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Initial Analyses and Demonstration of a Soil Moisture Smart Sensor Web

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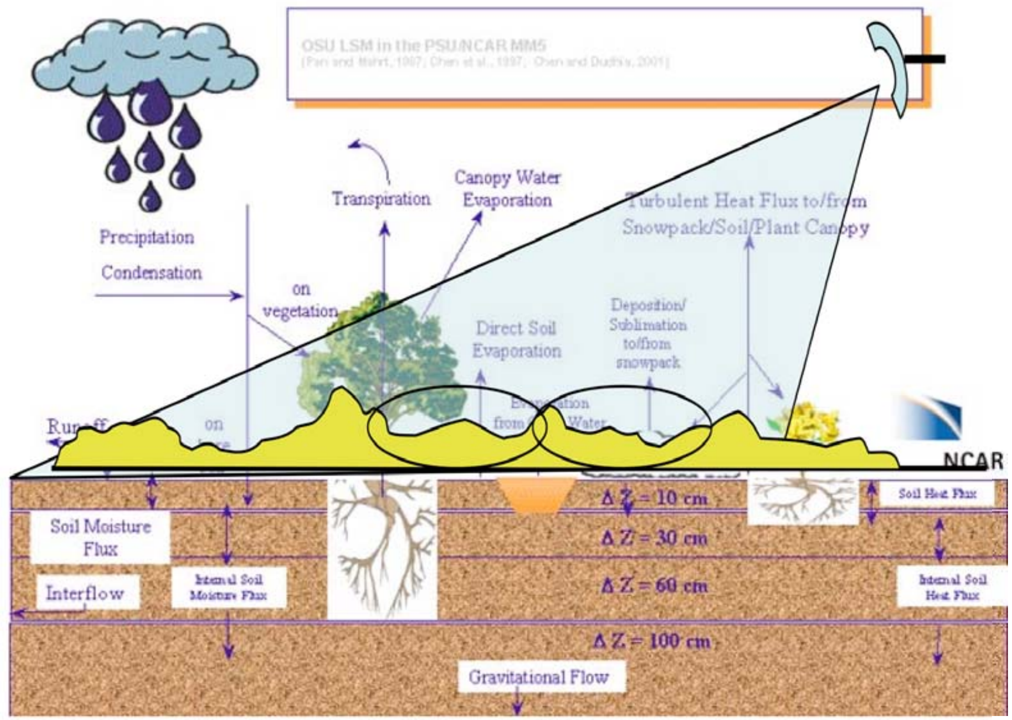
Problem Statement

- Variations of soil moisture are related to several physical processes: temperature, precipitation, vegetation, soil texture, topography, etc., each at a different scale
- Remote Sensing satellites give coarse-resolution estimates of a field mean. For soil moisture, e.g., the resolution is O(km) for radars and O(10km) for radiometers.



- ***Validation of remote-sensing-derived estimates is nontrivial***
  - Brute-force production of a ground-reference data set requires a dense sampling network
  - Estimating the field mean that is representative of the true mean requires sampling at varying scales

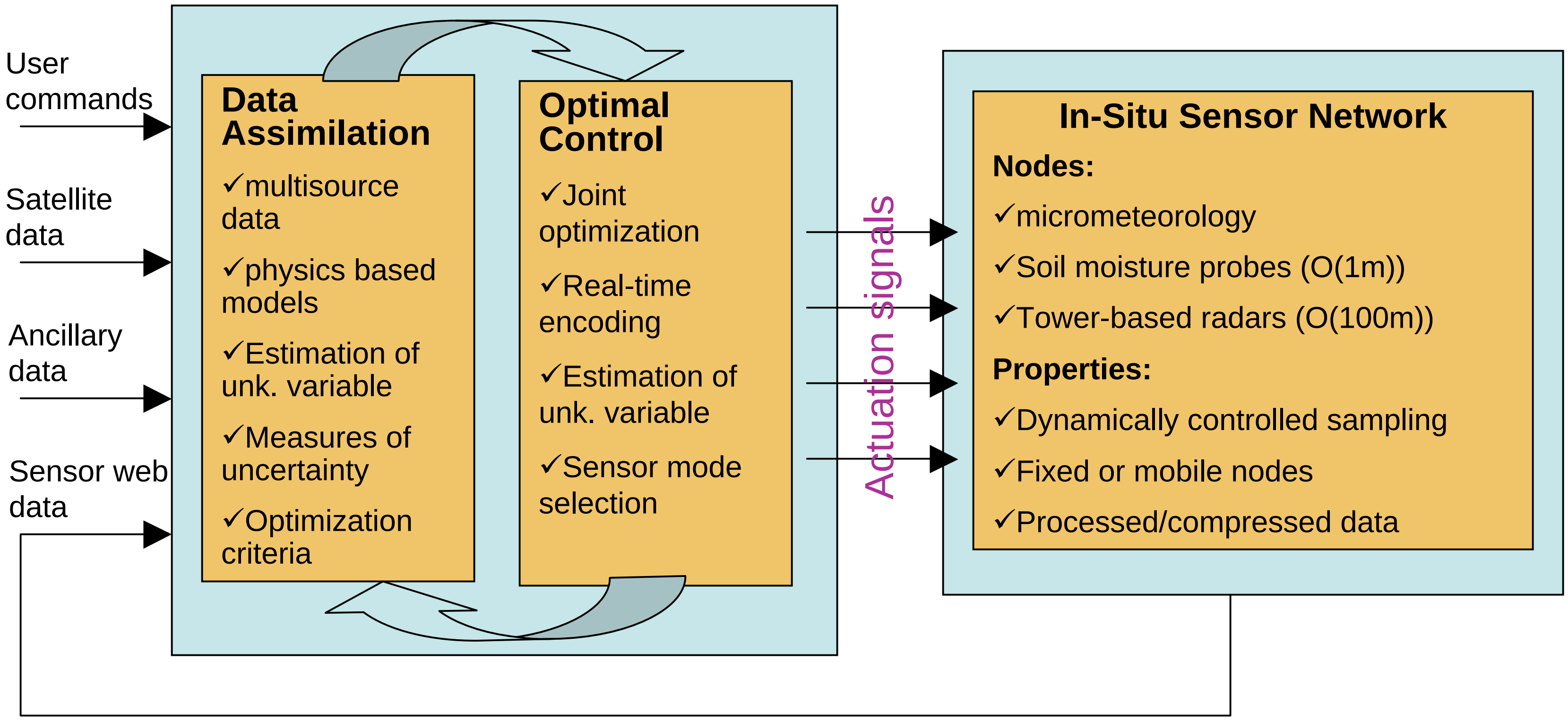
Overview

Objectives

- We are developing a “smart” in-situ sensor web to accomplish this sampling task using a spatially and temporally sparse network
- The approach is to develop a sensor web control system
  - Control system is guided by optimization criteria derived from physics-based sensor models and physics-based dynamic system evolution models
  - The dynamic system model is implemented within a data assimilation framework, which quantifies the relationships between the measured/estimated variable and the responsible physical processes
- The outcome can directly benefit the Soil Moisture Active-Passive (SMAP) mission validation activities

Overview

Overall Architecture



- The semi-closed system generates guidance to the sensor web, via actuators, for modifying its sampling characteristics
- Guidance is derived from coupled data assimilation and control system, antecedent sensor data, and ancillary data
- User command can also be incorporated

