

CHAPTER 6

PRODUCING REPRESENTATIVE SOIL MOISTURE DATA: SENSOR CALIBRATION AND POST-DEPLOYMENT STRATEGIES

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Learning Outcomes

Accuracy of sensor readings can be increased by conducting laboratory and field-based calibrations.

Post-deployment checks on measured data against modelled, remote sensed, or satellite data can help ensure site representativeness and provide climatological context.

Well-calibrated sensors ensure accurate measurement of soil moisture for the micro-site, while post-deployment and field validation help ensure site representativeness. While several peer-reviewed publications on sensor calibration exist, there is no clear scientific consensus on a calibration strategy for soil moisture sensors yet. *The recommendations in this chapter do not necessarily represent the latest literature but are conservatively based on popularly accepted methods and should be updated as necessary.*

WHAT MAKES SOIL MOISTURE SENSOR CALIBRATION DIFFERENT FROM OTHER TYPICAL MESONET SENSORS?

The calibration of soil moisture sensors differs from other sensors that a mesonet (environmental monitoring station) may deploy owing to its soil specificity. Calibration can vary with soil structure, bulk electrical conductivity, and soil texture. In reported literature, improvements are observed in sensor performance after applying a soil-specific calibration, and in some cases, they are significant enough not to be ignored. Hence, soil sensor calibration can be more important for certain sensor-site condition combinations like clayey soils or soils with high bulk electrical conductivity. Table 5 provides a concise summary of improvement in sensor performance after soil-specific calibration. Sensor performance varied based on different soil types. Therefore, sensors should be calibrated using soil samples specific to each site where they will be installed, if a network chooses to perform this calibration. There are other popular methods of soil sensor calibration that do not involve soils as the medium for calibration (such as calibration in air and distilled water). While these other methods can ensure a well-functioning sensor, they give no quantification of a sensor's performance in a specific soil. Sensors are also calibrated by manufacturers and have a factory determined calibration, which should be used and reported in the absence of other calibration exercises.

Soil sensor calibration often only needs to be performed for one sensor of each type. Sensors of the same make and model are generally calibrated well with each other, and a calibration equation developed for a specific sensor for a certain soil type can often be universally applied to all sensors of the same make for that soil type. This also allows for calibration to be done post-installation if representative soil samples are collected from the field. However, it should be noted that there are some sensors that exhibit sensor-to-sensor variability and require individual sensor calibration, such as CS – 229Ls. Such information on sensors is best obtained from sensor manufacturers.

Table 5. Improvement in sensor accuracy with soil-specific calibration (adapted from Cosh et al., 2021)

Sensor	Manufacturer	Type	Frequency	Outputs	Advertised accuracy (m ³ /m ³)	Factory calibrated accuracy (m ³ /m ³)	Soil-specific accuracy (m ³ /m ³)	Reference	Soil Texture	Soil Minerals (if specified, non-soil mediums are not listed)
In situ Sensors										
10HS	Meter	Cap.	70	V	±0.03	±0.073, ±0.053	±0.013, ±0.012	[1], [2]	Sand, loamy sand, sandy clay loam, silt loam, clay loam, silty clay loam, clay	Mineral, organic and mineral-saline
5TE	Meter	Cap.	70	Ka, EC, <i>T</i>	±0.03	±0.040, ±0.039	±0.026, ±0.013	[1], [3]	Sand, loamy sand, loam, sandy clay loam, silt loam, clay loam, silty clay loam, clay,	Mineral, organic and mineral-saline
CS616	CSI	TLO	175	period	±0.025	±0.057, ±0.129, ±0.073	–, ±0.025, ±0.063	[4], [1], [5]	Sand, loamy sand, sandy clay loam, silt loam, clay loam, silty clay loam, clay, 10-60% clay	Mineral, organic and mineral-saline
						±0.140, ±0.157	±0.027, ±0.016	[6], [3]	Sand*, sandy loam*, loam*, silt loam*, clay loam*, clay*, loam	

