Soil Moisture Sensing Controller And optimal Estimator (SoilSCAPE): First Deployment of the Wireless Sensor Network and Latest Progress on Soil Moisture Satellite Retrieval Validation Strategies

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Abstract – We develop wireless sensor network, control system, and data analysis technologies for dynamic and near-real-time validation of space-borne soil moisture measurements, in particular those from the Soil Moisture Active and Passive (SMAP) mission. Soil moisture fields are functions of variables that change over time across the range of scales from a few meters to several kilometers. We develop sensor placement policies based on spatial statistics of soil moisture, and for each location, develop dynamic scheduling policies based on physical models of soil moisture temporal dynamics and microwave sensor models for heterogeneous landscapes. Furthermore, we relate the ground-based estimates of the true mean to the space-based estimates through a physics-based landscape simulator and statistical aggregation procedure. An energy-efficient integrated communication and actuation platform is developed and used to command the sensors and transmit their data to a base station in near-real time. Full-scale field experiments were initiated in August 2010 with the deployment of the first full-scale wireless sensor network in Canton, Oklahoma, using our custom-built Ripple-1 architecture. This paper summarizes the results of the field deployment, status of the landscape simulator, and plans for the next set of deployments using the next generation network architecture and nodes, called Ripple-2.

I. INTRODUCTION

This project seeks to develop technologies for near real-time validation of space-borne soil moisture estimates, and in particular those derived from the Soil Moisture Active and Passive (SMAP) mission [1]. Soil moisture fields possess complex dynamics on multiple spatial and temporal scales. Furthermore, within the coarse resolution cells of SMAP ($O(km^2)$ to $O(10km^2)$) observed landscapes could exhibit significant heterogeneity [2-3]. Therefore, a traditional spatially uniform and temporally sparse sampling scheme is inadequate for SMAP product validation. Instead, a ground network of sensors needs to be designed that optimally captures the statistics of the soil moisture fields in space and time, and relates them to the aggregate space-based estimates. We leverage our previous work on soil moisture sensor scheduling [4-5] to solve the joint problems of optimum sensor placement and sensor scheduling for obtaining the true mean of soil moisture fields subject to accuracy and cost constraints. We further relate the ground-based estimates of the true mean of soil moisture to the space-based estimates through a physics-based statistical aggregation procedure. Full-scale field experiments prototype the system using ground sensors and radar data.

We develop the spatial placement design, wireless communication system, and dynamic operation rules for soil moisture stations that provide estimates that are near-real-time, autonomously operated (hence can operate over extended times), and are compatible with SMAP data products. The sensors will communicate with a coordinator, and actuate measurements only when their measurement significantly adds value to the across-network computation of the field mean. The principal technology innovations that make this possible are:

- optimal design of sensor node placement and scheduling based on modeled soil moisture spatial statistics, and joint placement, scheduling and mean estimation

- strategies for deriving large-scale space-based estimates of heterogeneous soil moisture that are compatible with ground-based estimates of true mean of soil moisture fields
- wireless communication protocols and actuation systems that configure the sampling within the network to yield large-scale field mean conditions.

Upon successful completion of the baseline project in 2012, the technology readiness level (TRL) is expected to be at 6, on-track for integration into an operational scenario for SMAP by the time it launches in 2014-2015 time frame. This paper describes the highlights of the second year of this project in the following areas:

1. Deployment of first full-scale network in Canton, OK
2. Remote sensor and hydrologic landscape simulators
3. Joint scheduling and estimation of field mean, with sensors that could be faulty

II. DEPLOYMENT OF THE FIRST FULL-SCALE NETWORK IN CANTON, OK

During the second year of this project, our remote sensing validation framework through optimal placement and scheduling of in-situ sensors was demonstrated through extensive laboratory and field experiments. Specifically, we successfully accomplished the following tasks: (1) the full-scale deployment, testing, and maintenance of our Ripple-1 system on a cattle farm in Canton, Oklahoma; (2) the construction of a near real-time data logging and online display system; (3) the design and development of the next generation Ripple-2 system. Details follow.

