Ground Network Design and Dynamic Operation for Validation of Space-Borne Soil Moisture Measurements

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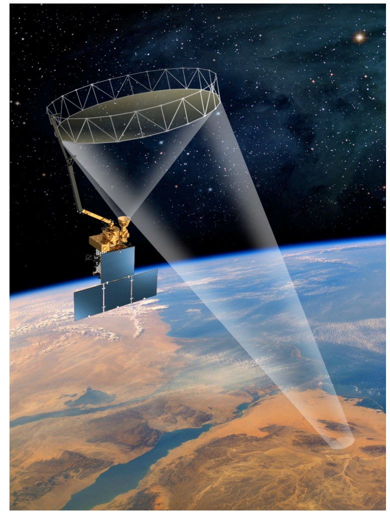
Technology Relevance: SMAP

SMAP Primary Science Objectives:

- Global high-resolution mapping of soil moisture and its freeze-thaw state to:
  - Link terrestrial water, energy, and carbon cycle processes
  - Estimate global water and energy fluxes at the land surface
  - Quantify net carbon flux in boreal landscapes
  - Extend weather and climate forecast skill
  - Develop improved flood and drought prediction capability



Mission Approach:

- GSFC L-band radiometer
- JPL L-band radar
- Common 6m rotating antenna for 3-day global repeat coverage
- Merged radar and radiometer data for high-accuracy, mid-resolution, soil moisture
- 670 km polar sun-sync

Development Status:

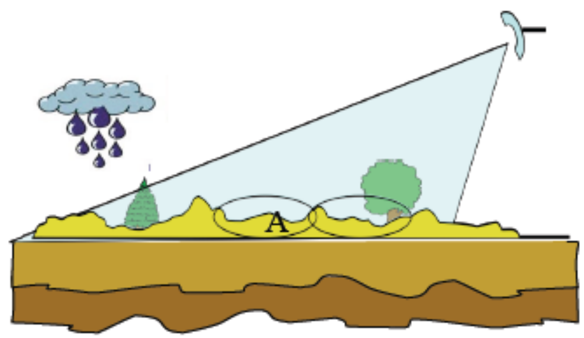
- Entered Phase B in January 2010
- Science Definition Team (SDT) selected in 2008
- Algorithms and Cal/Val workshop held in June 2009 and March 2010; Applications workshop September 2009
- Now completing mission trade studies

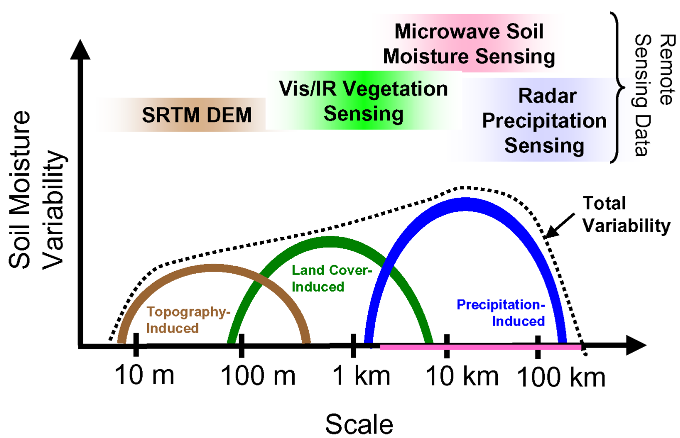
Development Objectives:

- Just completed KDP-B; now in Phase B
- Phase B will focus on further trade studies, risk reduction, requirements and interface maturation
- 2nd Algorithms Workshop March 2010
- Cal/Val Field Campaigns Summer 2010 (Oklahoma, Canada, Australia)
- Launch planned for late 2014

Technology Background

Soil moisture Sensing Controller And oPtimal Estimator (SoilSCAPE): develop technologies for near real-time validation of spaceborne soil moisture estimates





The Challenge for SMAP Validation:

- SMAP's radar and radiometer will measure soil moisture with different spatial resolutions
- Soil moisture varies on multiple spatial scales
  - ⇨ O(10 m) due to vegetation cover and topography
  - ⇨ O(100 m) due to topography and soil type
  - ⇨ O(1000m) due to cloud cover and precipitation
- Deploying validation sensors at all scales and with high density is infeasible
  - Old paradigm doesn't work
- Need smart and adaptive time and space sampling
  - Balance cost and accuracy
- This problem is at the boundary of the conventional instrument domain and information technologies domain

Objectives

SoilSCAPE Objectives are:

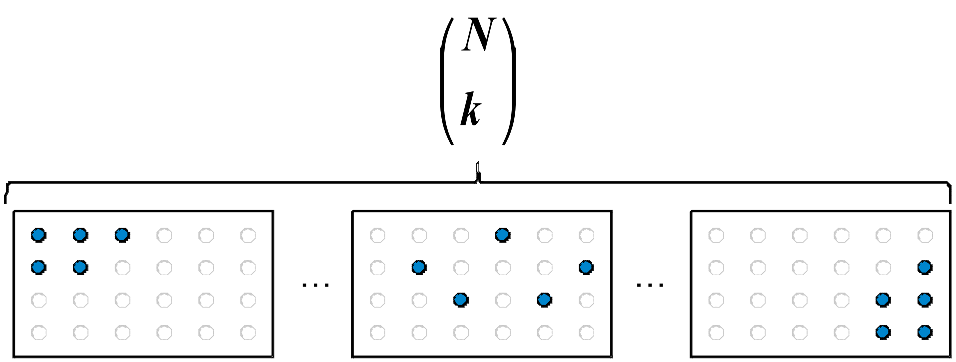
1. Optimal design of sensor node **placement and scheduling controller** based on modeled and measured soil moisture spatial and temporal statistics

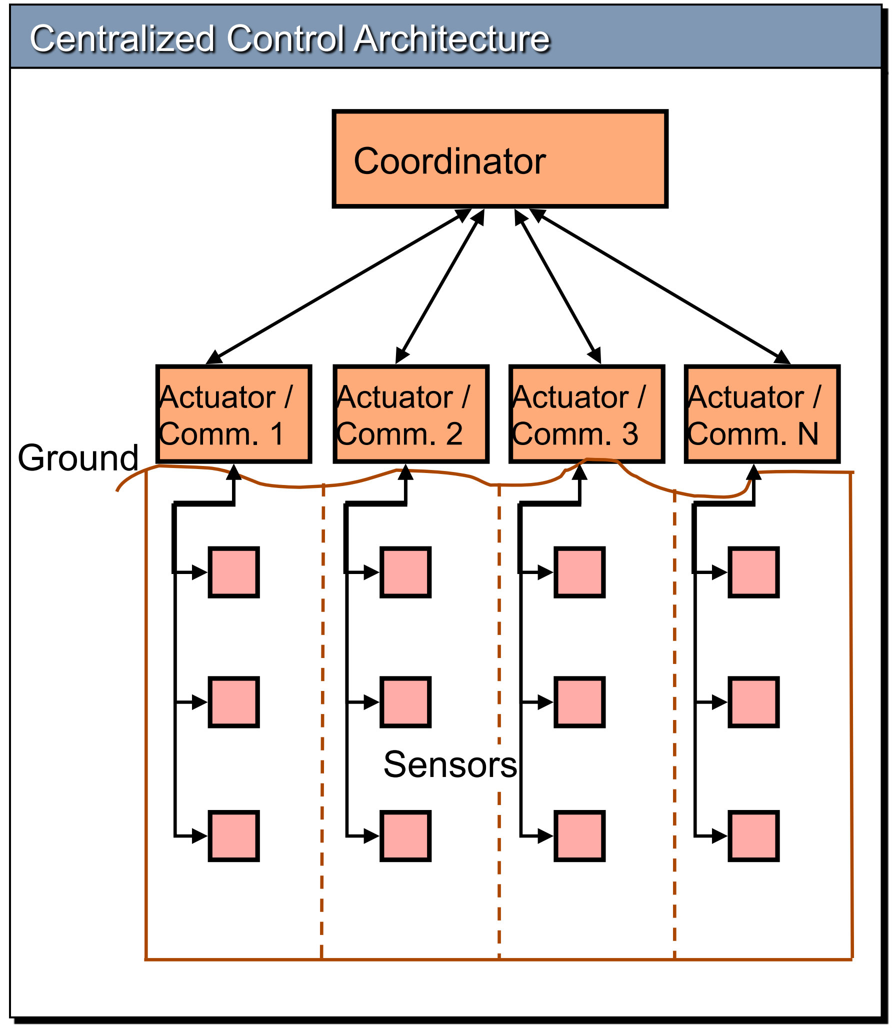
2. Derivation of large-scale remote sensing estimates of heterogeneous soil moisture, compatible with ground sensor network estimates of true mean of soil moisture field via a **landscape simulator**

3. Design and implementation of large-scale wireless **communication & actuation system** to configure sampling within the in-situ sensor network and to produce estimates of the soil moisture field mean

Control System overview:

- Design of sensor node placement and scheduling based on soil moisture spatial and temporal statistics
  - ⇨ Implemented through a “centralized control” architecture
  - ⇨ Initially will decouple sensor placement solution from sensor scheduling solution





Control System overview:

- Sensor placement assuming continuous-time sampling
  - Conducted studies on simulated data
  - Developed a cluster-based placement scheme
- Field mean estimation problem assuming a fixed placement
  - With a fixed placement, computed scheduling policies for sensors
  - Modified the estimation policy to estimate the mean value of soil moisture over the field of interest
- Methodology to address the joint placement and scheduling problem
  - Had previously developed scheduling controller independent of placement
  - Placement and scheduling problem are inter-related
  - Optimal placements should take into account the dynamic scheduling costs
  - Identified a methodology that incorporates the dynamic aspects of scheduling into the static placement problem

Sensor placement algorithms using simulated data

- tRIBS (TIN-based real-time integrated basin simulator; TIN: triangulated irregular network) is a landscape hydrology simulation tool developed at MIT; has been used here to investigate space/time soil moisture dynamics
- Assuming perfect measurements in time, address sensor placement as a stand-alone problem
- Exploit special properties of data
- Investigate a cluster-based placement scheme to better exploit the data features
- Experimental results

The stand-alone sensor placement problem

- A field with N possible locations to place sensors $V = \{v_1, v_2 \ldots v_N\}$
- Signal to be sensed assumed to be a random process; random variable X_i at location v_i
- If we place a sensor at v_i we observe perfectly X_i; otherwise we need to provide an estimate $\hat{X}_i$

- Want to select K locations to place sensors

$$\text{(P)} \qquad A^* = \arg\min_{A \subset V, |A|=K} E[\mathrm{err}(X_V, \hat{X}_V)]$$

- *err*() is some error measure; most commonly used is the MSE

$$E[\mathrm{err}(X_V, \hat{X}_V)] = \| X_V - \hat{X}_V \|^2$$

- This is a joint optimization: simultaneously determine the best subset and the best estimate
- Can limit the solution space, e.g., only consider linear estimates

One very commonly used approach

- Assume the underlying spatial random process is Gaussian
  - The best estimate for an unobserved location is the conditional mean of a Gaussian random variable, a linear estimator

$$\hat{x}_V = u_V + \Sigma_{VA} \Sigma^{-1}_{AA} (x_A - u_A)$$

  - Can use metrics like entropy and mutual information as alternative objective functions (though an approximate one to MSE) for subset selection

(MaxEN)

$$A^* = \arg\min_{A \subset V, |A|=K} H(X_{V \setminus A} \mid X_A)$$

$$= \arg\max_{A \subset V, |A|=K} H(X_A)$$

(MaxMI)

$$A^* = \arg\max_{A \subset V, |A|=K} \mathrm{MI}(X_{V \setminus A}, X_A)$$

$$= \arg\max_{A \subset V, |A|=K} H(X_{V \setminus A}) - H(X_{V \setminus A} \mid X_A)$$

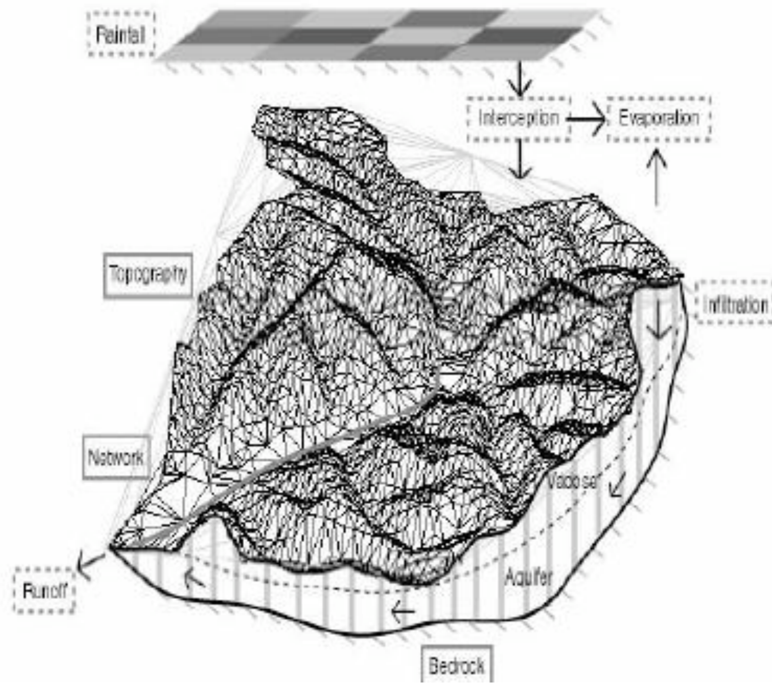
- They remain NP-hard
- Simple greedy algorithms shown to have good performance