Overview

System Test Bed

(1) Numerical Implementation

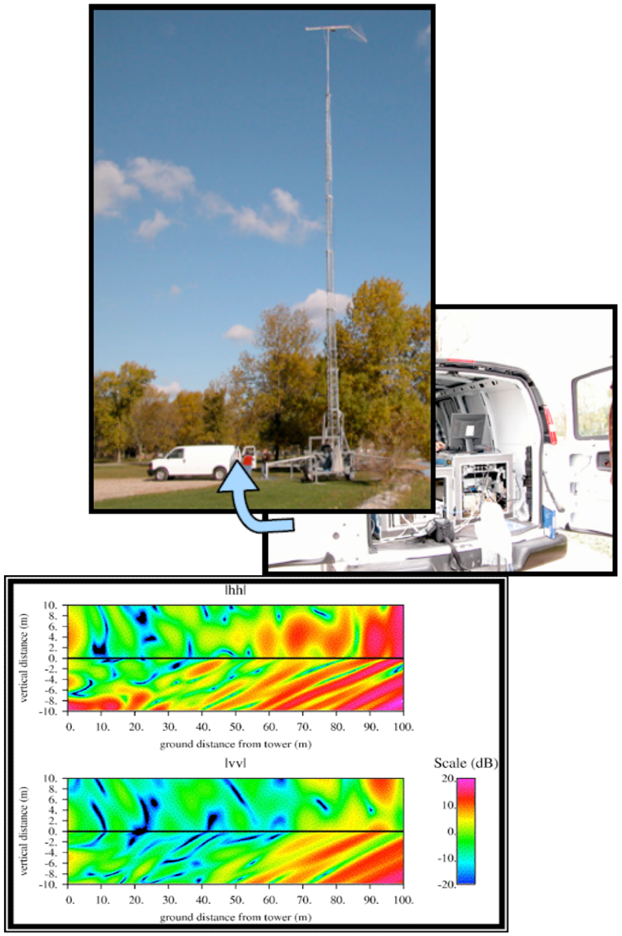
- Use actual and/or simulated field data, including remotely sensed and in-situ measurements
- Generate static estimates of soil moisture fields using sensor models
- Simulate soil moisture dynamic evolution model
- Numerically simulate the control system, initially with only one sensor node and later with more, using optimization criteria. Increase complexity up to available computational resources.

(2) Laboratory Demonstration

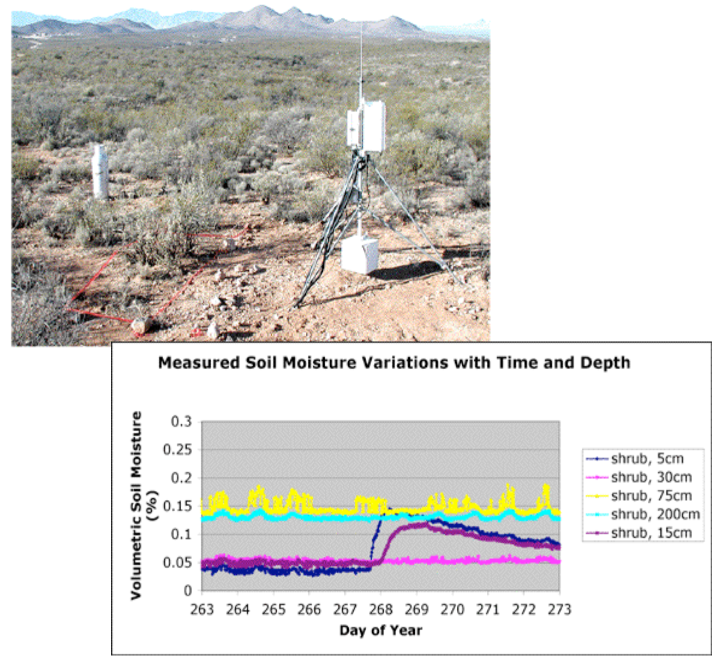
- Initialize the feedback loop with simulated or field data, then generate a set of control signals based on joint optimization
- Transmit control signal to sensor nodes; start with one, increase to half a dozen nodes for final demonstration
- Decode at actuator, and modify sensor settings
- Allow sensors to collect data; feed to assimilation system, feed to control system
- Repeat

Overview

Envisioned Field Demonstration Scenario



Field measurement at O(100m) and multiple depths with a single radar



Field measurement at O(1m) and multiple depths with multiple sensors

Project Components

Data Assimilation

Physical Model

- Dynamic evolution model of variable soil moisture fields (SWAP)
- $\underline{X}_{t+1} = f_t\,(\underline{X}_t, \underline{W}_t, \underline{a}_t)$

Measurement Model

- Soil moisture sensor observation models (probes, radars/radiometers)
- $Y_t^i = h_t^i(X_t^i, U_t^i) + V_t^i, \;\; i = 1,2,\ldots,L$

Control System

Control Strategies

- Estimation: $\hat{\underline{X}}_{t-1} = l_{t-1}(\underline{Y}_1,\ldots,\underline{Y}_{t-1},\underline{a}_1,\ldots,\underline{a}_{t-1},\underline{U}_1,\ldots,\underline{U}_{t-1})$
- Sensor configuration: $\underline{U}_t = g_t\,(\underline{Y}_1,\ldots,\underline{Y}_{t-1},\underline{a}_1,\ldots,\underline{a}_{t-1},\underline{U}_1,\ldots,\underline{U}_{t-1})$

Performance Criterion

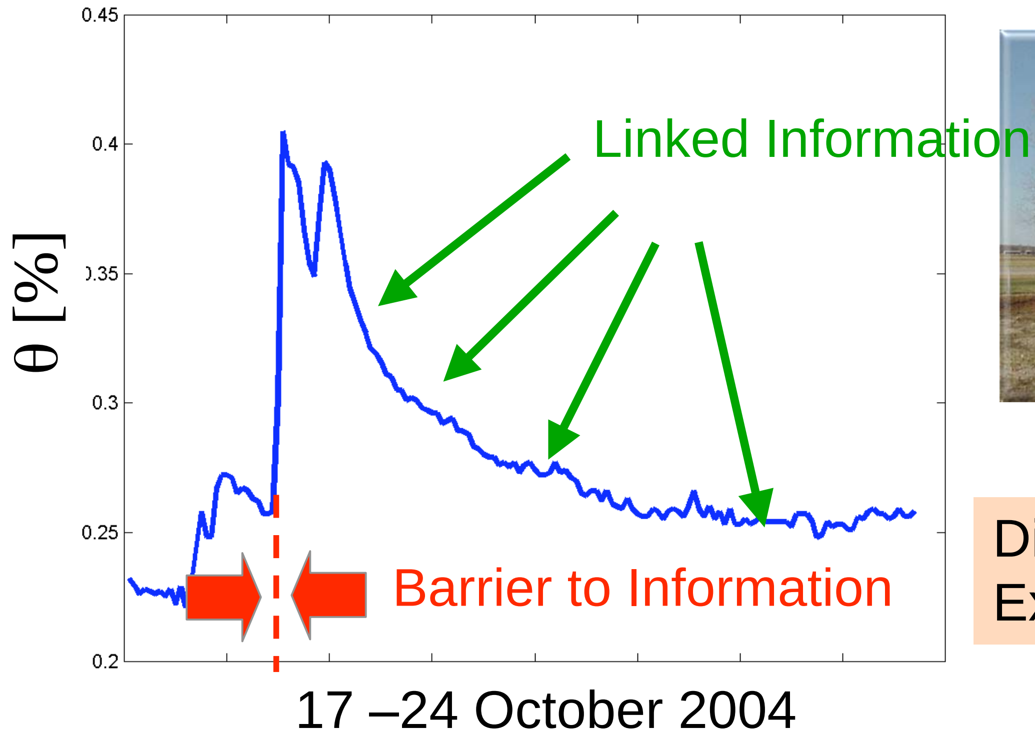
- Costs assessed to estimation error and energy consumption
- $J^{g,l} = \lim_{T\to\infty} \mathrm{E}^{g,l}\left\{\sum_{t=1}^{T} \alpha^{t-1}\left[\rho_t\,(\underline{X}_t, \hat{\underline{X}}_t, \underline{a}_t) + d\,(\underline{U}_t)\right]\right\}$

Experiments & Actuation

- Phase A
- Phase B

Soil Moisture Profile Evolution in Time and Depth

In Time:

