Original Research

The Soil Moisture Active Passive Marena, Oklahoma, In Situ Sensor Testbed (SMAP-MOISST): Testbed Design and Evaluation of In Situ Sensors

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In situ soil moisture monitoring networks are critical to the development of soil moisture remote sensing missions as well as agricultural and environmental management, weather forecasting, and many other endeavors. These in situ networks utilize a variety of sensors and installation practices, which confounds the development of a unified reference database for satellite calibration and validation programs. As part of the Soil Moisture Active Passive Mission, the Marena, Oklahoma, In Situ Sensor Testbed (SMAP-MOISST) was initiated to perform inter-comparisons and study sensor limitations. Soil moisture sensors that are deployed in major monitoring networks were included in the study, along with new and emerging technologies, such as the Cosmic Ray Soil Moisture Observing System (COSMOS), passive/active distributed temperature sensing (DTS), and global positioning system reflectometers (GPSR). Four profile stations were installed in May of 2010, and soil moisture was monitored to a depth of 1 m on an hourly basis. The four stations were distributed within a circular domain of approximately 600 m diameter, adequate to encompass the sensing range of COSMOS. The sensors included in the base station configuration included the Stevens Water Hydra Probe, Campbell Scientific 616 and 229, Decagon EC-TM, Delta-T Theta Probe, Acclima, and Sentek EnviroSMART capacitance system. In addition, the Pico TRIME system and additional time-domain reflectometry (TDR) systems were deployed when available. It was necessary to apply site-specific calibration to most sensors to reach an RMSE below 0.04 m^3 m^{-3}. For most sensor types, a single near surface sensor could be scaled to represent the areal-average of a field domain by simple linear regression, resulting in RMSE values around 0.03 m^3 m^{-3}.

Abbreviations: COSMOS, Cosmic Ray Soil Moisture Observing System; CRN, Climate Reference Network; DTS, distributed temperature sensing; GPS, global positioning system; GPSR, global positioning system reflectometers; RMSD, root mean squared difference; SMAP, Soil Moisture Active Passive Mission; SMAP-MOISST, Soil Moisture Active Passive Mission, the Marena, Oklahoma, In Situ Sensor Testbed; SMOS, Soil Moisture Ocean Salinity; TDR, time-domain reflectometry.

Core Ideas

- Soil moisture sensors have varying accuracies that can be improved with calibration.
- In situ sensors require scaling to improve their representativeness of large areas.
- Soil moisture sensors in profile have decreasing ability to accurately represent the surface soil moisture.

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In situ networks play a vital role in monitoring weather and climate. Advances in technology have enabled soil moisture[1] to be added to the suite of parameters measured across these networks (Schaefer et al., 2007; Illston et al., 2008). However, a variety of instruments and standards were developed as different networks incorporated this vital land surface parameter into their unique network designs. These differences do not present obstacles for research within individual networks, but once the science questions go

[1] *Soil moisture* is used in this study because it directly pertains to application to satellite products that have soil moisture in the title. Soil water content is a more applicable term, as soil can be moist by other means than water.

beyond the scale and domain of one network, these differences present a challenge. Having a standard methodology for recording in situ soil moisture would be ideal. However, there are already a significant number of networks that have been deployed, so standardization across networks would require retrofitting, and new sensor developments could require frequent retrofitting. In addition, there are practical considerations related to network installation that make some techniques undesirable in one location, but desirable in another. For instance, rocky soils often cannot accommodate installation of large sensors (Cosh et al., 2008). And, soils with high bulk electrical conductivity often degrade the performance of impedance and capacitance type sensors (Blonquist et al., 2005). Therefore, it is necessary to directly compare long-term data records from diverse in situ sensors installed at one location to facilitate large-scale scientific studies that span these different networks. Toward this end, a test bed was developed to determine how different types of in situ sensors perform at a single field site. Measurements were made over several years. Questions to be addressed include: What errors are associated with each sensor versus a ground truth? What is the durability of different sensors? Does the depth of the sensor installation influence how that sensor estimate is correlated to surface measurements?

Large-scale in situ soil moisture monitoring has a long history, beginning with the Global Soil Moisture Data Bank, which compiled data from some of the first large-scale soil moisture sampling endeavors, including gravimetric sampling of soil moisture on a 10-d interval across 141 stations throughout Ukraine beginning in 1958 (Robock et al., 2005). One of the first long-term soil moisture monitoring programs in the United States was initiated by the Illinois Water Survey and used sampling intervals on the order of several weeks to capture profile soil moisture at 17 sites throughout the state (Hollinger and Isard, 1994). Other state and national networks developed shortly thereafter, including the Oklahoma Mesonet (McPherson et al., 2007; Illston et al., 2008) and the USDA Soil Climate Analysis Network (Schaefer et al., 2007), which both utilized automated sensors recording data on an hourly or subhourly basis. Other preexisting meteorological networks eventually had soil moisture sensors added to their instrument configuration, such as the Climate Reference Network (CRN) (Diamond et al., 2013).

Table 1 shows a listing of selected large-scale networks that currently are operating throughout the world. Though this list is not exhaustive, it demonstrates that there are a variety of soil moisture sensors deployed in large-scale networks, as well as different measurement depths. To create a common standard for soil moisture monitoring across all of these networks, there is a need to compare the performance of these sensors. Jones et al. (2005) and Blonquist et al. (2005) described a large sensor comparison study, which compared seven different sensors in the laboratory, classifying them by the frequency of the measurement used in the sensor. That study focused on various liquids with known dielectric values, instead of natural soils. Their conclusions were that effects of dielectric relaxation, bulk electrical conductivity, and temperature on permittivity and soil moisture estimation are primarily dependent on the effective frequency of the sensor, with higher frequencies yielding better results. Vaz et al. (2013) conducted an extensive laboratory calibration exercise of eight electromagnetic sensors across a variety of soils. They compared factory and soil specific calibration, concluding that soil-specific calibration is preferable, and magnitudes of root mean squared differences tend to be on the order of 0.02 $m^3 m^{-3}$ volumetric soil moisture.