How the greedy algorithms work

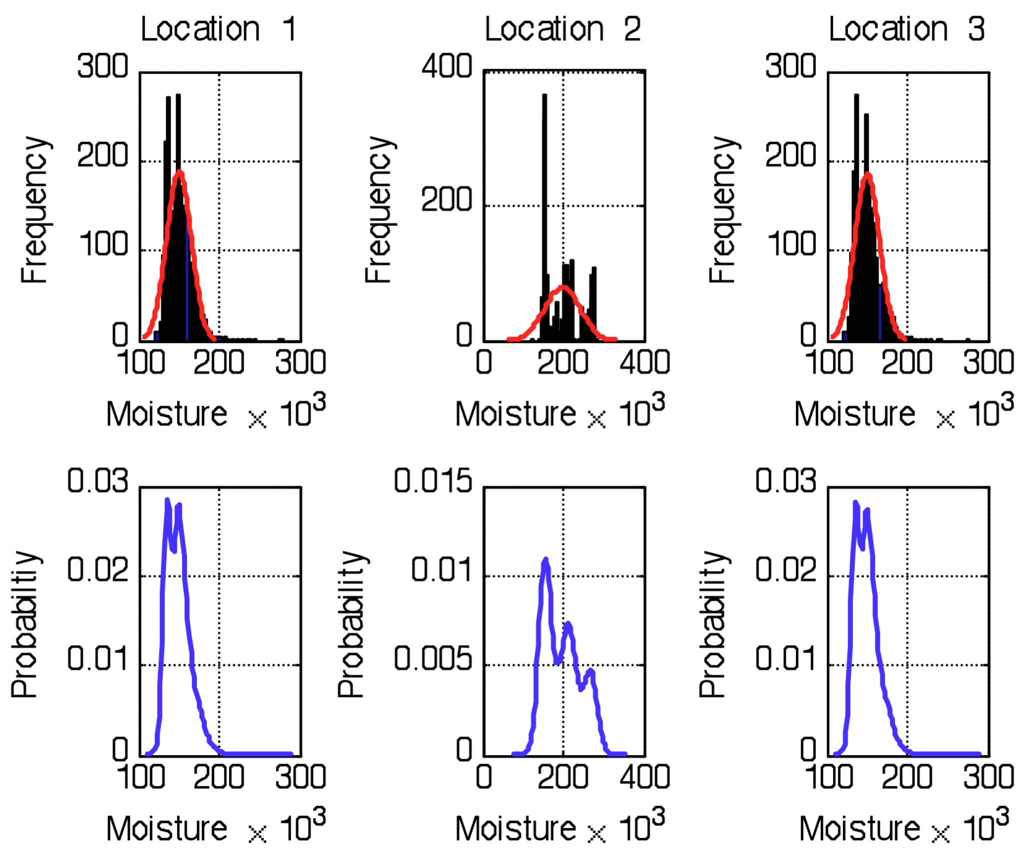
- Use certain training data to compute the mean, variances, and covariances at (and among) all locations
- Greedy placement:
  - At each step *t*, select one location that maximizes EN/MI (or minimizes MSE) given the set of locations already selected
  - Repeat till we have selected *K* locations
- Estimation/Prediction:
  - Conditional mean, also known as Gaussian regression
- How well does the Gaussian assumption hold for soil moisture data?
- How does this affect the design of good sensor placement and field estimation algorithms?

tRIBS simulation of soil moisture fields

- A 2km x 2km basin with 2400 locations (9 depths each) on a regular square grid
- Over a three-month period (simulated time), one snapshot per hour, a total of 2208 snapshots used in our experiments



Properties of the data: is the (surface) soil moisture process Gaussian?

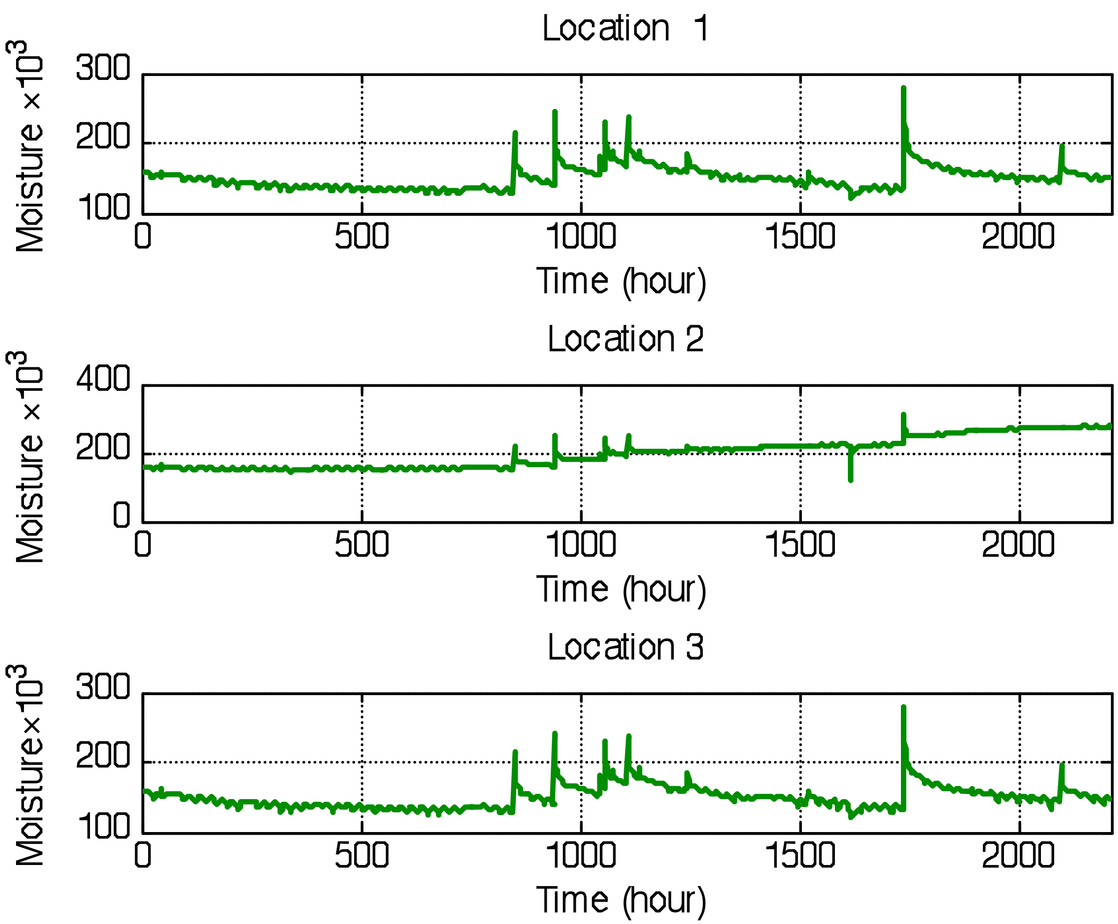


- Three randomly selected locations
- Surface soil moisture only
- Moisture readings amplified 1000x

- Top: histograms of moisture at these locations (black) and the estimated Gaussian kernel (red)
- Bottom: estimated pdf

- Observation: these are clearly non-Gaussian

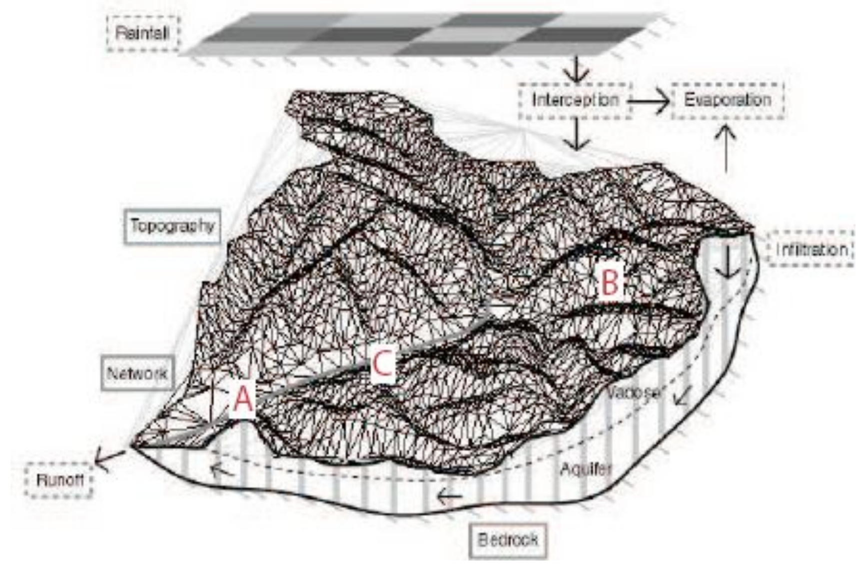
Temporal changes at these locations

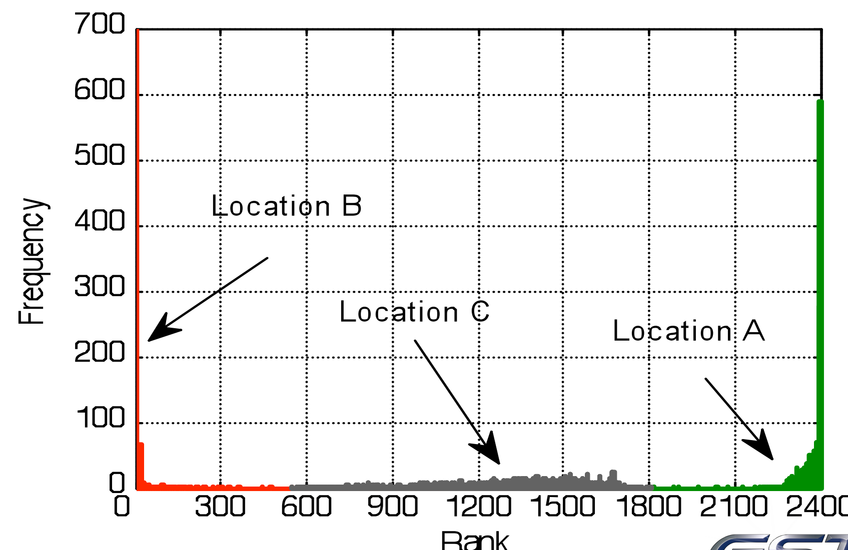


- The same three locations as in previous slide
- Figures show the change over time at these locations
- Figures show, qualitatively, how soil moisture is correlated between them
- Spikes correspond to rain events

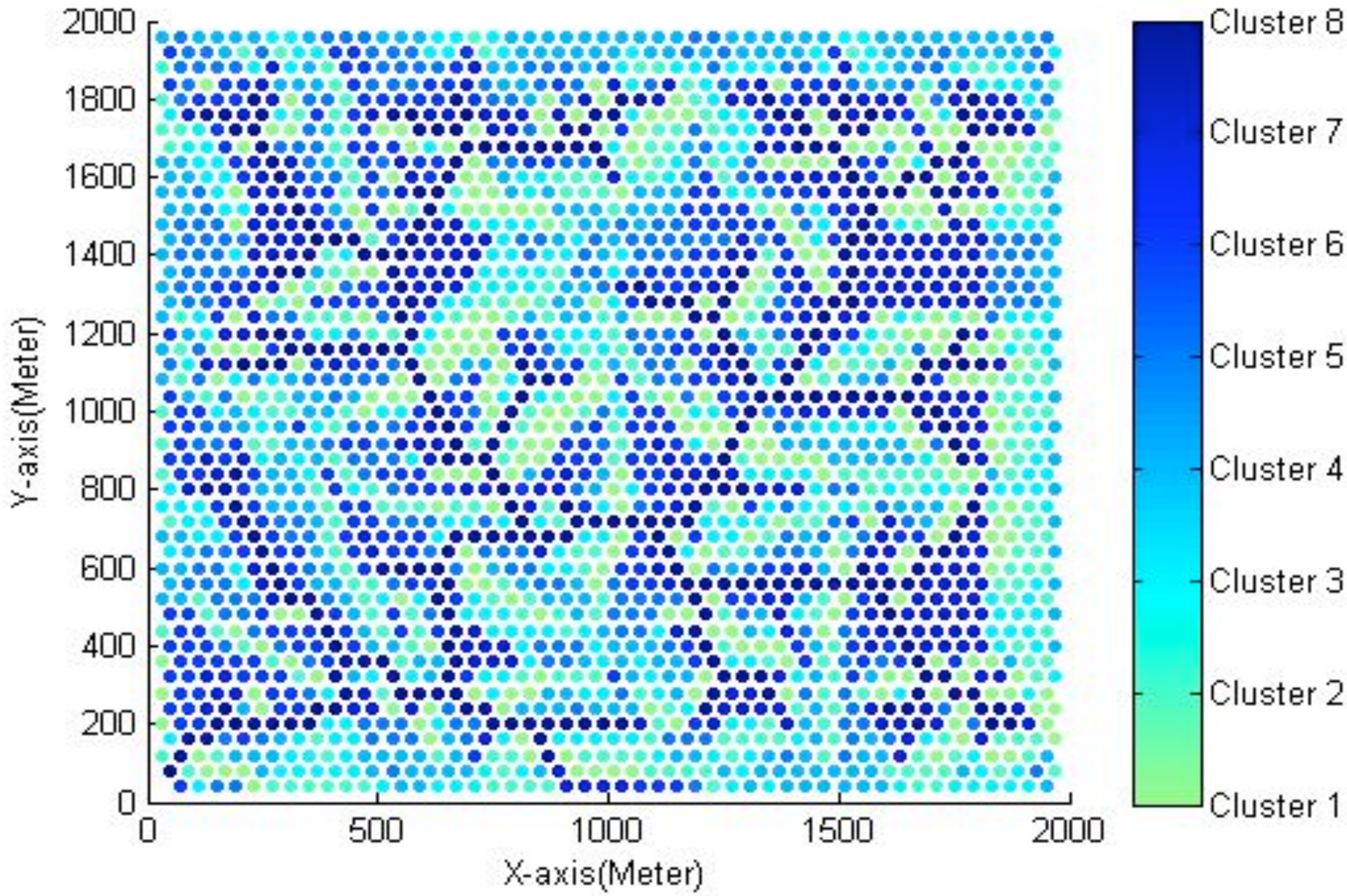
Observations

- Locations with similar features (soil type, vegetation cover, etc.) will show high correlation
- Most of these are relatively stable features over time
- May expect relative soil moisture values to hold steady even as absolute values vary over time
- Shown in bottom figure: histogram of a location's numerical rank in each snapshot