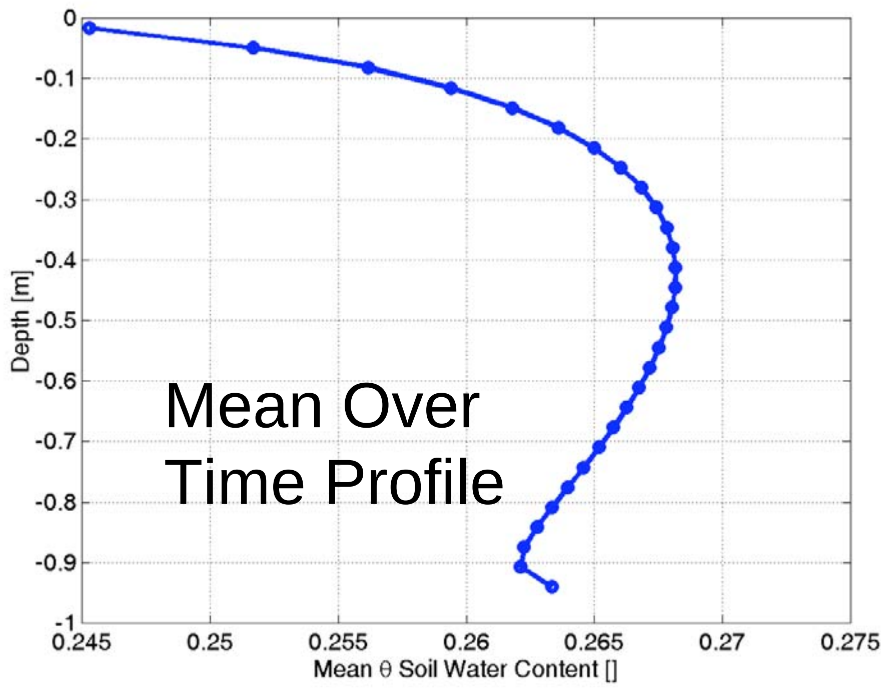


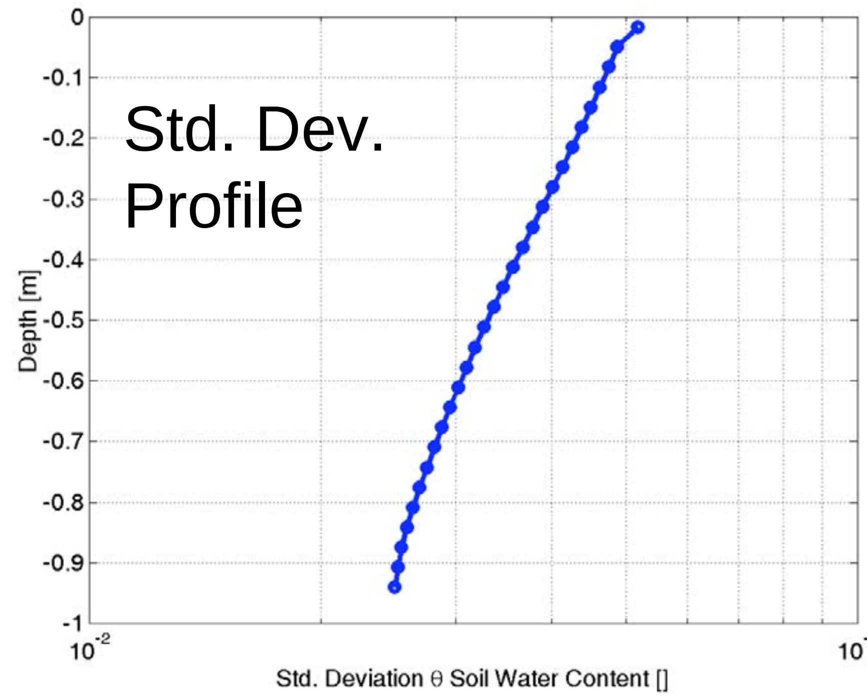
Newby Farm, Alabama
Site Number: 2059
Limestone County
Latitude: 34° 51' N
Longitude: 86° 53' W

Dissipative. But Forced With Exogenous Discontinuities.

Soil Moisture Profile Evolution in Time and Depth

In Space:

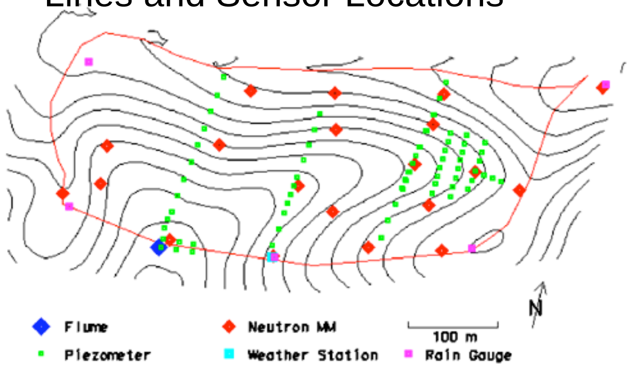




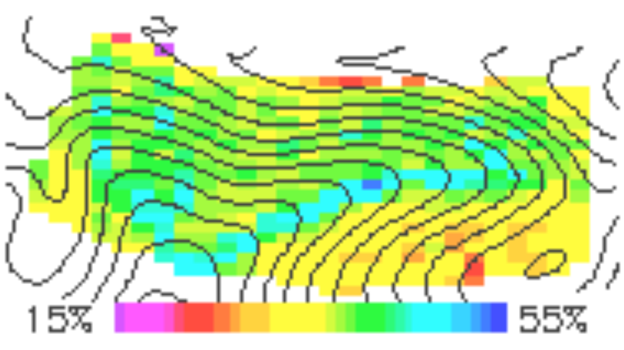
Amplitude Damped in –z Direction.
Phase Shift With Depth.

Soil Moisture Patterns as Function of Transverse Space

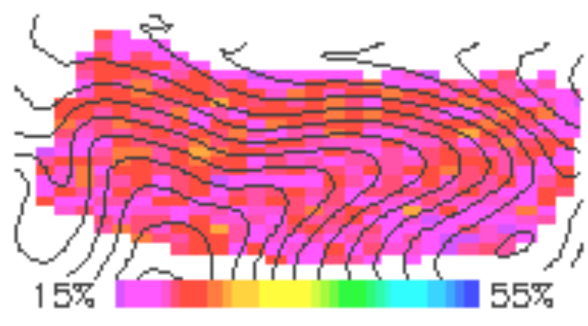
Basin Topography Contour Lines and Sensor Locations



Transverse plane spatial patterns of soil moisture state vector may also be included in the dynamic evolution model



Soil Moisture Pattern After Wetting Rainfall Event Follows Topography and Drainage Pattern

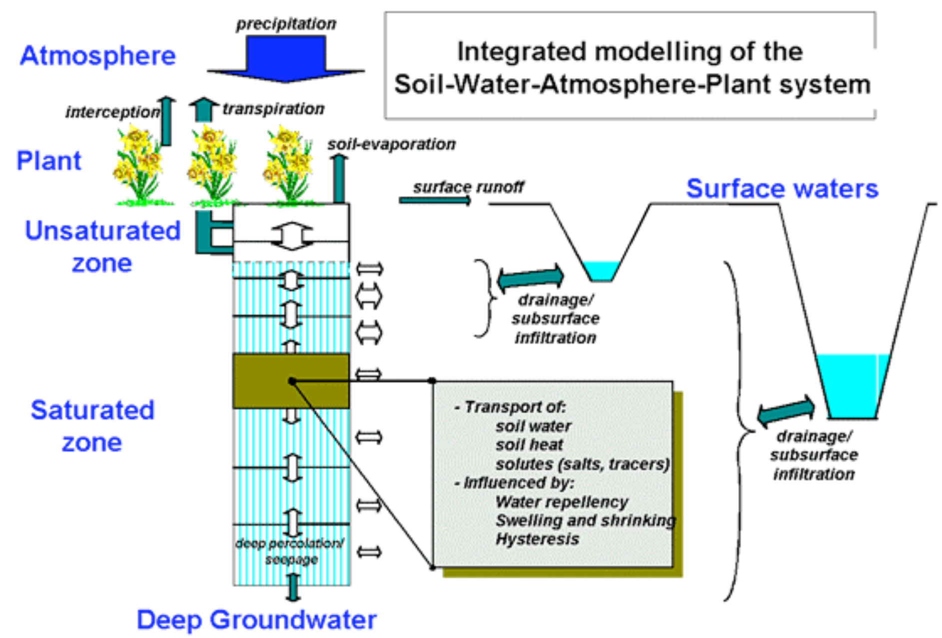


Soil Moisture Pattern After Dry-Down More Heterogeneous Due to Variations in Soil Texture and Vegetation Characteristics

From Western and Grayson, 1998: Water Resources Research, 34(10): pp 2765-2768.