Sensor	Manufacturer	Type	Frequency	Outputs	Advertised accuracy (m ³ /m ³)	Factory calibrated accuracy (m ³ /m ³)	Soil-specific accuracy (m ³ /m ³)	Reference	Soil Texture	Soil Minerals (if specified, non-soil mediums are not listed)
CS650/655	CSI	TLO	175	Ka, EC, <i>T</i>	±0.03	±0.073, ±0.078	±0.025, ±0.022	[7], [3]	loamy fine sand, loam, silty clay loam, clay loam, clay	
Digital TDT	Acclima	TDT	1,230	Ka, EC, <i>T</i>	±0.02	±0.049, ±0.080	–, ±0.025	[4], [5]	10-60% clay	
EC-5 ^c	Meter	Cap.	70	V	±0.03	–, ±0.054	±0.013, ±0.025	[8], [3]	silt loam, loam	
Field Connect	J. Deere	Cap.				±0.083	±0.026	[3]	loam	
Hydra Probe	Stevens	Imp.	50	Ka, EC, <i>T</i>	±0.01	±0.073, ±0.033, ±0.048	±0.056, ±0.022, ±0.028	[9], [10], [1]	Sand, loamy sand, loam, sandy clay loam, silt loam, clay loam, silty clay loam, sandy loam, clay loam, silty clay, clay	Kaolinite, gibbsite, vermiculite, montmorillonite, organic, mineral saline
						±0.040, ±0.102, ±0.010	±0.029, ±0.013, -	[5], [3], [11]	5-60% clay Sand, loam, silty clay loam, sandy clay loam, silt loam, clay	

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SM150/300	Delta-T	Imp.	100	V, T	±0.03	±0.037	±0.014	[1]	Sand, loamy sand, sandy clay loam, silt loam, clay loam, silty clay loam, clay	Mineral, organic and mineral-saline
TDR100 ^c / TDR200	Campbell	TDR	1,450	Ka, EC	–	±0.042, ±0.023	–, ±0.022	[4], [1]	Sand loamy sand, sandy clay loam, silt loam, clay loam, silty clay loam, clay	Mineral, organic and mineral-saline
TDR315	Acclima	TDR			–	±0.050, ±0.020	±0.016, –	[3], [11]	Sand, loam, silty clay loam, sandy clay loam, silt loam, clay	
Theta Probe	Delta-T	Imp.	100	V	±0.01	±0.066, ±0.029, ±0.030	–, ±0.015, ±0.028	[4], [1], [5]	5-60% clay, sand, loamy sand, sandy clay loam, silt loam, clay loam, silty clay loam, clay,	Mineral, organic and mineral-saline
Trime-PICO	IMKO	TDR	1,000	V	–	±0.042, –	±0.023, ±0.044	[5], [12]	5-60% clay Sand, loamy sand, loam, sandy loam,	

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WET	Delta-T	Cap.	20	Ka, EC, <i>T</i>	±0.03	±0.041, ±0.034	±0.029, ±0.025	[13], [1]	sandy clay loam, silt loam, clay loam, silty clay loam, clay, organic substrates, volcanic soils	Illite, Montmorillonite, mineral saline, organic, other mineral soil
Profile Sensors										
AquaCheck	–	Cap.			–	±0.163	±0.013	[3]	loam	
Diviner 2000	Sentek	Cap.	250	counts	–	±0.030–0.053, -	±0.025, ±0.018–0.044	[14], [15]	Silty clay loam, clay loam, silty clay, clay	Illite, montmorillonite, other mineral soil
EasyAg	Sentek	Cap.		–	±0.06	–	–			
EnviroSCAN	Sentek	Cap.	75	count		±0.018 – 0.073, -	±0.020, ±0.021–0.051	[14], [15]	Silty clay loam, clay loam, silty clay, clay	Illite, montmorillonite, other mineral soil
Gro-Point	ESI	TDT		current						
PR2/6	Delta-T	Cap.	100	V	±0.04	±0.091–1.30, -	±0.027, ±0.024–0.063	[14], [15]	Silty clay loam, clay loam, silty clay, clay	Illite, montmorillonite, other mineral soil

Sensor	Manufacturer	Type	Frequency	Outputs	Advertised accuracy (m ³ /m ³)	Factory calibrated accuracy (m ³ /m ³)	Soil-specific accuracy (m ³ /m ³)	Reference	Soil Texture	Soil Minerals (if specified, non-soil mediums are not listed)
SoilVUE-10	Campbell	TDR	1,450	Ka, EC, <i>T</i>	±0.02					
Trime-T3	IMKO	TDR		time (ps)	±0.03	±0.051-070	±0.02	[14]	Silty clay loam, clay loam, clay	Illite, montmorillonite