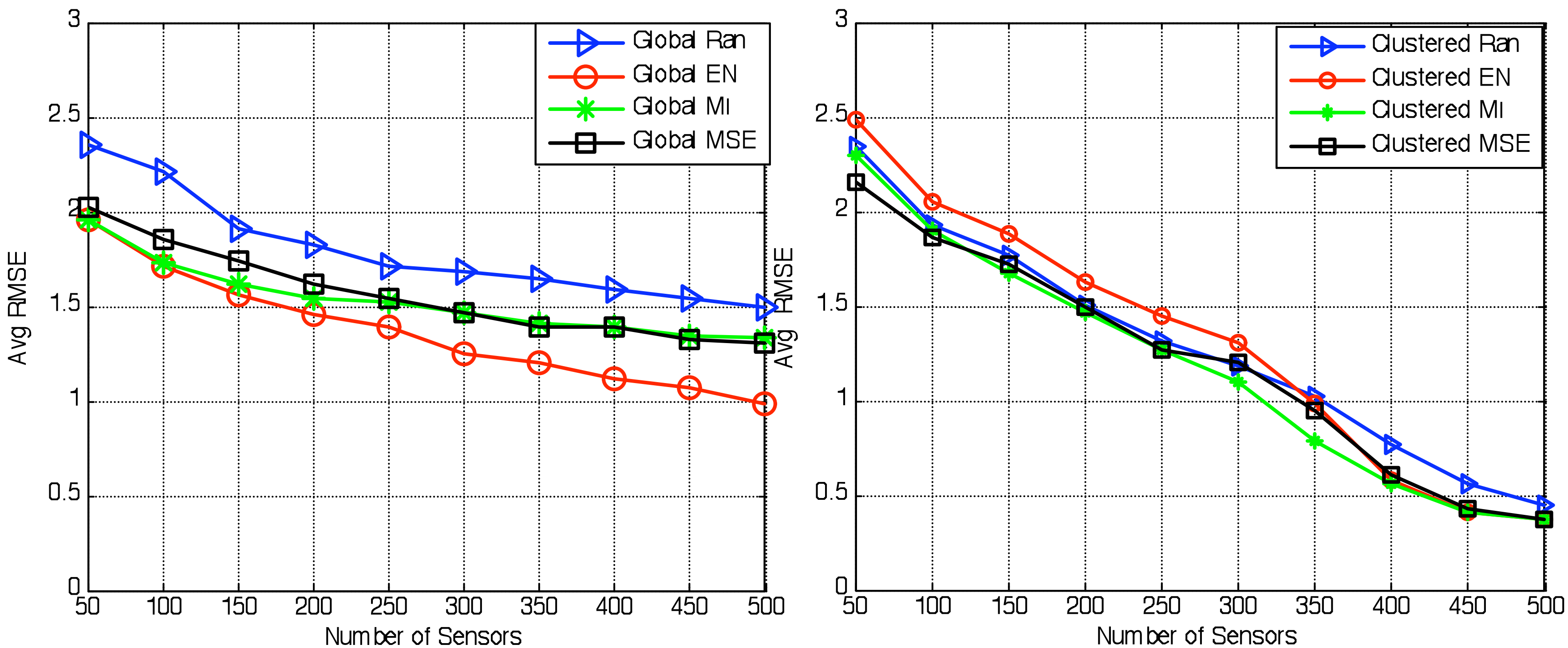
What does the clustering look like (W=8)



Placement using coarse-grained ordering

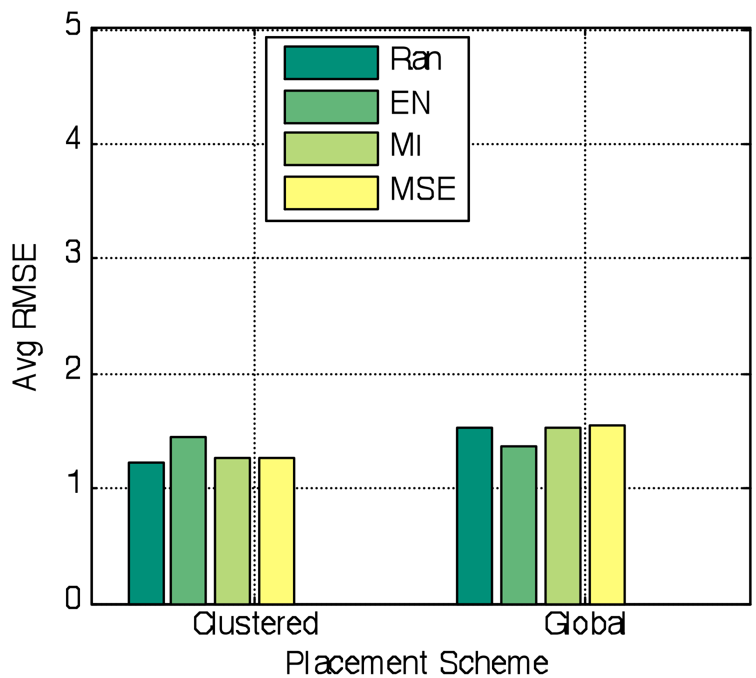
- Use a subset of simulated data for training, compute the mean, variances, and covariances at (and among) all locations
- Sensor placement:
  - Solve the placement problem independently for each cluster
  - Can allocate more sensors to clusters with higher average moisture (variance) levels
  - Place K_{i} sensors in cluster *i*, with $\sum_{i=1}^{W} K_i = K$
  - Within each cluster can use any existing scheme (e.g., max EN/MI)
- Field estimation:
  - Will use Gaussian regression

Clustered vs. global placement: size of the selected subset

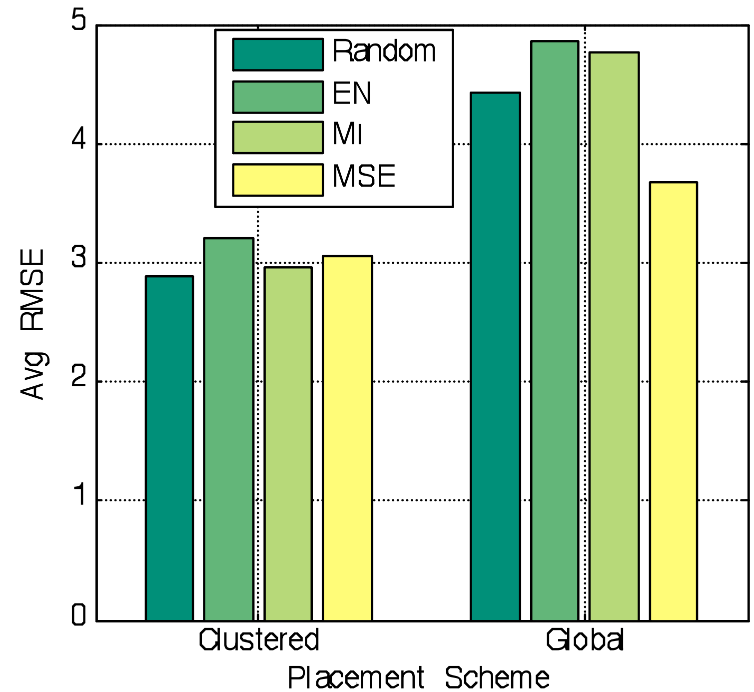


- Using the first 1500 snapshots for training and the last 700 for testing (out of 2208)
- Clustered schemes show advantage when placing sensors K>=200

Clustered vs. global placement: performance improvement



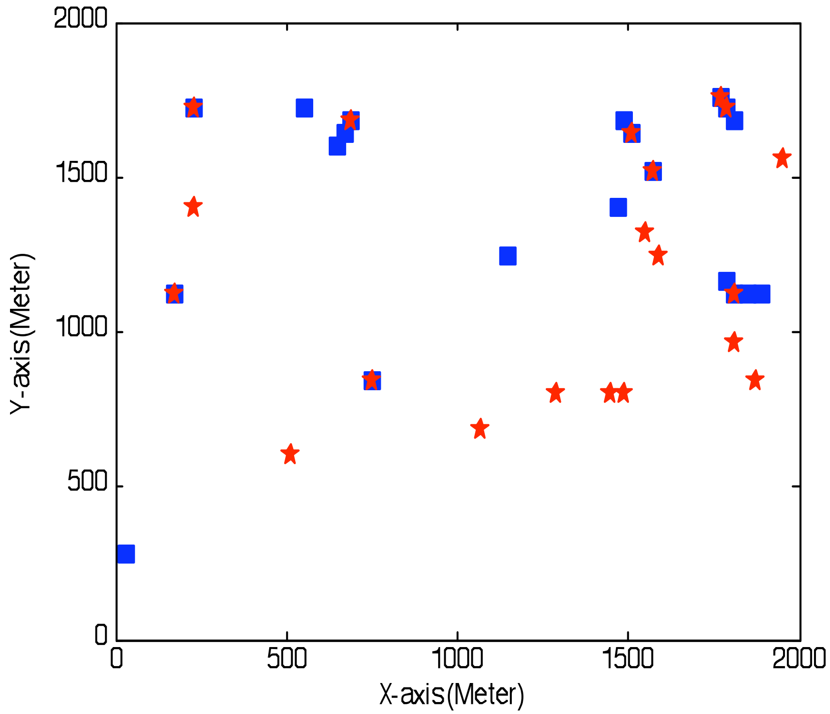
1500 training snapshots



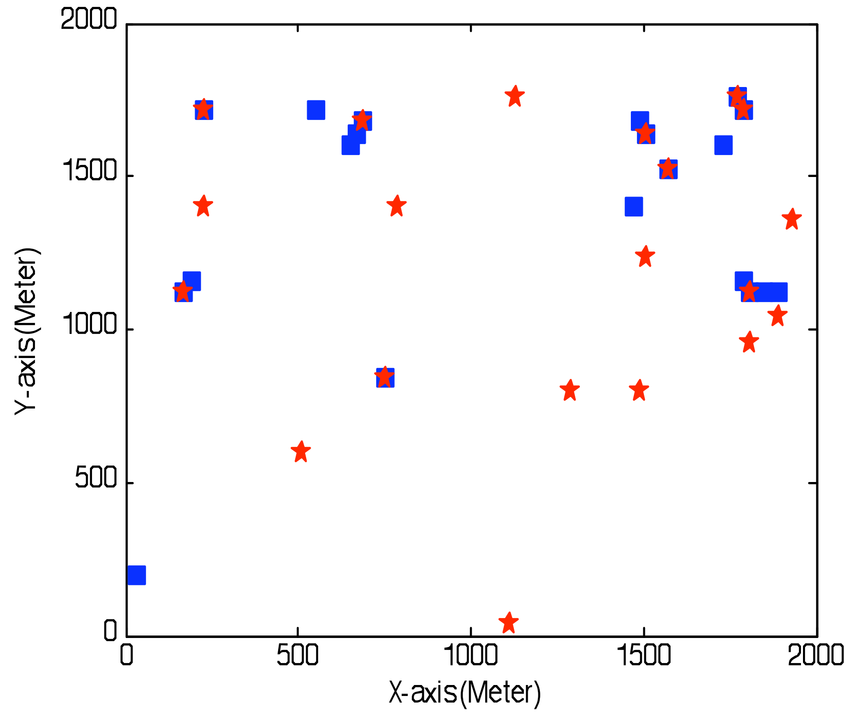
1000 training snapshots

- 250 sensors are placed
- Regardless of training amount, clustering results in better performance

A quick glance at the actual placement (20 sensors) under different schemes: Many features are similar between EN and MI approaches



