Ground Network Design and Dynamic Operation for Validation of Spaceborne Soil Moisture Measurements: Initial Developments and Results

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Abstract **–** We develop 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 a sensor placement policy based on nonstationary 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 statistical aggregation procedure. An integrated communication and actuation platform is developed and used to command the sensors and transmit their data to a base station in real time. Full-scale field experiments are planned in coordination with SMAP calibration/validation experiments to prototype the validation system. This paper summarizes the progress and results of the first year of the project, where we have developed and tested several candidate approaches for sensor placement based on analyses of simulated data, developed an analytical method for joint optimization of placement and scheduling of sensors, built a versatile landscape simulator for SMAP radar that can produce backscatter data at arbitrary spatial resolutions, and made progress on the development of multihop wireless sensor architecture and hardware.

I. Introduction

This project seeks to develop technologies for near real-time validation of spaceborne 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. 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 nonstationary statistics of the soil moisture fields in space and time, and relates them to the aggregate space-based estimates. Through a previous project under the NASA/ESTO Advanced Information System Technologies (AIST) task, we have gained significant expertise in the dynamic control of ground sensors based on temporal statistics of soil moisture fields. Here, we leverage our expertise 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 are planned to prototype the validation system using ground sensors and L-band 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 central 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
- 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
- telecommunication protocols and actuation systems that configure the sampling within the network to yield large-scale field mean conditions.

Upon successful completion of the 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. This paper describes progress towards three main objectives of this project:

Objective 1 – Optimal design of sensor node placement based on soil moisture spatial statistics

Objective 2 - Reconciling space-based estimates of soil moisture fields with ground-based estimates of its true mean for heterogeneous terrain

Objective 3 – Development of ground sensor actuation and telecommunication protocols, deployment, and field experiments

II. SENSOR PLACEMENT (OBJECTIVE 1)

The true mean of soil moisture fields is a function of time and of the state of the soil surface. Its determination ideally would require a very fine sampling of the area over a satellite footprint, both spatially and temporally. This, however, is cost prohibitive; manually installing these sensors is expensive, and their battery power does not allow us to continuously sample, as we need them to last a reasonably long period of time (months or even years). These considerations pose severe limitations on how many sensors can be made available, and how frequent they can be used/activated. The overall objective is thus to place and activate sensors such that the field mean may be estimated to a desired accuracy subject to budgetary constraints, e.g., the total number of sensors available, the total amount of available energy at each sensor, and bandwidth.

There are two elements to the above problem; one is the determination of the best set of locations within the sensing field to place a limited number of sensors (sensor related cost constraint), and the other is the optimal dynamic operation of these sensors, i.e., when and which to activate, once they are placed (energy constraint). These two elements are coupled. For instance, if energy of operation is a bigger concern than placement costs, then one can choose to place more sensors to compensate for a desired, reduced sampling rate. The reverse holds as well. In addition, activation and sampling decisions can influence where sensors should be placed and vice versa. But jointly considering and optimizing both elements leads to a problem whose complexity is prohibitive both analytically and computationally.

Here, we use a decomposition method, where we will solve the two problems sequentially in two steps, respectively: the placement step and the scheduling step. In the first step, we will address the sensor placement problem under the assumption that these sensors will be operated in a continuous sampling mode, i.e., assuming no loss of accuracy in the scheduling step. In the second step, we will address the sensor scheduling/activation problem for a fixed time horizon for fixed sensor locations. The two steps will then be iterated offline so as to compensate for certain loss of optimality due to the decomposition. It's worth noting that both steps are off-line procedures. In particular, a sensor placement solution will be obtained before field deployment, and similarly, sensor-scheduling algorithms will be derived and implemented ahead of real-time measurements. Afterwards, the actual operation of the system is real-time, in that all of our proposed communication and control architectures are in real-time, which in turn updates its estimate on the true mean of the field in real-time.

For the sensor placement problem, we must place a limited number of sensors so as: (i) to exploit effectively the spatial and temporal correlation of soil moisture across the area under consideration, and (ii) to minimize the cost of communication with the base station. A particularly challenging feature of this problem in our context is the fact that the spatial statistics of soil moisture fields are highly variable with time, reflecting rain pattern after storm, drainage pattern at beginning of dry-down, and soil and vegetation pattern later in dry-down [2]-[6]. This is very different from the common Gaussian assumption of a sensing field [7].