Deployment of Ripple-1 network in Canton, OK

A conceptual and architectural depiction of the Ripple data collection system is illustrated in the Figure 1. The system consists of a field element and a remote element. A wireless sensor network is deployed over a target field, along with a base station that performs data collection and sensing control, and a database collocated with the base station for local data storage. At each sensing site (where a sensor node is placed), 3 moisture sensors are deployed at different depths with wire connection to the sensor node on the ground. The base station receives sensing data from each sensor node, but can also control the sensor measurement schedules on demand. It also periodically (every half an hour) uploads the collected sensor data through a 3G connection to a database server located in our lab in the EECS building on the campus of U. Michigan, which then displayed on our project webpage at http://.soilscape.eecs.umich located on a department web server. The collected data, in both its raw and processed form can be downloaded in batches from the website; the calibration process and instructions are also available on the site. The database server and web server constitute the remote element of the architecture.

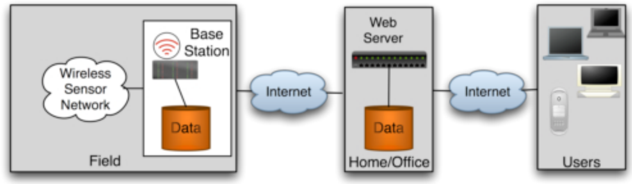

Figure 1. Global architecture of the Ripple wireless sensor network system

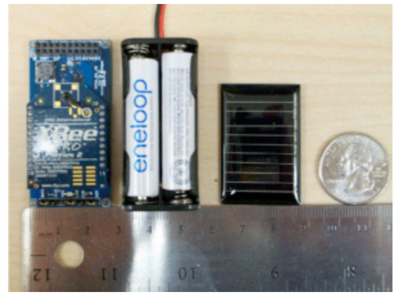

Figure 2. Ripple-1 end device

The Ripple-1 (Figure 2) system [4] is built using the ZigBee (IEEE 802.15.4 plus higher layer specifications) standard. We chose ZigBee as it allows the formation and self-configuration of a multi-hop network, which can potentially provide us with a desirable coverage. In addition, ZigBee is a relatively mature technology with many products on the market to choose from, which can significantly shorten our development and production cycle. The disadvantage with this choice is that a router node under the ZigBee specification cannot be put to sleep mode, which means it will consume significantly more energy and will require larger batteries and larger solar panels. For the end device (ED) we chose to use the Xbee Pro SOC as both the MCU and radio. It provides a fairly long range (up to 500 meters in field tests), and has generally low power consumption (295mA at 3.3V in transmission mode, 45mA at 3.3V in receive mode and less than 10 uA in sleep mode). On the other hand this chip almost completely encapsulates the implementation of the ZigBee protocol suite, leaving very limited room for reconfiguration and customization.

Our initial deployment occurred in August 2010 on a cattle farm in Canton, Oklahoma. Figure 3 (a) shows a satellite map of the target field with four major soil types.

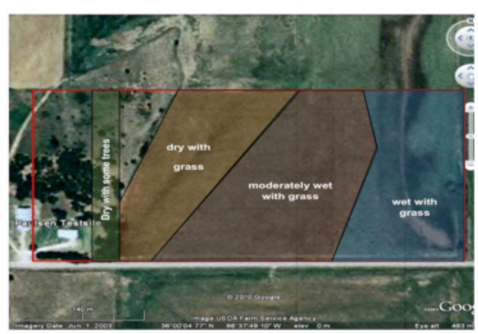

Figure 3 (a). Google-Earth satellite view of the Canton, OK site, with the 4 prominent soil textures

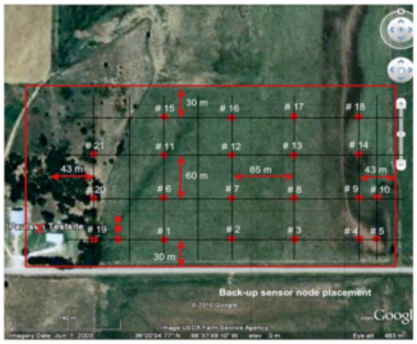

Figure 3 (b). Deployed network at canton, OK, showing the locations of sensor nodes (red circles), routers (red squares), and base station (red cross).

Figure 3(b) illustrates the deployment at a glance: we deployed 1 base station/coordinator, 3 router nodes, and 21 sensor nodes/end devices, each with 3 Decagon ECHO probes attached at depths 4cm, 13cm, and 30cm.

