SOIL MOISTURE DATA QUALITY GUIDANCE

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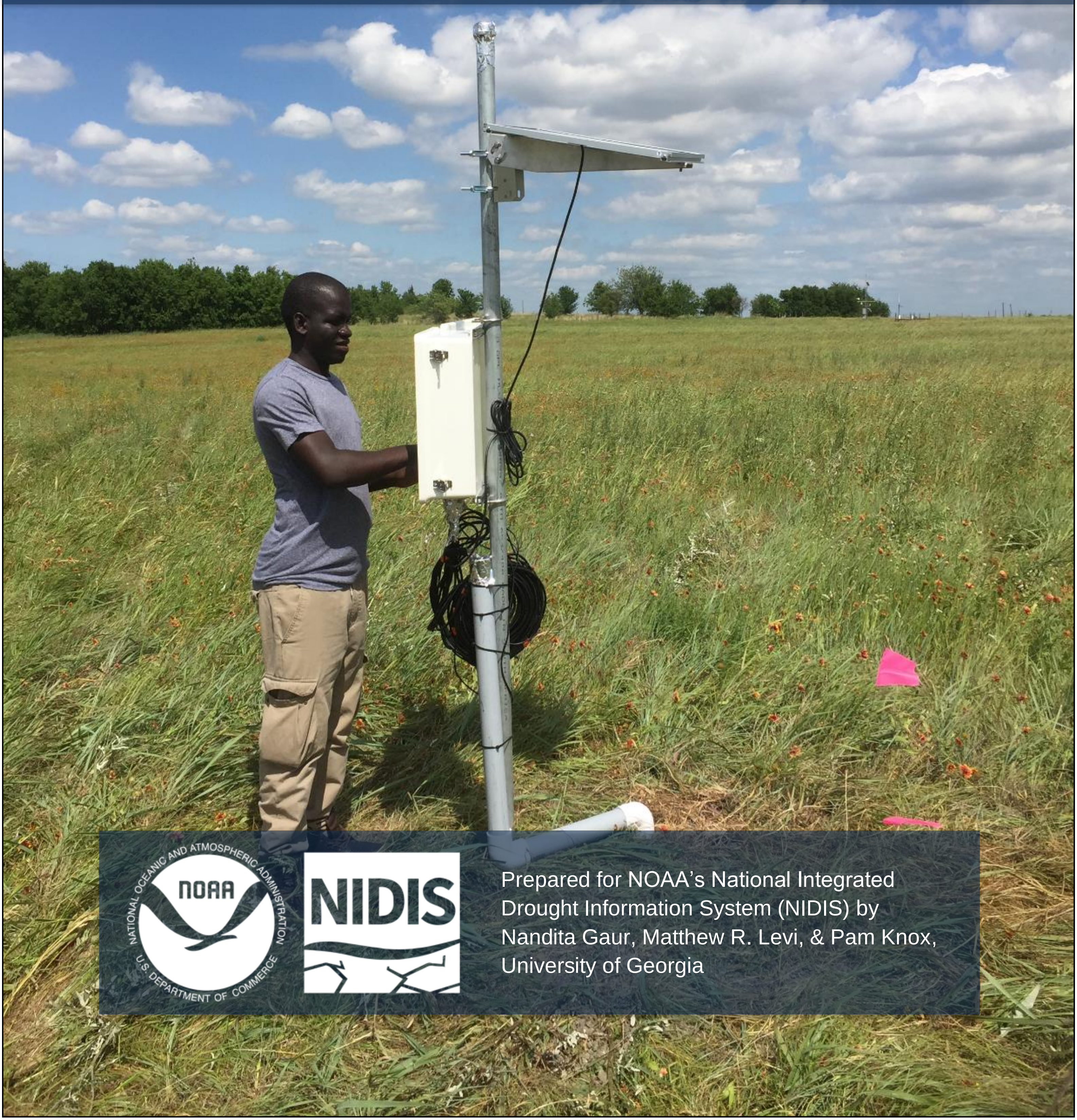

Prepared for NOAA's National Integrated Drought Information System (NIDIS) by Nandita Gaur, Matthew R. Levi, & Pam Knox, University of Georgia

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ABOUT THE NATIONAL COORDINATED SOIL MOISTURE MONITORING NETWORK

NOAA's National Integrated Drought Information System (NIDIS), working in collaboration with the U.S. Department of Agriculture (USDA) and other partners, is leading the effort to implement the National Coordinated Soil Moisture Monitoring Network (NCSMMN): a multi-institutional initiative to integrate soil moisture data from across the country and to capitalize on its transformative potential across sectors of the economy. The mission of the NCSMMN is to "advance coordinated, high quality, nationwide soil moisture information for the public good" by:

- Establishing a "network of networks"
- Building a community of practice and expertise
- Supporting research and development on innovative techniques to merge in situ soil moisture data with remotely-sensed and modeled hydrologic data

The 2021 *Strategy for the National Coordinated Soil Moisture Monitoring Network* describes a set of recommendations to solidify the NCSMMN's organizational structure and advance soil moisture monitoring and data application nationally. Included is a recommendation to "**Develop a Set of Criteria for High Quality Data Sources**.**"** This charge was created in recognition of the need for and value of a concerted, easily communicable approach to describing the quality of a data set for network operators, decision makers, resource managers, and others.

A working group was established to help fulfill this recommendation. The "Soil Moisture Data Quality Guidance" document is one of two resources generated in direct response to this recommendation. The working group spearheaded the creation of both this document and its companion, "Soil Moisture Metadata Quality Guidance," through an intensive multi-year process of information gathering, peer review, and feedback from both the network operator and the data user communities.

CHAPTER 1

INTRODUCTION

Nandita Gaur, Pam Knox, Matthew R. Levi

The Data Quality Guidance Document provides guidelines for standardizing soil moisture data collection by mesonets and other long-term monitoring networks. It introduces a tiering system for categorizing soil moisture data into 'Data Quality Tiers' and provides aspirational goals to improve the quality of soil moisture data.

The approach described in this document for categorizing networks into three tiers parallels a proposed tiering method for meteorological networks more broadly, as described by the World Meteorological Organization's Global Climate Observing System (WMO GCOS)[1]. However, this document differs from the WMO GCOS approach in that it is designed to specifically address challenges and needs associated with long-term soil moisture monitoring.

The document is designed to be used for self-assessment by monitoring networks and is intended to create greater transparency with respect to the quality of data for users of soil moisture data. This data quality guidance document is a companion to the "Soil Moisture Metadata Guidance" document (henceforth referred to as the Metadata Guidance document) and is part of a series of resources on long-term soil moisture monitoring that are being produced by the National Coordinated Soil Moisture Monitoring Network (NCSMMN) to standardize long-term soil moisture measurements.

BACKGROUND

The NCSMMN is led by the National Oceanic and Atmospheric Administration's (NOAA's) National Integrated Drought Information System (NIDIS). It is a collaborative effort among federal agencies, soil moisture scientists, mesonet operators, and others to plan for and support nationally coordinated soil moisture monitoring and data assimilation. As a key milestone of this effort, and in direct response to a Congressional requirement for a national soil moisture strategy, the NCSMMN community developed a "Strategy Document" in 2021. The "Strategy Document" provided a roadmap forward and delineated the resources and activities needed for implementing a coordinated national network; specifically, a network to provide coordinated, high-quality, nationwide soil moisture information for the public good. This Data Quality Guidance Document responds to two recommendations from the Strategy Document that are listed below.

1. Develop a set of criteria for high-quality soil moisture data sources.
2. Support research necessary to develop or improve NCSMMN methodologies.

[1] Proposal for formalization and standardization of tiered network approach across domains and observing system programs. 2022. https://gcos.wmo.int

Further resources on soil moisture and a full discussion of the objectives of the NCSMMN can be found in *A Strategy for the National Coordinated Soil Moisture Monitoring Network* (2021).