The sensor placement problem has been studied for a variety of application scenarios; examples include underwater sensing [8]-[9], structural fault detection [10], and detecting landslides [11]. Each application has considered a different objective than the one we aim at here, which is obtaining the best estimate of the field mean. To effectively address our sensor placement problem, we first need to discretize the continuous sensing field into a finite number of regions, each corresponding to a possible location to place a sensor. The resulting problem is highly challenging when the number N of possible sensor locations and the number M of available sensors (M<<N) are large, and a brute-force enumeration method is not an option. It is also non-trivial due to the special statistical features of soil moisture data, which are state dependent and dynamic over time. To be able to formulate the aforementioned optimization problem, one approach is to derive the steady-state statistics of soil moisture using probability distribution of the surface state. Alternatively, we can try to formulate and solve individual optimization problems, one for each surface state (i.e., with steady-state soil moisture statistics given that state). These result in potentially different sensor placement solutions, and will need to be combined, e.g., through some type of weighted average using surface state distribution. In this project we will explore both approaches.

For lack of real data, here we instead use simulated soil moisture data generated by a state-of-the-art soil moisture simulator, called the Triangulated Irregular-Networks (TIN)-based Real-time Integrate Basin Simulator (tRIBS) [12]-[13]. Soil moisture varies as a function of time and three-dimensional (3D) space in response to variable exogenous forcings such as rainfall, temperature, cloud cover, and solar radiation. It is also influenced by landscape parameters such as vegetation cover, soil type, and topography. The model is used to simulate long time-series realizations of the soil-moisture over a 2km x 2km basin with an arbitrary topography and drainage channels, a nominal version of which is shown in Figure 1.

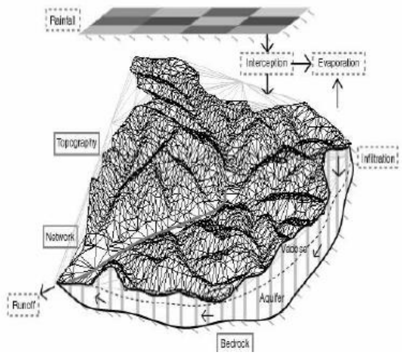


Figure 1. An example of tRIBS simulation domain showing a drainage basin with arbitrary topographic relief.

Soil moisture observations are collected at 9 different depths for each of the 2400 different surface locations over this sensing field. The entire data set consists of 2208 snapshots taken over a period of three months (in simulation time), once per hour. Each snapshot thus contains 2400 observation vectors; each location produces a vector of readings at 9 depths. For ease of presentation, in all of our results the values shown here as well as those used in our numerical studies have been multiplied by 1000.

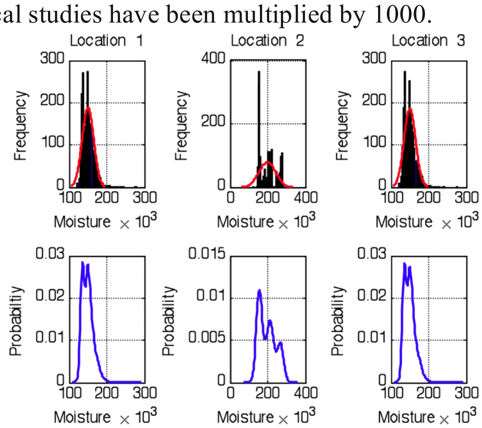


Figure 2. Distributions of soil moisture observed at 3 randomly selected locations (out of 2400) at the depth closest to surface over the three-month simulation period.

Figure 2 shows the soil moisture observed at 3 randomly selected locations at the depth closest to surface over the three-month simulation period. The top panels of Figure 2 show the histograms of each location and their corresponding Gaussian kernel density estimates, respectively. The figures on the bottom panels are the estimated PDFs of each, respectively. It can be clearly seen that the data do not follow a Gaussian distribution; indeed in all three cases the data exhibit a multimodal behavior (here a mode refers to a local maximum in the density function). While only three locations are shown here, we note that this is a general observation drawn from all locations in our data analysis. While we may still choose to use sensor placement and field estimation methods that were derived based on the Gaussian assumption, they must be carefully evaluated using the soil moisture data since clearly the assumption itself does not hold. This observation also motivates us to ask the question as to whether there are other features embedded in the data that may be of use in constructing good sensor placement algorithms.