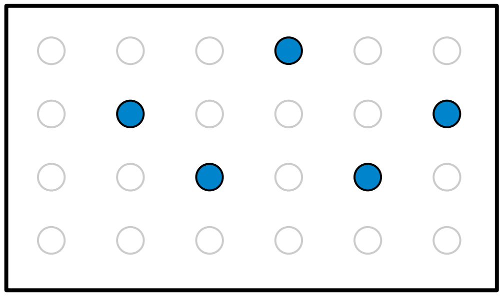
- Global MaxEN (blue)
- Clustered MaxEN (red)



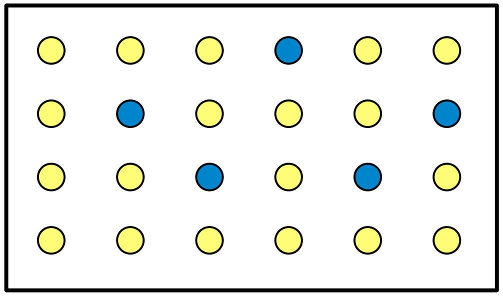
- Global MaxMI (blue)
- Clustered MaxMI (red)

Non-Gaussian Dynamic Mean Estimation with a Fixed Placement

- Currently, the scheduling objective is to estimate soil moisture evolution at *K* fixed lateral locations using sensors placed at those locations



- However, we are also interested in using the *K* sensors to estimate a mean value of the soil moisture over the area of interest



- Statistics are not Gaussian; estimation costs are dynamic

Mean Estimation : Solution Methodology

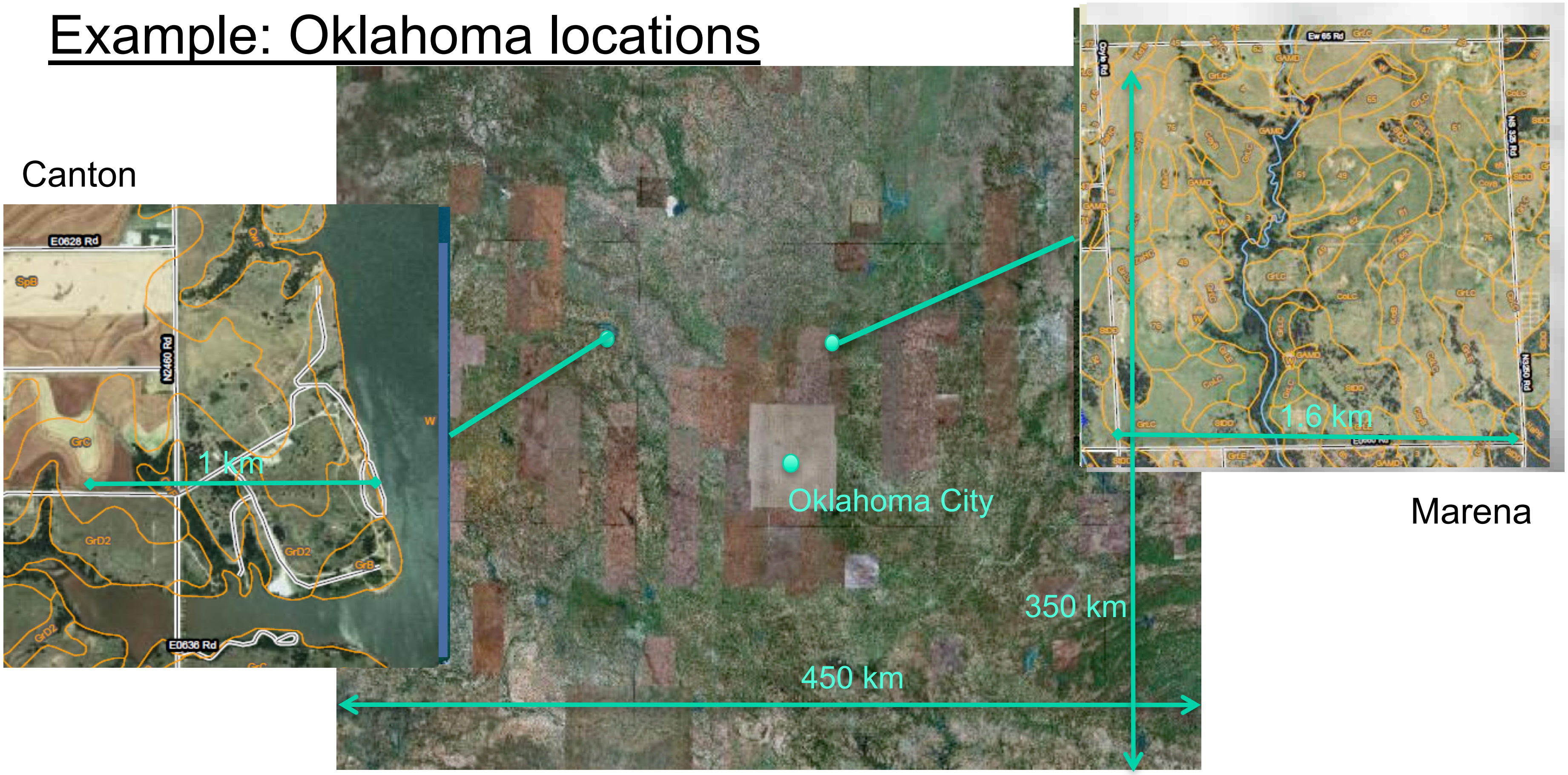
- Solve the scheduling problem independently for each sensor location
- Exploit the correlation among soil moisture values at different locations to find local estimates, $\hat{X}_t(location)$ using past measurements from all locations (Joint Estimation)
- Find the joint statistics of the field mean *M* and the local values of soil moisture at sensor locations
- Use the joint statistical model of the soil moisture at sensor locations and the field mean to convert the local estimates to a mean field estimate $\hat{M}_t$
- Performance of scheduler (dynamic problem) depends on placement (static problem), and vice versa
- Currently developing solution of joint placement and scheduling problems

Landscape Simulator Overview

- Proof-of-concept heterogeneous landscape simulator
  - Developed architecture of simulator
  - Implemented unified multi-layered multi-species vegetation model adaptable to various land cover types
  - Created a data base of input files using land cover types of NLCD 2001
- Visualization in Google Earth
  - Layers of information co-registered on whole Earth
- Preliminary aggregation studies
  - Investigated how coarse-resolution remote sensor measurements relate to finer-resolution measurements

Example: Oklahoma locations

Canton



Marena

Area around Oklahoma City, OK

1. Google Earth
2. Land cover type from NLCD 2001
3. Digital Elevation Map (DEM) / National Elevation Dataset (NED)
4. Soil type from USDA

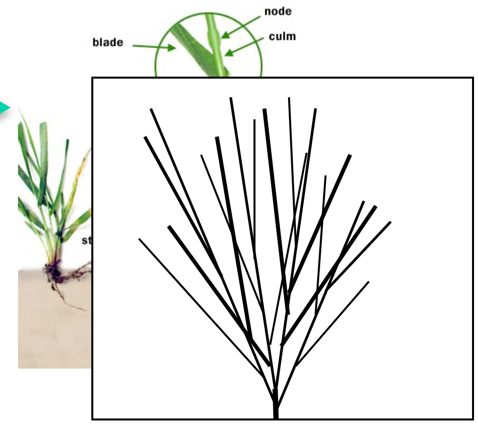
From land cover type to model

NLCD 2001 Land Cover Classification Legend

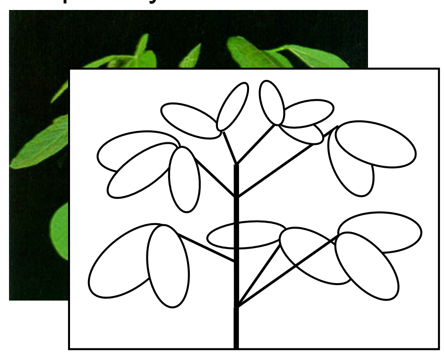
- 11 Open Water
- 12 Perennial Ice/Snow
- 21 Developed, Open Space
- 22 Developed, Low Intensity
- 23 Developed, Medium Intensity
- 24 Developed, High Intensity
- 31 Barren Land
- 41 Deciduous Forest
- 42 Evergreen Forest
- 43 Mixed Forest
- 51 Dwarf Scrub*
- 52 Shrub/ Scrub
- 71 Grassland/ Herbaceous
- 72 Sedge/ Herbaceous *
- 74 Moss *
- 81 Pasture Hay
- 82 Cultivated Crops
- 90 Woody Wetlands
- 95 Emergent Herbaceous Wetlands

* Alaska Only

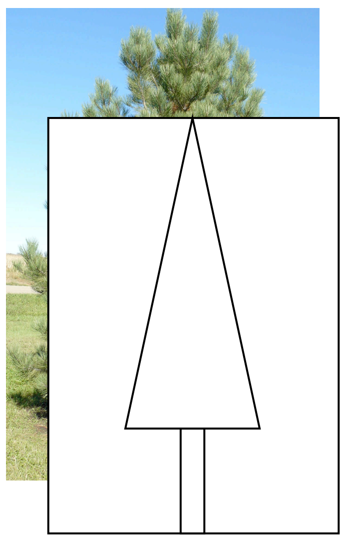
Grass/ Grassland



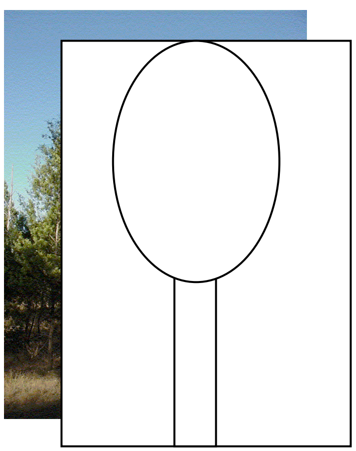
Crop – soybean



Evergreen tree



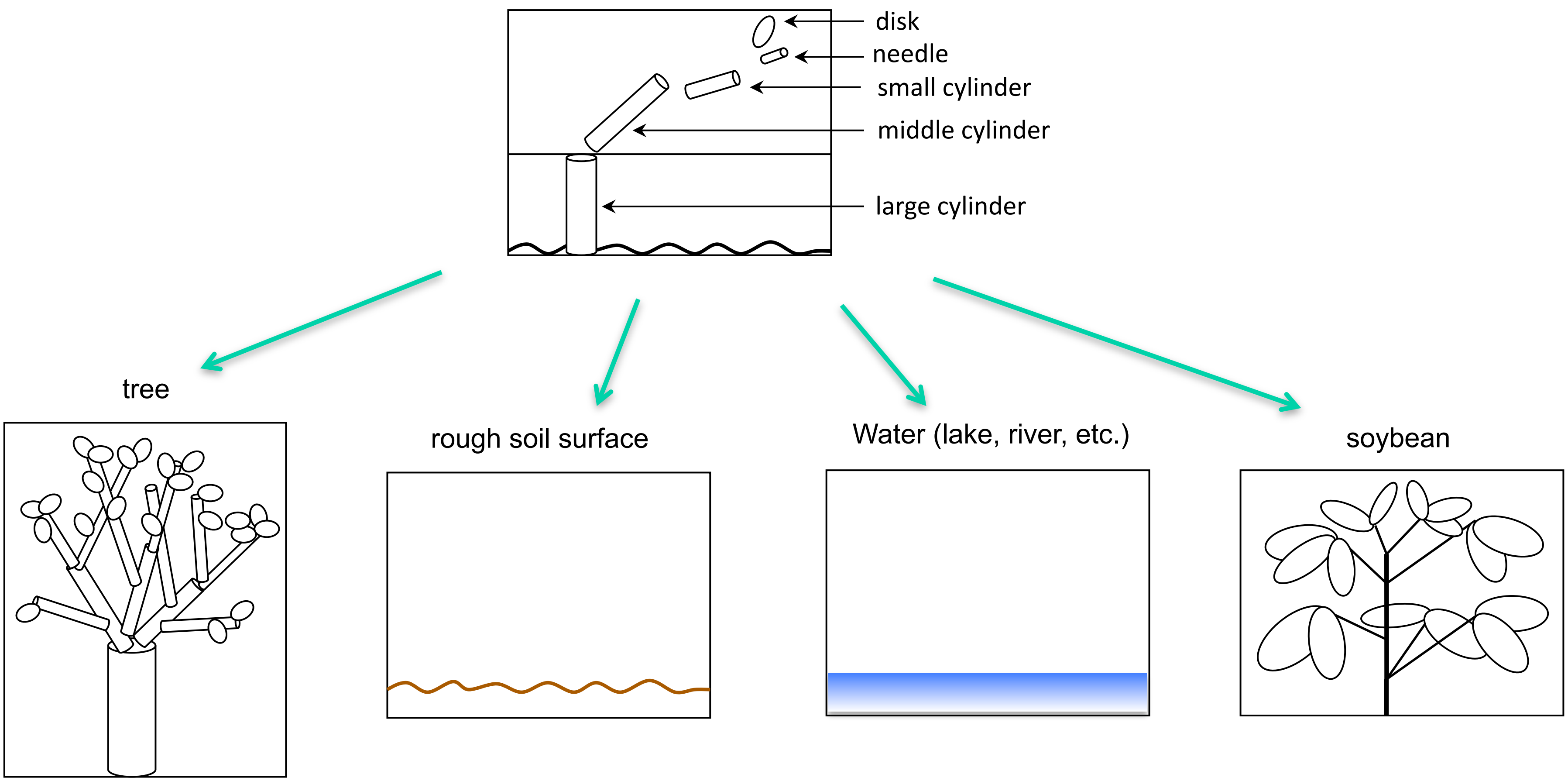
Deciduous tree



Available information & ancillary data is used to adapt model to specific landscape (via parameter input file)