Mittelbach et al. (2012) examined four different sensors and compared their performance against each other in situ. They determined that none of the sensors were able to meet an accuracy of 0.03 $m^3 m^{-3}$ using the manufacturer calibrations. They deployed their sensors in field conditions for approximately 2 yr and compared them to lysimeter measurements in the same field. Walker et al. (2004) compared three soil moisture sensors under field conditions. Some of the sensors in that study required a disturbed soil installation and a significant settling time for the sensors to acclimate to the soil environment. Therefore, a combination of thermogravimetric sampling, proxy dielectric sampling with a calibrated TDR probe, and hydrologic modeling were used to evaluate the sensors. The proxy measurements with the TDR probe allowed the soil near the in situ sensors to be sampled without significant disturbance, while providing a calibrated reference soil moisture estimate (a proxy for a thermo-gravimetric sample). Two of the sensor types recorded soil moisture changes that exceeded rainfall amounts during infiltration events, and the third produced physically impossible soil moisture estimates under wet soil conditions.

Evett et al. (2009) and Mazahrih et al. (2008) performed laboratory and field studies comparing five soil water sensors that were used in access tubes that could be installed to depths of 1 to 2 m without disturbance of the surrounding soil. The capacitance sensors included in these studies were inaccurate in the field, despite being calibrated in large soil columns using mass balance methods. Important effects of variable soil structure, small-scale variations in soil water content and bulk electrical conductivity, and temperature were shown to cause inaccuracies >0.04 $m^3 m^{-3}$. Results of these and other studies were summarized by Evett et al. (2012) in a review article that described why capacitance methods are physically unable to perform well in most soils due to the undefined geometric factor inherent in the electromagnetic equations pertaining to the capacitance measurement. A special issue of *Vadose Zone Journal* on soil water content sensing includes several papers comparing and evaluating soil water sensors (Evett and Parkin, 2005). A thorough overview of the recent state of soil moisture monitoring was done by Robinson et al. (2008), including a summary of the challenges faced by modern network scientists. To address some of these challenges a single point of reference testbed was established.

Table 1. Selected soil moisture networks.

Network name	Location	No. of sites	Type of sensor	Depths of sensors
Soil Climate Analysis Network	USA	180	Hydra	5, 10, 20, 50, 100 cm
Climate Reference Network	USA	114	Hydra	5, 10, 20, 50, 100 cm
National Ecological Observatory Network	USA	50	Capacitance	2–200 cm
Cosmic Ray Soil Moisture Observing System	USA	67	COSMOS	NA
Plate Boundary Observatory Network	USA	59	GPS	NA
Oklahoma Mesonet	Oklahoma, USA	108	CS-229	5, 25, 60, 75 cm
Atmospheric Radiation Measurement- Southern Great Plains Site	Oklahoma, USA	13	CS-229	5, 15, 25, 35, 60, 85, 125, 175 cm
Automated Weather Data Network	Nebraska, USA	53	Theta	10, 25, 50, 100 cm
Water & Atmospheric Resources Monitoring Program	Illinois, USA	19	Hydra	5, 10, 20, 50, 100, 150 cm
Automated Environmental Monitoring Network	Georgia, USA	81	TDR	30 cm
Environmental and Climate Observing Network (ECONet)	North Carolina, USA	12/38	Capacitance	10, 20, 30, 40 cm
West Texas Mesonet	Texas, USA	53	CS615	5, 20, 60, 75 cm
Chinese Ecosystem Research Network	China	31	Neutron	10–150 @ each 10 cm
Tibet-Obs	China	46	EC10	5, 10, 20, 40, 80 cm
Central Tibetan Plateau SMTMN	China	30	ECTM	0–5, 10, 20, 40 cm
OzNet	Australia	39	CS615/6	4, 15, 45, 75 cm
SMOSMANIA	France	12	Theta	5, 10, 20, 30 cm
Automatic Stations for Soil Hydrology	Mongolia	12	Trime TDR	3, 10, 40, 100 cm

Site Design and Soil Moisture Sensors

Here we describe a soil moisture sensor test bed, established in May of 2010, which was established to address the question of how different sensors perform versus each other at the same in situ location. The co-located records from this test bed constitute one of the more complete direct comparisons of sensor performance across the range of technologies currently in use. Thus, results from the test bed and related studies can guide the integration of diverse in situ resources at large scales for satellite validation and other purposes. We describe the test bed and summarize initial results. First, we discuss the test bed location and design. Second, the procedure for site-specific calibration, using both field and laboratory analyses, is explained. Third, performance of each sensor type is quantified, both in terms of accuracy compared to site-level validation data and failure rate. Future work will address in finer detail how the various sensor data records compare over time scales of months to years.

Large-scale soil moisture monitoring has been greatly advanced with recent satellite missions (Ochsner et al., 2013). The Soil Moisture Active Passive Mission (SMAP) was launched on January 31, 2015, as the first dedicated L-band active passive radiometer mission for soil moisture monitoring (Entekhabi et al., 2010). A simple reference or standard that has been adopted by both SMAP and the Soil Moisture Ocean Salinity (SMOS) (Kerr et al., 2010) mission, launched in 2009, is that any in situ sensors used in satellite calibration or validation efforts should be calibrated to thermogravimetrically determined volumetric soil moisture for the sensing depth of the satellite. This provides a universal standard of comparison, which is not biased toward a specific manufacturer's sensor (Topp and Ferre, 2002).