The data suggest that there is a rather stable coarse-grained ordering among the locations in terms of their relative soil moisture levels that could potentially be used in constructing good sensor placement algorithms using (greedy) global and cluster-based placement strategies. Suppose we divide the entire set of locations into M subsets each of size N_i, $i=1,2,\cdots,M$, as described above. Also assume that we are interested in placing a total of S sensors (i.e., selecting S out of the possible 2400 locations), with S_i allocated to the ith subset. We will examine the following variations of cluster-based sensor placement schemes:

(1) Clustered Random Placement, where the Si sensors in subset/cluster i are randomly selected out of the Ni locations.

(2) Clustered Deterministic Placement, where the placement of Si sensors in the ith subset/cluster follows one of the deterministic algorithms mentioned earlier, including (MaxEN ,MaxMI and MinMSE), respectively.

Figure 3 shows the comparison of results for cluster-based and global placement algorithms, for two different numbers of training data sets chosen from within the simulated data set.

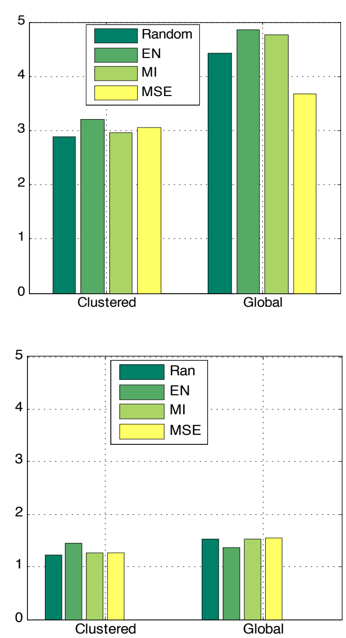


Figure 3. Comparison between cluster-based and global placement schemes, using 1500 (top) and 1000 (bottom) training snapshots.

III. RECONCILING GROUND-BASED AND SATELLITE-DERIVED SOIL MOISTURE ESTIMATES: LANDSCAPE SIMULATOR (OBJECTIVE 2)

An aspect of soil moisture estimation from satellite sensors that is rarely addressed is the fact that over the large (order of several km^2) resolution cell of the satellite, the scene could be highly heterogeneous. There are two separate problems that need to be addressed in this regard: (1) how to sample the field temporally and spatially with in-situ sensors to obtain a representation of the true mean over such a large resolution cell, and (2) how to relate the scattering and emission properties of the components of the heterogeneous scene to the aggregate remote sensor measurements. The first problem was discussed under Objective 1, namely to design a ground network that will properly sample the soil moisture field in space and time to produce an accurate estimate of its true mean. The second problem is complementary and addresses the 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. Nearly without exception, current algorithms for geophysical parameter estimation in general and soil moisture in particular, assume a homogeneous scene within each satellite resolution cell, an assumption that is usually not valid.

We address this problem by developing a full landscape simulator using existing in-house numerical radar scattering models that have been based on the work in [14]. Our model currently assumes a resolution cell that has homogeneous scattering properties, e.g., vegetation that is uniformly distributed over the pixel and soil moisture that is constant over that pixel. The model is capable of incorporating multiple canopy types within each pixel, and is also capable of incorporating a nonzero surface slope in each pixel. To develop the full landscape simulator in forward mode, we break down heterogeneous scenes into smaller sub-blocks to which the homogeneous assumption can be applied. The scattering model is applied to each sub-block according to given vegetation, topography, soil type, and moisture properties of that sub-block. Each simulation results in one value of the overall distribution. The total forward scattering measurement as taken by the satellite will be predicted by constructing multi-level aggregate blocks. Starting from the smallest sub-blocks, groups of 4, 16, 64, etc., sub-blocks will be averaged to investigate the scaling-up properties of the scene (Figure 4), and therefore achieve an optimal strategy to form the value of satellite measurement from the coarse resolution cell. Both uniform and nonuniform sub-block aggregation can be considered.

If the scene within one SMAP radar pixel were homogeneous, any of the existing retrieval algorithms could be applied to the aggregate backscattering coefficient measurements to obtain a mean value for soil moisture over that pixel. However, since the scene is heterogeneous and the scattering process is nonlinear, the mean backscattering coefficient over the large pixel will not yield the correct value for the mean soil moisture within that pixel. To remedy this problem, we will develop a correlation data base for the aggregate values of scattering coefficients with respect to various scene properties, and derive location-specific spatial disaggregation rules for different types of landscape.