WHAT IS SOIL MOISTURE AND WHAT UNITS IS IT MEASURED IN?

Soil moisture is defined as the amount of water present in the soil. It is either measured gravimetrically (i.e., on a weight basis) or volumetrically (i.e., on a volume basis). Gravimetric soil moisture is the mass of water per unit mass of dry soil, which can be converted to volumetric soil moisture (referred to as Soil Water Content (SWC) in this report) by multiplying it by the soil bulk density and dividing by the density of water. In situ probes indirectly measure SWC, while gravimetric soil moisture can only be measured in the lab from mass loss by heating soils for 24 hours at 105 °C. Soil bulk density can be measured from volumetric soil cores or clods to determine dry soil mass in a fixed volume. These methods are detailed in several Natural Resources Conservation Service (NRCS) documents.

In relation to stakeholders, however, soil moisture is often useful in other units, such as plant available water[2], percentile[3], and fraction available water[4]. In this document, the term "stakeholder" refers to users of soil moisture data, tools, or products. Fortunately, SWC as reported by in situ probes can easily be converted to all other units of soil moisture required by stakeholders, provided relevant soil properties are measured or estimated (as described in the Metadata Guidance document). Refer to Appendix D of this document for conversions between different units of soil moisture.

NEED FOR SOIL MOISTURE DATA QUALITY GUIDANCE

Soil moisture has been identified as a critical land surface variable for improving the quality of several hydrological applications that impact human life and enhance our understanding of the biosphere. Consequently, significant efforts are being made to expand soil moisture monitoring efforts. The combined benefits of these efforts, however, are limited since there is a large variability in how Soil Water Content (SWC) is measured and reported, which limits the utility of this important state variable for many applications. For stakeholders to seamlessly utilize soil moisture data collected by disparate monitoring agencies, it is essential to create a standardized method of measuring and reporting moisture data through a standardized guidance document. Factors that create variability in the measurement and reporting of SWC include:

1. Spatial and temporal representativeness of measured data
2. Accuracy of sensors and the volume of soil that the sensors measurement represents
3. Units in which SWC is reported

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[2] Plant available water (PAW) is calculated as the difference between SWC at field capacity and SWC at wilting point for the entire root zone of the soil. PAW is typically expressed in units of length.
[3] Soil moisture percentiles are reported in values ranging from 0-100 and provide an estimate of soil moisture conditions as compared to historical conditions for the region. More details can be found in Ford et al. (2016).
[4] The *fraction* of plant available water (FAW) is a way to normalize SWC across different soils. FAW represents a normalized difference of SWC at a given time in relation to the difference between SWC at field capacity and SWC at wilting point for a specific soil depth. FAW typically ranges between 0 – 1.

4. Selection criteria for soil moisture sensors
5. Methods to produce useful data, and
6. Frequency of measurement, processing, and dissemination of data.

This document serves as an accessible guide for collecting, maintaining, and producing accurate and representative soil moisture data using in situ sensors. Key data applications by stakeholders considered in this document include agricultural monitoring, water resources, hydrologic and weather predictions, wildfire prediction, and drought and flood early warning.

SCOPE OF DOCUMENT

The scope of this document is restricted to recommendations for network operators of long-term monitoring networks that deploy in situ soil moisture sensors. The 'Data Quality Tier' system that the document introduces should be used for categorizing the quality of soil moisture data produced by such networks. These tiers are based on quality parameters that were identified through a literature review and through input from the soil moisture monitoring and applications communities.

Specifically, the document offers direction to network operators for:

- Planning and anticipating resource needs for a long-term monitoring program,
- Understanding and fulfilling diverse stakeholder data requirements,
- Site selection,
- Sensor selection,
- Laboratory and field-based sensor calibrations,
- Quality control and quality assurance protocols, and
- Self-assessment of network data quality according to standards herein.

Note: The Data Quality Tiers are aspirational, providing network operators a means to self-evaluate their data quality and develop long-term network goals. They also provide stakeholders a short-hand approach for assessing characteristics and utility of a data set for their desired application. There is no mandate or formal evaluation associated with these tiers. The document is simply providing guidance and best practices to improve soil moisture data collection.

PROCESS OVERVIEW

The Data Quality Guidance document has been compiled based on a review of existing literature, input from stakeholders of soil moisture data, surveys of existing soil moisture networks, and discussion with experts in soil moisture monitoring and measurement, which included scientists from: federal agencies, including the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) and Agricultural Research Service (ARS), the National Oceanic and Atmospheric Administration (NOAA), the United States Geological Survey (USGS), the United States Department of Energy (DOE); as well as universities; operators of state mesonets; and other long-term environmental monitoring networks. A working group of various experts and stakeholders met for six months and discussed each aspect of this report prior to its compilation. Contributors are listed at the end of the document.

DOCUMENT GUIDE

DOCUMENT STRUCTURE

The document is divided into nine chapters and five appendices. Chapters 2-8 provide detailed guidelines for establishing a soil moisture sensor network, from planning to reporting quality soil moisture data. Each chapter has an orange box that describes the learning outcome of that chapter. The appendices serve as checklists or handy reference guides for a quick overview of the entire document. The first and last chapter provide a general introduction and conclusion to this document.

The level of detail provided in chapters 2-8 of this document is recommended for those new to in situ soil moisture monitoring and/or those seeking clarification and background information on quality issues. Appendices A-E are designed to serve as a quick review checklist and are strongly recommended for those intending to apply the data quality principles in an actual operational setting. Note that using the appendices without any background in soil moisture monitoring runs the risk of missing key issues. See below for a list of the appendices.

- *Appendix A:* Checklist for planning a new station or network.
- *Appendix B:* Sensor calibration practices required for different tiers of soil moisture data quality at the time of sensor installation or at the time of upgrading the data quality tier of your stations/network.
- *Appendix C:* QA/QC activities.
- *Appendix D:* Guide for converting between different soil moisture units.
- *Appendix E:* Checklist for existing network operators for determining Tiers or upgrading stations to Tier I, II or III.

GETTING THE MOST OUT OF THIS DOCUMENT

This document will be most helpful if used in conjunction with other documents that have been created as part of the larger effort by the NCSMMN. This includes documents describing sensor installation, operations and maintenance, and data verification steps (Caldwell et al., 2022), data collection and data logger programming (Patrignani et al., 2022; https://soilwater.github.io/mist/), and metadata to ensure consistent reporting between data providers (Metadata Guidance document).

CHAPTER 2

PLANNING A LONG-TERM SOIL MOISTURE MONITORING NETWORK

Pam Knox, Nandita Gaur

Learning Outcomes

Collection of metadata prior to network establishment has the capacity to affect the quality of long-term SWC monitoring and should be considered during the planning stage.

Resource allocation for long-term site and data maintenance should be a part of network planning and/or new site establishment.

Soil moisture data can be collected either across a long time period (long-term) or temporarily over discrete periods. In this document, temporary data are defined as data designed to be collected over short time periods to support answers to very specific management or basic hydrologic research questions. The collection of such datasets is supported by pre-determined and guaranteed availability of resources. Data collected over the long term but marked by discrete periods of collection are also considered temporary. Such datasets are not considered in this document.

Long-term monitoring networks considered in this document differ from temporary and/or discrete data collection in three main ways. First, long-term networks often serve multiple stakeholders. Secondly, they are designed to produce consistent and continuous data over long periods (>10 years), continually, and at high temporal frequency (e.g., 15 minutes, hourly, etc.). Finally, resources supporting the network are often inconsistent and may become available all at once or in phases. More often than not, networks' resources come with a lot of uncertainty. Hence, a sound planning exercise at the time of installation can help fulfil immediate stakeholder needs and allocate resources in a manner that allows room for planned growth if resources should become available in the future.