- **Current**: selection of pre-determined input files based on land cover type
- **Prospective**: generate input file based on more diverse combinations of ancillary data

From land cover type to model: One model



Model is general enough to represent various land cover types

Model:

- Can simulate multi-layer vegetation and multiple vegetation types simultaneously
- Builds on existing single species forest model (Durden et al., 1989)
  - Scattering from layers of arbitrarily oriented dielectric cylinders above a rough dielectric surface
  - Extended to multi-layer multi-species discrete scatterer model with rough surface representing ground
  - Simulation of full Stokes matrix and polarization signature
- Analysis is based on wave theory; distorted Born approximation
  - Scattering and transmission matrices are formed, from which Stokes matrices are calculated

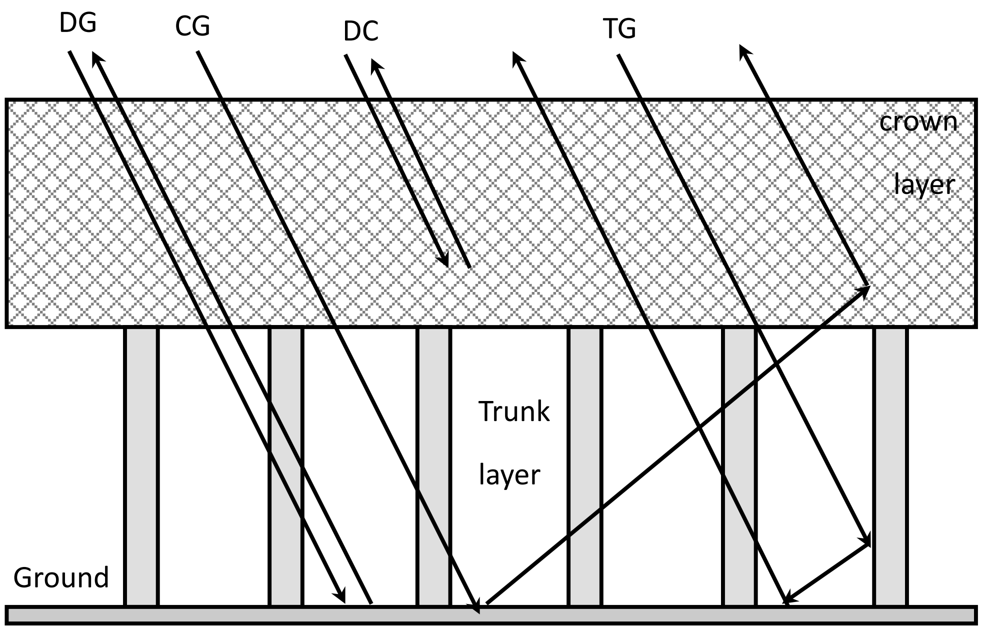
Model (2):

Species-specific parameters:

- Set of 27 parameters define geometry and structure of single species:
  - Soft- or hardwood
  - Dielectric characteristics of leaves, branches, trunks, soil
  - Densities, lengths, radii
  - Probability density function (pdf's) for orientation of branches, trunks

- Allometric relations exist for different species, ideally unique relationships
  - Knowledge of plant anatomy results in species-specific relations for modeling

Single species geometry:



Model considers four scattering mechanisms:

- Direct backscatter from crown layer (DC)
- Direct backscattering from ground (DG)
- Specular crown scattering followed by ground reflection (CG) modified for surface roughness
- Specular trunk scattering followed by ground reflection (TG)

Single species setup:

- Total Stokes matrix found by summing the matrices of the different scattering mechanisms

$$M_{Total} = M_b + T_b T_t M_g T_t T_b + T_b T_t M_{bg} T_t T_b + T_b T_t M_{tg} T_t T_b$$

M: Stokes matrix for backscattering

T: Stokes matrix for transmission through layer

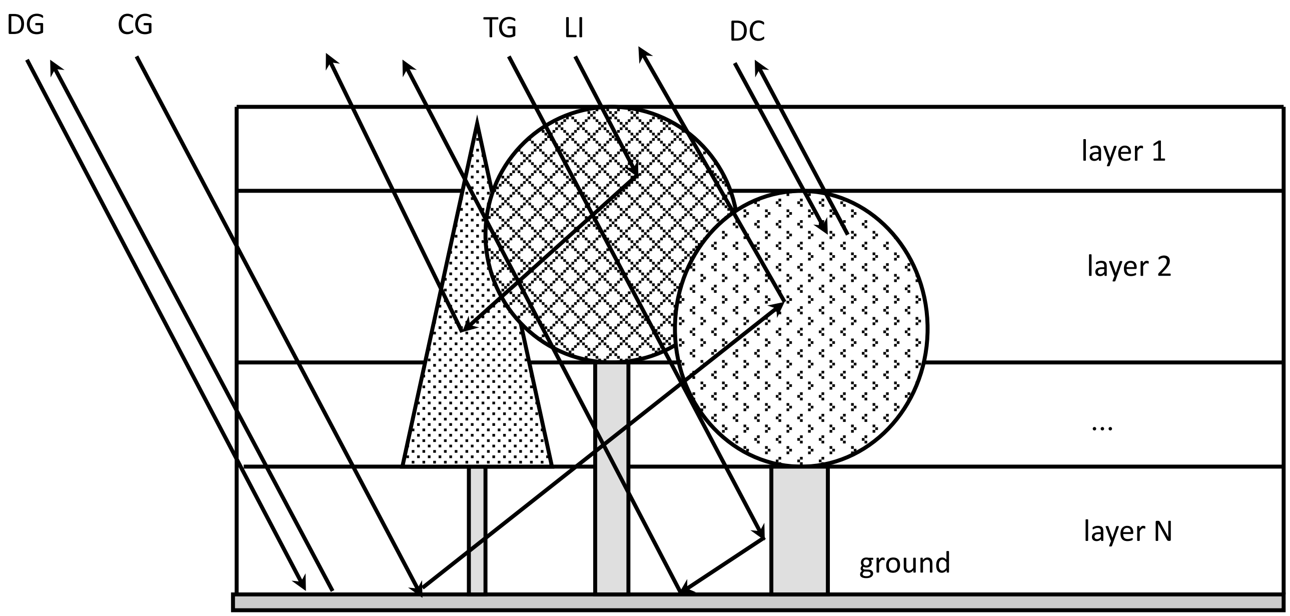
b: Branch layer

t: Trunk layer

g: Ground

Multi-species geometry:

- Introduction of more species will result in N layers
- Determination of layer composition, including that of overlapping layers is an important step
- Model proceeds with methodical calculation of layer scattering, attenuation and interaction



Multi-species setup:

M: Stokes matrix for backscattering
T: Stokes matrix for transmission through layer
b: Branch layer
t: Trunk layer
g: Ground

- Total Stokes matrix for multi-species model:

$$M_{Total} = M_b + M_g + M_{bg} + M_{tg} + M_{li}$$

$$M_b = M_{bL1} + T_{L1} M_{bL2} T_{L1} + T_{L1} T_{L2} \ldots T_{LN-1} M_{bLN} T_{LN-1} \ldots T_{L2} T_{L1}$$

$$M_g = T_{L1} T_{L2} \ldots T_{LN-1} M_{gLN} T_{LN-1} \ldots T_{L2} T_{L1}$$

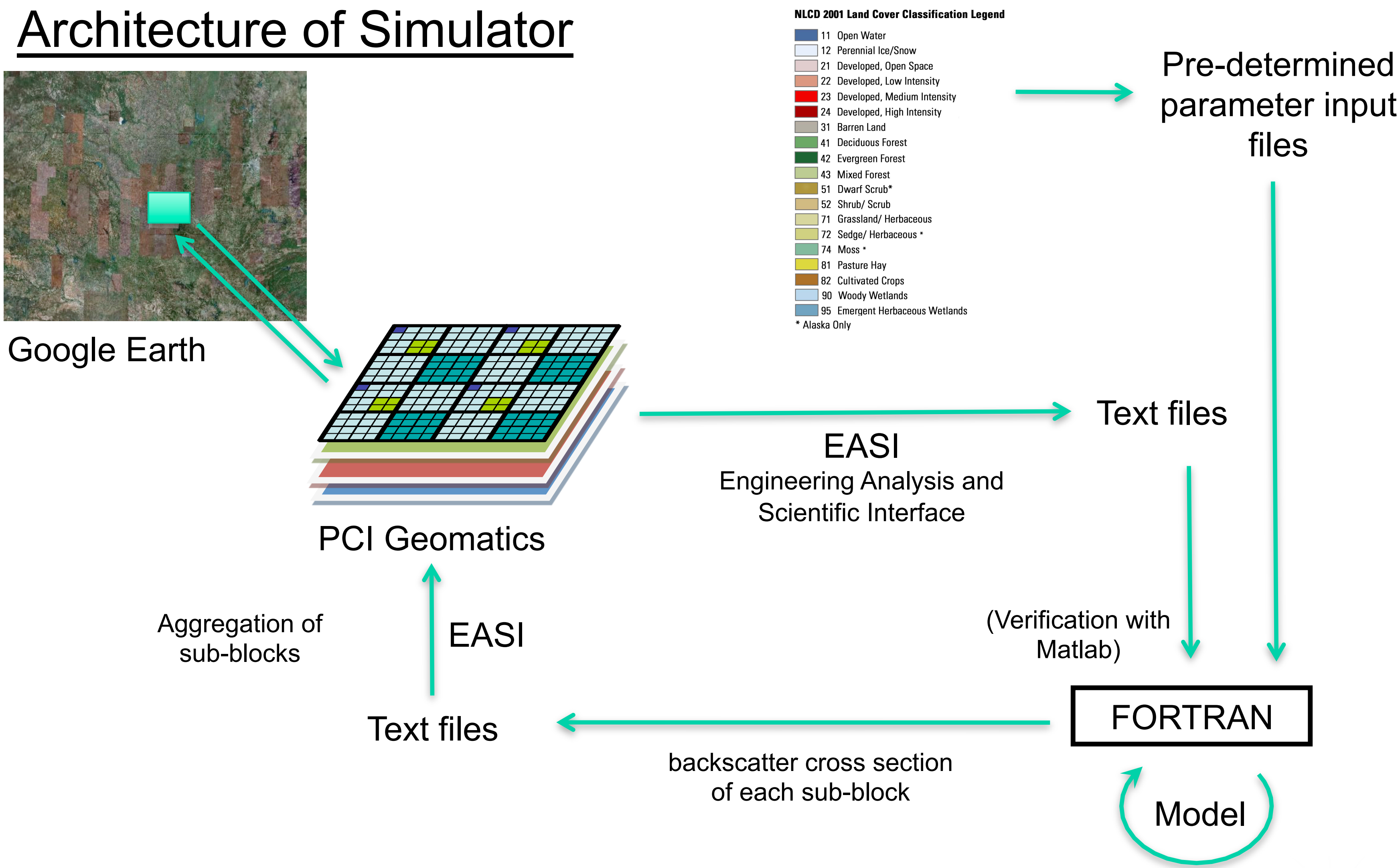
$$M_{bg} = T_{L1} T_{L2} \ldots T_{LN-1} M_{bg1LN} T_{LN-1} \ldots T_{L2} T_{L1} + T_{L1} T_{L2} \ldots T_{LN-1} M_{bg2LN} T_{LN-1} \ldots T_{L2} T_{L1} + \cdots$$