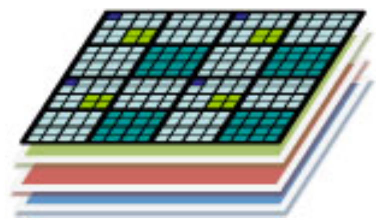


Figure 4. Landscape simulator will aggregate the homogeneous sub-blocks (dark blue) into blocks of 4 (light green), 16 (dark green), 64, etc., to achieve a statistically representative mean value for the scene. Many input data layers will be used to produce the finest-resolution simulated data.

We have developed a proof-of-concept heterogeneous landscape simulator was to investigate these aggregation strategies. The landscape simulator is based on a unified multi-layered multi-species model adaptable to various landcover types [15]. 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. Two example locations were considered: Marena, Oklahoma and Canton, Oklahoma. Marena is a rather homogeneous grassland area with sparse tree coverage surrounded by roads. The topography is smooth with a shallow valley running through the middle of the selected area. Canton is heterogeneous with land cover types ranging from deciduous forest, evergreen forest over grassland and crop to open space (concrete roads) and open water. Sample Google Earth images for these areas are shown in Figure 5.

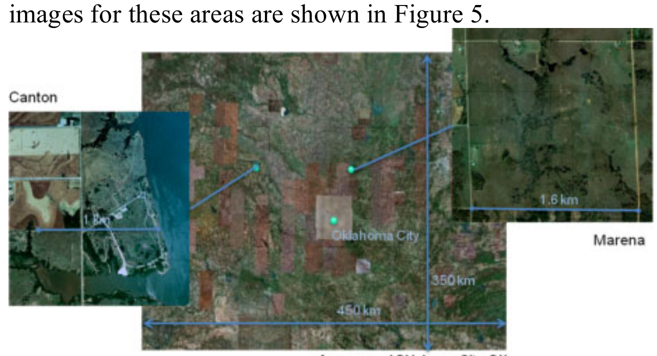


Figure 5. Canton and Marena, Oklahoma, are two study sites whose landscape data layers were created, coregistered, and ingested using Google Earth.

The architecture of the landscape simulator can be seen in Figure 6. The image processing software package PCI Geomatics is used to overlay different layers of landscape input information and to co-register them. With the Engineering Analysis and Scientific Interface (EASI) meta-language, the data can be handled and the information about the land cover type can be extracted and saved in text files. The parameter input files have been prepared based on the land cover types available in NLCD 2001. The text files containing the land cover type specification and the parameter input files are then used by the multispecies vegetation scattering model, which is coded in FORTRAN. It outputs the backscatter cross section of each NLCD pixel in a text file. This text file is then read in to Matlab to investigate and visualize different aggregation types: blocks of 4, 16, 64, etc. can be formed to achieve a statistically representative mean value for the backscattering cross section of the scene, up to the resolution cell size of SMAP. The resulting text file is read into PCI Geomatics where the data can be co-registered and visualized. The layers can also be exported to Google Earth for visualization.

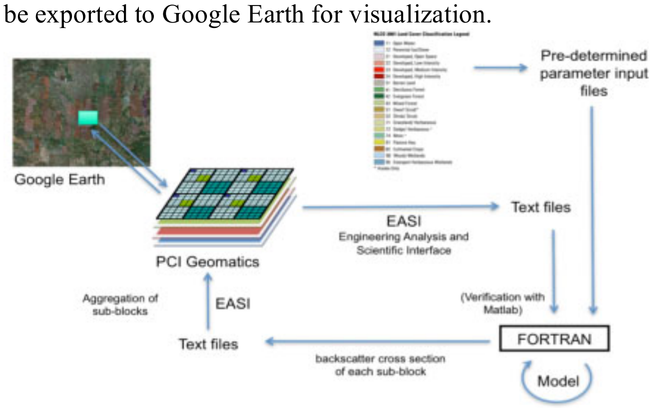
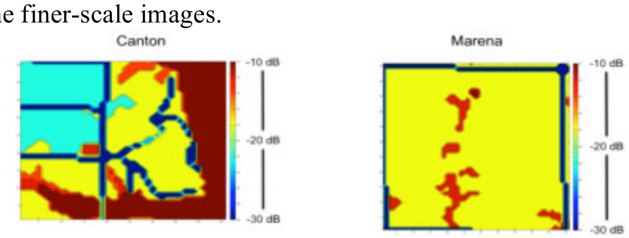