The factors described in the following sections of this chapter should be incorporated into network planning. These recommendations were identified based on a survey of existing long-term monitoring networks (Table 1).

INVOLVEMENT OF LOCAL SOIL EXPERTS

Soil experts are best involved prior to planning sensor installation at any site. Soil Water Content (SWC) is often reported in different units based on stakeholder needs (Chapter 3), and several of these units require ancillary information that must be collected at the time of installation. A quality soil moisture dataset also requires field-based information, which is best collected by a soil expert at the time of sensor installation. Experts may include soils staff at a local National Resources Conservation Service (NRCS) office, university, or private company. Network operators can also reach out to the NCSMMN at soilmoisture@noaa.org or the American Association of State Climatologists (AASC)'s mesonet community as a contact point (https://stateclimate.org/) for recommendations. In addition to a soil expert, it is useful to reach out to other nearby, existing long-term networks for other ancillary information in the region. The specific soil-based ancillary information that should be collected at the site is described in the Metadata Guidance document.

Table 1. List of networks that responded to the survey

	Participating networks	Contact names	State
1	Alabama Mesonet	Lee Ellenburg	Alabama
2	Delaware Environmental Observing System	Kevin Brinson	Delaware
3	Florida Automated Weather Network (FAWN)	William Lusher	Florida
4	University of Georgia	Pam Knox	Georgia
5	Hawaii Mesonet	Thomas Giambelluca	Hawaii
6	Purdue Mesonet	Beth Hall	Indiana
7	Kansas Mesonet	Chip Redmond	Kansas
8	Manitoba Agricultural Weather Network	Timi Ojo	Manitoba, Canada
9	Michigan State University Enviroweather	Keith Mason	Michigan
10	Automated Weather Data Network	Jamie Lahowetz	Nebraska
11	Rutgers New Jersey Weather Network	Dave Robinson	New Jersey
12	NC ECONet	Sean Heuser	North Carolina
13	North Dakota Agricultural Weather Network	James Hyde	North Dakota
14	Oklahoma Mesonet	Ethan Becker	Oklahoma
15	National Ecological Observatory Network (NEON)	Edward Ayres	National network, U.S.
16	Atmospheric Radiation Measurement (ARM) user facility	Jenni Kyrouac	National network, U.S.
17	U.S. Climate Reference Network (USCRN)	Ronald Leeper	National network, U.S.

Note: The above list was compiled based on a survey of existing long-term monitoring networks. Information was collected using a *Google Form* that was sent out to mesonet operators in the American Association of State Climatologists (AASC) network and the soil moisture working group.

SITE SELECTION TO ENSURE DATA LONGEVITY

Station longevity is critical for many applications of soil moisture data, given that stakeholder needs often require long-term time series analysis. Hence while sites should be regionally and locally representative, choosing a site that is expected to be available for long-term installation is advised. The longevity of quality soil moisture data from a site differs from other typical weather-based measurements that are collected at long-term monitoring sites because soil moisture sensors are harder to re-orient or move post-installation. This includes avoiding having the site move even as little as a few meters, since it will entail uninstalling the soil moisture sensor. Such movement could also significantly alter the moisture dynamics that are recorded by the sensor, and any field-based calibration exercise and collection of ancillary data for the site will need to be repeated for the new location. Moving sensors can also limit the use of that site for long-term comparisons. Factors that may cause a site to move include changes in ownership of land, management activities, etc. For example, operational challenges like vehicular movement in agricultural lands or operational difficulties associated with burning a forested site could require a site to be moved. Public versus private lands may have different permitting requirements. For example, if public lands are used, compliance with Section 106 of the National Historic Preservation Act of 1966 (NHPA) is required.

SENSOR SELECTION

Sensor selection should primarily be driven by performance in specific soils (Mane et al., 2024). However, a network operator may also need to consider the availability of future resources, since some sensors may have more maintenance and post-validation requirements than others. Additionally, while it is also possible that different sites within a network can be served by different types of sensors depending on the soil, using the same sensors across all stations is preferable for maintaining consistency over the long term. Such a case may arise when soils across a network span a wide range of bulk electrical conductivity values, and certain soils require more expensive sensing technology, while others can be serviced by cheaper sensing technology (Chapter 5). In such a case, a network operator would need to plan for either (1) using different sensors at different sites, which may be problematic in the long run for operation and maintenance; or (2) managing resources to purchase standardized sensors for all locations, which may end up being considerably more expensive. Network operators will need to make executive decisions based on their specific funding availability. Standardization is helpful in scenarios where future funding is limited, especially for trained personnel. It is highly recommended to reach out to the soils department of the state's land-grant universities, other regional networks collecting soil moisture data, or other mesonets to solicit guidance regarding the choice of sensors. The NCSMMN community can also provide this type of guidance.

DOCUMENTATION OF INSTALLATION PROTOCOLS

Resources must be invested in carefully documenting protocols followed at the time of installation. This is important since personnel changes can cause loss of information that may not be easily reclaimed at a later point without significant investment of additional resources. Since each site is different and sensors are installed in the subsurface, documentation of protocols must be done independently for each site. Proper documentation also enables transparency for stakeholders. Standardized protocols as developed by NEON (https://data.neonscience.org/data-products/DP1.00094.001) and Oklahoma Mesonet (McPherson et al., 2007) are good examples.

AUTOMATION OF NETWORKS AND DATA STORAGE NEEDS

Resources allocated for automation of sites can also help mitigate issues pertaining to uncertain future funding. Automation includes data telemetry and automated quality control protocols developed by experts. Resources must either be allocated for maintaining servers of information, which require dedicated and trained personnel, or developing partnerships with existing data management companies. There are several private companies that offer these services. However, it should be noted that either of these choices comes with its own set of associated costs.

PLANNING RESOURCES FOR ANCILLARY DATA

To ensure high-quality soil moisture data, long-term measurements should be accompanied by relevant atmospheric and biophysical measurements. These measurements are useful for implementing several quality control and quality assurance practices (Chapter 7). At a minimum, atmospheric data should include rainfall measurements. Further, depending on resources available, air temperature, relative humidity, and additional datasets that help measure the water budget in greater detail can be added. In terms of biophysical datasets, soil temperature data are essential and must be collected for quality control practices. Other recommended biophysical measurements are detailed in the Metadata Guidance document.

CHAPTER 3

DATA REQUIREMENTS OF COMMON STAKEHOLDERS FOR SOIL MOISTURE DATA

Richard Heim, Zamir Libohova, Mark Brusberg, Vinit Sehgal, John Kabrick

Learning Outcomes

Understanding current and potential stakeholder needs should inform network planning and data quality and assurance goals.

In this chapter, data quality needs for several common stakeholders have been summarized from the perspective of soil moisture measurement units and depths, accuracy, ancillary data, time span, and latency of data.

Stakeholders require several different categories of information (Table 2) associated with each measurement of soil moisture to make the best use of data. As one example, soil moisture data needs to be expressed in units that can be related to drought intensities when used for drought monitoring purposes. The U.S. Drought Monitor (USDM) methodology that uses a percentile approach for magnitude category thresholds to express the rarity of an event is based on an assessment of numerous drought indicators and related datasets (Svoboda et al., 2002, *Table 1*). The drought data and indicators, including soil moisture, need to be expressed as percentiles, or units that can be related to historical percentiles, to be most effective for drought monitoring purposes. To convert raw volumetric values into a meaningful percentile equivalent, a multi-year period of record is needed to provide an adequate historical context. If the length of the record is too short to provide such a historical context, then the data ideally should be expressed in terms that have meaning to vegetation. For example, is the amount of water in the soil sufficient to meet the needs of the crops or ecosystem vegetation? Or is it below some threshold whereby the plants will experience some level of drought-related stress?