Integrative Model: Soil Moisture and Heat Advection-Diffusion

- Models time and depth variations of soil moisture
- Incorporates Surface Energy Balance: Micrometeorological Data Such as Precipitation, Winds, Air Temperature and Humidity
- Incorporates Soil Physics: Flow Dynamics, Amplitude and Phase Characteristics

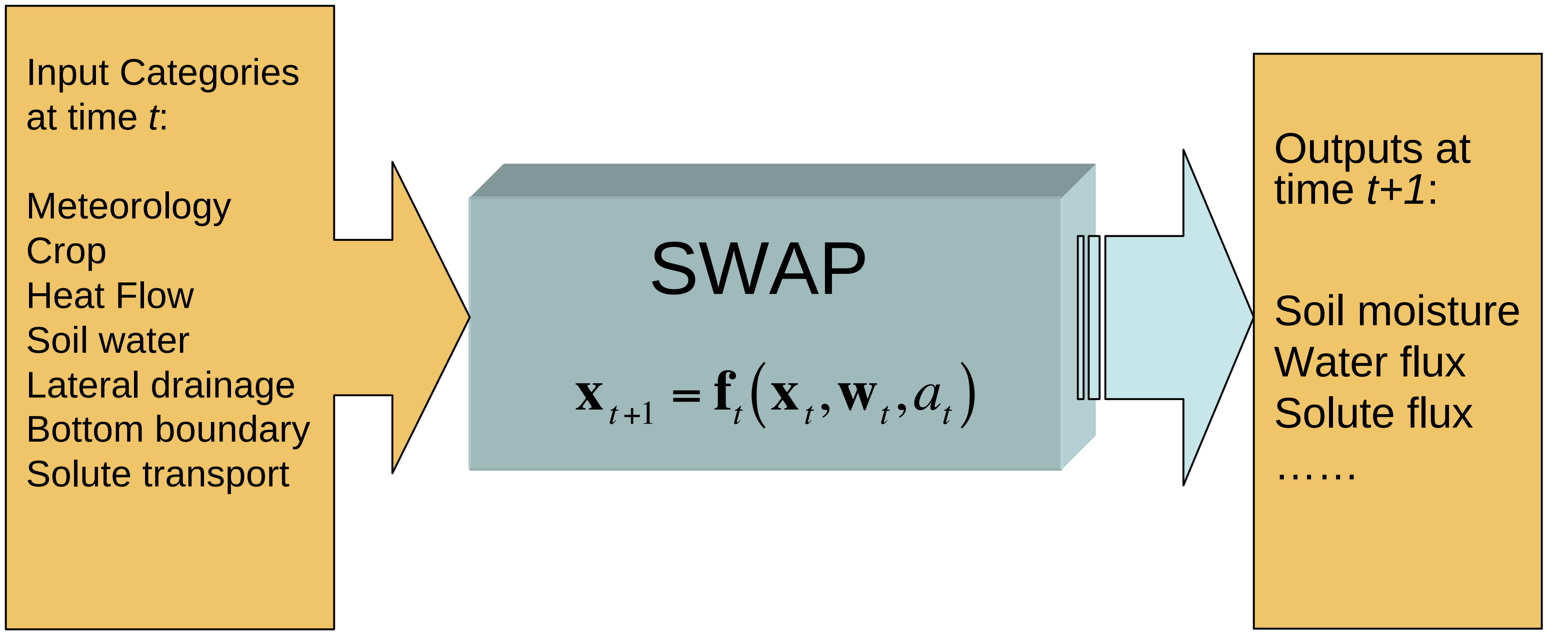


SWAP Model Developed in Netherlands

Among Community Standards

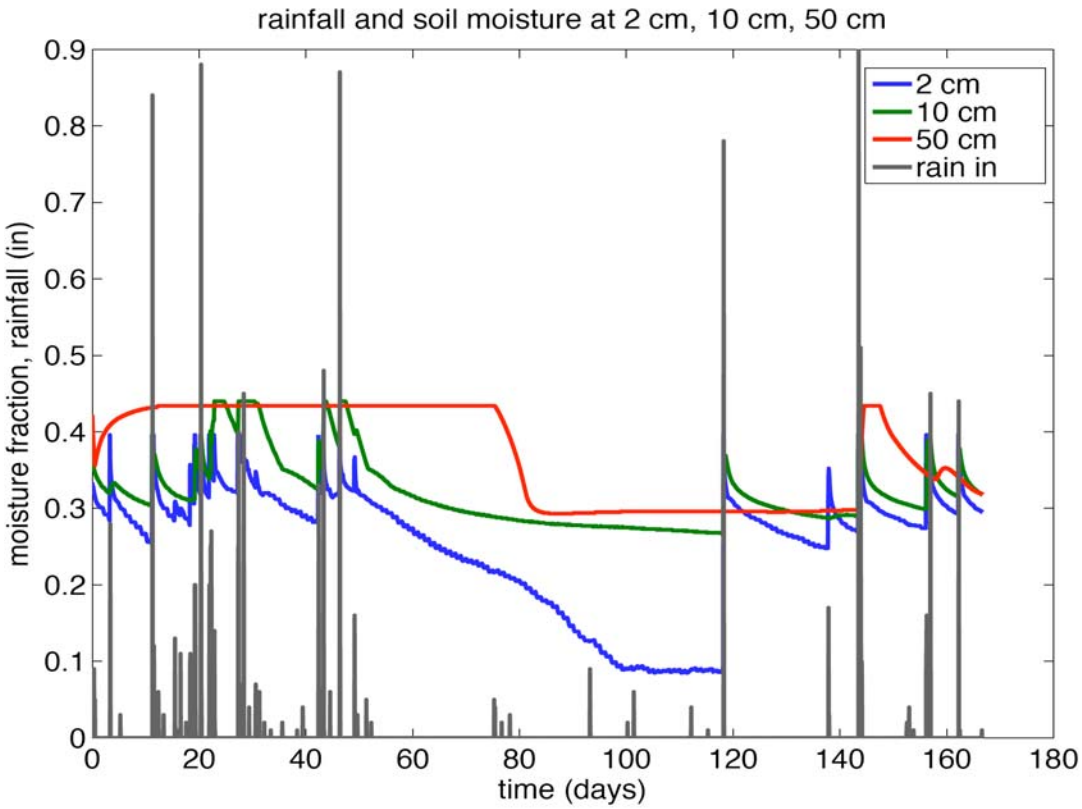
$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} K(\psi) \frac{\partial(\psi(\theta) + z)}{\partial z} - R(\theta)$$

$$C(\theta)\frac{\partial T}{\partial t} = \frac{\partial}{\partial z} D(\theta)\frac{\partial T}{\partial z}$$



- All parameters fixed at specific values for a hypothetical location
- Simulations performed at 1-hour intervals for a period of 20 years
- Actual rainfall values incorporated
- Other measured meteorological conditions also applied
- Soil moisture range calculated is 6% to 43%

Sample Soil Moisture Simulation Results from SWAP



- Soil moisture changes in response to rainfall
- Small amounts of rainfall do not present a significant trigger to soil moisture change
- Variations follow different patterns at different depths, much faster at surface
- This example generated for Tampa, FL

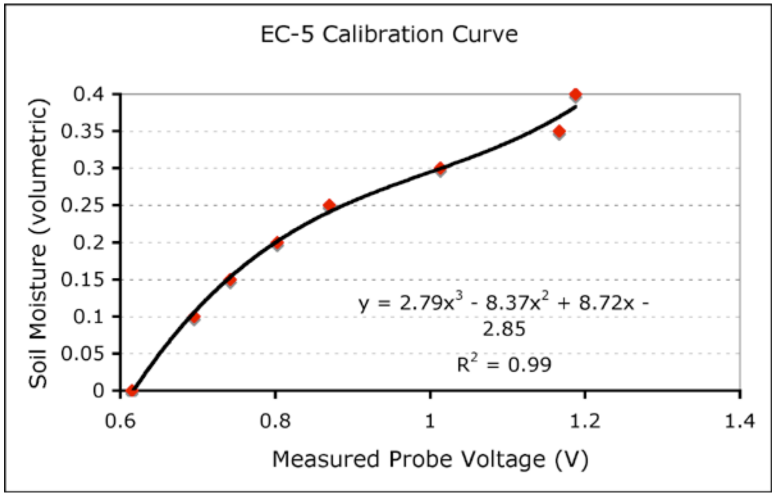
Goykhman/Farhadi

Static Sensor Models

- Validation sensors make observations that are translated into estimates of unknowns variables
- For observation time *t*, measurements are related to unknowns via a model h_t. Sensor models are static but can include probabilistic nature of unknowns at time *t*.
- Models and unknowns could be scalar (1-D) or vector (N-D)
- Different sensors allow estimates of the unknowns at different spatial scales
- Sensors could be in-situ (moisture probes) or remote (tower-based, airborne, or spaceborne SARs and radiometers)
- Estimation of unknowns could be a complex task, depending on the degree of model nonlinearity, measurement noise, and sensor calibration