Figure 6. Architecture of Landscape simulator

First results of aggregation strategies have been investigated. Figure 7 shows the actual backscatter coefficient simulated for each 30m pixel. The second row in Figure 7 shows the backscattering coefficient with the aggregation strategy of amalgamating 16 pixels into one block. A more realistic case is shown in the bottom row of Figure 7 where a single block represents the whole scene as would be measured by a satellite sensor such as the SMAP radar. The 2km aggregated radar backscattering coefficient values are seen to have significantly less information than the finer-scale images.



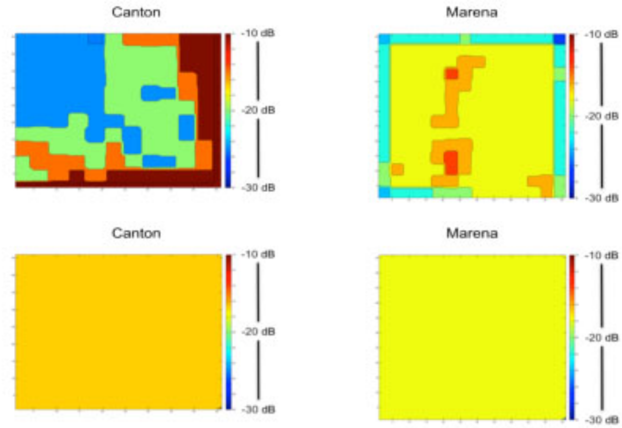


Figure 7. L-band HH backscatter coefficient (dB); blocks containing averages of 1 x 1 (1st row), 4 x 4 (2nd row row), and all pixels (3rd row).

IV. Wireless Communication and Actuation System (Objective 3)

To achieve the objective of collecting surface-to-depth soil profiles at distributed locations, we need a network consisting of soil-moisture probes as well as ground wireless transceiver modules (referred to below as nodes or sensor nodes) that actuate and control the sensor probes and send collected data back to a base station. These devices are to be deployed in the field and are expected to operate for long periods of time (on the order of at least months) without direct human intervention. In this section we present Ripple-1, the ground wireless sensor node we designed for this project, as well as a ZigBee based wireless communication network we designed using Ripple-1.

Our system shares some of the obvious and common requirements as many other systems. These include long lifetime, high reliability, ease in deployment and maintenance, ability to support multi-hop communication, scalability, and relatively long-range wireless communication. Long-range for our application means distances on the order of 100s of meters to a mile, as we need to cover a sufficiently large area to be able to observe spatial variability in soil moisture.

In addition, our system has the following distinguishing features. Firstly, in terms of data flow, it operates in a "data pull" mode rather than a "data push" mode, since the measurement decision is made at the base station using antecedent data and *a priori* statistical information. This makes many data push (or clock-driven or event-driven data collection) paradigms [16] unsuitable. Our sensor nodes need to be highly responsive to base station commands. Secondly, our system potentially has a very wide range of sampling and data rates, sampling from once per minute to once per hour or 10s of hours depending on exogenous weather conditions and antecedent moisture values. Both of these features make duty cycling mechanisms very challenging to design.

Finally, we want to have a low-cost design and a relatively easy-to-maintain system. Some of the more specific requirements include: large network size (more than

30 nodes) and extendibility; low cost (< $100 per node) and small form; up to eight sensor channels on each node to enable measurement of soil moisture at multiple depths, as well as temperature, precipitation, or other environmental variables; and the ability to work in extreme temperature environments.

The requirements listed in the preceding three paragraphs rule out most (if not all) of existing sensor platforms available on the market. These include MICA2 [17], TelosB [18], BTnode [19], and Fleck 3 (CSIRO ICT Centre), to name a few, which, in particular, do not meet the requirement for long-range operation. We used the Narada [20] sensing and actuation boards in the early phase of this project and collected some initial results. However, it was found to be too energy-consuming for our scenario, with insufficient communication range.