TLO: Transmission line oscillator; Cap.: Capacitance; TDR: Time Domain Reflectometer; Imp.: Impedance

LABORATORY-BASED SOIL-SPECIFIC CALIBRATION

Calibration for data quality purposes is defined as the adjustment of an electronic signal from a sensor to the specific conditions of the installation. For most electromagnetic sensors, a popular and often sufficient calibration method (described below) involves batch mixing of the soil and packing to a specific dry density for different moisture conditions, as described below and in Appendix B. However, several alternate methods are available that may be better for certain sensors (Table 6). These alternate methods may be sensor-specific and involve research-grade activities.

Table 6. Soil moisture sensor details

Soil moisture sensor	Method	Reference
CS 65x (Campbell)	Downward infiltration	Caldwell et al., 2018
Stevens hydra probe	Dry down evaporation	Burns et al., 2014
CS 229-L	Sensor unit specific calibration	Illston et al., 2008

CALIBRATION RECOMMENDATIONS

DISCLAIMER: *A poorly done soil-specific laboratory-based calibration will increase the error beyond what is reported by the manufacturer.* Hence, recommendations for calibration given below should be strictly followed.

Soil sensors should preferably be calibrated using the batch mixing method described in Caldwell et al., 2018 or by [METER Group](#). A recent study from Rowlandson et al. (2018) showed that soil moisture calibration curves are very sensitive to the range of moisture values they are calibrated for, and it is important to cover the entire range of expected moisture when developing calibration curves. We recommend using at least a 4-6 point calibration (where at least 4 to 6 measurements are taken to establish reading-SWC relationship) since the relationship between the response variable and soil moisture is often not linear in the way a two-point calibration would assume it to be.

1. Soils that represent soil conditions in the field are the most important variable for planning calibration (Rowlandson et al., 2013; Vaz et al., 2013; Cosh et al., 2005). Hence, soil moisture sensors should be calibrated for all soil textures that are found at the site at each installation depth. If a soil sensor is expected to measure across different soil horizons, care must be taken to collect soils from both horizons to mimic soil conditions in the field. Note that if a capacitance or impedance-based sensor is chosen for high clay (high bulk electrical conductivity) soils, accuracy targets may not be achieved (Mazahrih et al., 2008; Evett et al., 2009; Evett et al., 2012).

2. Soil from the site should be baked until completely dry, and soil sample volume and density recorded. The soil sample should then be mixed with water in batches. Full demonstrations of this technique, such as that provided by [METER Group](#) can be found online.



Figure 5. Sensor calibration in lab. Image Credit: Leo Rivera.

3. Soil calibration must be done at the same bulk density as measured in the field. Note that it is often difficult to repack soils to the same density as observed in the field, and in such cases, efforts must be made to be within $\pm 0.2 \text{ g/cm}^3$ of the field-based bulk density. In the case of swell-shrink soils with large variations in bulk density, multiple bulk densities of soil must be considered. The differences in calibrated soil moisture at different bulk densities should be included as an accuracy metric that may be important to several stakeholders. Note that network operators can reach out to the NCSMMN if they require recommendations for measuring bulk density for soils at their sites.
4. The calibration equation must be developed between volumetric soil moisture (measured using gravimetric soil moisture and bulk density of the soil sample) and the response variable of the sensor (often permittivity for probes that measure it).
5. Ideally, ambient temperatures for conducting calibration should match the average temperatures experienced by the sensors in the soil.
6. Depending on the instrument, there are other useful diagnostics that can be verified before or during deployment. For example, the [Stevens HydraProbe Manual](#) (section 3.14) suggests testing operation of a potentially problematic probe by performing a test in distilled water. This is useful to do before deployment alongside a temperature calibration to ensure sensor operation.
7. The results of each calibration test must be documented. Examples of high-quality documentation of test results provided by the Oklahoma Mesonet are shown below. The documentation describes the test, date of the test, person conducting the test, and the result.