During the testing and operation of the above field deployment we encountered the following technical problems. The network was not very stable: there are disruptions to normal behavior during which the system suffers from significant data loss. Our initial diagnosis was that the quality of the router-base station connection was unstable, causing end devices to switch parent-child association. This switching took a long time to complete due to the low duty cycle of the end device, as well as the low refreshing rate of the child-tables on the routers. Secondly, the 3G connection was also found to be unstable, and the 3G card interface failed regularly.

To fix the above problems we took a second trip in early September 2010, during which we automated all operations on the base station, including system restart, machine reboot and 3G connection restart. We also installed two more routers to improve the quality of the connection to the base station, but we had to remove one of the original routers due to battery heat damage. We saw significant data quality improvement following this maintenance trip.

However, later in September 2010 our battery backup died and the system had to be shut down. Then in October the sensor nodes in the field sustained significant damage from both weather and cattle. We took a third trip in late November 2010 to assess the damage and perform repair. We replaced the original desktop (which served as the base station) with a Netbook, removing the need for a battery backup. We repaired solar panel connections on many sensor nodes and overall recovered about 10 nodes. But the remaining two original routers were deemed beyond repair and decommissioned. We have continued to receive data but the system has not been as stable as before.

Design and development of Ripple-2

Building on the experience and lessons learned in the deployment, operation and maintenance of Ripple-1, we started to design an improved, second generation system Ripple-2 during the second half of Year 2. This new system adopts a two-tiered hierarchy: the lower layer consists of a local coordinator (LC) node and multiple sensor nodes or end devices (ED) associated with the LC node. The upper layer consists of LC node(s) and a base station. The LC node may be equipped with two radio interfaces, allowing it to communicate within the two layers using different radio technologies, effectively rendering the two layers logically separate. The lower layer uses the IEEE 802.15.4 standard but not the ZigBee suite (i.e., we do not use the ZigBee MAC and network layers). The advantages of this design include: (1) flexibility in developing our own protocol on top of 802.15.4 for the lower layer and multiple candidate solutions for the upper layer; (2) the logical separation between the two layers makes the sleep scheduling of the ED nodes much easier to control; (3) a different radio solution for the upper layer can allow the system to span over much longer distances; and (4) this system architecture can be easily scaled up. We are currently in the process of upgrading the Canton site to Ripple-2.

Near real-time data upload and online display

The Ripple-1 system uses a 3G connection to periodically (every half an hour) upload soil moisture data to a database server located in our lab. Upon storage the raw data gets converted through a customized calibration process, the result of which can be queried, displayed/visualized, and cross-compared on our project webpage. The collected data, in both its raw and processed form can be batch-downloaded from the website; the calibration process and instructions are also available on the site. An example of the web display is shown in Figure 4 below.

Figure 4. SoilSCAPE webpage display and interactive data query

We are currently focusing on three tasks. The first is the continued maintenance and upgrade of the Canton, OK, site. The second is a 30-node Ripple-2 deployment at the University of Michigan Matthaei Botanical Gardens (our "Laboratory environment," which is scheduled for June 2011. The third is an augmentation of the current project to install a large Ripple-2 network on the Tonzi Ranch, CA, starting late summer/early fall of 2011.

III. Landscape Simulator and Matching in-situ and Satellite-based Soil Moisture Retrievals

The problem of designing a ground network that will properly sample the soil moisture field in space and time to produce an accurate estimate of its true mean has been discussed already. In this section, we discuss the complementary mean estimation "aggregation" problem from the point of view of the satellite. The two values of the soil moisture field mean, one obtained from the satellite and the other from the ground sensors, must be compatible for the validation scenario to be successful. Regardless of the accuracy of the radar and radiometer retrieval algorithms, the mean value of soil moisture obtained from satellite data is not necessarily the same as the true mean as estimated from the ground sensors. A physics-based spatial aggregation strategy has to be developed to correlate in-situ and space-based estimates of soil moisture.

In the second year of the project the proof-of-concept heterogeneous landscape simulator was improved to more accurately investigate aggregation strategies. Two simulators have been investigated: (1) a land surface hydrology simulator MOBIDIC (Modello Bilancio Idrologico DIstributo e Continuo (fully distributed raster-based hydrologic model)) and (2) remote sensor (radar) backscattering cross section simulator.

