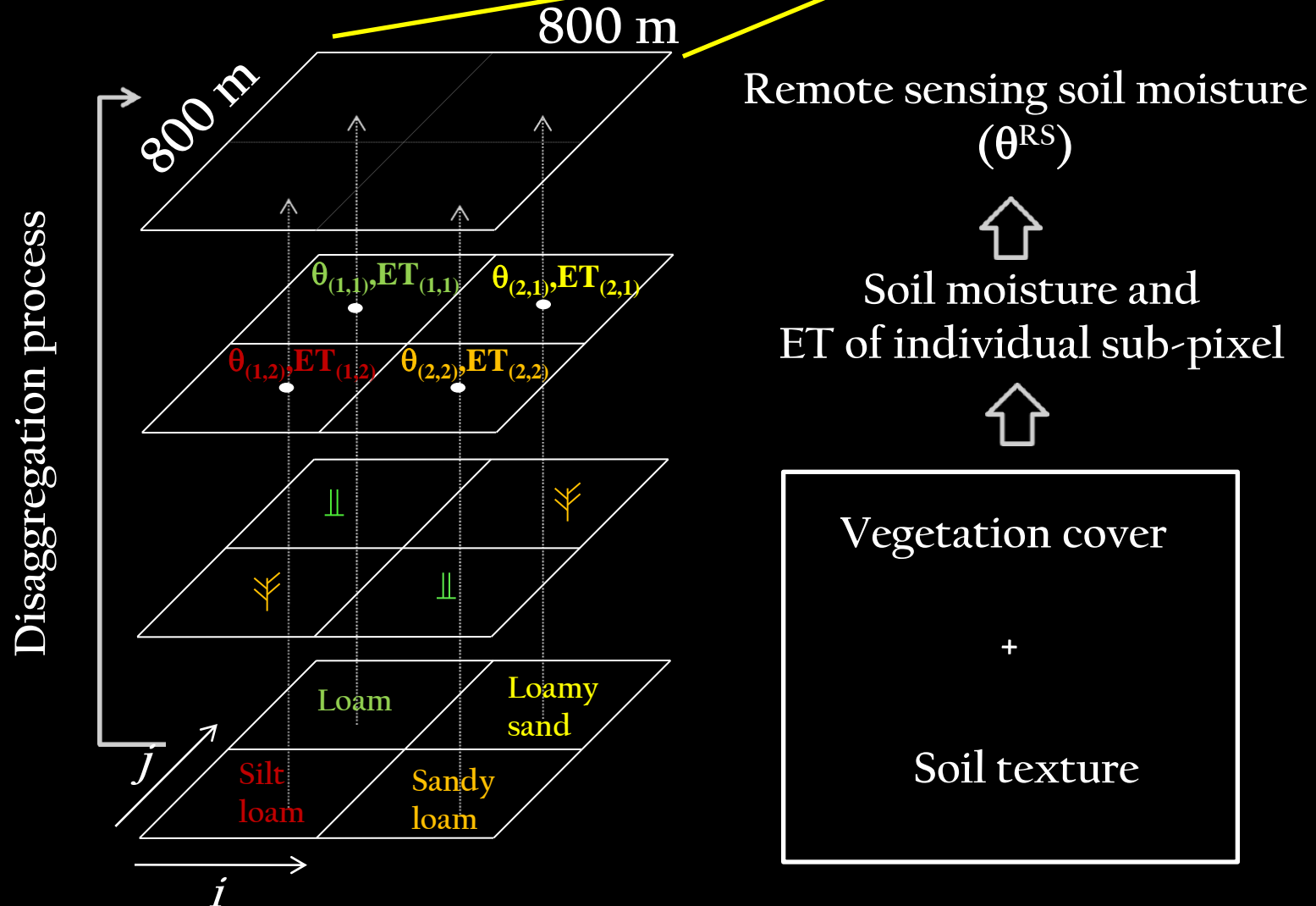
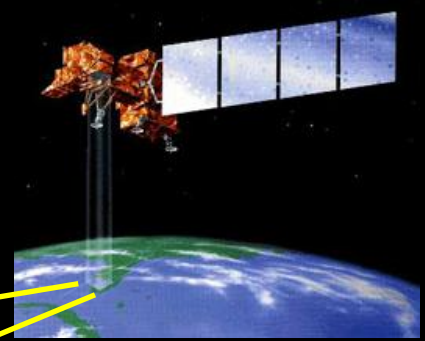
This result showed that the model performance is affected by the variability of soil textures and layers in the soil column.