A broad set of criteria was established when site selection was initiated for the in situ sensor testbed. Critical to the study was long-term access to a moderate to low vegetation site with low topographic relief. In addition, the site had to have a spatial dimension of approximately 600 by 600 m to accommodate the scale of some of the sensors to be included in the study. After reviewing several locations and evaluating their advantages, a location approximately 13 km southwest of Stillwater, OK was selected and research relationships established with Oklahoma State University, the University of Oklahoma, and external partners. Shown in Fig. 1, a pasture managed by the Oklahoma State University Range Research Station provided an ideal location. It affords long-term access, is secure, and already contains an in situ soil moisture station of interest, the Oklahoma Mesonet Marena (MARE) station (McPherson et al., 2007). This station is named for the nearby historical community of Marena, hence the testbed adopted the name, Soil Moisture Active Passive Marena, Oklahoma, In Situ Sensor Testbed (SMAP-MOISST).

The predominant soil series is Grainola silty clay loam (fine, mixed, active, thermic Udertic Haplustalfs), which are moderately deep, well-drained soils formed in material weathered from shale. However, the soil texture varies with depth and landscape position. Figure 3 contains a plot of the soil clay percentage for each profile at each base station. The topography of the site is gently rolling with elevations ranging from 315 to 330 m above sea level. Vegetation across much of the site is typical of tallgrass

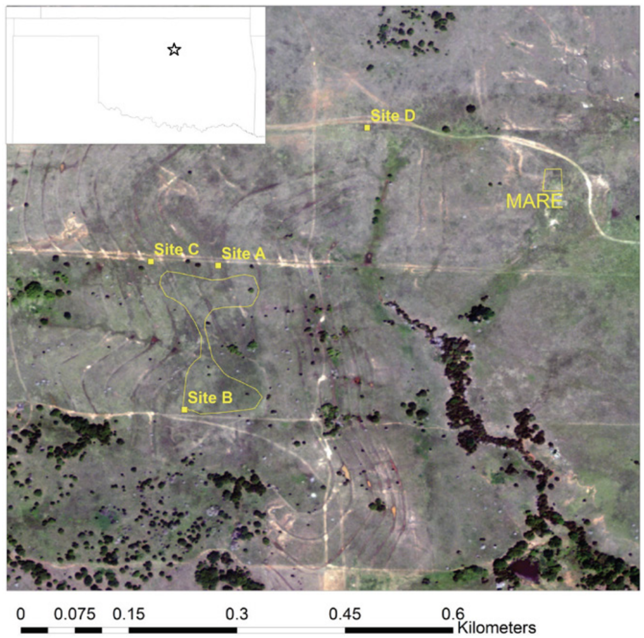

Fig. 1. Map of the Soil Moisture Active Passive Mission, the Marena, Oklahoma, In Situ Sensor Testbed (SMAP-MOISST), southwest of Stillwater, OK.

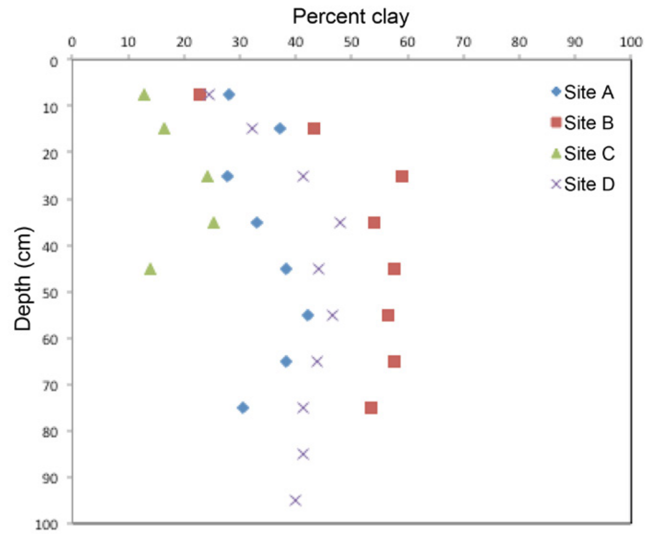

Fig. 2. Percent clay at each base station as a function of depth from surface.

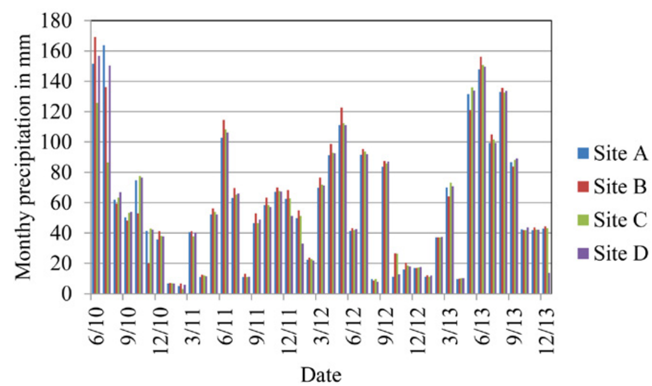

Fig. 3. Monthly precipitation in millimeters for the four base stations.

prairie, with some localized areas representative of cross timbers vegetation (Fuhlendorf and Engle, 2004). The pasture is burned every third year to prevent eastern redcedar (*Juniperus virginiana* L.) encroachment and maintain the ecological integrity of the site. There is a fence bisecting the site and terracing to prevent erosion, and cattle graze in the pasture throughout the year at a moderate stocking rate.