In the following, we discuss the progress on each simulator. The emphasis has been to generate simulation results from these models for the Canton, OK field site.

Land Surface Hydrology Simulator (MOBIDIC):

We had initially used the tRIBS model [6-7]. More recently, we have switched to the MOBIDIC model, also developed partially at MIT. The MOBIDIC model was used for simulation of hourly soil moisture (with uncalibrated MOBIDIC model) for 1-year (2007), 5-year (2005-10), and 9-month (8/1/2010-3/11/2011) windows for the Canton site. Several data layers needed to set up the model were collected from publicly available resources. The following figures (Figures 5-8) show highlights of the simulations. The catchment area modeled is larger than the wireless sensor field, to capture the pertinent hydrologic effects.

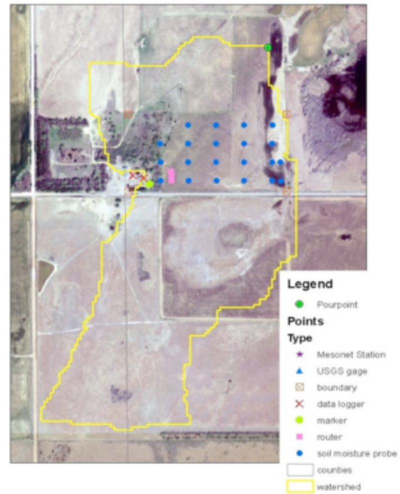

Figure 5. Simulation domain for MOBIDIC, showing the location of the pourpoint on top right. The blue dots show the locations of the SoilSCAPE sensor nodes.

The simulations are done based on best available resolution available from the base data (10m DEM from USGS, for example).

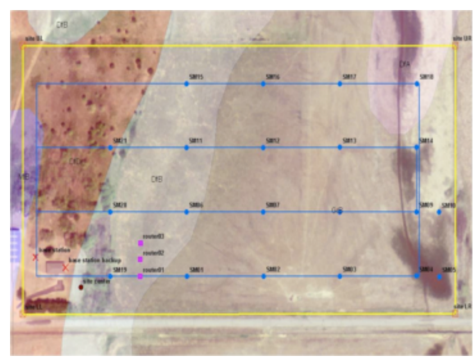

Figure 6. Soil maps from SURRGO, shown underneath the locations of the sensor nodes.

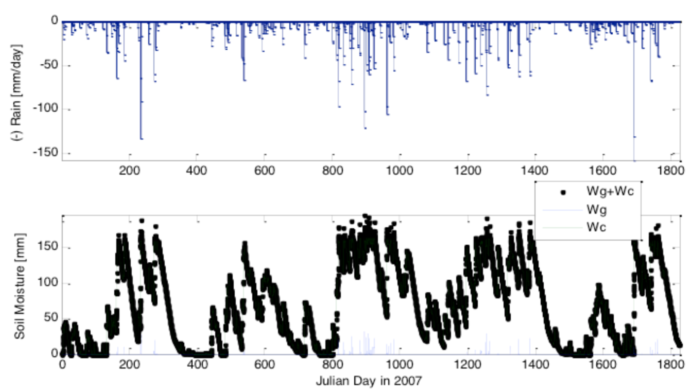

Figure 7. MOBIDIC sample outputs: (top) rainfall records and (bottom) soil moisture.

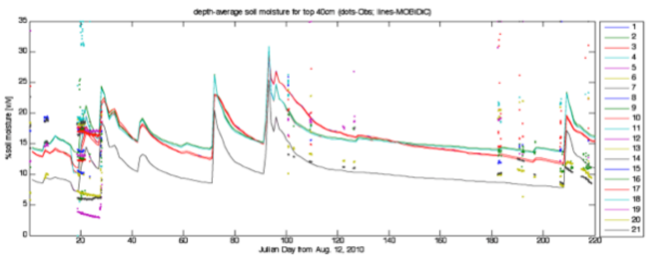

Figure 8. MOBIDIC sample outputs: Daily aggregated volumetric soil moisture starting August 12, 2010.