		Certificate of Calibration		Sensor Serial No 278785 Test Type Sensor Type Test Facility	As Left HydraProbe Pro diH2O / dH2O Bath
Distilled Water Test				Test Date Reference Sensor	20220630 Fluke 2122-0084RC
				Prob Desc / Comment:	
Voltage 1 (V)					1.602
Voltage 2 (V)					0.725
Voltage 3 (V)					0.137
Voltage 4 (V)					0.845
Soil Values Calculated by Campbell Scientific's HydraProbe CRBasic Instruction					
Soil Type Used For Calculations					1 (Sand)
Real Dielectric Constant					79.3
Temperature Corrected Imaginary Dielectric Constant					-1.004
Water Content (fraction by volume)					4.733
Salinity (grams of NaCl per liter)					-0.005
Soil Conductivity (Siemens per meter)					-0.003
Temperature Corrected Soil Conductivity (Siemens per meter)					-0.003
Temperature Corrected Soil Water Conductivity					0.000
Hydra Probe Temperature (°C)					22.07
Reference Temperature (°C)					21.81
Temperature Corrected Real Dielectric Constant					80.5 PASS
Imaginary Dielectric Constant					-0.962 PASS
Temperature Error @ Reference Temperature (°C)					0.26 PASS
SDI-12 Sensor Onboard Verification Command					0 PASS
PASS / FAIL Criteria According to the manufacturer, a correctly operating sensor should meet all of the following conditions while submerged in distilled water:					
1. The Temperature Corrected Real Dielectric Constant is between 75 and 85. 2. The Imaginary Dielectric Constant is less than 5. 3. The temperature error is within ± 0.6 °C for the analog Hydra Probe and ± 0.3 °C for the Hydra Probe II. 4. The response to the SDI-12 sensor onboard verification command must equal 0.					
Methodology: The sensor was submerged in distilled water along with a reference thermistor and allowed to thermally stabilize for at least 30 minutes before the 4 sensor voltages were sampled and processed using Campbell Scientific's HydraProbe CRBasic instruction.					
Traceability: The Fluke Electronics Model 5610 Reference Thermistor Serial No. 2122-0084RC was calibrated on Apr 26 2022 by Fluke Calibration compliant to ISO/IEC 17025:2005 and ANSI/NCSL Z540-1-1994 outlined in Calibration Report No. JN202204097-013.					
Py 1.0		Calibrated by: E. Becker			

Figure 6a. An example of a certificate of calibration listing details on the sensor, calibration methods, and test results of each calibration method. This is an example of an actual calibration conducted by the Oklahoma Mesonet.