■ Spatial scaling algorithms



Deterministic Disaggregation algorithm



Results - Soil Moisture

■ LW 21 site (ESTAR, 800 m × 800 m)

● Obs. (*in-situ*)

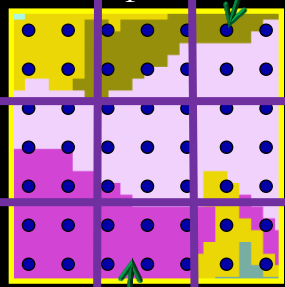
— Average

⋯ +95PCI

⋯ -95PCI

49 *in-situ* SM
sampling points

Soil map

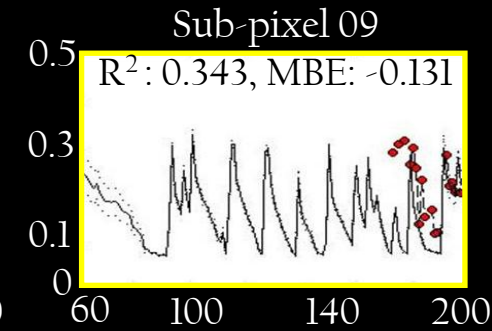
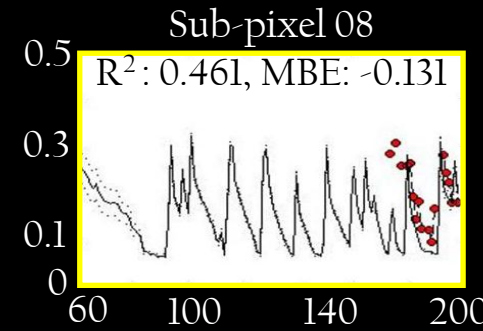
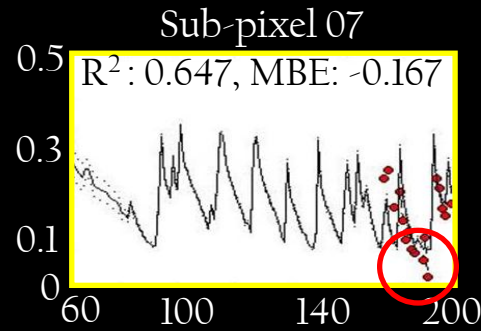
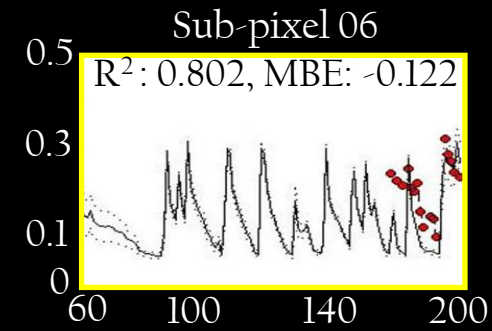
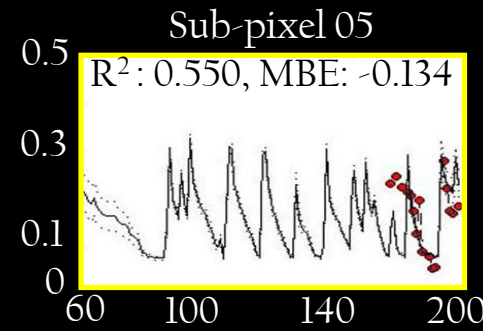
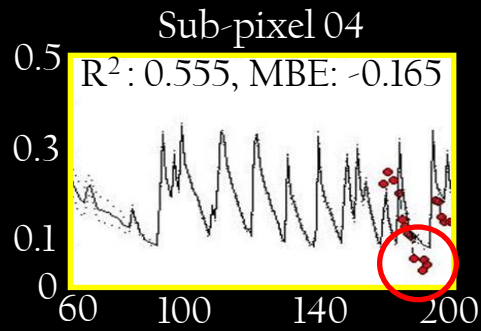
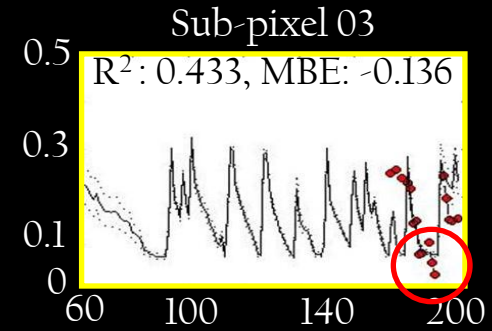
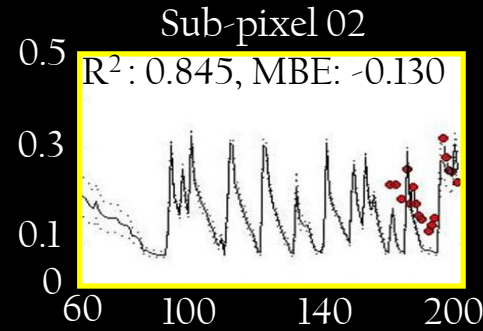
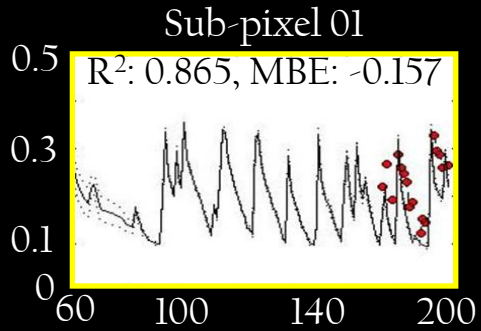