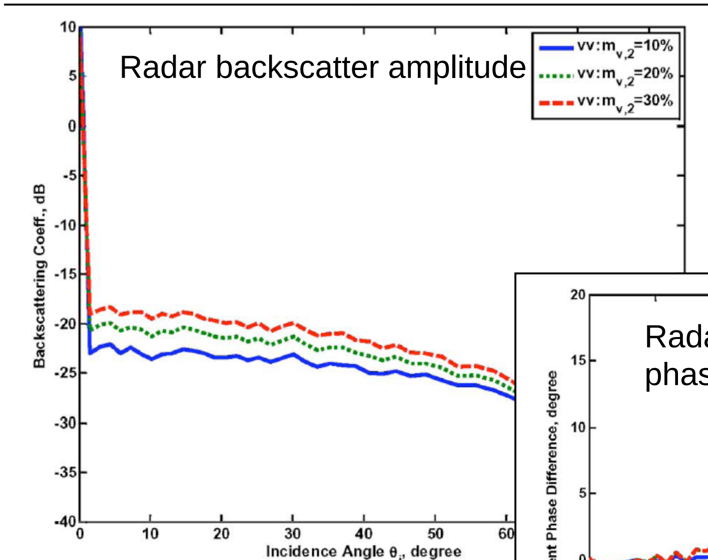
Static Sensor Model Example: in-situ probe

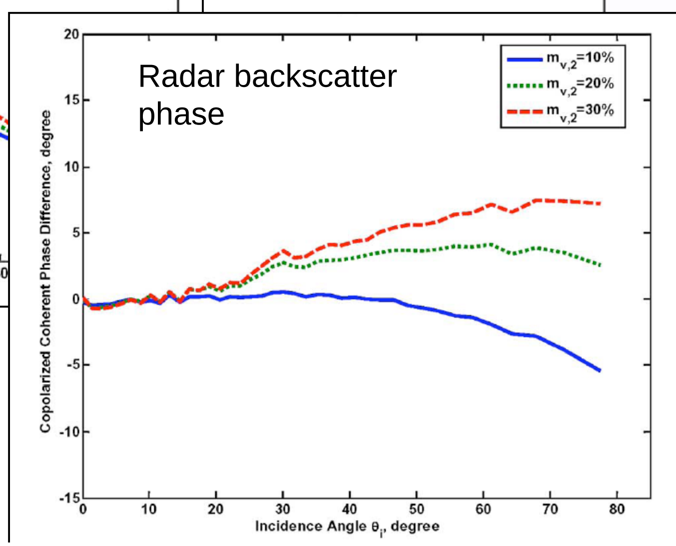
- Capacitance probes from Decagon, model ECH_2O EC-5
- Developed sensor model and calibration curve
  - Small calibration and retrieval error ("noise-free" is a good assumption)
  - Retrieval model is simple and amounts to solving a polynomial function
- Verified in lab that these sensors are highly stable
- In field, sensors will have self-calibration schedules at regular intervals
  - Conditions such as large temperature changes will alter schedule

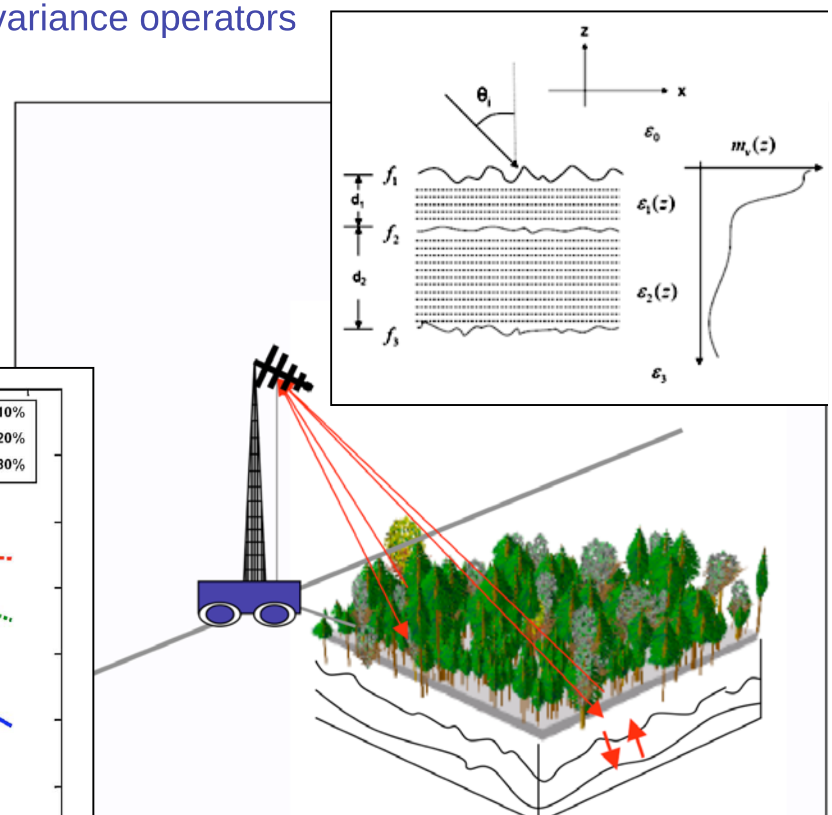


Static Sensor Model Example: remote sensors

- Models are typically much more complicated than in-situ counterparts; typically numerical
- Soil moisture inversion algorithms under development:
  - Unknowns are estimated via nonlinear optimization algorithms and approximate polynomial models
  - Statistical properties of unknowns are integrated via covariance operators
  - Absolute estimation accuracy ~2-4%







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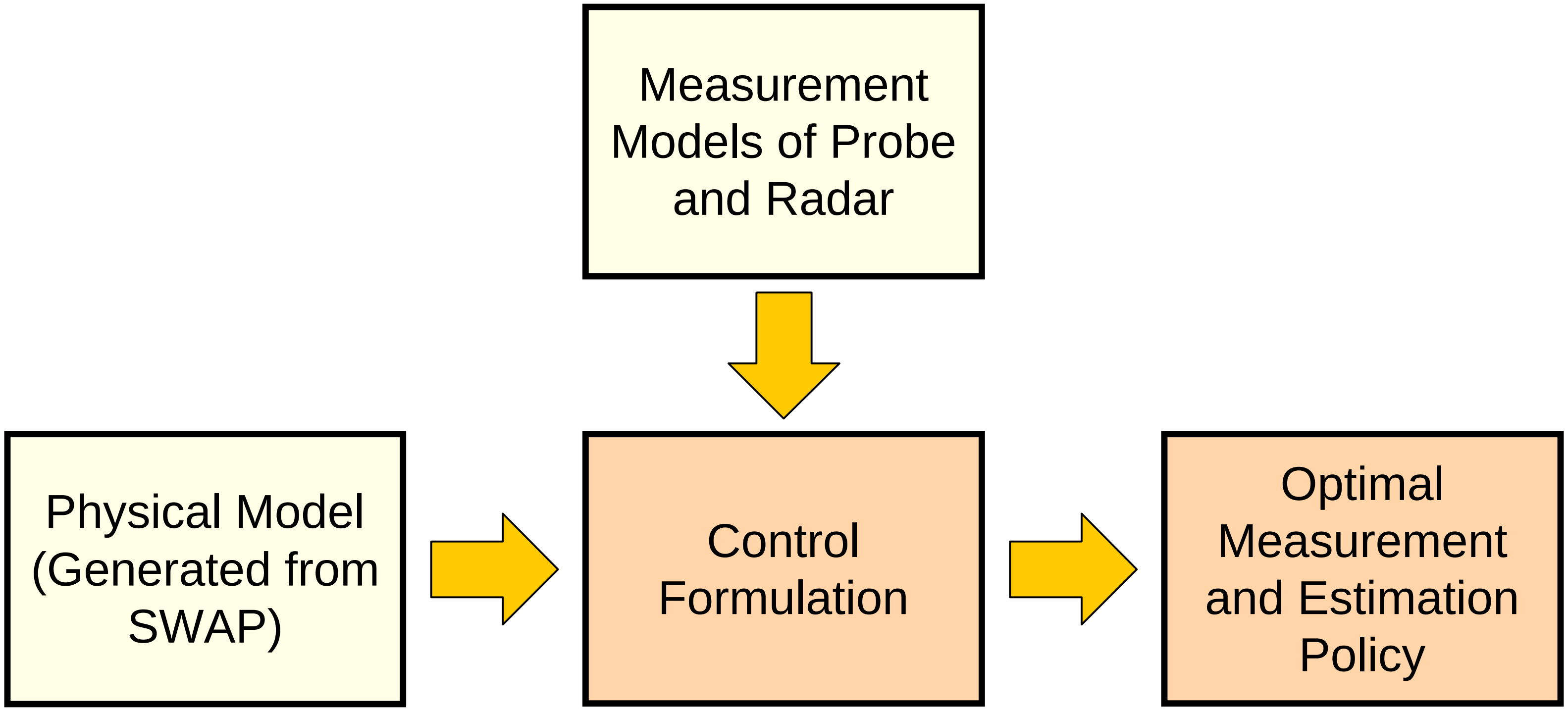
Overview of Control Formulation