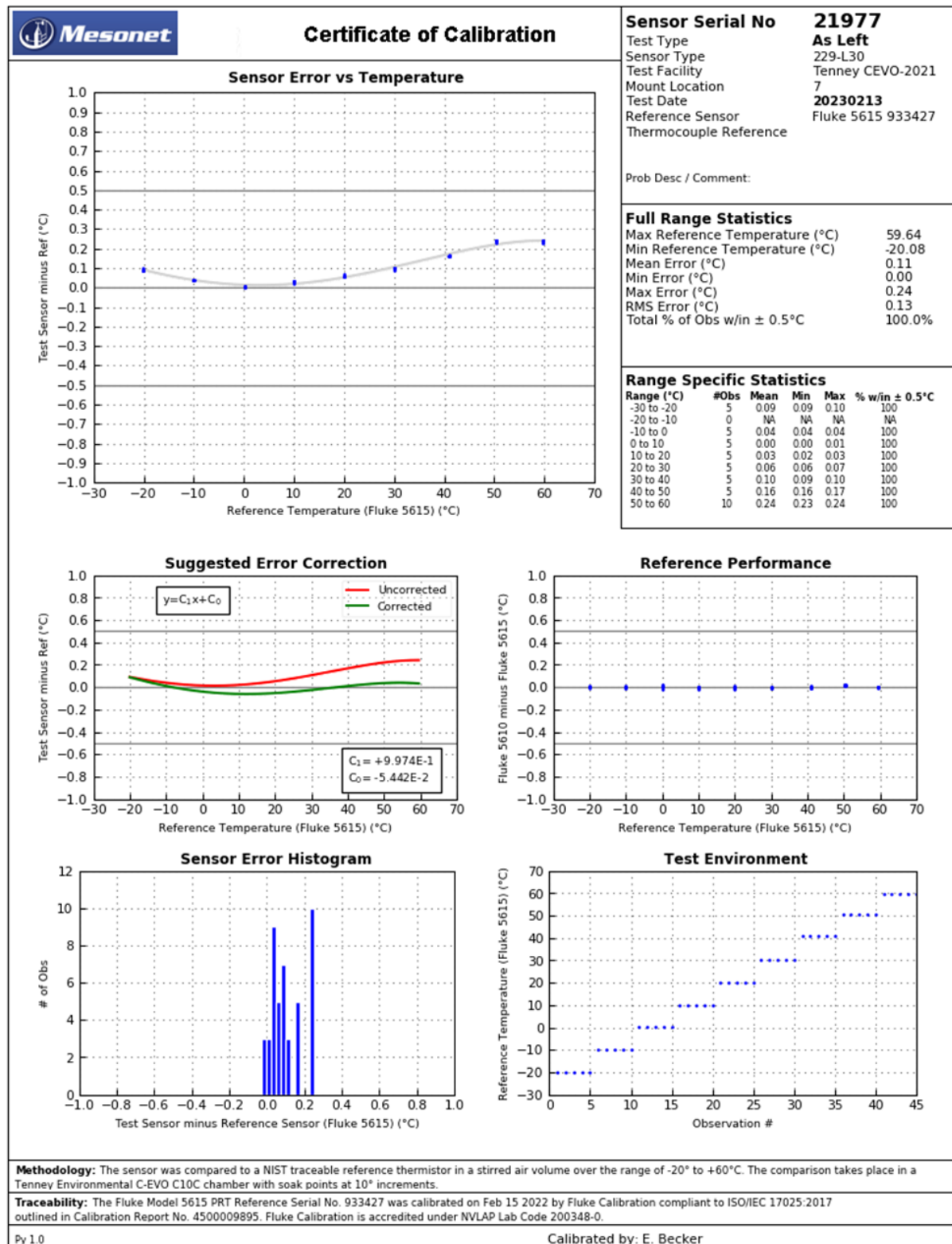


Figure 6b. An example certificate of calibration describing error statistics and suggested error correction. This is an example of an actual calibration conducted by the Oklahoma Mesonet.

FIELD CALIBRATION OF SENSORS

Field calibration of sensors can also be considered a rough upscaling exercise that allows the sensor to represent a larger area surrounding it. Field specific gravimetric calibration should be reported in addition to a soil-specific calibration. Field calibration of sensors can be conducted as explained below.

1. Collect soil samples from several locations (at least 5) in the area surrounding the soil sensors (i.e., an area with no variability in meteorological conditions). These locations must have the same soil series as the site where the sensors are installed, and samples must be collected under different wetness conditions (~ 6-10 time-points total) that are preferably spread across different seasons. Ideally, soil samples should be collected from each depth at which the soil sensors are installed, although in practice it can be challenging to collect samples below ~30 cm depths.
2. Soil samples should be of a known volume to that ensure bulk density and volumetric soil moisture can be calculated from gravimetric soil moisture, as explained in Appendix D.
3. The average soil moisture value across all measured locations should be used to calibrate the installed soil moisture sensor. The calibration function can be estimated as explained in Chapter 6 of the [METER Group calibration document](#) for soil/point specific calibration⁸. This process must be done for each soil depth separately, and the new calibration equation must be developed using the raw data (voltages) that the sensor measures. Linear or non-linear regression equations may be developed.

UPSCALING AND OTHER POST-DEPLOYMENT CHECKS

Post-deployment activities should be used to assess the spatial representativeness and accuracy of the dataset. *These can also be used in lieu of field calibration.* Post-deployment activities are best conducted in consultation with a soil moisture expert. Network operators can reach out to the NCSMMN or the American Association of State Climatologists (AASC) mesonet community for connecting with experts who can aid this effort.

The measurement volume of most in situ sensors is on the order of 10s of cm³, which cannot provide the landscape scale of information often desired by data users. However, these measurements are highly correlated to larger local domains that have similar soil textures and landscape conditions and that experience similar hydroclimatic conditions, such as precipitation, evaporation, and solar radiation. By taking advantage of this correlation and homogeneous parameters at the landscape scale, points in space can be used to approximate larger regions, which can have a significant impact on applications requiring soil moisture information at a larger scale, such as drought monitoring or flood forecasting. This process is known as upscaling.