Silt loam (dominant)

Vegetation



Soil moisture ($\text{cm}^3 \text{cm}^{-3}$)

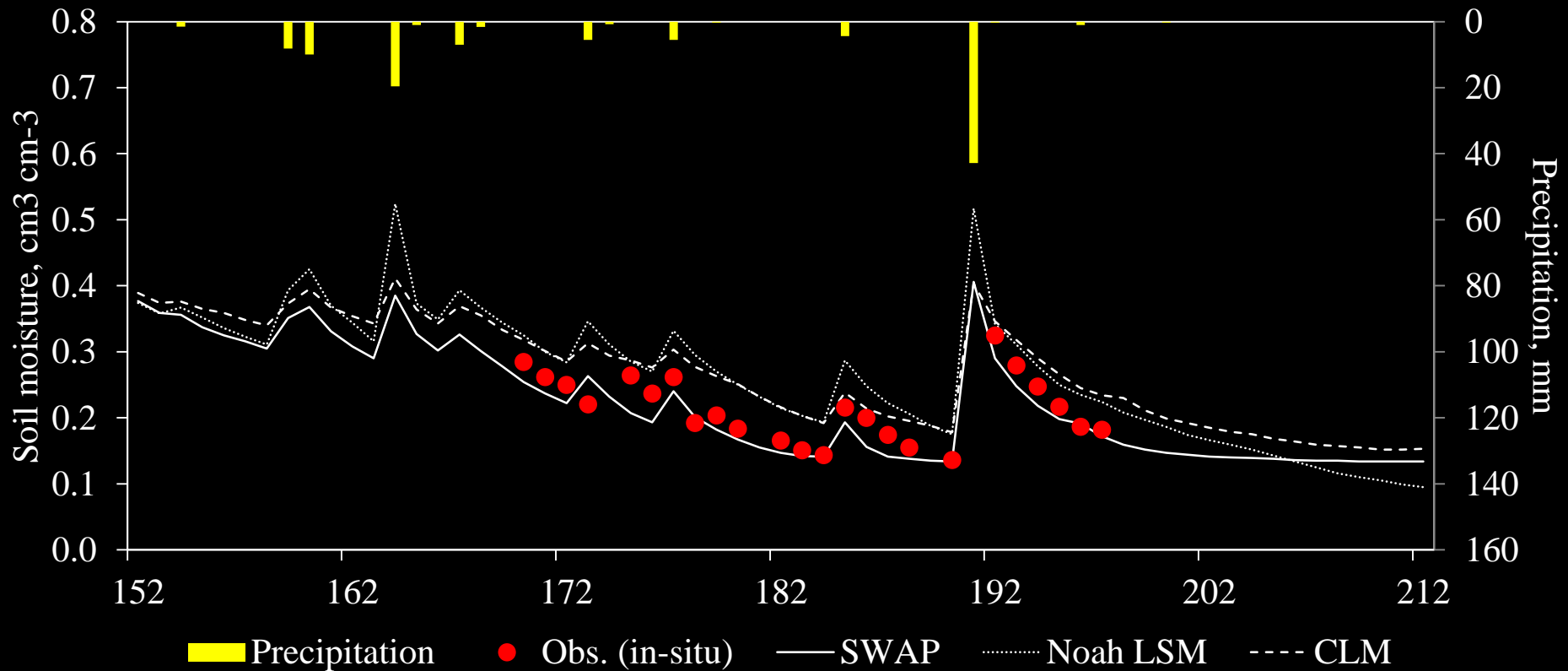


DOY

Results

- Comparison of *in-situ* and average (for the upscaled sub-pixels) soil moisture dynamics for SWAP, CLM, and Noah LSM.

SWAP-R²: 0.913, RMSE: 0.029 **Noah LSM-R²: 0.877, RMSE: 0.058** **CLM-R²: 0.927, RMSE: 0.051**



In order to support the robustness of our approach, we tested various hydrological models in the upscaling process only.