Radar Simulator:

This landscape simulator is based on a unified multi-layered multi-species model adaptable to various landcover types [8]. A land cover classification scheme for the United States is readily available through the National Land Cover Database (NLCD) and a data-base of input files for the unified model using these land cover types has been created. The different aggregation strategies can then be visualized in Google Earth where layers of information are co-registered on the whole Earth. More details on this simulator can be found in [9].

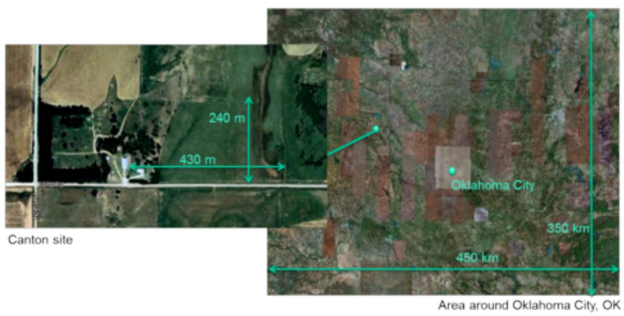

Figure 9. Canton in Oklahoma, a study site whose landscape data layers were created, co-registered, and ingested using Google Earth.

The Canton, Oklahoma (at 36° 0' 2.05" N, 98° 37' 58.55" W) site is a rather homogeneous grassland area with a sparse tree line between the grassland and the property owner's house located on the far west end of the private property. The topography is smooth with a drainage channel on the east side and a raising slope towards the west. The Canton location with respect to Oklahoma City is seen in Figure 9.

Using available data layers such as soil type maps and in-situ soil probe analysis over the extent of the Canton site, each soil area is assigned a specific soil type characterized by the percentage of sand (S), clay (C) and bulk density (Rb). This is shown in Figure 10.

With this basic information, several sample setups are created to investigate forward modeling. Three setups are first simulated and can be seen in Figure 11. The top row shows the case where different land cover types are taken into account (according to NLCD 2006; grass (beige), crop (brown), developed open space (light red) and some forest (green) and shrub (light brown)), different soil types according to Table 1 and uniform soil moisture of 4 percent is assumed over the whole scene. The second example setup (in the middle row of Figure 11) shows the same scene with the same landcover and soil types, but with a more realistic soil moisture (SM) distribution ("Loamy sand" with 10% SM, "Sandy loam" with 20% SM, "Sandy" with 5% SM, "Sandy clay loam" with 30% SM). The third example setup (in the bottom row of Figure 11) uses the same parameters as the second setup, but adds a 10 percent slope for the "Loamy sand" type. The simulated radar backscatter coefficients over the scene are vastly different from each other, which makes the point that physics-based modeling is essential. Several other cases where also simulated but are not shown here for brevity.

Table 1. Assumed soil types for regions shown in Figure 10.

# 0:	loamy sand	S = 83.05%	C = 6.99%	Rb = 1.64 g/cm3
# 1:	sandy loam	S = 70.33%	C = 11.85%	Rb = 1.54 g/cm3
# 2:	sandy	S = 91.92%	C = 2.43%	Rb = 1.50 g/cm3
# 3:	sandy loam	S = 70.33%	C = 11.85%	Rb = 1.54 g/cm3
# 4:	sandy clay loam	S = 60.77%	C = 26.75%	Rb = 1.40 g/cm3

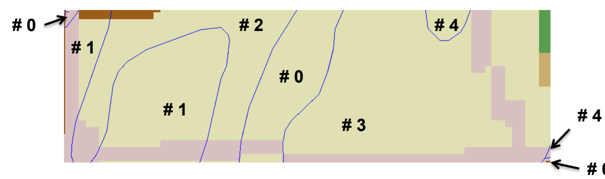

Figure 10. Maps showing NLCD 2006 over Canton site with overlay of soil type map and respective soil type.