Figure 8 shows the architecture of a Ripple-1 system. At the network level, the system consists of a number of sensor nodes deployed over a target field, a base station that performs data collection and sensing control, also deployed in the field, and an off-field database used to store data that also allows remote data access, e.g., from office/home or on the move. At each sensing site (where a sensor node is placed), a number (3-5) of moisture probes are also deployed vertically underground with wire connection to the sensor node on the ground. This forms the configuration of a single sensor location.

A web site (hosted on a server on the U. Michigan campus) has been developed to provide an interface for users to access and visualize collected data, and to override scheduling algorithms run on the base station. The connection between the base station, the database and the web server is through a 3G Internet card installed on the base station. Thus any device with Internet access, including PCs and smart phones can browse the web server and access data and control.

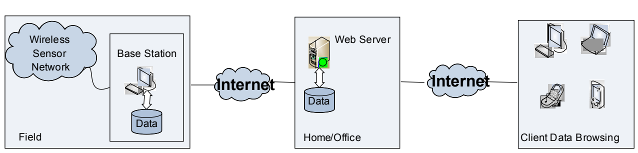


Figure 8. Ripple-1 system architecture

In searching for a low-power, low-cost, reliable, and multi-hop solution, we converged on the ZigBee technology [21]. Currently, ZigBee is the only standards-based technology on the market that targets low-cost and low-power networking applications (e.g., home networks). It is built on the IEEE 802.15.4 standard that specifies the physical (PHY) and media access control (MAC) layers. Specifically, ZigBee specifies the network, security, and application layers, and defines three types of logic devices:

- Coordinator: this is the most capable device that establishes the network and assists in routing data. A single network only has one coordinator.
- Router: it supports data routing and can talk to the coordinator, end devices, and other routers.
- End device: it has just enough functionality to talk to its parent node (either the coordinator or a router).

The topology of a typical ZigBee network can be a star, mesh or cluster tree (also called star-mesh hybrid). Our field-deployed network is shown in Figure 9; it consists of a single coordinator/base station, 2 router nodes and 11 end devices.

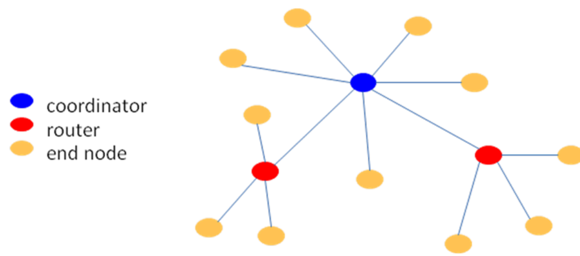


Figure 9. ZigBee mesh topology

Having identified ZigBee as the network solution, we surveyed currently available chips for building our sensor node. Among these we decided that the XBee PRO ZB module by Digi International [22] is a good candidate that has relatively long battery life, is reliable, low-cost, and industry-standard. To provide superior communication range (up to 1 mile), the XBee PRO ZB module is equipped with a built-in low noise amplifier and a power amplifier. An Xbee PRO ZB module with different firmware versions can act as one of the three logic device types in a ZigBee network.

The final version of the Ripple-1 node, including a weather-proof enclosure, is shown in Figure 10. This module is field-deployable and has been tested and used in initial demonstrations of our sensor web technology.