Better understanding of the water cycle

Unifying platform

Water resources management

Natural disasters

Agriculture

*Better soil parameter estimations
and soil water flow*

Vertical
heterogeneity

Evapotranspiration
component

Spatial
variability

Non-parameteric
evolutionary
scheme

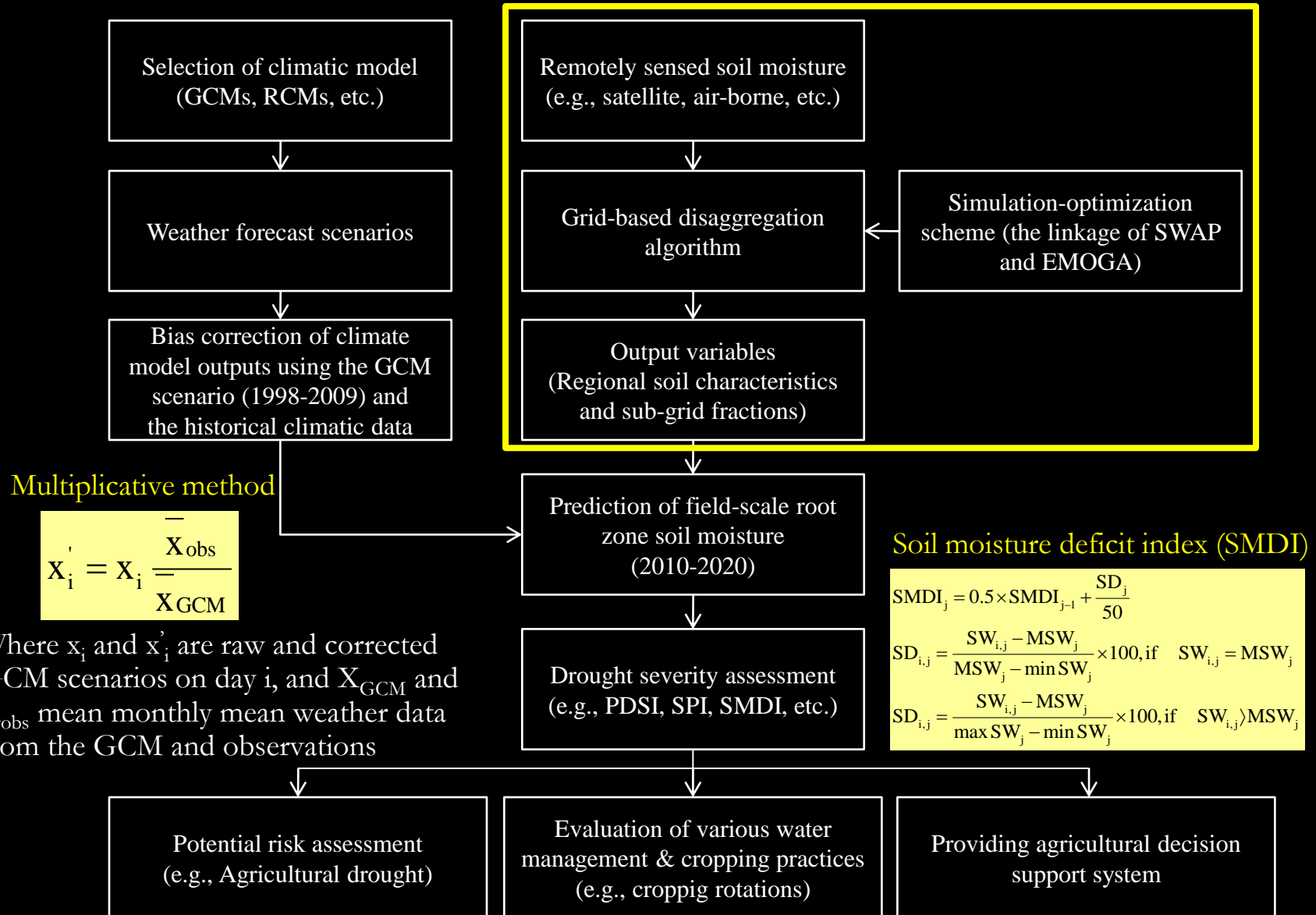
Increasing Drought Severity

- Drought is one of the most severe environmental outcomes of the climate change
- Texas suffered under an intense drought driven by La Niña with a total damage of \$ 7.6 billion
- Drought severity assessment using precipitation data
- Agricultural drought influenced by not only weather conditions, but also by root zone soil moisture
- No study of finer-scale drought severity evaluations using remotely sensed soil moisture

- To develop a drought severity assessment framework using remotely sensed soil moisture products
 - Global circulation model (GCM) based climate forecasts