Overview of Control Formulation (cont.)

Physical Model

- Take as input a joint time series of soil moisture, rainfall, solar radiation, etc.
- Quantize soil moisture and any other observed parameters
- Assuming a Markovian model, generate a transition probability matrix

Measurement Model

- For probe, assume perfect observations
- From radar model, generate matrix of observation probabilities

Control Actions

- Determine whether or not to measure soil moisture at each sensor
- Make an estimate of soil moisture

Costs and Optimization Criterion

- Energy consumption cost for using sensor(s)
- Distortion cost for incorrect estimates
- Minimize infinite horizon discounted expected cost

$$J^{g,l} = \lim_{T \to \infty} \mathrm{E}^{g,l} \left\{ \sum_{t=1}^{T} \alpha^{t-1} \left[\rho_t \, (\underline{X}_t, \hat{\underline{X}}_t, \underline{a}_t) + d\,(\underline{U}_t) \right] \right\}$$

Liu/Mahajan/Nayyar/Shuman/Teneketzis

Solution Method

- Formulate optimal control problem as Partially Observable Markov Decision Process (POMDP)
- Numerically solve POMDP using POMDP solver
  - Use Cassandra's POMDP solver (www.pomdp.org) or other similar technique
  - Hardware limitations may prevent the POMDP solver from converging

Numerical Studies

Case 1

Single noiseless sensor

- 9 soil moisture quantization levels (0-15,15-25,25-28,28-31,31-33,33-35,35-38,38-41,over 41%)
- Rain is modeled, not observed
- Cost of taking a soil moisture measurement is 0.5
- Distortion is L1-norm (number of quantiles off)
- Discount factor is 0.5

Case 2

Single noiseless sensor with rainfall observations

- Same as Case 1 except rainfall is observed at every time step
- Rainfall is quantized into 2 levels – low or high

Case 3

Two sensors at the same location – one noisy and one noiseless

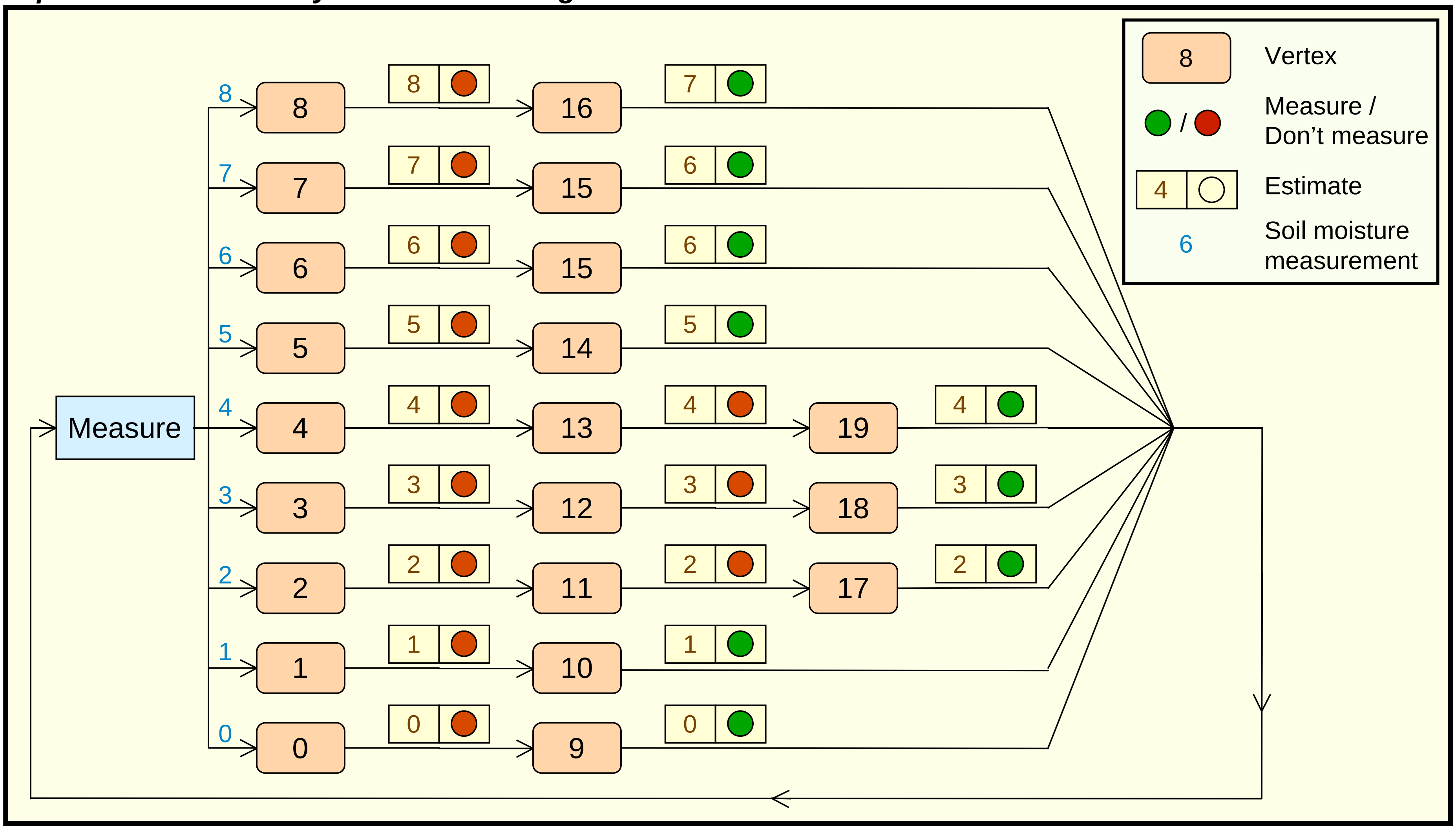
- Cost of noiseless sensor remains 0.5; cost of noisy sensor is 0.48
- Noisy sensor measures correct quantile with 96% accuracy

Case 4

Two noiseless sensors at different depths

- Soil moisture levels at the two depths are correlated
- At each decision point, may use none, either, or both of the sensors

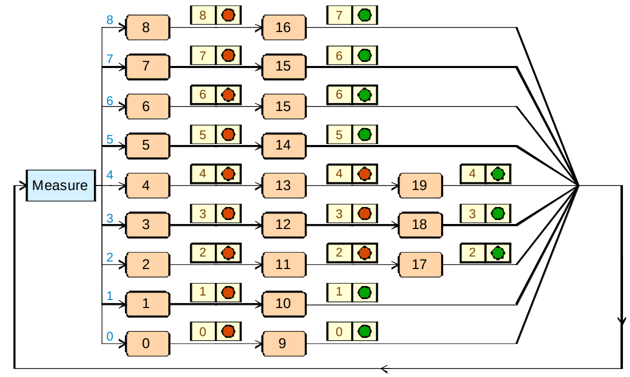
Optimal Control Policy for Case 1 – Single Noiseless Sensor



Note: Measurements and estimates "0,1,2,…,8" represent the soil moisture quantile (e.g., "3" represents the 28%-31% quantile)

Liu/Mahajan/Nayyar/Shuman/Teneketzis

Observations / Sensitivity Analysis for Case 1



- General characteristics of solution
  - After each measurement, do not take a measurement for some time
  - Duration of the “no measurement” phase depends on the measurement value and value of rainfall (if observed)
  - During the “no measurement” phase, generate estimates based on current belief
  - Algorithm convergence robust to change in problem parameters

- Sensitivity to measurement cost
  - Increase in measurement cost increases the duration of the “no measurement” phase

- Sensitivity to distortion function
  - For an L2-norm distortion function, duration of “no measurement” phase decreases
  - For probability-of-error distortion function, duration of “no measurement” phase increases

- Sensitivity to discount factor
  - Increase in discount factor decreases the duration of the “no measurement” phase

Numerical Studies (cont.)