Another use of soil moisture data is in the field of digital soil mapping. Soil moisture dynamics are closely related to soil development and spatial variability. US soil survey has relied on topographic maps or digital elevation models that represent only water surface redistribution over the landscape but that are used to infer properties and processes for subsurface. However, recent advancements with distributed hydrological models that simulate soil moisture trends over time and with depth show that, when validated with soil moisture *sensor* data, these models can be used to map soils and properties across surface (2D), depth (1D), and time (1D), which provides a 4D approach to soil mapping (4DSM) (Owens et al., 2024; Libohova et al., 2024) (Figure 1).

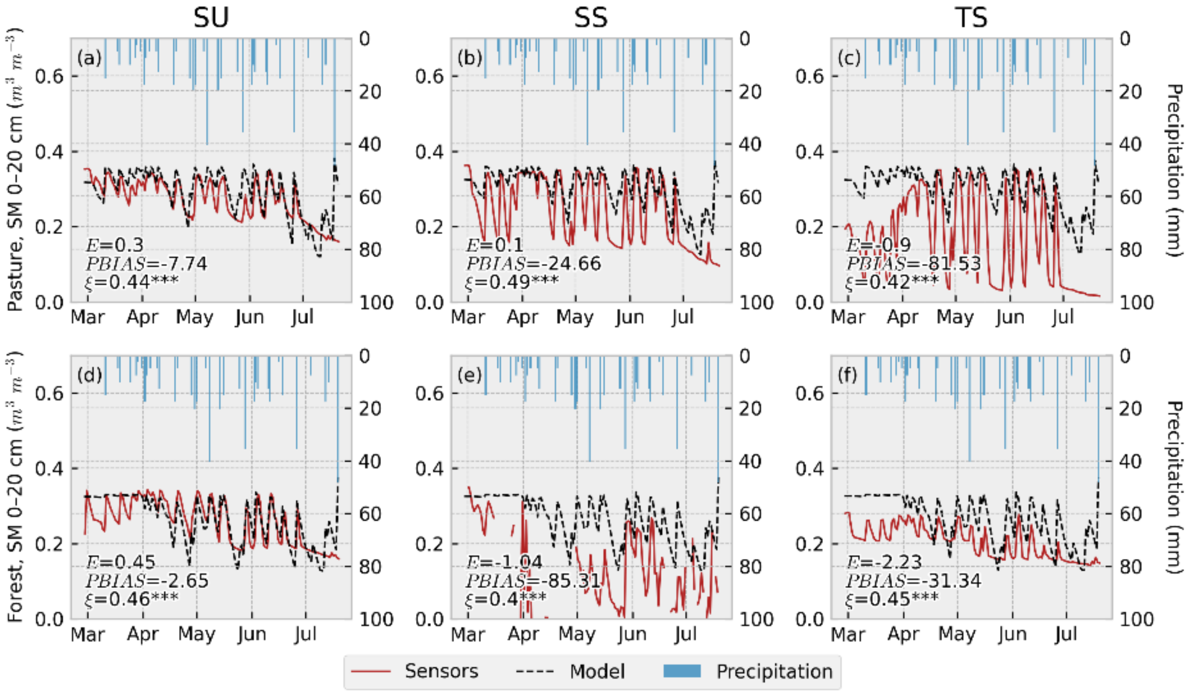


Figure 1. A comparison between soil moisture content (SM) from sensors and simulated (model) for depth 0–20 cm by a Distributed Hydrology Model (DHM) for two catchments under pasture and forest. Sensors are located at the summit (SU), sideslope (SS), and toeslope (TS) of each catchment. Figure Credit: Libohova et al., 2024.

Indicators such as Nash-Sutcliffe efficiency (E) (Nash and Sutcliffe, 1970), percent bias (PBIAS) (Onyutha, 2021), and the Chatterjee's correlation coefficient (ξ) (Chatterjee, 2021) can be used to compare simulated and observed data (Figure 1). Hydrological models informed by soil moisture data offer the advantage of producing high resolution soil moisture maps that can fill the gaps between sensors. Such applications require numerically accurate soil moisture data.

The data requirements and data needs of the various stakeholders that participated or were represented in the working group meetings for this document are listed in Table 2. This table can be used by network operators to consider example needs of data users for planning their soil moisture data collection efforts. However, *each data user is different*, and early engagement with a network's direct intended users can help support alignment with user needs and suitability of future data for its intended applications.

Table 2. Stakeholder requirements. (In cases where information was unavailable for a particular category, the field was marked by a '-')

Application	Data Latency	Depth (m)	Units	Agencies/Organizations	Critical Data Need
Flood / Stream forecasting	< 3 hours	-	-	U.S. Army Corp of Engineers (USACE), National Weather Service (NWS) River Forecast Centers	Low latency
Crop Water Demand, crop forecasting	Daily to Weekly	0 - 1	m^3/m^3	National Agricultural Statistics Service (NASS)	Soil Water Content (SWC) at field capacity and SWC at wilting point[5] for the entire soil profile; historical anomalies
Drought monitoring	Daily to Weekly	Root zone and/or below	Moisture percentiles	United States Department of Agriculture (USDA), National Oceanic and Atmospheric Administration (NOAA), National Drought Mitigation Center (NDMC), State Climate Offices, Agriculture and Agri-Food Canada (AAFC)	Long-term datasets for statistical comparisons, Soil Water Content (SWC) at field capacity, and SWC at wilting point
Validation datasets for models and RS	Weekly	0-1	m^3/m^3	Broader Research Community, AAFC	Numerically accurate soil moisture data

[5] Refer to the Metadata Guidance document for definition of wilting point.

Application	Data Latency	Depth (m)	Units	Agencies/Organizations	Critical Data Need
Precision agriculture	Hourly	0-2	m^3/m^3	AAFC	Spatially distributed soil moisture information, SWC at field capacity, and SWC at wilting point
Planting/Harvesting guidance	Daily	0.1	m^3/m^3	USDA	Spatially distributed near-surface soil moisture information. Collocated with temperature.
Trafficability (for forestry applications too, not limited to agriculture)	Daily	0-0.2	% capacity for soil type	Department of Defense, USDA, US Forest Service	Spatially distributed near-surface soil moisture information
Fire management/ forecasting	Daily	0.05/0.1/0.2	% Plant Available Water or m^3/m^3	State Forest Services / Weather Forecast offices	Soil Water Content (SWC) at field capacity and SWC at wilting point
Understanding ecosystem ecology processes (e.g., plant water status, species distribution, etc.)	NRT to daily depending on ecosystem type/research question	Plant rooting depths, permafrost layer	m^3/m^3	Long-Term Ecological Research (LTER) Network, NEON, USFS, individual researchers	Soil Water Content (SWC) at field capacity and SWC at wilting point
Water table recharge	Monthly	> 1	mm, m^3/m^3	United States Geological Survey (USGS), AAFC	Long-term datasets
Forest management/ forest harvesting	Weekly	0.05/0.1/0.2 2/4/8 inches	m/m, % field capacity	U.S. Forest Service	Long-term datasets

Application	Data Latency	Depth (m)	Units	Agencies/Organizations	Critical Data Need
Forest health (disease/pests) monitoring	Weekly-Monthly	0-2	m^3/m^3	USDA (FS, APHIS)	Long-term datasets; Minimum Soil Water Content (SWC) requirements of indigenous vegetation
Climatology (drought, etc.)	Monthly	0-1			Long-term datasets
Weather forecasting	Sub-daily	0.05		NWS/ECMWF	Low latency
Carbon cycle modeling/monitoring			m^3/m^3, kPa		SWC at field capacity and SWC at wilting point
Biogenic volatile organic compounds	Daily	0.05-0.1	m^3/m^3	EPA, Texas Commission on Environmental Quality	
Preferential flow and solute transport	15 min-30 min	0-1	m^3/m^3		High-frequency data
Wastewater and application	Monthly	-	mm		Spatially distributed soil moisture information
Freeze/Thaw	Hourly	.1	By occurrence	USDA	Co-located with soil temperatures
Landslides	-	-	-	Department of Transportation	Low latency
Atmospheric process/land-atmosphere interaction studies	-	Near-surface, root zone	m^3/m^3	DOE Atmospheric Radiation Measurement (ARM) user facility	Co-located with (representative of conditions at) atmospheric measurements
Mapping soils and properties with depth and over time	Daily to Weekly	0-2m	m^3/m^3	United States Department of Agriculture/ Natural Resources Conservation Service/Agriculture Research Service.	Spatially distributed soil moisture information at variable depth intervals. Numerically accurate moisture data. Soil characteristics of full profile.