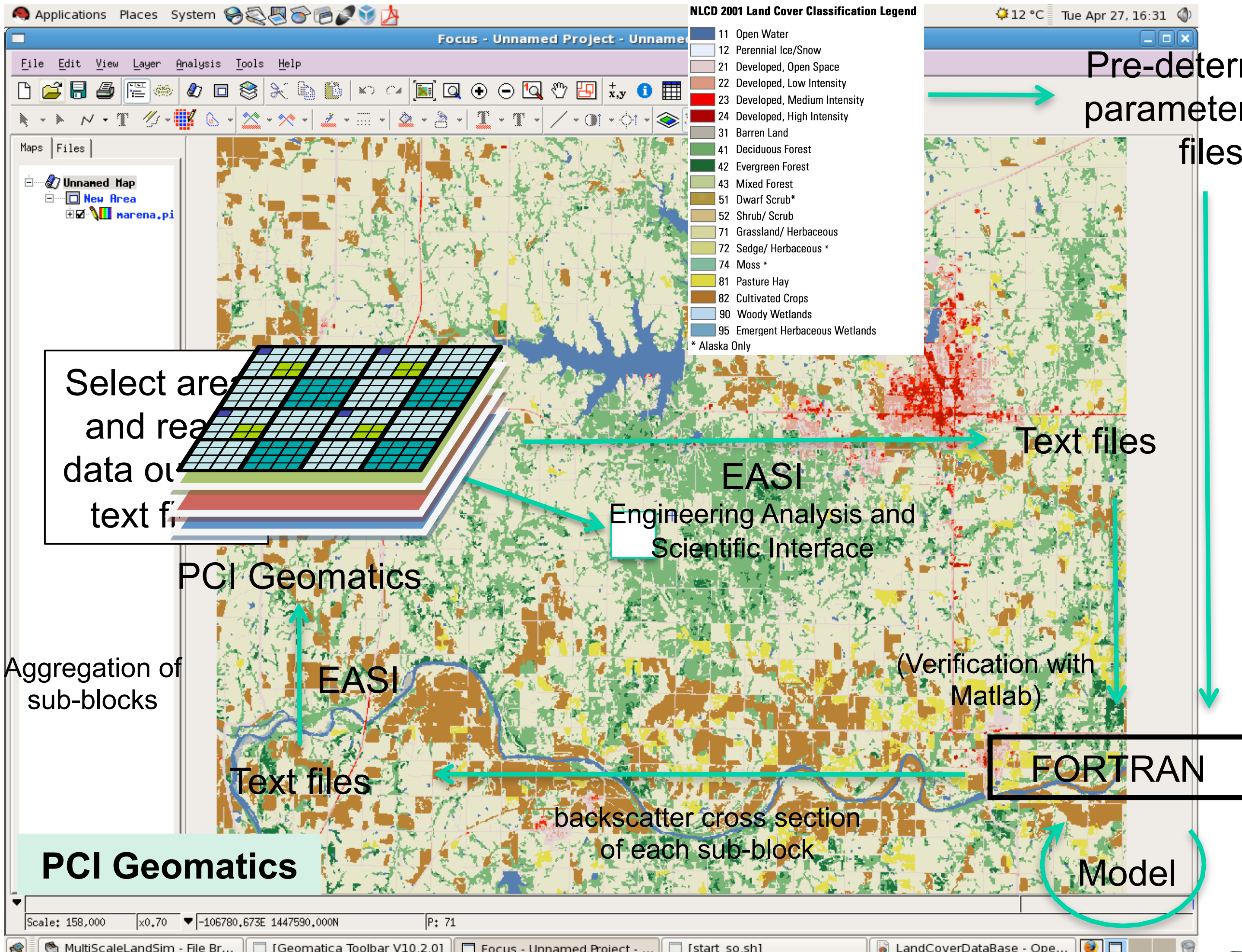
$$M_{tg} = T_{L1} T_{L2} \ldots T_{LN-1} M_{tg1LN} T_{LN-1} \ldots T_{L2} T_{L1} + T_{L1} T_{L2} \ldots T_{LN-1} M_{tg2LN} T_{LN-1} \ldots T_{L2} T_{L1} + \cdots$$

$$M_{li} = M_{liL1s1L2s2} T_{L1} + M_{liL1s1L3s2} T_{L2} T_{L1} + \ldots + T_{L1} M_{liL2s1L3s2} T_{L2} T_{L1} + \ldots + \ldots + T_{L1} M_{liL2L3} T_{L2} T_{L1} + \cdots$$

TL1, ...TLN: can contain combination of crown and trunk layer, depending on geometry

Architecture of Simulator

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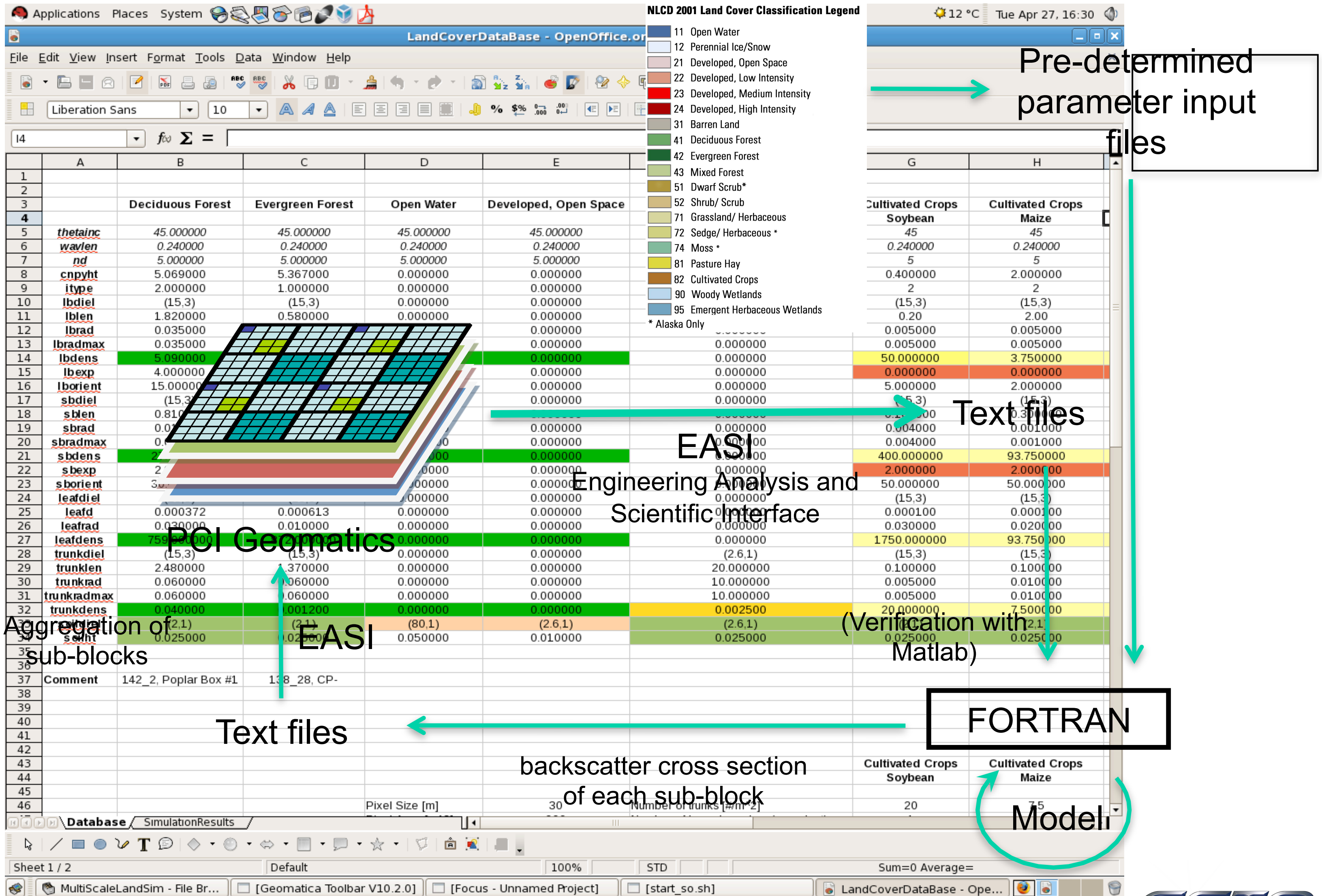
72 Sedge/ Herbaceous *
74 Moss *
81 Pasture Hay
82 Cultivated Crops
90 Woody Wetlands
95 Emergent Herbaceous Wetlands
* Alaska Only
Focus - Unnamed Project
Pre-determined parameter input files
Select area and read data out to text files
Text files
EASI
Engineering Analysis and Scientific Interface
PCI Geomatics
Aggregation of sub-blocks
EASI
(Verification with Matlab)
FORTRAN
Text files
backscatter cross section of each sub-block
Model
PCI Geomatics