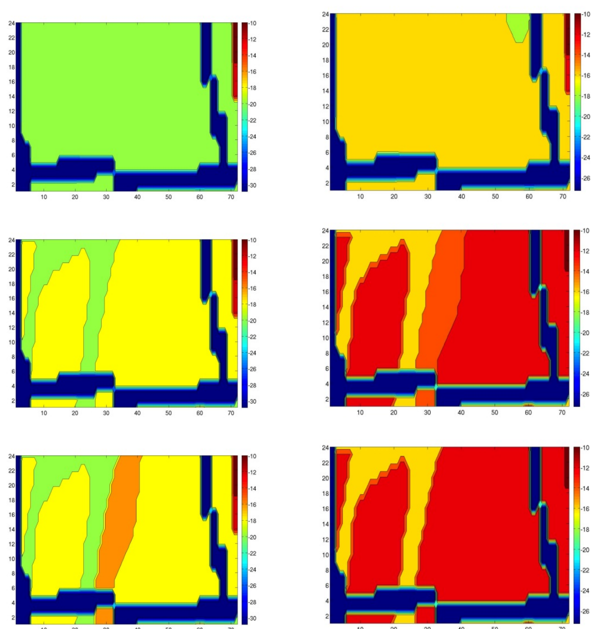

Figure 11. Radar backscatter coefficient in dB for L-band in HH (left) and VV (right) polarization over Canton site; uniform soil moisture of 4 % (top row), realistic artificial soil moisture distribution (middle row), realistic artificial soil moisture distribution with slope of 10 degrees in "loamy sand" type.

For a more thorough analysis, the simulated area has been expanded to an area of about 1.5km x 1.5km as can be seen in the Google Earth image in Figure 12, coinciding with large parts of the MOBIDIC land surface hydrology simulator. An uniform soil moisture of 4 percent is assumed over the whole area. The same aggregation study is shown for this scene and can be seen in Figure 13.

Figure 12. Google Earth image of extended simulation area.

Assuming that a satellite like SMAP will only see one radar backscattering coefficient for the whole scene, as shown in Figure 13 (bottom row), a retrieval based on a land cover type assumption can be done. This means that it is explicitly assumed that the whole scene has the same land cover and soil type, based on which the soil moisture can be retrieved. The results for such a scenario are given in Table 2. It is shown that the soil moisture retrieval based on the assumption of a homogeneous scene can produce erroneous results. As a reminder, the soil moisture was assumed to be uniform over the whole scene as 4 percent, and only the land cover and soil type were changed. Generally, retrievals using only HH polarization alone lead to overestimation while retrievals using only VV lead to underestimation. For the case of the deciduous forest, the soil moisture is not retrievable. This is due to the dominant volume scattering of the branches. In general it may be possible to retrieve soil moisture underneath a forest with radar observations at L-band, given that proper assumptions can be made about the scene, which is not the case in this scenario.

Currently we are using the radar landscape simulator in full-blown aggregation and disaggregation studies for the Canton site as well as the Michigan Matthaei botanical gardens. At Matthaei, we also plan to deploy the tower radar as a surrogate for the "remote sensor" and therefore to perform scaled versions of the aggregation/disaggregation tests. The tower radar may also be deployed at the Canton site.

IV. Placement and Scheduling with Sensor Failures

In the first year of the project, we had developed sensor placement strategies through the following tasks:

- Developed empirical sensor placement strategies assuming continuous sampling (Conducted studied on simulated data representing soil moisture dynamics in time for a 3D field; Developed a cluster based placement scheme)
- Investigated 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)
- Developed a methodology to address the joint placement and scheduling problem (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)