Case 1

Single noiseless sensor

- 9 soil moisture quantization levels (0-15,15-25,25-28,28-31,31-33,33-35,35-38,38-41,over 41%)
- Rain is modeled, not observed
- Cost of taking a soil moisture measurement is 0.5
- Distortion is L1-norm (number of quantiles off)
- Discount factor is 0.5

Case 2

Single noiseless sensor with rainfall observations

- Same as Case 1 except rainfall is observed at every time step
- Rainfall is quantized into 2 levels – low or high

Case 3

Two sensors at the same location – one noisy and one noiseless

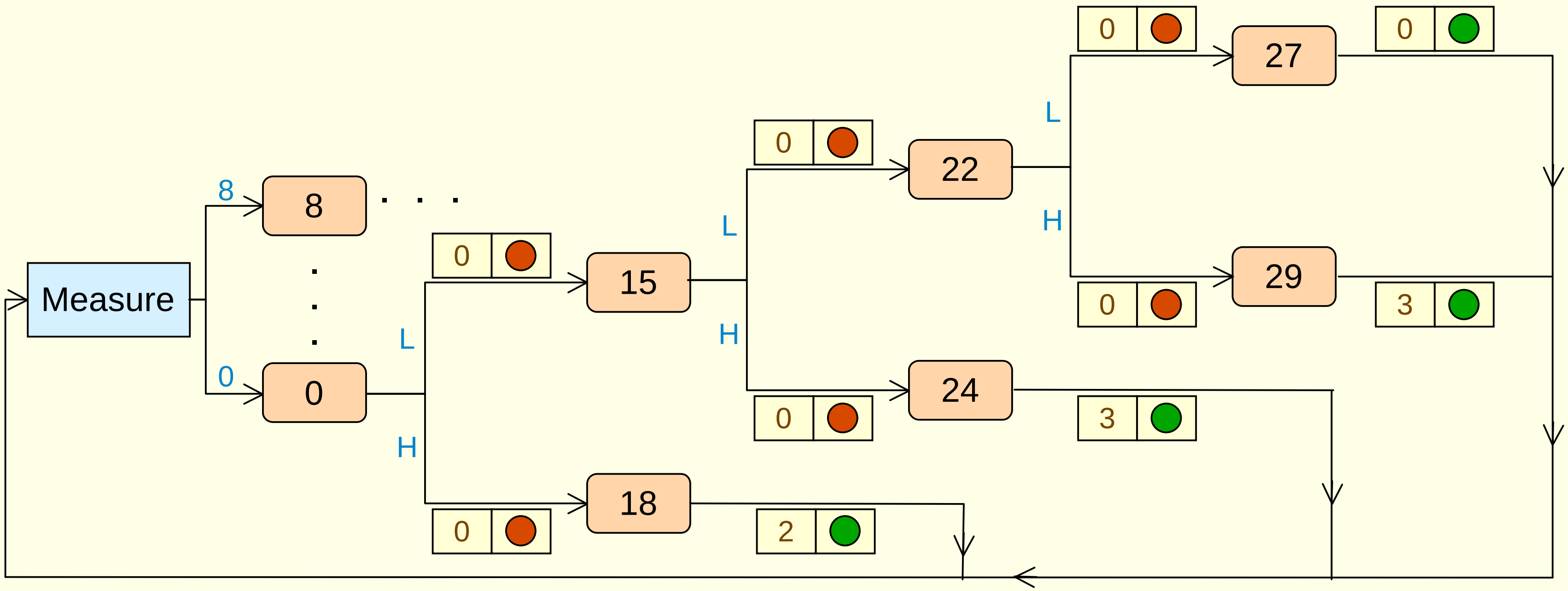
- Cost of noiseless sensor remains 0.5; cost of noisy sensor is 0.48
- Noisy sensor measures correct quantile with 96% accuracy

Case 4

Two noiseless sensors at different depths

- Soil moisture levels at the two depths are correlated
- At each decision point, may use none, either, or both of the sensors

Optimal Control Policy for Case 2 – Single Noiseless Sensor with Rainfall Observations



- Control policy takes rainfall into account
- Duration of "no measurement" phase depends on rainfall realization
- Policy graph contains approximately 600 vertices
- Convergence of algorithm is slower than Case 1, and depends on cost of measurement and distortion function

Numerical Studies (cont.)

Case 1

Single noiseless sensor

•9 soil moisture quantization levels (0-15,15-25,25-28,28-31,31-33,33-35,35-38,38-41,over 41%)

•No other physical parameter (rain, solar radiation, etc.) is observed

•Cost of taking a soil moisture measurement is 0.5

•Distortion is L1-norm (number of quantiles off)

•Discount factor is 0.5

Case 2

Single noiseless sensor with rainfall observations

•Same as Case 1 except rainfall is observed at every time step

•Rainfall is quantized into 2 levels – low or high

Case 3

Two sensors at the same location – one noisy and one noiseless

• Cost of noiseless sensor remains 0.5; cost of noisy sensor is 0.48

• Noisy sensor measures correct quantile with 96% accuracy

Case 4

Two noiseless sensors at different depths

• Soil moisture levels at the two depths are correlated

• At each decision point, may use none, either, or both of the sensors

Observations for Cases 3 and 4

Case 3

- Policies are of a similar nature to Case 1 with measurements followed by "no measurement" phases
- Choice of using one sensor or the other is sensitive to relative measurement costs and accuracy of the noisy sensor
  - If noisy sensor is too expensive, it may be optimal to not use it
  - Similarly, if noiseless sensor is too expensive, it may be optimal to only use noisy sensor
- The number of vertices in the policy graph is around 100
- Algorithm converges slower than Case 1, and does not converge for many choices of measurement costs and noise model