The average annual temperature is 15.6°C, and annual precipitation averages 876 mm based on the most recent 15 yr of data from the Marena station. Approximately 65% of the precipitation occurs during the spring and summer, with the climatological peak spanning mid-March through mid-June. Convective storms (occasionally severe) are a critical component of the warm-season precipitation and are fed by low-level water vapor transport from the Gulf of Mexico. During some thunderstorm events, precipitation totals of ~100 mm or more may occur. Precipitation is less intense during winter and is associated with synoptic-scale midlatitude storms. Precipitation was ~50% below normal in 2011, associated with the central plains drought (Fig. 3).

The soil moisture record from Marena shows surface soil moisture is very dynamic and generally follows the annual cycle of soil moisture for the region described by Illston et al. (2004): there are many dry-downs each year, with variable peak soil moisture and dry-down length. This makes the site ideal for soil moisture validation compared to either much more dry or wet sites where near-surface soil moisture would be less dynamic. Vegetation varies seasonally and in response to precipitation and soil moisture variations. Grasses are dormant during the winter months, although standing litter is abundant at this time. Vegetation green-up occurs in spring, with the highest biomass and vegetation water content typically occurring during early summer.

To provide replication, four instrument base stations were installed in May of 2010 (Sites A, B, C, and D; see Fig. 1). These stations consisted of multiple profiles of soil moisture sensors co-located within a 1-m-deep soil pit. Table 2 contains a list of the sensors and their installed depths at each of the four base stations. Each station is also equipped with a TE525 (Texas Electronics) tipping bucket rain gauge. The sensors in the study included: the Hydra Probe II (Seyfried and Murdock, 2004, 2005; Stevens Water Inc.), CS-616 Water Content Reflectometer and CS-229 Matric Potential Sensor (Campbell Scientific, Inc.), the ACC-TDT time domain transmission sensor (Acclima, Inc.), ECTM (Decagon, Inc.), EnviroSMART (Sentek Sensor Technologies, Inc.), Trime Pico-32 (IMKO GmbH), and the Theta Probe (Delta-T Devices). At Site A, a conventional TDR system (Evett, 2000a,b; Evett et al., 2005) was installed, with 24 TDR probes. In addition, the COSMOS (Hydroinnova, LLC), a passive distributed temperature

Table 2. Configuration of each Base station deployed in Marena Oklahoma In Situ Sensor Testbed (SMAP-MOISST).

Site	Sensors/system	Depths
		cm
Site A	Hydra	2.5, 5, 10, 20, 50, 90
	Theta	5, 10, 20, 50, 90
	CS-229	5, 10, 20, 50, 90
	CS-616	5, 10, 20, 50, 90
	Acclima	5, 10, 20, 50, 90
	Trime	2.5, 5, 10
	Sentek	10, 20, 50
	ECTM	5, 10,20, 50, 90
	TDR	2.5, 5, 10, 15, 20, 35, 50, 90 2.5, 5, 10, 15, 20, 35, 50, 90 Four at 7.5 Four at 2.5
	COSMOS	0–∼30
	GPS	0–1, Surface
	Flux	
Site B	Hydra	2.5, 5, 10, 20, 50, 100
	Theta	5, 10, 20, 50, 100
	CS-229	5, 10, 20, 50, 100
	CS-616	5, 10, 20, 50, 100
	Acclima	5, 10, 20, 50, 100
	Trime	2.5, 5, 10
	Sentek	10, 20, 50, 100
	ECTM	5, 10,20, 50, 100
Site C	Hydra	2.5, 5, 10, 20, 30, 40
	Theta	5, 10, 20, 30, 40
	CS-229	5, 10, 20, 30, 40
	CS-616	5, 10, 20, 30, 40
	Acclima	5, 10, 20, 30, 40
	ECTM	5, 10, 20, 30, 40
	GPS	3-m tower
Site D	Hydra	2.5, 5, 10, 20, 50, 100
	Theta	5, 10, 20, 50, 100
	CS-229	5, 10, 20, 50, 100
	CS-616	5, 10, 20, 50, 100
	Acclima	5, 10, 20, 50, 100
	Sentek	10, 20, 50, 100
	ECTM	5, 10, 20, 50, 100
	GPS	3-m tower

sensing system (Oryx DTS), an active (heated) distributed temperature sensing system (Ultima DTS, Silixa Ltd.), and four GPSR were also deployed within the domain. Figure 4 shows the instrument setup for Site A, which is located in the center of the study area. These sensors were representative of the major existing and upcoming technologies of soil moisture sensing deployed in the United States and internationally. Additional technologies, such as neutron probes and lysimeters, were determined to no longer be significantly utilized in real-time soil moisture monitoring (Table

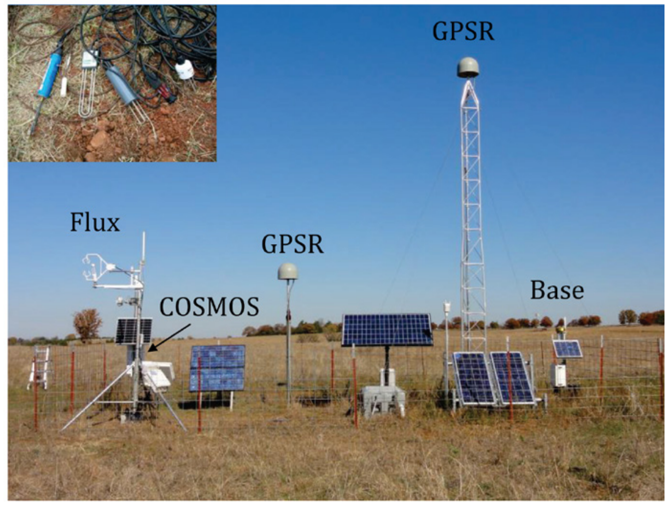

Fig. 4. The instrumentation at Site A (central station). A flux station is to the left with the COSMOS station immediately behind. Two GPSRs are featured at 2.5 and 5 m. To the far right is the sensor base station.