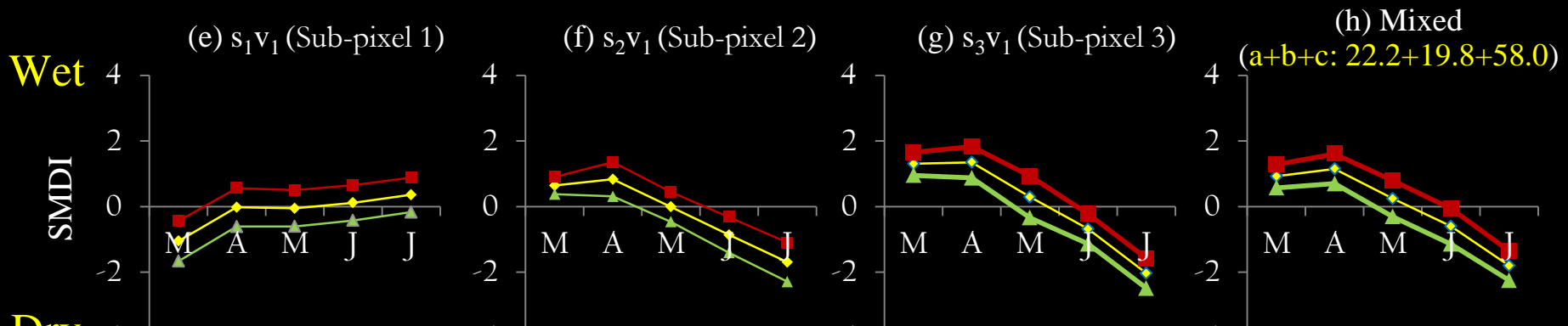
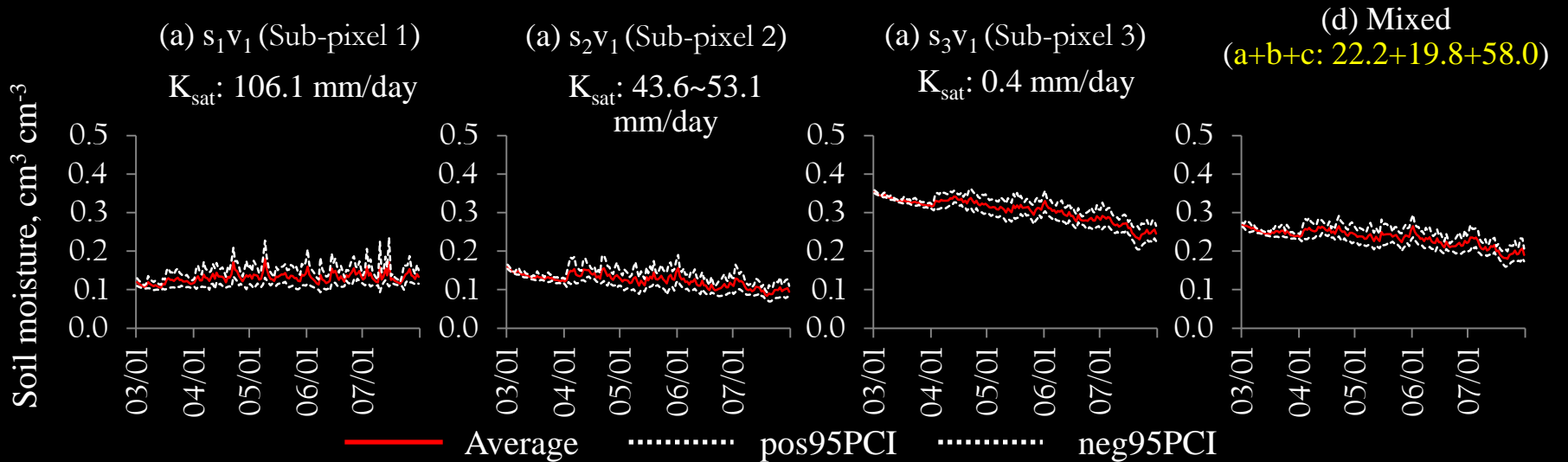
- To evaluate the finer-scale drought severity under various environmental factors
 - Various soil textures, vegetations, soil depths, shallow ground water tables, etc.