CHAPTER 4

ENVIRONMENTAL CONSIDERATIONS FOR STATION SITING

Mike Cosh, Vinit Sehgal, Nandita Gaur

> **Learning Outcomes**
> Following appropriate methods for site selection can help maximize representativeness of long-term soil moisture measurements and support data quality.

The aspiration for siting an in situ sensor is that it provides representative information about moisture conditions in the general area around it. While the typically small support scale of an in situ sensor (of the orders of 10s of cm^3 of soil) makes it impossible to provide large-scale estimates, carefully considering the heterogeneity of the surrounding area as part of site selection (followed by field calibration) can allow the sensor to be representative of the general area surrounding it to a certain extent. In this chapter, we provide information on environmental factors that must be accounted for during site selection to make the measurements representative for the general area around to the maximum extent possible. This information must be used in combination with practical siting considerations described in Chapter 2 of this document and Chapter 4 of the NCSMMN Strategy Document (*A Strategy for the National Coordinated Soil Moisture Monitoring Network*, 2021).

CONSIDERATIONS FOR STATION SITING

Spatial representativeness of an in situ soil moisture measurement for the general area is mainly limited by the large spatial and temporal variability of soil moisture. One strategy to account for this variability and maximize representation is by utilizing upscaling methods prior to sensor siting. Upscaling methods typically require additional soil moisture measurements in a larger area before actually installing a station. Alternatively, biophysical factors, such as precipitation, soils, vegetation, and topography or a combination thereof that affect variability in soil moisture can be incorporated into the network design (Gaur and Mohanty, 2013, 2019). It should be noted that while the spatial dependence of soil moisture on these heterogeneous variables is strong, it is non-deterministic and can change with seasons and hydroclimates (Sehgal et al., 2021). Consequently, the spatial representativeness based on this method will change with seasons even if other landscape factors remain the same. Both methods of sensor siting are described below.

PROCESS OVERVIEW

Sensor siting is a multi-step and multi-scale process. Stations must first be regionally sited using either the upscaling or biophysical method approach, after which the exact soil profile where the sensors will be installed needs to be examined for representativeness. We refer to the latter as micro-site selection. A nested approach to site selection may be taken as well.

Method I: Upscaling Strategies Based on Time Stability Analysis

Crow et al. (2011) reviewed several upscaling strategies that can help determine ideal siting locations. Each strategy has its own data requirements. While this guidance document recommends referring to cited works for methodological details, provided here is a short overview of the resources necessary to conduct upscaling via a time stability exercise. Time stability is one of the very few upscaling exercises that work for upscaling point scale data measured with in situ sensors.

Time Stability Analysis Using Temporary Stations or Intensive Field Campaigns

Time stable locations (Vachaud et al., 1985; Vanderlinden et al., 2012) are locations within the landscape that continually represent the average moisture conditions of the entire landscape or a pre-determined region that needs to be represented. In other words, time stable areas are representative of average landscape-scale conditions regardless of season. To identify time stable locations, intensive soil moisture campaigns (Cosh et al., 2008, 2013) or the intensive installation of temporary soil moisture monitoring stations is required. Soil moisture must be measured at these sites repeatedly through different seasons for at least one calendar year to identify a site that reports the average of the entire area (Coopersmith et al., 2013). Once a time stable location is identified, it may be assumed to remain stable across years and assumed to report average values for that region (Cosh et al., 2006; Coopersmith et al., 2021). This site can then be used as the site to install long-term soil moisture sensors.

Method II: Using Maps of Biophysical Variables

Several qualitative factors need to be considered in the biophysical variables method, and, therefore, operators will often have to make several executive decisions while implementing this method. Documentation must include a justification of those decisions because qualitative factors may change with time in a region. The stepwise implementation of this method is described below. Note, however, since station siting depends primarily on stakeholder requirements, the first basis of site selection should be a physical variable that the stakeholder wants to monitor and measurement of this physical variable should be considered before any of the factors mentioned below. For example, if the stakeholder need is to measure a specific land-cover type (forest floors, pasture, cropland), then it should form the primary variable of interest in determining site locations.

Developing a Nested Siting Design

The dominant drivers of soil moisture variability change with scale (Figure 2). Hence, these factors can be used to nest the site design for a regional-scale network. Following this approach, a two-step siting plan followed by micro-site selection is recommended. One example of a nested-site design for validating remotely sensed soil moisture at 40-km is given in Caldwell et al. (2019).

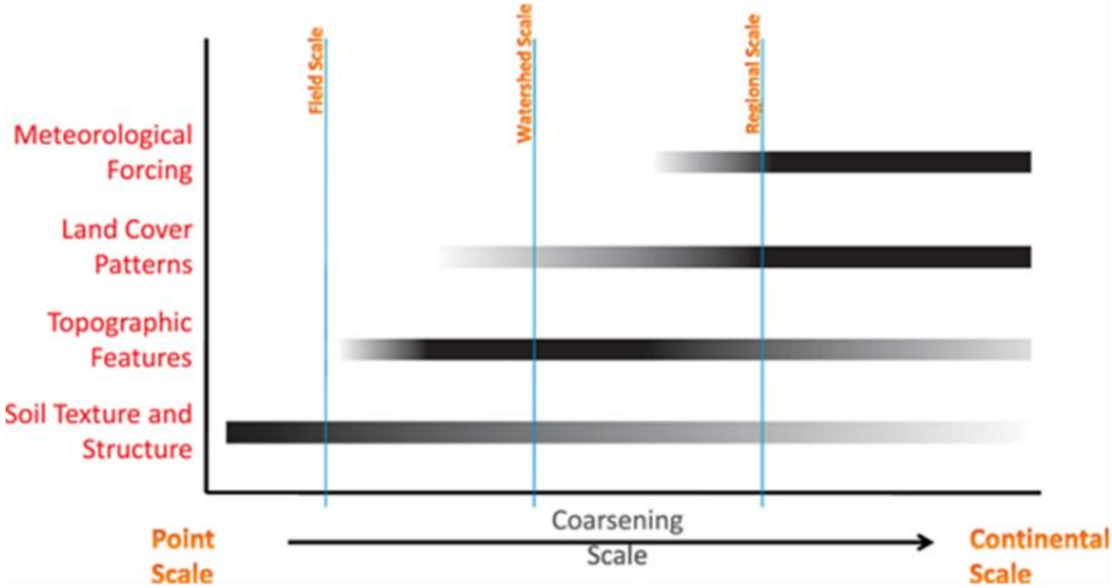


Figure 2. Dominant controls of soil moisture variability. Shades of gray indicate degree of control, with darkest gray being the strongest control. Figure Credit: Crow et al., 2012.