1) and therefore were not included in this study, especially considering the requirements of deploying such equipment.

The special case of the Campbell Scientific 229 matric potential sensor should be discussed. This sensor consists of a heating element that is encased in a ceramic matrix. The current is briefly applied to the heating element, and the resulting temperature rise is correlated with the amount of water within the matrix. From the temperature rise, it is possible to estimate the matric potential of the ceramic, which is assumed to be in equilibrium with the surrounding soil. From the soil matric potential estimates, it is possible to estimate the volumetric soil moisture if the soil water retention curve is known (Illston et al., 2008). This sensor is the soil moisture sensor used by the Oklahoma Mesonet. Sensor-specific calibration coefficients for the CS-229 sensors used in this study were developed in the same manner as those developed for the Oklahoma Mesonet following the method described by Illston et al. (2008). Recently, site- and depth-specific soil water retention parameters were determined (Scott et al., 2013) for the Oklahoma Mesonet stations, and similar analysis was done for each of the four main stations at SMAP-MOISST.

Also included in the design of the testbed, the Passive Soil DTS is an experimental method of estimating soil moisture based on DTS (Steele-Dunne et al., 2010; Dong et al., 2015). Several fiber-optic cables in a vertical profile are buried below the surface and used as thermal sensors, measuring propagation of temperature changes due to the diurnal cycle. Current technology allows these cables to be in excess of 10 km in length, and DTS equipment allows measurement of temperatures every 1 m. The passive soil DTS concept is based on the fact that soil moisture influences soil thermal diffusivity. Therefore, observing temperature dynamics can yield information on changes in soil moisture content. However, deriving soil moisture is complicated by the uncertainty and nonuniqueness in the relationship between thermal diffusivity and soil moisture.

The active soil DTS (Sayde et al., 2010) is also being tested at the site. A total of 4900 m of fiber optic sensing cables were deployed at 3 depths (5, 10, and 15 cm) along a path that is consisting of two sections: (i) a highly resolved multi-scale spiral 75 by 65 m in size with a total path length of 670 m and (ii) a 770-m transect (Fig. 5). This installation can yield more than 30,000 spatially distributed soil water content measurements every day. Similar to the passive method, the active soil DTS method relays on observing the thermal response of soil to heat perturbation to reveal soil water content. In the case of the passive method, the source of the heat perturbation is the diurnal temperature fluctuation. For the active soil DTS, the metallic components of the fiber optic cable are used as electrical resistance heater to inject heat pulses at a constant rate. The thermal integral method (Sayde et al., 2010) is used to translate the thermal response of the soil to the heat pulse into soil water contents. The thermal response (T_c) is quantified as the cumulative temperature increase from conditions before heating over the duration of the heat pulse. The main challenge of this method is to develop in situ calibration curves relating T_c to soil water content that account for spatial variability of the soil thermal properties along the fiber optic path. For that, extensive soil thermal properties and soil water content sampling are being conducted and the results of the calibration will be presented in further publications.

Global positioning system (GPS) antennas and receivers developed for geodetic purposes can be used to estimate soil moisture (Larson et al., 2008). A GPS signal travels directly between the transmitting satellite and receiving antenna as well as reflecting off the land before reaching the antenna. Reflected GPS signals can be used to estimate soil moisture because the characteristics of the reflected signal depend on permittivity of the soil, surface roughness, and elevation angle of the satellite. The GPS-interferometric reflectometry method uses a single antenna and receiver to measure fluctuations in the signal/noise ratio, which result from the direct and reflected signals shifting in and out of phase as a transmitting satellite rises or sets (Larson et al., 2010; Zavorotny et al., 2010). Small et al. (2015) showed that phase of the interferogram provides a good estimate of average soil moisture in the top 5 cm of the soil profile, although adjustments for vegetation are required at some sites. As different GPS satellites rise and set throughout the day, reflections are measured from different azimuths around the antenna. At SMAP-MOISST, three antennas were installed 2.0 m above the ground and a fourth 5.0 m above the ground, yielding a sensing footprint extending approximately 25 m and 40 m from the antenna, respectively.

COSMOS involves measuring low-energy cosmic-ray induced neutrons above the ground. The intensity of neutrons is inversely correlated with soil water content and with water in any form above

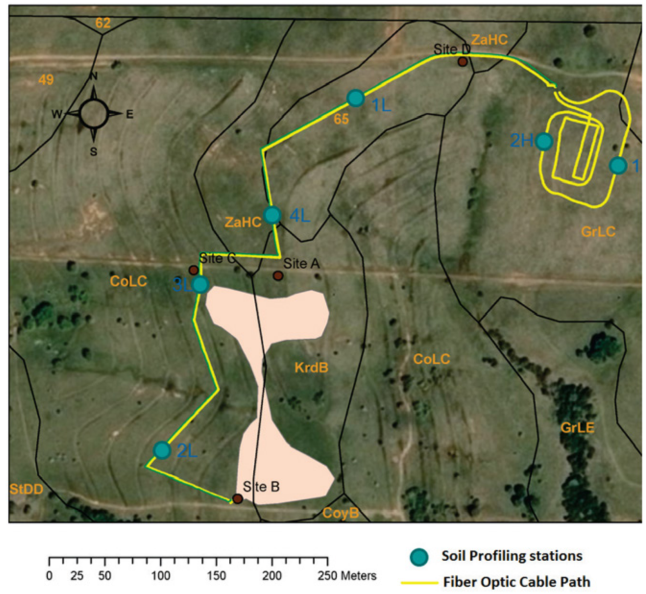

Fig. 5. Actively heated fiber optic cable path.