Upscaling can be accomplished by a variety of methods, including field experimentation, temporal stability, and numerical modeling. Each of these methods can be combined in a variety of ways or used separately to increase the representativeness of an in situ network station. Additionally, these methods of validation can be applied at multiple time scales. Since sensor performance and response of a sensor to a soil moisture signal can vary with wetted area

⁸ <https://publications.metergroup.com/Sales and Support/METER Environment/Website Articles/Method a soil specific calibrations for meter soil moisture sensors.pdf>

and temperature, such activities are best spread across seasons and across multiple years, if extreme years are expected.

There are several ways to conduct field validation that operators can choose from, depending on access to resources. Some of the activities described below will be more labor intensive, while others would be more cost intensive. Some of the activities may also require sophisticated statistical expertise.

COMPARISONS WITH OTHER STATIONS WITHIN OR OUTSIDE THE NETWORK

Temporal Stability

This method will provide a rank of wetness to the site being monitored relative to the general wetness in the area. It is a critical concept used for the characterization of soil moisture using the idea that there are consistent patterns in soil moisture over time. While this consistent pattern will have variability for any given day, different locations will have relative ranks of soil moisture values if studied over a long period of time. The soil texture, land position, and vegetation can all influence soil moisture dynamics and condition the soil towards a fixed relative rank, while local precipitation or overland flow introduce a randomness to pattern. The concept of temporal stability for soil moisture was first introduced by Vachaud et al. (1985) and has been employed across monitoring networks by many others (Martinez-Fernandez and Ceballos, 2003; Cosh et al., 2006). This method can be employed using several stations within the same network or by partnering with other networks producing soil moisture data.

One way of verifying representativeness of a sensor installation is to install an additional temporary station or stations to provide independent estimates of soil moisture. These additional stations can be operated for a short time-period, and the time series can be used to statistically improve the confidence in the long-term time series via a new in situ calibration equation. Some studies have demonstrated this methodology for longer term sensors (Coopersmith et al., 2016; Cosh et al., 2013; Heathman et al., 2012). This is especially useful for agricultural environments that have field disturbances where long-term installations cannot exist within the domain.

COMPARISONS WITH OTHER TYPES OF SENSORS

Portable Sensor Verification

Handheld sensors are also a viable option for quickly determining how soil moisture is distributed across the landscape, at least at the surface. There is a long history of field experimentation with handheld sensors, often based on the same technology as long-term, installed sensors, so calibrations of the sensors themselves can be identical. Handheld sensor sampling campaigns can be used to provide a sense of scale for a long-term installation (Cosh, et al., 2005). This type of measurement is often combined with remote sensing or proximal sensing systems, like the COSMOS cosmic ray neutron system (Coopersmith et al., 2014; Dong et al., 2014) or aircraft-based measurements (Colliander et al., 2012). In the future, this type of campaign will be applicable to satellite remote sensing from active sensors like the NISAR mission which will be able to provide a 200-meter resolution soil moisture product for comparison to in situ installations. At that scale, pixels will be more homogeneous, and confidence can increase in the correspondence between a remote sensing scale and an in situ footprint.

Proximal Sensing Methods

Proximal sensing is a convergence of remote sensing and other technologies that can monitor across larger footprints of the landscape without installing in the physical matrix of the soil. The Cosmic Ray Soil Moisture Observing System (COSMOS, Zreda et al., 2012) is a system in which the neutrons that are generated by cosmic rays are measured to determine an estimate of the amount of water within a 200-300 m radius for an approximate depth of 20 cm of soil. These systems can be used to validate the equivalent depth of moisture estimates from the in situ sensors. Comparison with a COSMOS sensor can also provide insight into in situ sensors' representativeness of the area.

Small Uncrewed Aerial Systems for Soil Moisture Monitoring

Ge et al. (2021) is one of the first studies to use drone-based hyperspectral sensors to produce field resolution soil moisture estimates which would be capable of informing precision agriculture. Similarly, Kim et al. (2024) established the viability of a drone-based L-band system to estimate soil moisture across an agricultural domain.