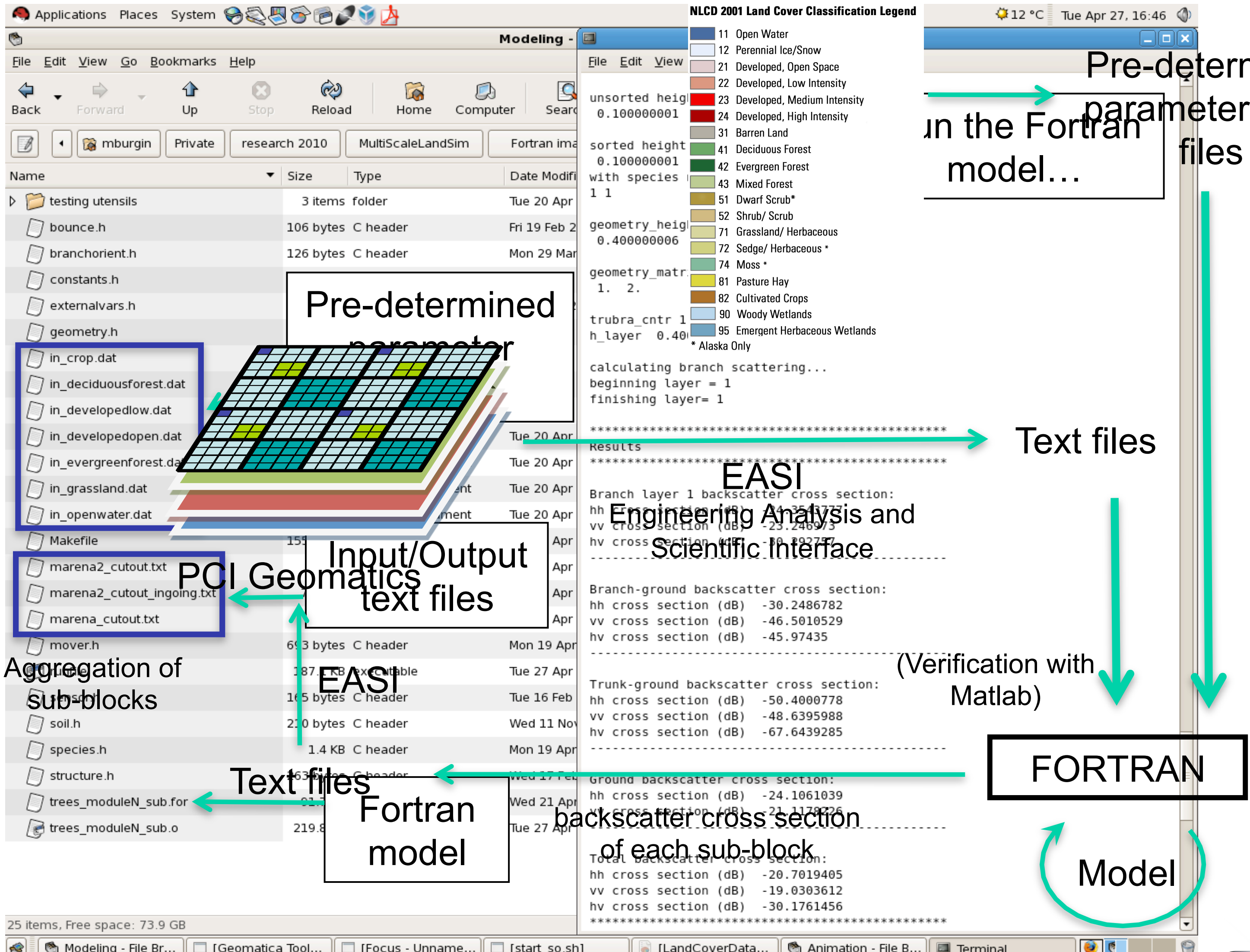
Control System

Landscape Simulator

Communication & Actuation

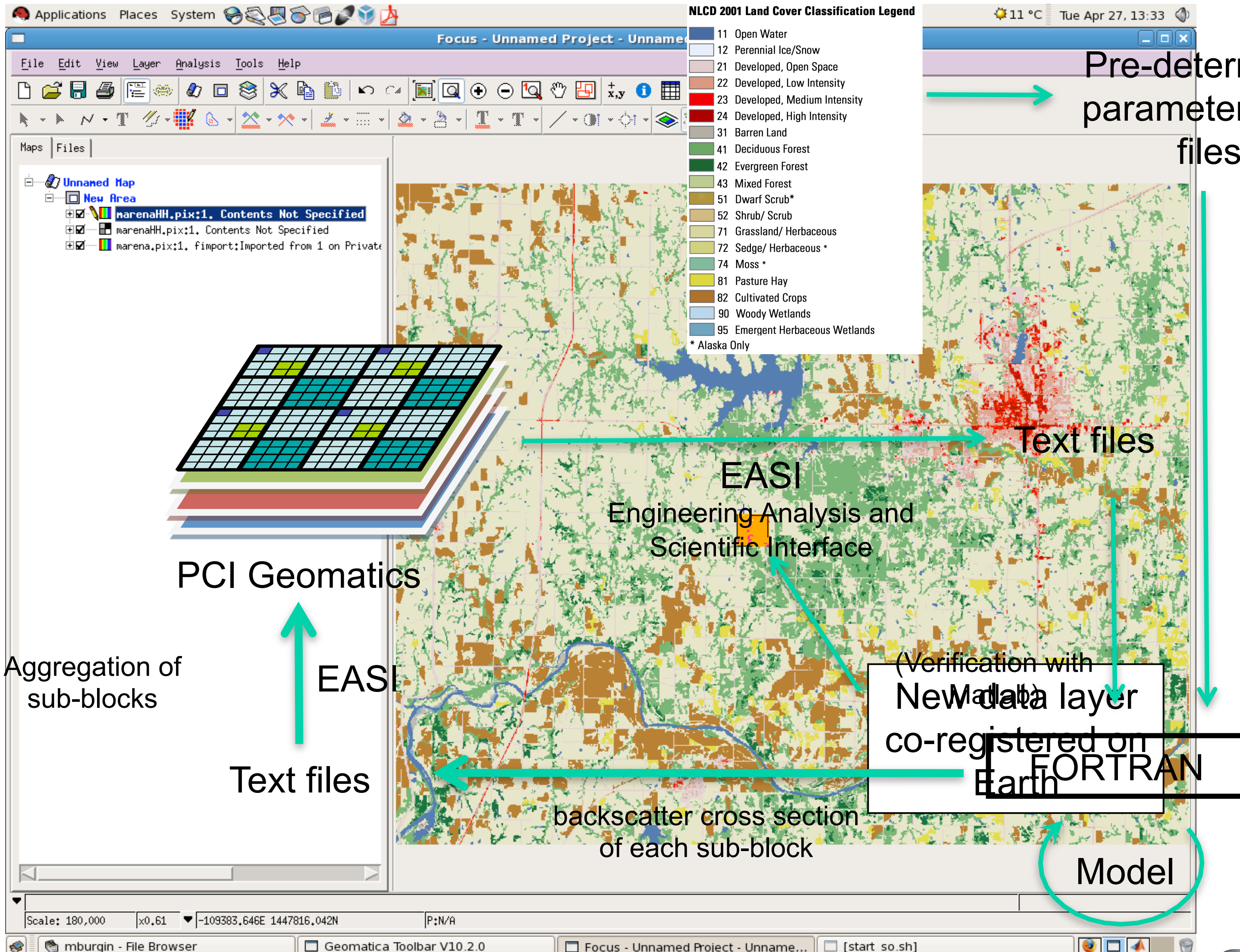


ESTO Earth Science Technology Office

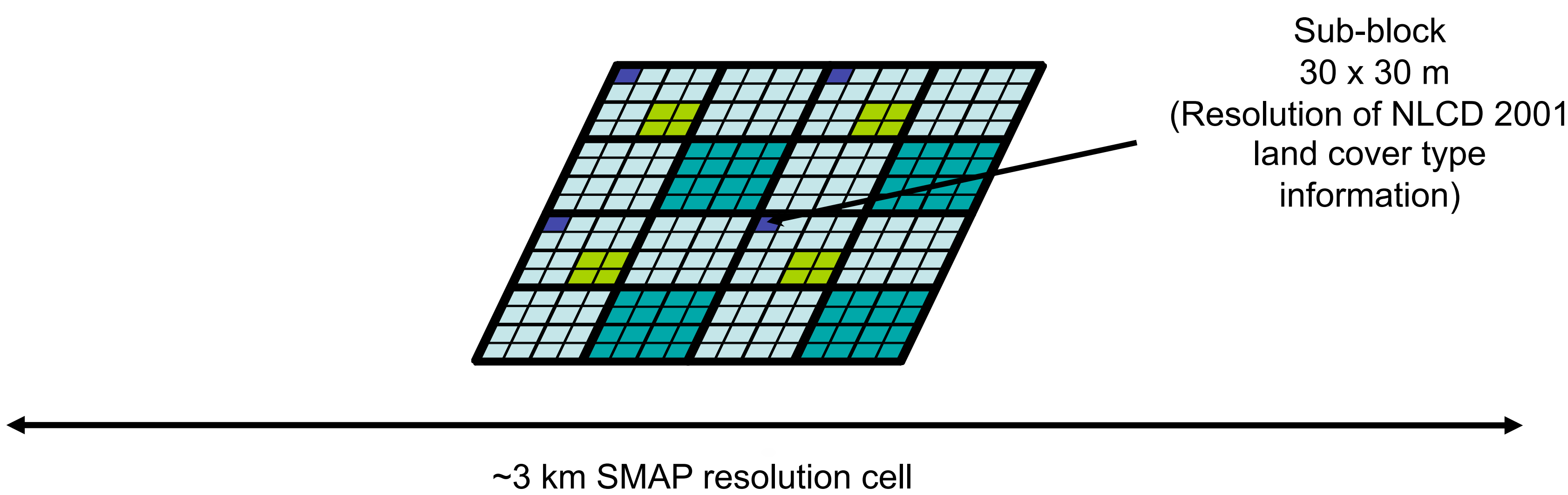


Earth Science Technology Office

Control System | **Landscape Simulator** | Communication & Actuation



Architecture, con't.

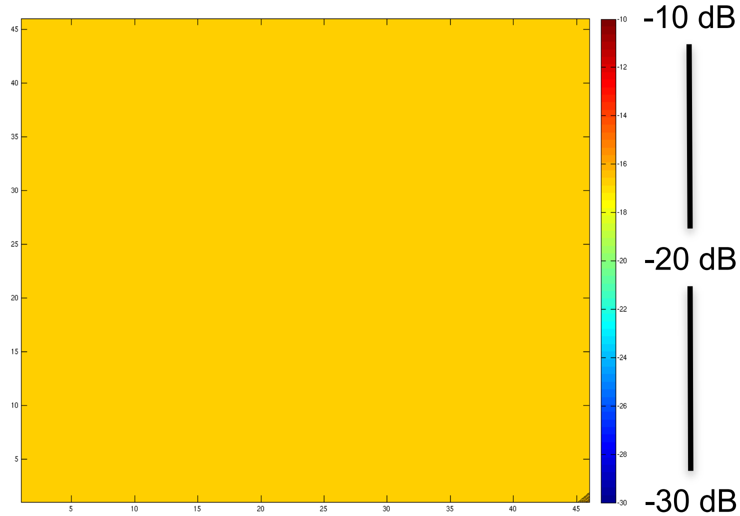


- Backscatter cross section from each sub-block is calculated
- Aggregation types can be investigated: blocks of 4 (light green), 16 (dark green), 64, etc., to achieve a statistically representative mean value for the backscattering cross section of the scene (e.g., for one SMAP pixel)
- Final result can be exported to PCI & Google Earth for visualization
- Will be used in the future as basis for *disaggregation* analysis for SMAP retrievals

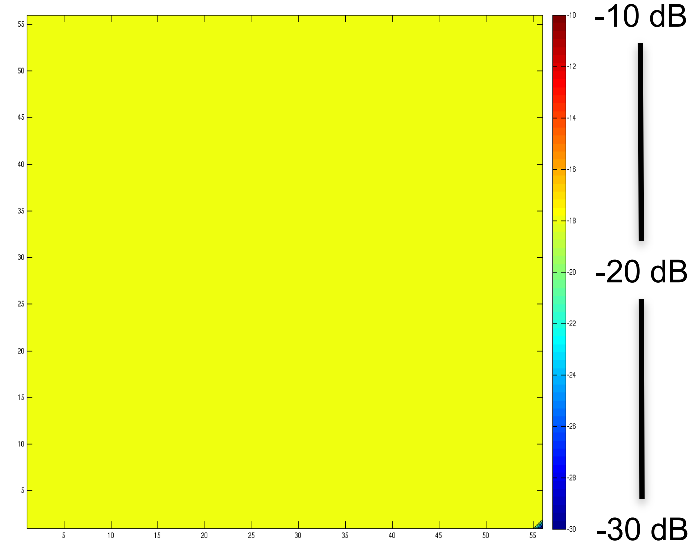
First results:

HH backscatter coefficient in dB for L-band

Canton



Marena

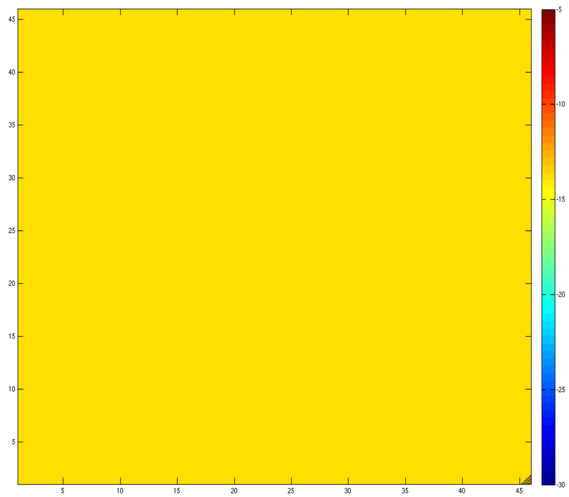


1. Google Earth
2. Land cover type from NLCD 2001
3. Backscatter coefficient
   a) Block of 1 x 1 sub-blocks
   b) Block of 2 x 2 sub-blocks
   c) Block of 4 x 4 sub-blocks
   d) Block containing all sub-blocks

- The final aggregation stage is similar to what SMAP radar sees
- Landscape detail is lost
- Current aggregation simply shows linear averaging; in reality SMAP data might correspond to some other (nonuniform or nonlinear) aggregation

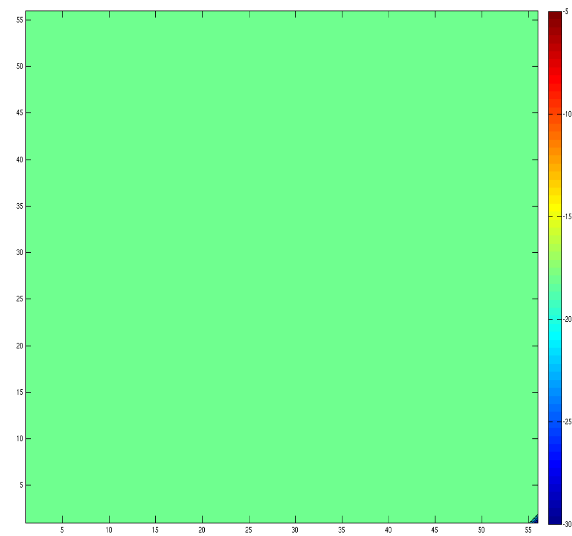
First results: VV backscatter coefficient in dB for L-band

Canton



-5 dB
-17.5 dB
-30 dB

Marena



-5 dB
-17.5 dB
-30 dB

1. Google Earth
2. Land cover type from NLCD 2001
3. Backscatter coefficient
   a) Block of 1 x 1 sub-blocks
   b) Block of 2 x 2 sub-blocks
   c) Block of 4 x 4 sub-blocks
   d) Block containing all sub-blocks

- VV results are similar to HH
- This aggregation simply shows linear averaging; in reality SMAP data might correspond to some other (nonuniform or nonlinear) aggregation

Ongoing Activities

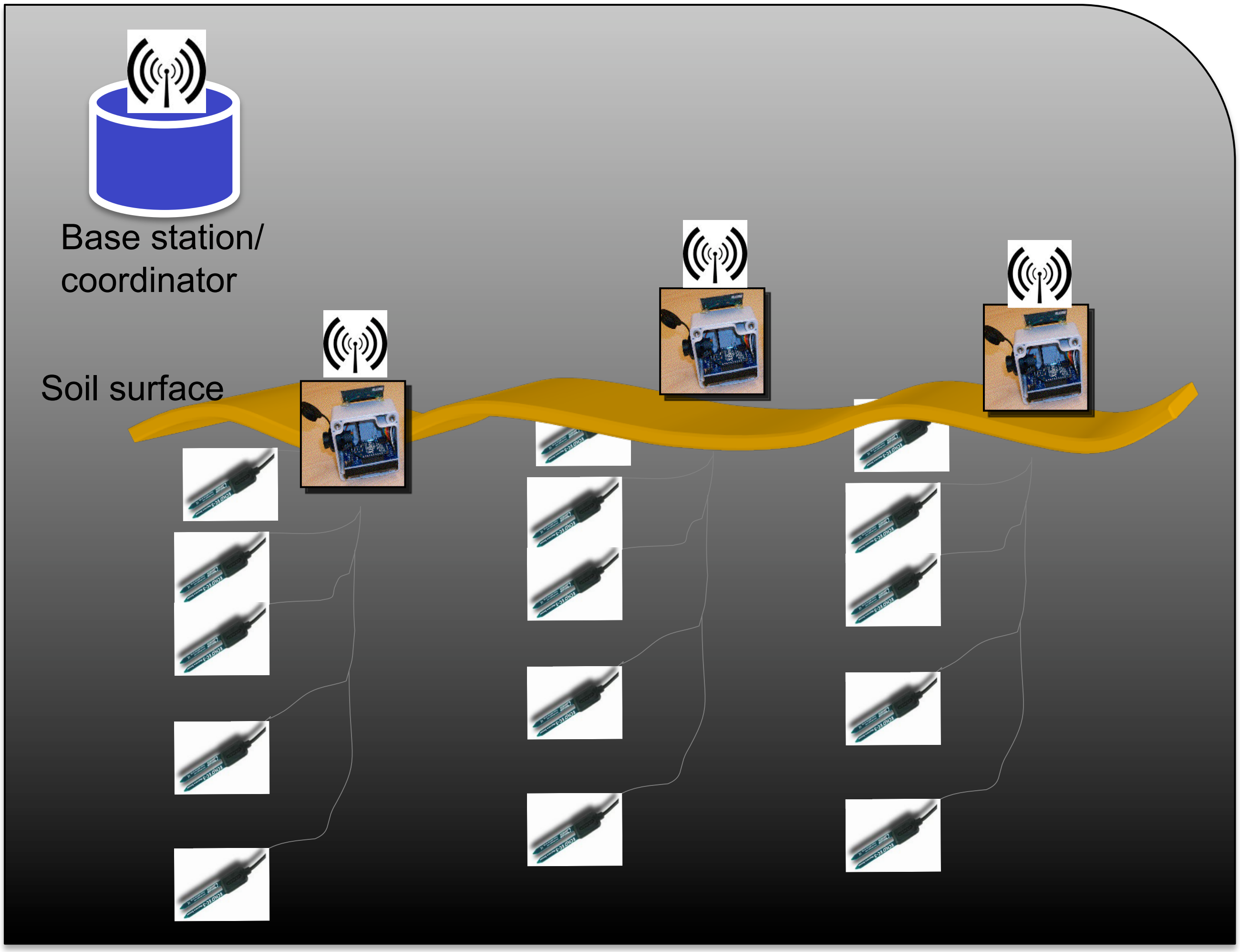
- Improve modeling and finalize landscape simulator:
  - Search for and integrate more available information
  - Use more ancillary data to build input files of sub-blocks to make modeling as realistic as possible
  - Integrate topography (slope, etc.)