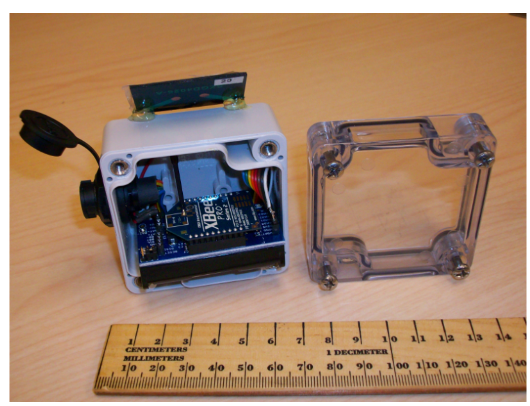


Figure 10. Ripple-1 node with weather-proof enclosure

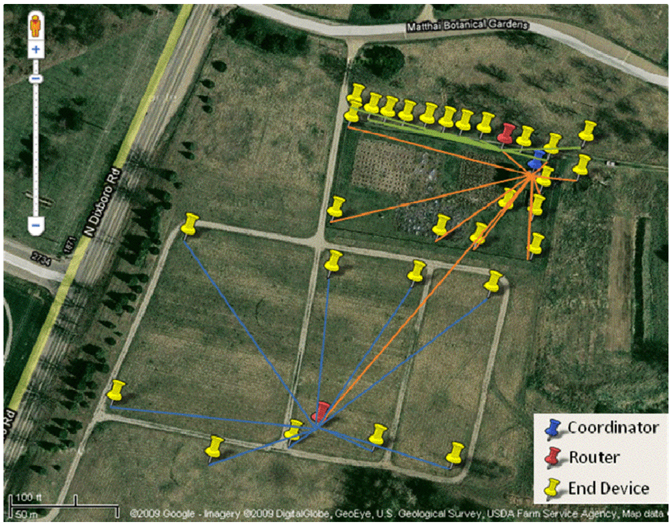


Figure 11. Aerial view of field validation site at the University of Michigan (UM) Matthaei Botanical Gardens.

V. FIELD EXPERIMENTS

The Ripple-1 nodes have been fully tested and verified in the laboratory as well as in the field. The sensor scheduling problem has also been tested in simulations and using field data [23], [24]. Thirty Ripple-1 nodes have been deployed and tested at the University of Michigan Matthaei Botanical Gardens, as shown in Figure 11. Our next field validation goals are (1) to validate the sensor placement scheme at the same location (for which we have already validated sensor scheduling policies during a precious AIST project), and (2) develop and test the placement and joint placement-scheduling algorithms at a larger, more representative, environment.

As part of the preparatory calibration and validation work, the SMAP project is deploying a network of ground sensors in Marena, OK, this spring and summer. The deployment aims to answer the following questions:

- How do different sensors perform given the same hydrologic inputs of rainfall and evaporation?
- How can the measurements from different sensors with different sampling scales particularly the COSMOS and GPS systems of soil moisture monitoring, compare given the variation in scale of measurement?
- How do different sampling intervals impact the soil moisture estimates, given instantaneous measurements versus time averaged measurements?
- How can networks which measure soil moisture by different fundamental methods, capacitance, FDR, TDR, reflectometry, be compared to a standard of gravimetric validation?
- How do the orientations of installation influence the data record and effectiveness of the sensor?

The Marena location is managed by the Oklahoma State University Range Research Management Station and contains one of the stations of the Oklahoma Mesonet, which has a long term lease. It is a grazed cattle pasture. The soil is sandy clay loam/loam. There is a fence bisecting the field and some terracing to prevent erosion. Sections of the field are burned for weed control every three years with the next scheduled burn to take place in 2012. There is a small amount of topography.

The SMAP deployment plans to install and cross-compare eight different in-situ sensor types, and is not primarily concerned with the effects of landscape heterogeneity. Our project, on the other hand, has as a main focus the impact of landscape heterogeneity on in-situ network design. Therefore, the two efforts are highly complementary. We therefore plan to deploy the first version of our designed network concurrently with the SMAP team.

Since the Marena, OK, site is not very heterogeneous, nor has much topography, we plan to deploy a network at a nearby site, in Canton, OK. This site has sufficient landscape variability and topography to allow proper testing of our adaptive network placement and scheduling designs. The two sites are within about 100 miles of each other. Prior to the field installation at either of these sites, we plan to acquire as much information as possible about the landcover, weather patterns, and hydrology of the areas, which we plan to use in new tRIBS simulations. Having the results of the tRIBS simulations will allow us to derive appropriate placement and scheduling designs before prior to field installations. Even though we plan to deploy a denser network than required by our placement solution (to make sure validation data are available), having the prior design will help with economizing the dense network deployment.

VI. 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. The sensors communicate with a central 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
- 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
- telecommunication protocols and actuation systems that configure the sampling within the network to yield large-scale field mean conditions.

In the first year of this project, we have made advances in all of the above areas to the point that we are ready to test the first full version of the wireless network based on the results of our analysis and hardware development, in a relevant field environment. In the first year, the technology readiness level (TRL) has been advanced to 3.

ACKNOWLEDGEMENT

This work was carried out at the University of Michigan and at the Massachusetts Institute of Technology through a grant from the National Aeronautics and Space Administration Earth Science Technology Office, Advanced Information Systems Technologies program.

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