Step 1: Regional Siting of Stations

Meteorological forcings: The large-scale design of a network must be driven by variability in meteorological forcings (variables such as precipitation, temperature, relative humidity, wind speed, and more). Of these variables, precipitation is the single most important factor that changes the absolute value of soil moisture as a step function. Subsequent soil moisture dry downs depend non-linearly upon soils, topography, and vegetation. Hence, if there are predictable rainfall patterns expected in a region, soil moisture stations should be installed to first capture regional variability in precipitation to the best extent possible. In the absence of a comprehensive coverage of meteorological forcings, dominant ecoregions can be used as an indicator of the coexistence of soil, vegetation, and climate patterns which are observed to yield governing controls over the variability in the hydrologic state of soil moisture at a regional scale (Sehgal and Mohanty, 2024).

Step 2: Local Siting of Stations

A representative soil texture and structure should be considered the next most important variable for station siting, given that vegetation and topography are controlled for. While topography and vegetation aid movement and redistribution of water, soils exert a more intimate role on the actual capacity of the soil profile to hold water (Gaur and Mohanty, 2013, 2016). The capacity of the sub-surface to hold water and trigger runoff or infiltration and provide water for plants depends primarily on the type of soil (texture, structure, mineralogy and organic matter). Hence, one approach for regional representation could be to select uniform landscape locations and maintain uniform vegetation covers across the network while ensuring soil type representation of the region. This theory is also supported by some measurement evidence for near-surface soil moisture, wherein Gaur and Mohanty (2013) showed that near-surface soil moisture measured using theta probes in Little Washita, Oklahoma was most dominantly controlled by the soil at the support scale of in situ soil moisture measurements, when compared to topography and vegetation-based factors. Note that this study was conducted only during the growing season for grasslands and crops (soybean, corn, and wheat) and using only near-surface soil moisture data.

Controlling for vegetation type or terrain across all network stations may be more difficult for networks operating in forests or rangeland terrain.

Representative soils for the region can be identified by consulting available SSURGO soil survey maps from (NRCS) and selecting the soil series that is most spatially representative of the region. When possible, soil types should be ground-truthed (Metadata Guidance document). While locations with no slope to a mild slope that are easily accessible for most parts of the year may be desirable for installing sensors (Joshi et al., 2011), for regions that are dominated by sloping landscapes or with specific soils that 'live' on those sloping landscapes, installation on slopes would be preferred, unless soil moisture stations cannot be installed safely.

Note that multiple land-covers intersecting with the same soil series will create variability in moisture and impact site representativeness. Under such circumstances, stakeholder requirements and intended data application must take precedence in terms of desired land-cover. Otherwise, the spatially dominant land cover may be chosen for best representation, which can be followed by post-deployment activities (Chapter 6) to provide estimates on site representation to stakeholders. Table 3 can be used as a quick help guide to compare the two methods of macro-site (network scale) site selection.

Table 3. Comparison of resources required for the two methods of macro-site selection

Method based on upscaling	Method based on biophysical maps
A wait time of around 6 to 12 months is needed before site locations can be determined.	No wait time required.
Cost and resource-intensive upfront. It will require acquiring several additional soil moisture sensors and data loggers and access to the area surrounding the site.	No additional resources required upfront.
Provides quantified information on site representativeness and can provide data for field calibration of sensors upfront, thus reducing the need for post-deployment calibration, which satisfies a requirement for producing Tier I soil moisture data.	Provides qualitative information only. Post-deployment field-based calibration will be required to produce Tier I data.
Less uncertainty in final site representation but comes at higher upfront costs	Uncertainty rests in the reliability of maps and representation of measurements cannot be assess *a priori*.

Micro-site selection

Once a site is regionally located using either of the two methods, network operators must consult with a local soils expert for micro-site selection (Chapter 2). The soil profile must be examined to make sure that sensors are not installed in a locally disturbed area such as fill material from adjacent construction activities or an old, buried road. Identifying prior site disturbance can be carried out using a combination of activities. The easiest and most non-invasive activity is to contact the appropriate administrative or technical support staff for the area to ensure no utilities are buried at the location. This may include surveys for utility lines, cultural resources, and the like. A buried utility at the location or close to the site is indicative of disturbance to the surrounding soil. Contacting a utility locator is strongly recommended, in any case, to avoid disrupting local utilities.

The next activity involves selecting a suitable site around the station that is not likely to be disturbed and auguring to the depth of interest (e.g., 1m). The soil horizons (Figure 3) must be characterized as per NRCS recommendations[6] during auguring, and if any discrepancy such as unexpected soil textures, colors, or depth of layering is observed, the hole must be discarded and another location a reasonable distance away from the first one must be tested the same way. Unexpected soil texture, color, gravel, charcoal, or even trash may indicate fill material, buried pipes, or old roads, and consequently, any soil moisture measurements made at the location will not be spatially representative. This process must be repeated around the base station until an augured hole displays expected soil characteristics for the area (e.g., brown topsoil transitioning to red subsoil). This procedure is best conducted by someone trained in soil science.

Figure 3. Borehole for soil sensor installation with tape (left) and sensor inserted (right). Note that soil horizons that vary in soil color, texture, and structure. A soil scientist can help describe this profile. This information can be useful for stakeholders for interpreting soil moisture data measured in the soil profile. Image Credit: Matthew R. Levi, University of Georgia.

[6] Further information can be found at: https://www.nrcs.usda.gov/conservation-basics/natural-resource-concerns/soil/soil-survey

CHAPTER 5

SENSOR SELECTION

Todd Caldwell, Leo Rivera, Mike Cosh, Nandita Gaur

Learning Outcomes

There are essentially four classes of sensor technologies; each may have an influence on data quality. No one sensor is the best fit for every purpose.

Recommendations from this chapter should be combined with those in Chapter 2 before making a network-level decision.

Today, there are many options in soil moisture sensors. Sensor choice is an important factor in producing long-term, quality data. Soil properties, site conditions, climate, and, to some extent, stakeholder data needs can drive the choice of sensor. It is important to note that few, if any, in situ sensors directly measure the amount of water in the soil. Most in situ soil moisture sensors infer soil water content (SWC) from an electromagnetic response. An electromagnetic signal at a particular frequency or range of frequencies is generated and propagated along the sensor tines, which are in direct contact with the soil. Water, with its unique dielectric properties, changes the bulk electrical properties of the soils, causing a measurable change in the electromagnetic signal recorded by the sensor. Commercially available sensors fall into four classes depending on the type of electromagnetic signal propagated and the method of measuring the response, including (1) capacitance, (2) impedance or frequency domain reflectometry (FDR), (3) time-domain reflectometry (TDR), and (4) transmission line oscillators (TLO) (Cosh et al., 2021).

Each technology uses a transfer equation to estimate SWC from the measured electromagnetic response. Soil properties like clay, salinity, and temperature induce a soil-based dependency in the function of particular technologies that impacts the relationship between the measured response variable of the soil and SWC. This means that certain technologies may be unsuitable for estimating water content in certain soil types. Broadly speaking, high clay content, organic matter, and/or saline soils often need special attention in terms of selecting an appropriate sensor. However, even if a sensing technology is suitable for various sites and soil types, the standardized transfer equations between soil properties and soil moisture that are provided by the factory may be insufficient because of differences in correlative relationships for the standard lab version of a soil type compared to sensor reading and SWC relationships for exact soil conditions in the field. Hence, the selection of an appropriate sensor followed by a soil-specific calibration are baseline steps required for producing good quality soil moisture data.

The various available technologies for soil moisture sensing, along with their advantages and disadvantages are provided in Table 4. Today, most sensors are low-power with internal processors that convert signals to SWC and use serial data interface at 1,200 baud (SDI-12) communication protocols to transmit digital data along a single communication cable (http://www.sdi-12.org/). The common communication wire of SDI-12 sensors forms a single circuit along with a power and ground wire, making wiring straightforward. Along with SWC, many sensors provide useful ancillary data including soil temperature and bulk electrical conductivity (BEC). These additional data provide important diagnostic information on sensor functionality (Caldwell et al., 2022).