ground (Zreda et al., 2008; Köhli et al., 2015). The measurements are insensitive to soil chemistry, texture, and topography. The system provides noninvasive, no contact measurements and automated data collection and data transfer to an online COSMOS network database. The estimated measurements are of integrated soil moisture over a footprint of ~400 m in diameter, over a depth of 0 to 70 cm (dry) and 0 to 12 cm (wet) (Desilets and Zreda, 2013; Köhli et al., 2015). The precision is based on the number of counts (2% easily achievable). Both liquid and frozen water phases are measured. It is also possible to estimate vegetation biomass via this technique (Franz et al., 2013). New research has extended the use of this technology to mobile applications, allowing for the possibility of soil moisture mapping at large scales (Chrisman and Zreda, 2013; Dong et al., 2014; Franz et al., 2015).

Methods of Analysis

There are two distinct concepts, calibration and scaling, which are important to the interpretation of in situ data. Calibration in this study refers to the specific correction or adjustment of the in situ sensor's soil moisture estimate for the specific soil type where it is installed. It should be noted that the COSMOS sensor is not specifically in situ, but a remote sensing sensor, as is the GPSR. These are still calibrated per established calibration methods, which are usually short in time frame. Scaling in this study refers to the development of an equation or function that relates the data series from a specific sensor type to a larger scale areal-average soil moisture.

This study made use of both repacked soil samples in the laboratory and in situ field sampling to get a full range of soil moisture conditions for calibration. Initially, in situ instruments were temporarily installed in the field and measurements taken. The soil that was measured was then sampled volumetrically, and gravimetric soil moisture was determined via the thermogravimetric method (Evett, 2008). This provided a limited range of mostly dry soil moisture conditions. Two additional methods were employed, the first being laboratory calibration with manually wetted, repacked soil. This provided a good number of wet end data points. To ensure that the laboratory method was accurately representing field conditions, a final method was employed. In the field, several test plots were randomly selected and manually inundated with water to varying degrees. The Hydra, CS-616, Acclima, ECTM, Trime, and Theta Probe were inserted into the moistened soil, and soil moisture readings from each were recorded. The moistened soil was then sampled volumetrically. For logistical reasons, this in situ calibration approach was not used for the EnviroSMART or the CS-229 sensors.

Results and Discussion

Calibration

The Theta, Hydra, ECTM, CS-616, Trime, and Acclima sensors were calibrated for the SMAP-MOISST site using a combination of field and laboratory techniques. Table 3 provides RMSE values for each sensor based on the manufacturer's suggested factory calibration. The soil moisture estimates from the manufacturer's calibration were then recalibrated specifically for this site by fitting a simple linear equation that minimized the RMSE between the measured and estimated soil moisture values. The results of this site-specific calibration are also presented in Table 3 and in Fig. 6. The SMAP satellite mission has an accuracy target of ±0.04 m^3 m^{-3} (Entekhabi et al., 2010), so in situ sensors used for purposes of satellite validation should have RMSE values at or below this level. The Theta and Hydra sensors satisfied that requirement at this site using the manufacturers' calibrations, while the Trime sensor nearly met the threshold, having a 0.042 m^3 m^{-3} RMSE for the factory calibration. The other sensors performed worse for this site, with RMSE values well beyond the estimated error from the manufacturer, which is typically in the range of 0.01 to 0.03 m^3 m^{-3} (Table 3).

After the soil-specific calibration was applied, all but the CS-616 sensor exhibited RMSE values below the 0.040 m^3 m^{-3} threshold, indicating that with proper site-specific calibration, most of these sensors were acceptable under the conditions extant during the tests. Figure 7 contains the time series of data from Site A for the soil moisture sensors, which were part of the base configuration. These soil moisture values were based on the site-specific calibrations. There were a wide range of soil moisture estimates among the sensor estimates, each with varying dynamic ranges. This variety of ranges was observed at the other base stations as well. Also, sensor malfunctions were observed occasionally, related to power supply issues, but these were not included in error calculations.

Table 3. Root mean square errors for the factory calibration and a soil specific calibration for the Soil Moisture Active Passive Mission, the Marena, Oklahoma, In Situ Sensor Testbed (SMAP-MOISST) site.

Sensor	Factory-listed accuracy	Bias with factory calibration	RMSE factory calibration	RMSE soil-specific calibration
			m^3 m^{-3}	
Theta	0.01	0.014	0.030	0.028
Hydra	0.01–0.03	0.020	0.040	0.029
ECTM	0.03	0.076	0.081	0.036
CS-616	0.025	−0.023	0.073	0.063
Trime	0.01–0.03	0.005	0.042	0.023
Acclima	0.01	0.074	0.080	0.025
CS-229	N/A	–	–	–
Enviro-SMART†	N/A	–	–	–

† EnviroSMART arrays are on a single data port that may have failed, affecting all sensors in the array.