- Investigate forward-mode multi-scale aggregation/disaggregation
  - Can a coarse resolution measurement be represented as a weighted sum of the fine-resolution ones? What statistical rules apply?
  - Study sensitivity of answer to above question to perturbations in soil moisture

Wireless Comm and Actuation System Overview

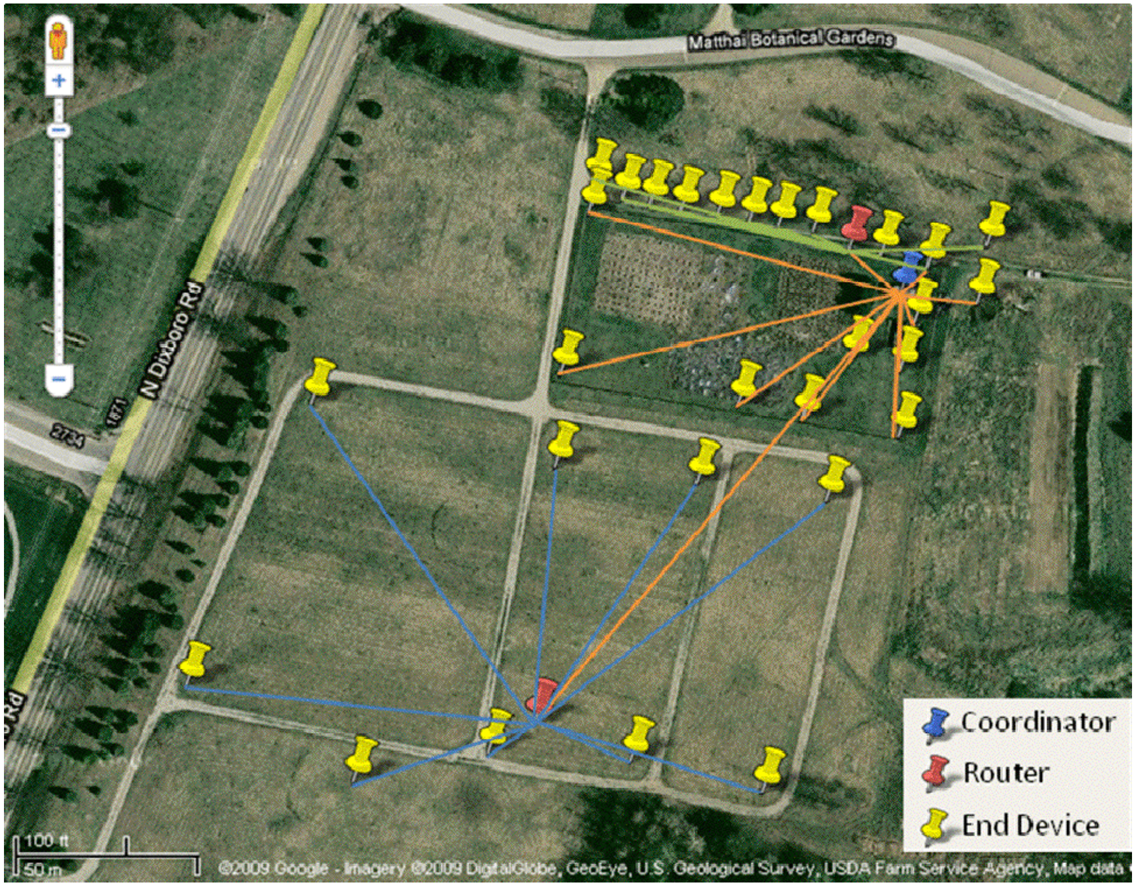
- Developed and successfully tested “Ripple-1” wireless sensor nodes for field deployment at U of M Matthaei Botanical Gardens
- Started on the design of “Ripple-2” ground unit platform to provide better energy efficiency for router nodes
- Webpage released, with a backend database to store and retrieve real-time soil moisture data collected at the Botanical Gardens

Functional view



- Soil moisture observations provided by sparse set of sensors in the field
- Each sensor sends data to coordinating center via a wireless network
- Base station assimilates data, generates control, and sends that to actuators at sensor locations

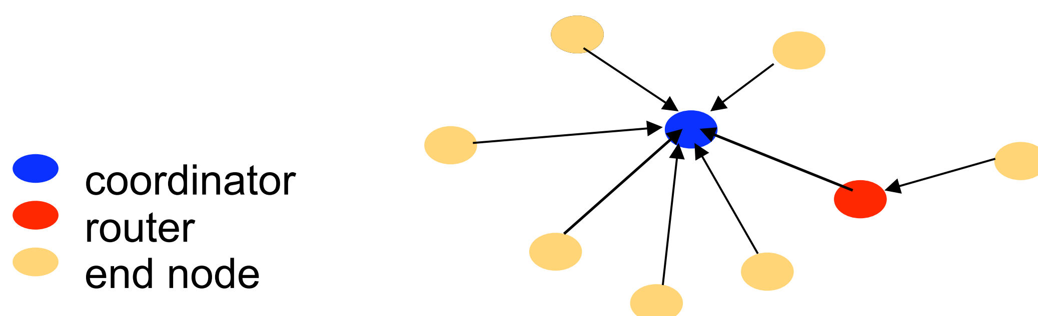
Field Deployment: Matthaei Botanical Gardens



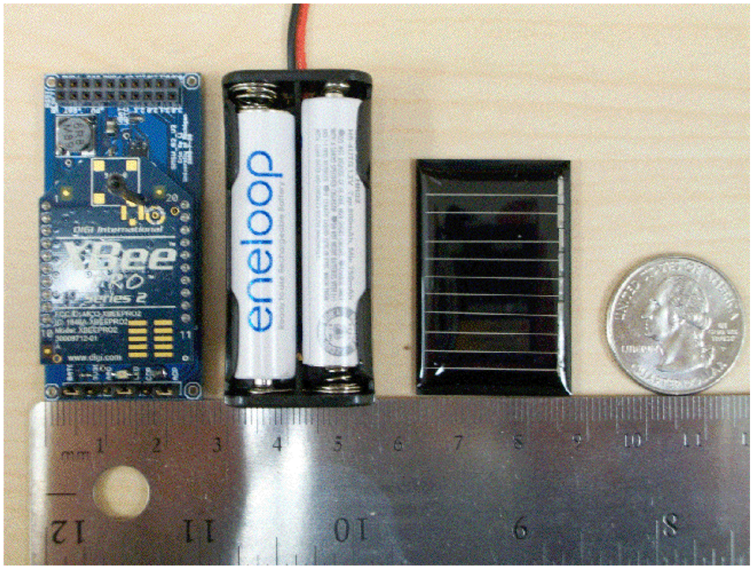
Thirty Ripple-1 sensor node were built and successfully deployed at Matthaei during our AIST-05 project. Figure shows the Zigbee network formed by these sensor nodes.

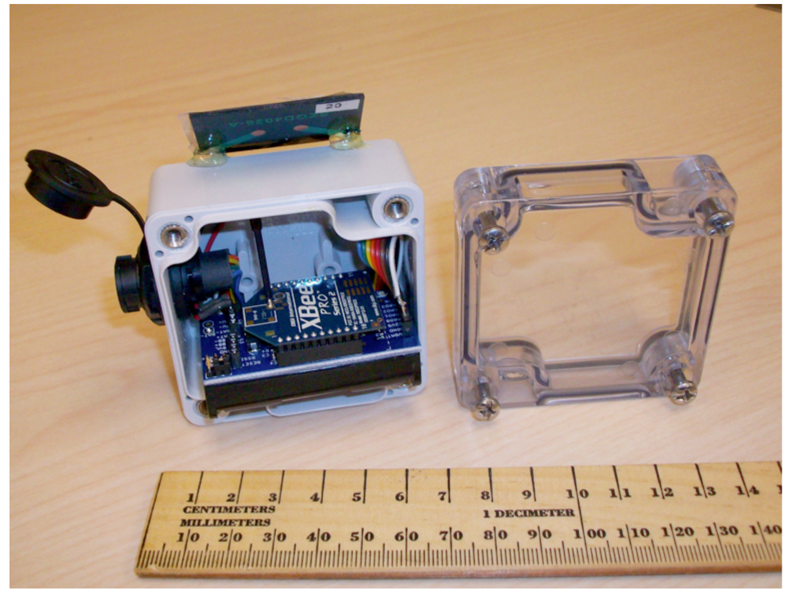
Ripple-1 ZigBee Network

- A multi-hop network consisting of three types of logic devices
- An end device is heavily duty cycled; the base station is plugged in; the router currently needs more power than desired
- Can remotely access sensors and control data collection
- Can remotely set the sensor and transceiver on cyclic sleep mode to better control energy consumption



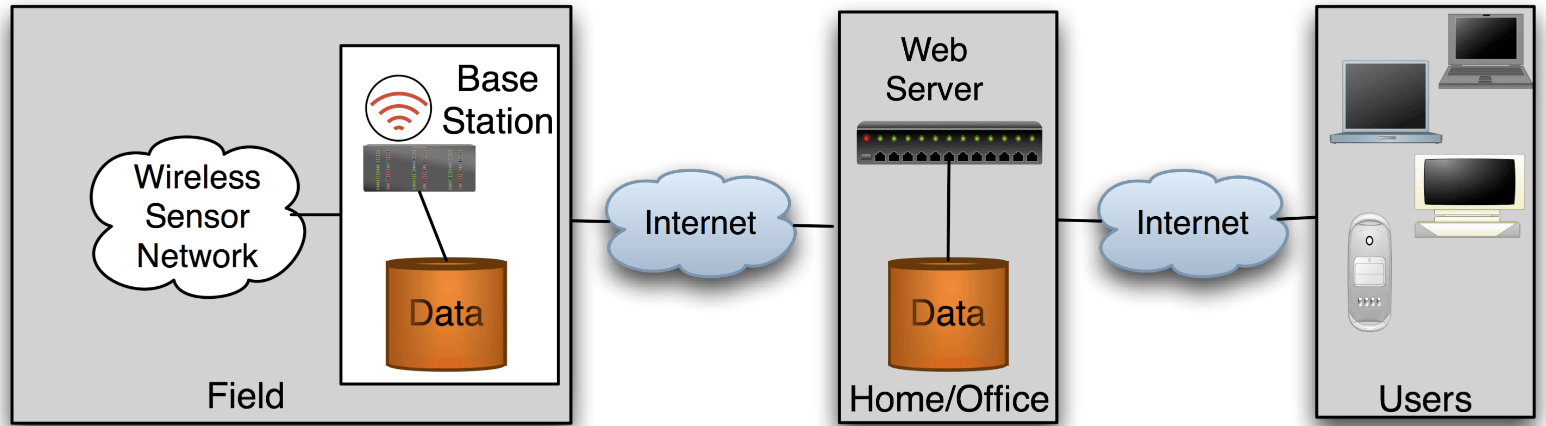
AIST-05: The Ripple-1 Node





- Xbee Pro SOC module serves as MCU and radio
  - Long Communication Range: up to 1 mile (1600 m)
  - Low Power Consumption
    - ✓ 295mA @3.3 V (TX)
    - ✓ 45 mA @3.3 V (RX)
    - ✓ < 10 uA (Sleep)

Global architecture of the Ripple system



- In target field
  - A sensor network consisting of multiple wireless ground units and sensors
  - An indoor base station; data stored in a database
  - Scheduling policy run on the base station
- On UM campus
  - Web site hosted on a server (soilscape.eecs.umich.edu)
  - Real-time data query and display
  - Enable mobile access

Plans for Deploying at SMAP 2010 Field Sites

- SMAP has deployed a network of ground sensors in Marena, OK, this spring
  - Primary goal is to benchmark various in-situ sensors against each other
  - May also investigate issues related to scaling of soil moisture measurements, but limited scope
- We plan to deploy networks concurrently
  - Marena, OK (interleaved with SMAP sensors)
  - Canton, OK (our network only)
  - Sites are within ~ 100 miles of each other, but Canton has more heterogeneity and allows better testing of optimal placement strategies

Summary

- Tested several candidate approaches for sensor placement optimization
  - Implemented and verified empirical placement strategies; started developing analytical joint placement/scheduling methodology
- Built landscape simulator
  - Simulator architecture developed, implemented, and tested; preliminary scaling studies performed
- Developed wireless sensor actuation and communication nodes
  - Multihop architecture investigated
- Ongoing collaborations with SMAP algorithms and cal/val team
  - Continually collaborating with team; will install in one or two of SMAP cal/val nodes (one in Oklahoma, another TBD)
- Various project elements at TRLs of 3 to 4