Comparison with Modeled Soil Moisture

Land-surface modeling is capable of high temporal and spatial resolution estimates of surface and profile soil moisture. These models can be either physically-based models, statistical models, or artificial intelligence-based models. Vergopolan et al. (2020) produced a five-year sequence of 30 m daily soil moisture maps for the continental U.S. for the near-surface, as well as 1 m integrated depth, based on a physically-based model combined with assimilated remote sensing information. Du et al. (2022) produced a 3 m soil moisture product from Planet SuperDove and SMAP data using machine learning. This approaches the scale of in situ monitoring, though few networks or installations are capable of providing a spatial resolution of this magnitude. Models, however, are limited by training data, availability of land surface ancillary information, and structural errors, and not all models are suitable for accurate representation of all landscape types. Hence, when comparing soil moisture values between in situ sensors and soil moisture predicted from physically-based models, matching both absolute values and temporal trends would be ideal. However, because sensors and models could be based on different assumptions and principles, assessing for temporal trends would be more realistic (Owens et al., 2024). It is advisable to conduct such a comparison in consultation with a modeling expert.

METRICS OF DETERMINING ACCURACY OF IN SITU SOIL MOISTURE DATA

Results from calibration or post-deployment activities should be presented using scientifically accepted statistical indices and metrics for quantifying soil moisture accuracies (Entekhabi et al., 2010). These indices include climatological references and standardization or comparison with other comparative variables to assess the accuracy of the measurements.

CLIMATOLOGICAL AND EVENT COMPARISON

Standardization of soil moisture observations (percentiles or deviation from normal) from a site based on climatological records helps bring the observations into a climatological anomaly perspective, and, thus, they can be compared with known drought or flood events (Leeper et al., 2019). Soil moisture datasets can also be compared with meteorological observations, such as precipitation and temperature, as a general check to ensure proper functioning of the sensors. Examples of these comparative approaches are provided below.

Nash–Sutcliffe Model Efficiency Coefficient (NSE)

The Nash-Sutcliffe model is used to quantify the percentage variance of the reference data that is explained by a test dataset. When the test data matches perfectly with the reference data, the Nash-Sutcliffe model efficiency coefficient equals 1 (NSE=1) (that the model is performing well). NSE = 0 indicates that the test data offers the same sum of the squared errors as the mean of the reference data (that the model is not performing well). For the following, o is the reference dataset and y is the observed dataset, and N are the total samples. NSE is given as:

$$NSE = 1 - \frac{\sum_{i=1}^N (y_i - o_i)^2}{\sum_{i=1}^N (y_i - \bar{o})^2}$$

Mean Squared Error (MSE)

Mean squared error (MSE) measures the amount of error in statistical models. It assesses the average squared difference between the observed and predicted values. When a model has no error, the MSE equals zero. As model error increases, its value increases.

$$MSE = \frac{\sum (y_i - \bar{y}_i)}{N}$$

Unbiased Root Mean Squared Error (ubRMSE)

Remote sensing measurements may contain a systematic bias compared to in situ observations. The unbiased root mean squared error (ubRMSE) addresses this by modifying the commonly used index root-mean squared error to remove the bias from the observed and reference dataset:

$$ubRMSE = \sqrt{\frac{\sum ((y_i - \bar{y}) - (o - \bar{o}))^2}{N}}$$

Anomaly Correlation Coefficient (R_d)

This index is a modified version of the Pearson correlation coefficient, where the observations and the reference dataset are normalized according to a climatological mean (c), thereby providing a measure of the linear association between the observation and reference anomalies as:

$$R_d = \frac{\sum (y_i - c)(o_i - c)}{\sqrt{\sum (y_i - c)^2} \sqrt{\sum (o_i - c)^2}}$$

R_d can range between [-1,1]; where a value of 1 and -1 indicates a perfect positive and negative correlation, respectively. $R_d=0$ indicates that the two datasets are not correlated.

Triple Collocation Error

The triple collocation technique is a powerful tool to estimate the root mean square error (Chen et al., 2018) while simultaneously solving for systematic differences in the climatologies of a set of three independent data sources. This approach allows a simultaneous estimation of the error structure and the cross-calibration of a set of at least three linearly related datasets with uncorrelated errors⁹. These datasets are spatially and temporarily collocated and have mutually independent error structures and no systematic biases.

⁹ In some cases, a triple collocation approach can yield a lumped estimate of sensor measurement and representativeness uncertainty. This challenge is described more explicitly in Gruber et al. (2013) and Miralles et al. (2010).