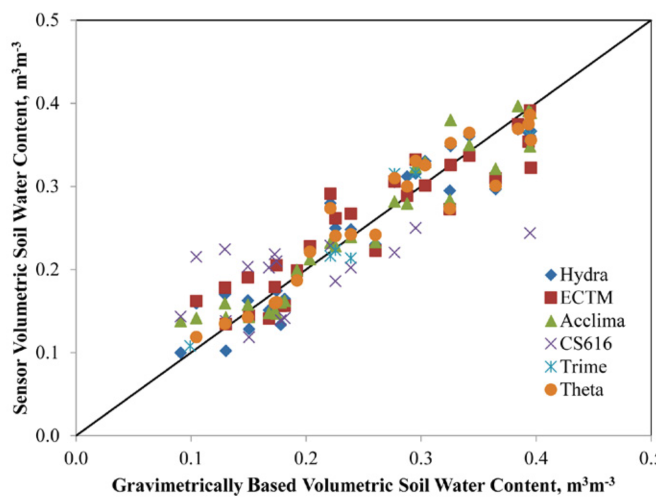

Fig. 6. Calibrated volumetric soil moisture from physical sampling versus the sensor estimate.

Another issue of importance in this study is the continuity of the sensor record. The value of an in situ network is proportional to the length of the data record available. When a sensor fails, that sensor must be replaced or at least reinstalled after repair. This produces a discontinuity in the data record. Any replacement sensor would not be easily reinserted into the same soil in the exact same position, introducing an unavoidable installation bias. One method of compensating for this problem is redundant sensors. For instance, there were three profiles of Hydra Probe profiles installed within meters of each other near Site D, mimicking the Climate Reference Network installations. Table 4 shows the root mean squared differences (RMSD) and correlation coefficients between the triplicate sensors for the 5-cm depth. The RMSDs between the three 5-cm-depth Hydra Probe sensors ranged between 0.028 and 0.054 m^3 m^{-3} when computed for the first 3 yr of installation. Some of this variability may be due to sensor-to-sensor variability

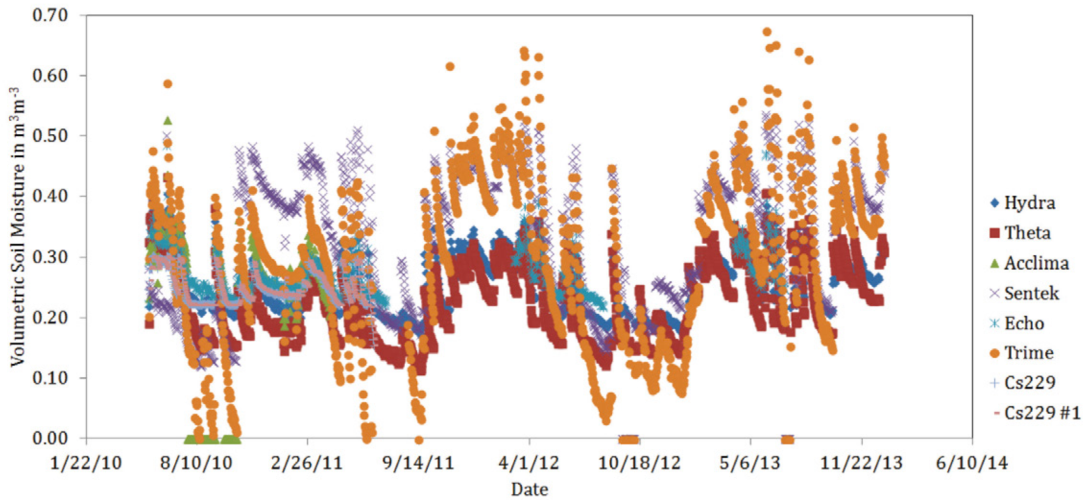

Fig. 7. An example time series of the Site A data series for water content at the 5-cm depth.

(Chávez and Evett, 2012). Coopersmith et al. (2015) determined the intersensor variability for the Hydraprobe to be approximately 0.01 $m^3 m^{-3}$ using triple collocation. This level of small-scale spatial variability still does not account for bias that would have a more significant impact on data continuity. This variability may be a result of installation variability or microvariations in local soil texture.

Field-Scale Validation of Calibrated Sensors

In situ stations are often installed in locations that might not represent the larger landscape; for example, there might be different land cover or different maintenance regime. To get an estimate of the ability of a single sensor to approximate a larger scale, a periodic scaling experiment was conducted as part of SMAP-MOISST. This required large-scale sampling of the 0- to 5-cm soil moisture, which is the primary depth of interest to the remote sensing community (Entekhabi et al., 2010; Kerr et al., 2010).

Figure 8 shows the radial sampling pattern used in this study. Eight samples were taken in eight directions at sampling distances of 50 m between sites. This sampling design was to complement the COSMOS system footprint, which was thought to have an approximate radius of 300 m (Desilets and Zreda, 2013). The sampling was completed on 14 dates between July 2010 and September 2012. This sampling was accomplished using a calibrated Theta Probe because gravimetric sampling would have been prohibitively time-consuming and disruptive to the site. The sensor estimates for selected depths for each sensor type from Site A were compared to the arithmetic average of all the soil moisture measurements from the radial sampling, and RMSE values are given in Table 5, shown as "Unscaled." The in situ sensors used in this study are for the 2.5-cm (if available), 5-cm, and 10-cm depths of installation, as these are usually the shallowest depths available for large-scale networks. Some sensors accurately represented the larger landscape with RMSE values less than 0.04 $m^3 m^{-3}$. However, some RMSE

Table 4. Root mean square differences (RMSD) between the CRN installed 5 cm soil moisture values. The correlation coefficients (r) are also shown.