Agricultural Drought Severity Platform



Results

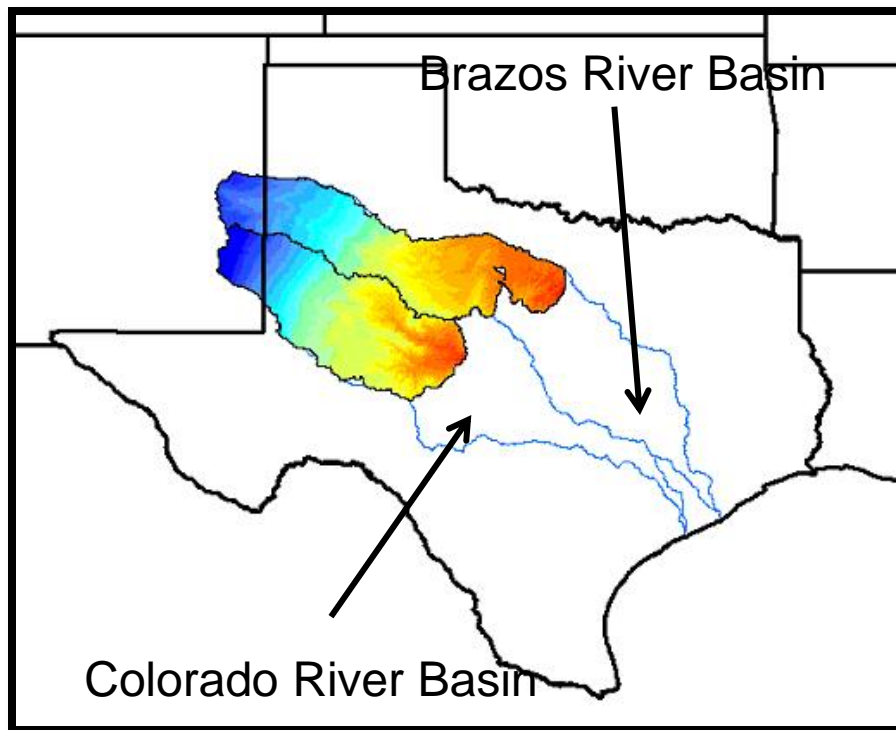
- Predicted root zone soil moisture at the WC1 site during 2010-2020



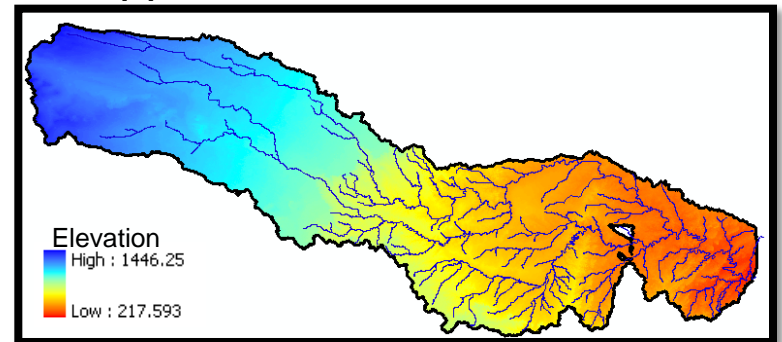
Although the SMDI values have some uncertainties, this results showed that the sub-pixels within the RS product can be partially affected by the drought severity.

Soil moisture estimates in Northern Texas

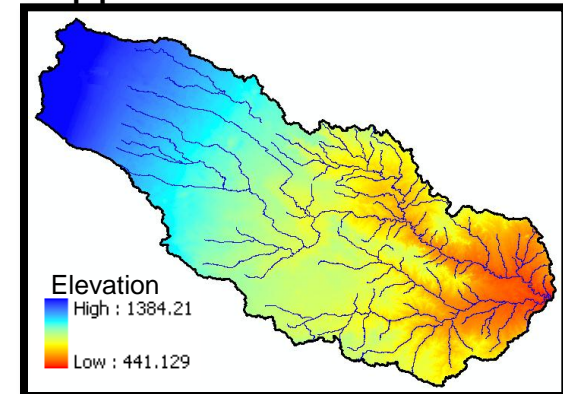
- Estimating soil moisture dynamics using land surface model (Community Land Model, CLM)



Upper Brazos river



Upper Colorado river



Ongoing work...

- **Improve subsurface process including soil moisture interaction with groundwater in the land surface models (CLM)**
- **Develop scaling approach for hydraulic parameters of hydrologic components (surface, subsurface, and recharge/discharge)**
- **Forecast drought severity using the Bayesian multi-scale averaging of land surface models at regional scale in Texas**