Case 4

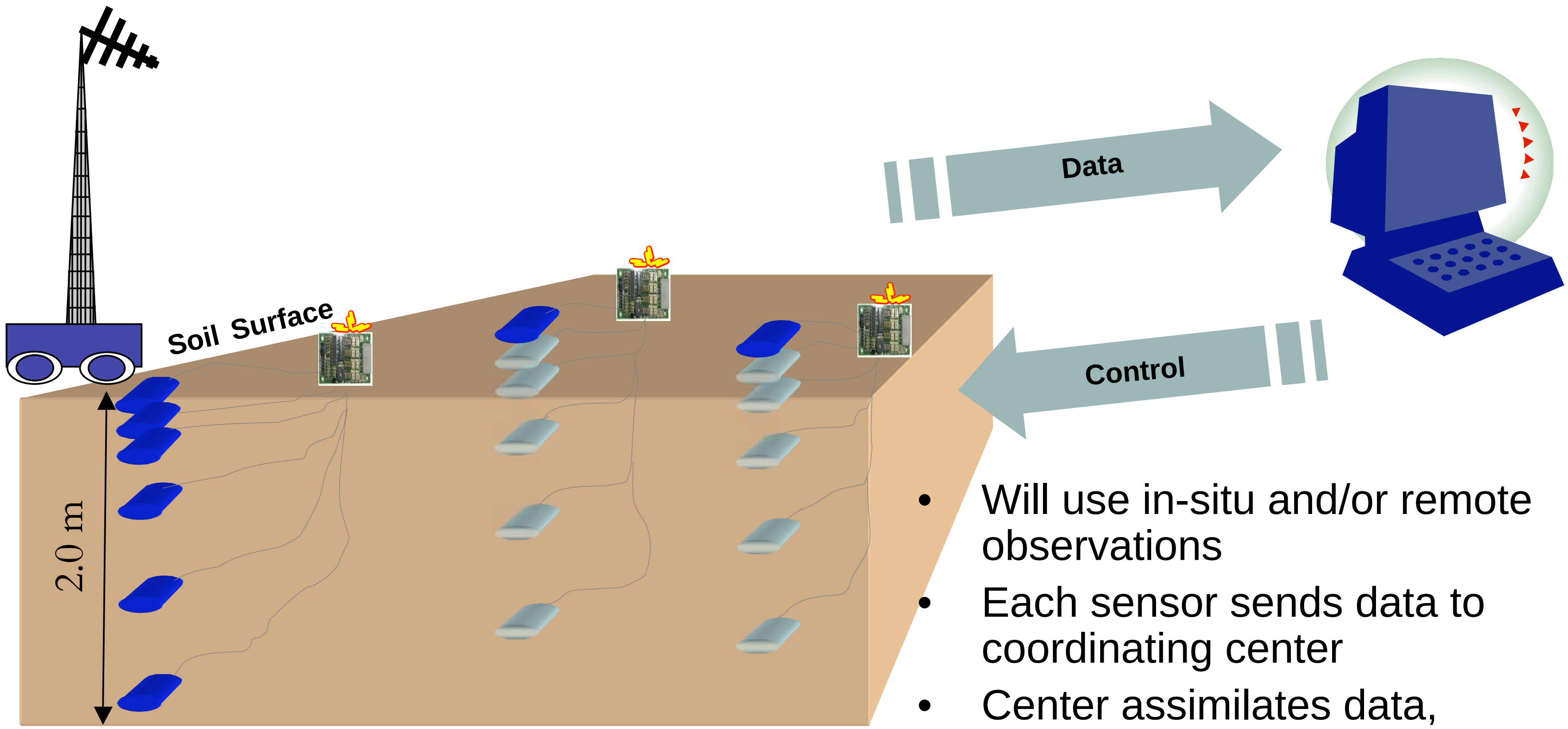
- Soil moisture at higher layer is quantized in 3 values and moisture at lower layer is quantized in 2 values
- Rarely use both sensors at the same time
- With this quantization, the number of vertices in the policy graph is around 4000
- Algorithm converges slower than Case 3, and does not always converge or for finer quantization levels

Plans and Work in Progress

- Improve numerical robustness of multiple sensor studies by integrating POMDP solver with CPLEX (a commercial library for solving linear programs)
- Investigate various approximation algorithms for POMDPs
- Identify structural properties of optimal measurement policies for multiple sensors
- Use the measurement model of the radar to determine the observation matrix for noisy sensors

- Future work
  - Examine two or more same-type sensors on surface, but at different locations
  - Consider scaling properties of optimal measurement policies
  - Consider the case of a total energy constraint
  - Investigate supercomputing or parallel computing options to speed up POMDP solver

Overview of experimental setup

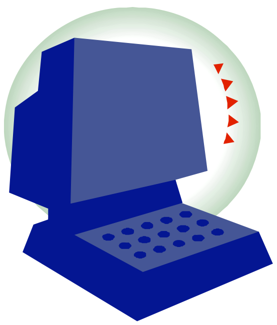


- Will use in-situ and/or remote observations
- Each sensor sends data to coordinating center
- Center assimilates data, generates control
- Center sends control commands to actuators at sensor locations

Phase A

- Proof of concept: Implementation of the feedback control loop
  - Successful communication between base station and ground station
  - Successful sensor actuation -- activation
  - Implementation of the data assimilation algorithms and control algorithms
  - Implementation of data processing on the ground wireless unit
- Lab experiment and measurement
  - How often does the sensor need to be activated
  - Estimate on power consumption at the ground wireless unit
  - Algorithmic complexity and memory requirement at the base station

Phase A Experiment



Base station:
- receive sensor data
- run sensor model
- run data assimilation
- derive control signal
- transmit

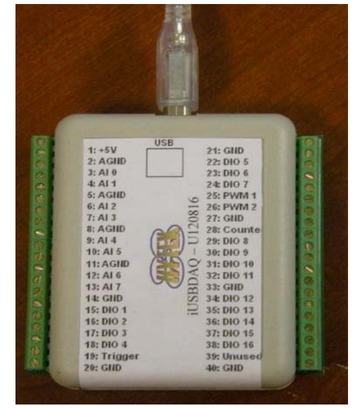
Data/Control

Ground wireless unit

Actuator

In-situ or remote sensors

iUSBDAQ - U120816



- Device choice for Phase A
  - Desktop as ground wireless unit with actuator attached
  - Actuation control unit is HYTEK iUSBDAQ-U120816
  - Laptop/desktop as base station and coordinator
  - In-situ soil moisture probes: Decagon ECH$_2$O EC-5

Phase A Experiment Sample Results

- 48 hour run to observe dry-down in lab after initial "rainfall"
- 49 regular hourly samples (conventional)
- 16 samples prescribed by control system
- New sampling strategy results in 67% savings in number of measurements

Goykhman/Liu

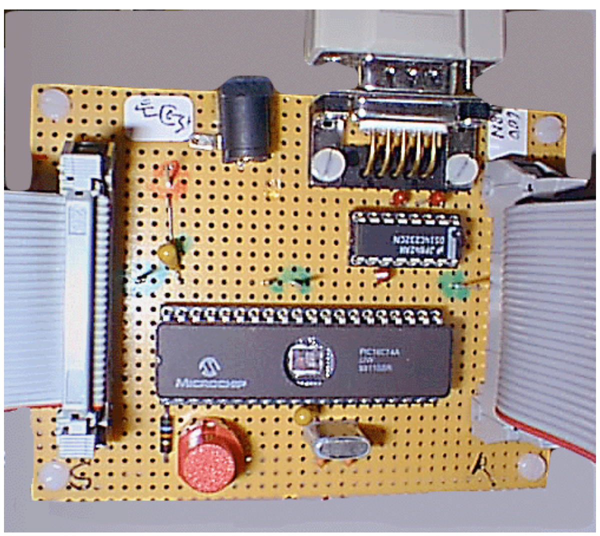
Phase B

Phase 1	Phase 2	Phase 3
Phase A	Phase B	

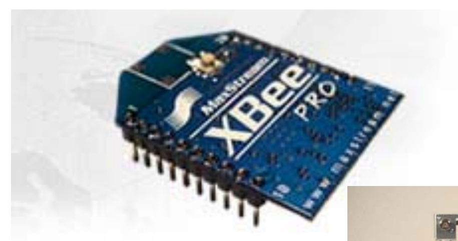
- Multiple sensors, including remote sensing, multiple sites
- Application specific hardware to increase the communication range (replace the current choice of a laptop for the ground unit)
- Better and more energy efficient devices
  - Possibility of solar power use
  - Minimum manual maintenance
  - Reduce cost and size
- Accuracy of algorithm against ground truth or benchmark
- Trade-off between sensor self-calibration schedule and cost

Phase B Experiment

- Replace ground station computer with PIC microcontroller
  - Wide selection depending on the application
  - Uses a small fraction of energy used by the laptop
  - Costs only a few $
  - Can be interfaced with Transmitter/Receiver modules



- ZigBee RF tx/rcv Module
  - ISM 2.4 GHz operating frequency
  - High output power
  - Can add a directional antenna to boost the range
  - Replaces computer wireless card



Liu

Summary and Next Steps

- We are developing a "smart" in-situ sensor web for validation of satellite data using a spatially and temporally sparse network via a control system
  - Control system is guided by optimization criteria derived from physics-based sensor models and physics-based dynamic system evolution models
  - Soil moisture dynamics currently implemented for depth variations; under development for lateral variations
- The outcome can directly benefit SMAP and other decadal survey missions
- Control strategy is formulated and implemented for a low-dimensional system; numerical implementation for higher-D systems is on-going
- End-to-end system is being implemented in lab; demonstrated for low-D, under development for higher-D and high-efficiency field-analog devices
- Low-noise sensor models being investigated in parallel