5 cm	Site 1	Site 2	Site 3
RMSD			
Site 1	0	0.054	0.028
Site 2		0	0.039
Site 3			0
r			
Site 1	1	0.855	0.964
Site 2		1	0.922
Site 3			1

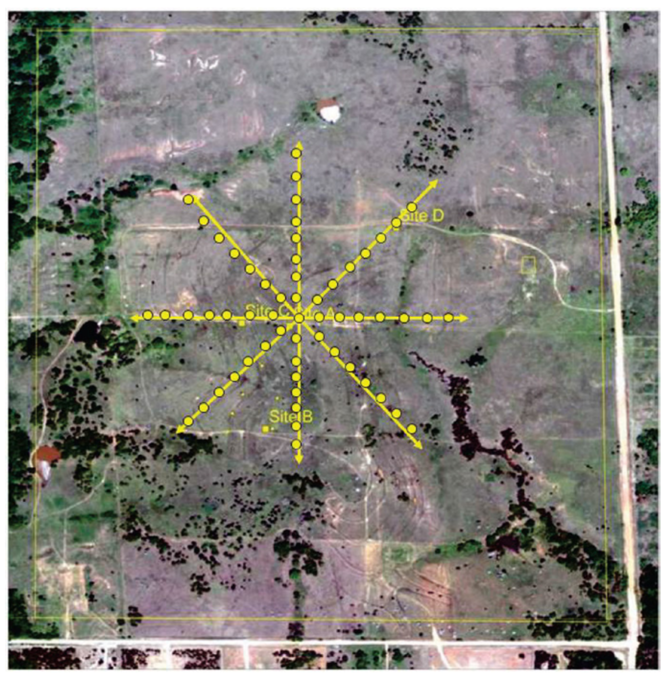

Fig. 8. Sampling pattern for scaling of the surface sensors.

Table 5. Root mean square error for Site A profile soil moisture estimates compared to the large-scale sampled average.

Sensor	Unscaled				Scaled			
	2.5 cm	5 cm	10 cm	Variable depth	2.5 cm	5 cm	10 cm	Variable depth
				$m^3\ m^{-3}$				
CS-616		0.110	0.140			0.036	0.046	
Hydra	0.048	0.062	0.079		0.021	0.035	0.047	
Theta		0.058	0.063			0.030	0.039	
Acclima		0.030	0.053			0.027	0.047	
Sentek			0.178				0.064	
ECTM		0.047	0.055			0.032	0.043	
Trime	0.083	0.085	0.110		0.026	0.032	0.042	
CS229		0.071	0.129			0.043	0.050	
TDR	0.020	0.045	0.070		0.013	0.039	0.053	
GPSR				0.050				0.036
COSMOS				0.048				0.035

values were as high as 0.08 $m^3\ m^{-3}$, which may have been a result of minor biases in the installation at Site A, due to natural variations in soil texture, preferential flow paths in the vadose zone, and installation geometry. To correct for these biases, a best-fit linear equation was calculated to minimize the RMSE of the sensor at Site A relative to the areal average. Different sensor depths at Site A were compared to the 0- to 5-cm areal average to determine how that depth was correlated to the surface and how much error would be introduced to a validation program if deeper sensors were used. The results of the scaling are shown in Table 5 ("Scaled"), and there was significant improvement in the RMSE values. As this is an improvement over the unscaled errors, the scaled RMSE values must be equal to or less than the unscaled RMSE values. For example, the ECTM sensor RMSE was reduced from 0.081 to 0.036 $m^3\ m^{-3}$. Most dramatic was the Acclima sensor, for which the RMSE was reduced from 0.080 to 0.025 $m^3\ m^{-3}$, indicating that the Acclima sensor at Site A could accurately represent the field average 0- to 5-cm soil moisture with a site-specific scaling relationship. Alternatively, the RMSE for the CS-616 sensor did improve from 0.073 to 0.065 $m^3\ m^{-3}$, but this is still not sufficient for purposes of satellite validation (Entekhabi et al., 2010). This scaling does require the supporting data collection (e.g., radial sampling or similar) to provide a basis for the regression relationship.

Smaller RMSE values were obtained for data from the shallow depths (2.5 cm), than for the deeper depths (10 cm), which is reasonable considering the proximity to the surface sampling scheme. There are disadvantages to the shallow installations, however, as on more than one occasion, the 2.5-cm sensor was dislodged from its original location by cattle activity. This is a common problem with in situ sensor installation, so often the depth of installation is increased to 5 cm to ameliorate this issue.

Also in this table, the COSMOS estimate was compared to the 0- to 5-cm depth average of 64 points in the field, even though COSMOS has a variable integration depth. Further analysis is necessary to determine how accurate the COSMOS sensor was across the full sensing depth. However, the focus of this study has been on surface estimation; the comparison to just the surface samples is critical to informing the remote sensing community for validation purposes.

Conclusions

Soil moisture sensors vary in their performance in the field in both calibration, scaling, and durability. A test bed was developed to create a reference point of comparison across a diversity of in situ soil moisture sensors. It was necessary to apply site-specific calibration to most sensors to reach an RMSE below 0.04 $m^3\ m^{-3}$. For most sensor types, a single near surface sensor could be scaled to represent the areal average of a field domain by simple linear regression, resulting in RMSE values around 0.03 $m^3\ m^{-3}$. This does require some supporting field measurements to develop this relationship, but there was a considerable improvement over the RMSE values from using the unscaled data. The sensor performance we observed may be unique to this location, and results may vary in other locations.

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