Physical structure of most sensors includes parallel tines of varying number (2 to 4 tines) and length (10 to 30 cm), a sensor head that encloses the electronics, and a cable that transmits power and receives data from the data collection platform. The configuration of the tines and their length affect the size of the measurement volume. A thermistor for temperature measurements is generally housed inside the sensor head in contact with one of the tines. The attenuation of the signal (reduction of the electrical signal) along the tines is often used to estimate bulk electrical conductivity. Lastly, the cable generally contains continuous wires for sensor power, data transmission, and grounding. The cables itself are shielded to reduce external noise and sheathed in flexible plastic. Some sensors have cables that can be directly buried while others need additional external protection (e.g., PVC conduit).

In the most general terms, lower frequency operation and less durable cables are found in less expensive probes. High operating frequencies may not require soil-specific calibrations but come with a higher cost. Finally, sensor life expectancy may be correlated to sensor cost, but it also takes overall experiences of the entire soil moisture community to determine if there are particular issues that may appear for a given area or soil. *There is no single sensor that is perfect for all soils and climates.*

Table 4. Commercially available sensor technologies

Sensing Technology	Advantages	Limitations	Example Sensors	References
Capacitance Capacitor charge time, which depends on the apparent dielectric permittivity of the soil	• Less expensive • Shorter tines, easier installation • Some are easily installed at depth in a borehole	• Operates at lower frequencies that can lead to temperature sensitivity and lower accuracy in clay or saline soils • Can respond to some property of the soil–water system that is not Soil Water Content (SWC) alone	TEROS-series, ECH -20, EC-5, WET	Wyseure et al., 1997; Evett et al., 2005, 2012; Fares et al., 2011; Mittelbach et al., 2012; Datta et al., 2018; Ferrarezi et al., 2020; Wilson et al., 2020
Impedance or Frequency Domain Reflectometry (FDR) Probe impedance to measure the dielectric permittivity, based on a swept frequency collected over a wide range	• Use a range of lower frequencies • Shorter tines, easier installation	• Interference in high-salinity soils • Soil texture dependence in calibration equations	HydraProbe, ThetaProbe, WET-2	Seyfried et al., 2005; Kelleners et al., 2009; Cosh et al., 2005, 2016

Time-Domain Reflectometry (TDR) Travel time for ~1000 MHz wave to propagate along a transmission line; a waveform is collected and analyzed	• Considered most accurate and least sensitive to soil type • May avoid need for soil-specific calibration • Insensitive to temperature and bulk electrical conductivity (BEC)	• Installation can be challenging for sensors with longer tines and an independent coaxial signal wire • Signal attenuation in high salinity due to collapse of waveform • More expensive	TDR-315, SoilVUE10, TDR-200,	Topp et al., 1980; Wilson et al., 2020, 2023
Transmission Line Oscillators Similar to TDR, but generally at a lower frequency and no waveform collected	• Two tines, easier installation • Simple electronics and no need for full waveform analysis	• Sensitive to temperature and BEC • Sensitive to air-gaps	CS615, CS655, CS655, PICO32, PICO64	Chandler et al., 2004; Caldwell et al., 2018; Patrignani et al., 2022.

SENSOR SELECTION CRITERIA

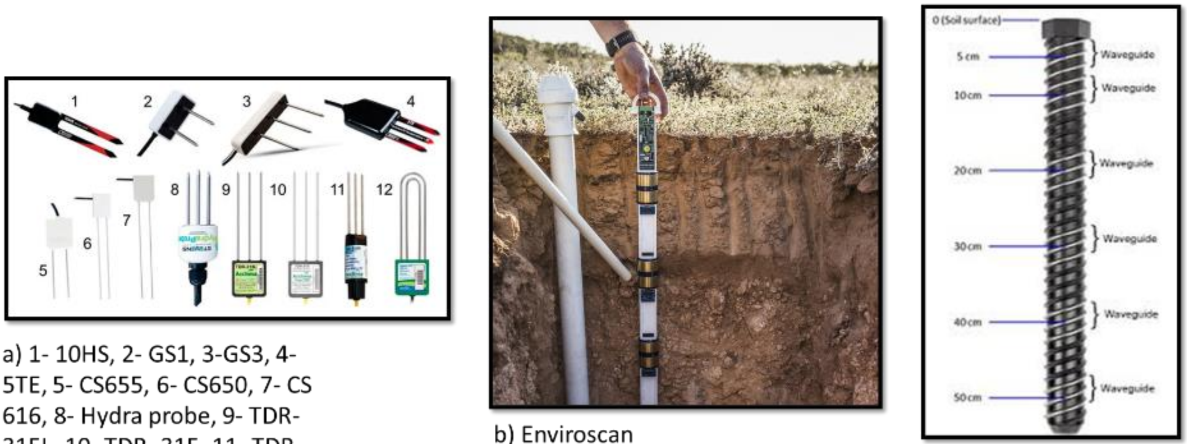
The most common in situ soil moisture sensors primarily differ in the specific frequency and technology used for estimating the dielectric constant of the bulk soil, size of the sensor, and method of installation (Table 4). *The following factors, along with limitations of the several sensors mentioned in Table 4, should be considered when selecting an appropriate sensor for your network.*

Soil Type

Typically, soils with large bulk electrical conductivity (BEC) attenuate electromagnetic signals and are problematic for in situ sensors. Such problematic soils include soils with high clay content, high organic matter, and/or high salinity. Under such conditions, it is best to select a sensor that works with high frequencies, has shorter tines, and reports bulk electrical conductivity as a response variable. Bulk electrical conductivity values can also aid the quality control process later.

Sensor Configuration and Installation Techniques

Varying sensor configurations can provide different information about sub-surface soil moisture. Most in situ soil moisture sensors have tines that must be physically pushed into the soil, as shown in Figure 4a (Ferrarezi et al., 2020). Shorter, more stout tines can be more easily inserted and, therefore, be useful in hard or dry soils, but short tines may also decrease the sensing volume. Regardless, the tines of any in situ sensors must be pushed into undisturbed soil in a way that ensures complete contact with the soil. Gaps around the tines or incomplete insertion will affect the quality of SWC by decoupling the electromagnetic wave from the soil or reducing the measured permittivity by including air. These sensors can be installed in different orientations from horizontal to vertical or on angles. There are advantages to each orientation, but generally, a horizontal installation ensures a depth-specific reading, proper protection of the sensor electronics, and thermally consistent conditions along the entire probe (Caldwell et al., 2022). Note: Buried probes are difficult to remove and should be protected if used to monitor activities such as prescribed burning or around active farm operations such as tilling. Lastly, buried in situ sensors are difficult to troubleshoot or replace when issues arise.



a) 1- 10HS, 2- GS1, 3-GS3, 4-5TE, 5- CS655, 6- CS650, 7- CS 616, 8- Hydra probe, 9- TDR-315L, 10- TDR- 315, 11- TDR-310S, 12- TDT ACC-SEN-SDI

b) Enviroscan

c) Soil Vue

Figure 4. (4a) Sensors divided based on installation requirements. Image Credit: Ferrarezi et al., 2020. (4b) An overlaid image visualizing an Environscan sensor inserted in the soil. Image Credit: Sentek PTY Ltd. (4c) Diagram of a Soil Vue sensor. Image Credit: Sentek PTY Ltd.