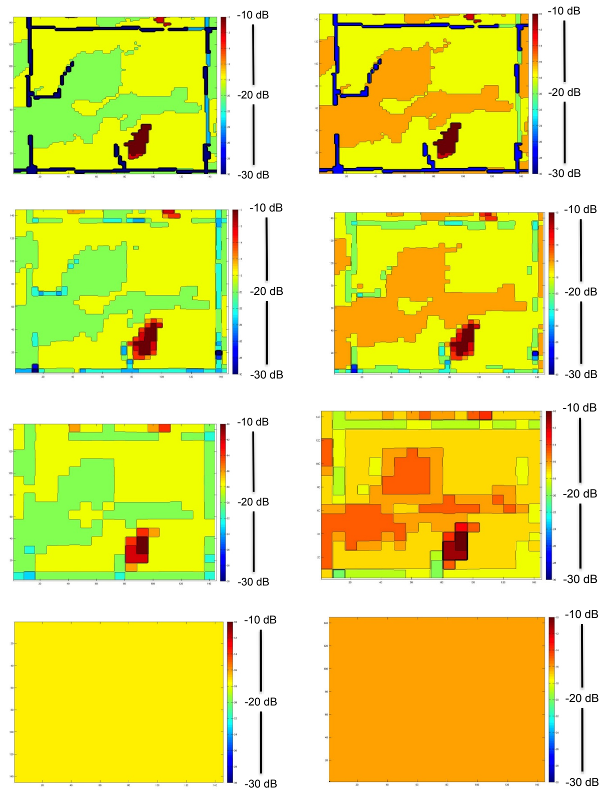

Figure 13. Radar backscatter coefficient in dB for L-band in HH (left) and VV (right) polarization; blocks containing 1 x 1 pixel (top), blocks containing 4 x 4 pixels (second row), blocks containing 8 x 8 pixels (third row), block containing average of all pixels (bottom).

Table 2: Retrieval of soil moisture based on land cover and soil type assumption.

Land cover type	Soil type	Polarization	Soil moisture (in percent)
Grassland	Loamy sand	HH	14
Grassland	Loamy sand	VV	2.8
Grassland	Sandy loam	HH	16
Grassland	Sandy loam	VV	3.8
Grassland	Sandy	HH	14
Grassland	Sandy	VV	2.5
Grassland	Sandy clay loam	HH	18
Grassland	Sandy clay loam	VV	4.5
Crop	Loamy sand	HH	10
Crop	Loamy sand	VV	3
Deciduous forest	Loamy sand	HH	N/A
Deciduous forest	Loamy sand	VV	N/A

In Year 2 of the project, we have advanced the placement analysis in several ways:

- Initial formulation and studies on the placement problem with sensor failures (Evaluation of placements under random sensor failures; A heuristic modification of the placement algorithm to address possibility of sensor failures)

- Performance evaluation of sensor scheduling and estimation methodologies on the new hydrologic land surface model MOBIDIC data for Canton site
- Explored methodologies to address the coupled placement and scheduling problem (Ideally, optimal placements should take into account the dynamic scheduling costs; Can we classify locations into groups/clusters with similar dynamic costs and solve a separate placement problem for each cluster?)

Evaluating sensor placements with random sensor failures

Sensors may fail due to hardware or software failures. In our approach, we assume that: sensor failures are observable and permanent; and within one time period (say 1 day), a sensor may fail with probability p. We would like to evaluate the performance of different sensor placements determined by different placement algorithms under the above assumptions about sensor failures.

We investigated two placement strategies using simulated soil moisture evolution data, the uniform placement strategy and the greedy strategy. The former strategy places sensors uniformly over the field of interest. We used the minimum MSE version of the greedy algorithm to find another sensor placement. We simulated sensor failures over time and calculated the accumulated estimation error under these two placements. Figure 14 shows the estimation errors under the two placements with different probabilities of sensor failures over a period of 3600 hours.

The sharp increase in the accumulated estimation error when the probability of sensor failure exceeds 0.001 is due to the following fact: almost all sensors fail over the period of 3600 hours and the accumulated estimation errors then is due to predictions and not actual measurements.

Mean estimation: dynamic scheduling and fixed placement

In our earlier project AIST-05, we investigated the problem of dynamic scheduling and estimation of soil moisture at multiple locations. We computed independent scheduling policies for each sensor location and a joint estimation policy that uses the joint statistics and measurements from all locations to come up with soil moisture estimates for all locations. The ultimate objective of the sensor network is to estimate the temporal evolution of the *mean value* of soil moisture over a field of interest using sensors placed at only a subset of all locations in the field. Moreover, this estimation should be done in an energy efficient manner by dynamically scheduling measurements at each sensor.

From our studies in the earlier project, we concluded that the joint scheduling problem for all sensors is computationally infeasible for practical networks. This prompted the independent scheduling architecture where each sensor's scheduling policy is determined independently of other sensors using only the local statistics. The dynamic scheduling policy for a sensor selects the timing of measurements based on the statistical information and the past available measurements from that location alone. The algorithms developed in AIST-05 solve the problem of finding these scheduling policies. While each sensor is scheduled independently, the estimation of soil moisture at a location can use past measurements made at other locations because of the correlations among soil moisture at different locations. The estimation policy in AIST-05 exploits the correlations across sensors and uses past measurements from all sensors to estimate soil moisture at each sensor.

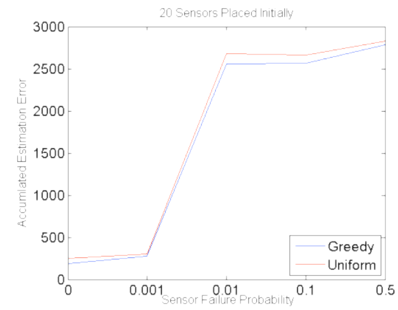

Figure 14. Comparison of two placements under sensor failures

In Year I of the current project, we built on our previous solutions to address the mean estimation problem. Specifically, we used the algorithms of AIST-05 to find the scheduling policy for each sensor location and the estimates of soil moistures at each sensor's location. We developed a joint statistical model (a joint probability mass function **Q**) of the mean and the moisture values at each sensor location using simulated data from a hypothetical location and a specified placement. We first used the estimation policy from the AIST-05 project that at each time produces estimates of the soil moisture at each location. We treated these estimates as true values of the moisture and used the statistical model **Q** to estimate the field mean**.**

In Year 2, we applied the above methodology to the MOBIDIC data for the Canton site. We used simulated data for the Canton site where 21 sensors were placed in Aug. 2010. The data was simulated for a period of six months at hourly time resolution. Thus, a total of 5260 snapshots of soil moisture values for the Canton site were used in our experiments. About half of these data points were used to learn spatial and temporal statistics of soil moisture. The remaining snapshots were used as test data to evaluate the performance of the scheduling and estimation methodology described above. Figure 15 presents a realization of the true mean and estimated mean of the soil moisture over the field.

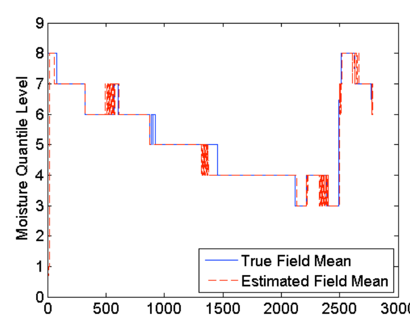

Figure 15. Comparison of the true value of mean soil moisture and the estimate.

The joint scheduling and placement problem

Under the dynamic scheduling policy, a sensor location is not sampled at every time instant. At the instants when a sensor location is not sampled, the moisture value at that sensor location may have to be estimated from past measurements and measurements of other sensors. A sensor placement calculated under the assumption of continuous sampling may choose sensor locations that have high estimation errors between the true moisture value at that location and the local estimate. Also, not all sensor locations incur the same measurement cost under dynamic scheduling. Thus, a solution calculated under continuous sampling may select sensor locations with high measurement costs.

To address the overall optimization problem, we need to incorporate the dynamic costs of scheduling and estimation into the sensor placement objective. Given the combinatorial nature of the problem and the difficulty of evaluating the dynamic costs of each placement, we developed a methodology that approximates the dynamic costs of selecting a placement through a 3-step approach (classification, independent scheduling and estimation representative within each class, and placement based on suitable optimization criteria). Unlike the actual costs, which are hard to evaluate, these costs can be evaluated easily and incorporated into the placement objective. This approach is currently under evaluation and its results will be reported in our future work.

V. CONCLUSIONS

We are developing technologies for the long-standing problem of validation of large-footprint satellite-derived estimates of soil moisture, with specific application to the SMAP mission. We develop the spatial placement design, wireless communication system, and dynamic operation policies for soil moisture in-situ sensors that provide estimates that are near-real-time, autonomously operated, and are compatible with SMAP data products. In the second year of the project, we have made advances in the areas of wireless sensor network architecture (deployed the first full-scale wireless network in Canton, Oklahoma, and based on its lessons learned, developed new efficient architecture for a scalable dense network), made major enhancements to radar and hydrology land surface models and performed extensive simulations for the sensor network field site, developed strategies for sensor placement taking into account the probability of sensor failures, developed strategies for mean field estimation using a sparse set of measurements over a heterogeneous field, and made formal connections to the SMAP mission through becoming a Core Cal/Val Site for SMAP. The latter is in large due to recent plans to install a large (150-node, 500-sensor) network. The technology readiness level (TRL) had an entry level of 2 was advanced to 3 in the first year. In year 2, various parts of the project are at TRLs of 3 to 5.

ACKNOWLEDGEMENT

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