Borehole sensors can either be installed from the surface, in a plastic tube, without direct soil contact (Figure 4b) or in a pre-augured borehole. Either method is relatively easier to manage when working in a place where operational activities require sensors to be removed, but the limited soil-contact can reduce total sensitivity to changing soil moisture conditions. Direct insertion sensors, like Soil Vue (Figure 4c), are new and require skill for installation to ensure complete contact with the soil. Wilson et al. (2023) highlights low accuracies in Soil Water Content (SWC) estimation from the use of such sensors, since installation is not easy and often results in poor contact with the soil. Refer to [Caldwell et al., 2022](https://app.jove.com/v/64498/in-situ-soil-moisture-sensors-in-undisturbed-soils)[7] for more detailed instructions

[7] https://app.jove.com/v/64498/in-situ-soil-moisture-sensors-in-undisturbed-soils

for installation of different soil moisture sensors. Further general information about sensor installation and maintenance can be found in the NCSMMN Strategic Plan, Chapter 5.

Sensor Size

Generally, the length and separation of the sensor tines determine the total volume of soil measured. Soil moisture is inherently heterogeneous, particularly at smaller scale. Estimations or measurements of a larger volume of soil may provide better spatial representation, while a smaller volume may be more variable or miss important processes like preferential flow. For shallow installations (i.e., 5-cm or less), sensor with larger measurement volumes may also incorporate the air above the surface and be biased towards lower SWC. In problematic soils with high bulk electrical conductivity, larger waveguides (Figure 4b) can cause more errors and should be avoided (Caldwell et al., 2022).

General Recommendations

There is no specific sensor that will meet every network's needs, and technologies are constantly changing. For example, non-contact technologies, such as cosmic ray neutron sensing (Zreda et al., 2012) or gamma-attenuation (Baldoncini et al., 2018), may become more operational as research continues to make advances. After following these guidelines, consultation with members of the soil moisture community is recommended before making large investments. A point of contact can either be determined by contacting vendors of the different moisture sensors, by connecting with mesonet listservs, or if need be, by searching for the same sensor type in the metadata provided by other networks.

CHAPTER 6

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

Mike Cosh, Leo Rivera, Ed Ayres, Vinit Sehgal, Ethan Becker, Todd Caldwell, Nandita Gaur

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, *T*	±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, *T*	±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, *T*	±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, *T*	±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	

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)
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,	

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)
WET	Delta-T	Cap.	20	Ka, EC, *T*	±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, *T*	±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.

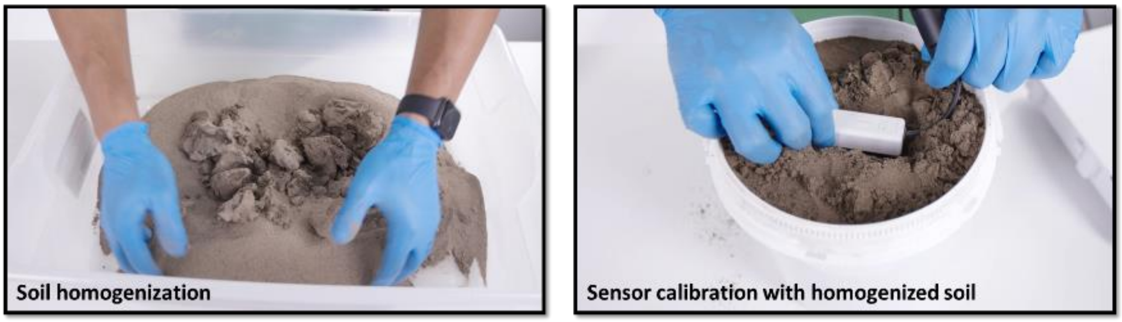


Figure 5. Sensor calibration in lab. Image Credit: Leo Rivera.

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 +/- 0.2 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.

Mesonet **Certificate of Calibration**

Sensor Serial No	**278785**
Test Type	**As Left**
Sensor Type	HydraProbe Pro
Test Facility	diH2O / dH2O Bath
Test Date	**20220630**
Reference Sensor	Fluke 2122-0084RC

Prob Desc / Comment:

Distilled Water Test

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:

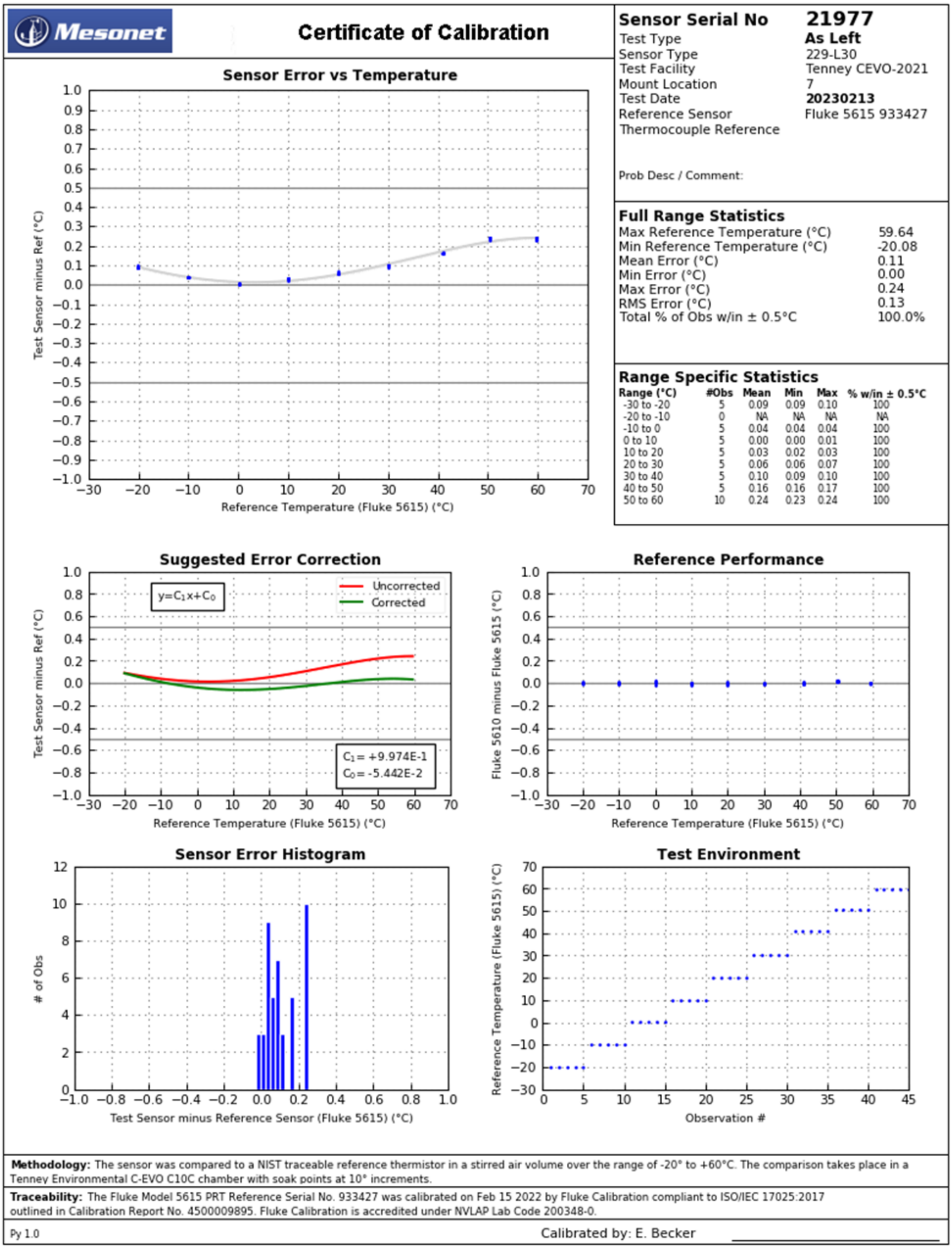
1. *The Temperature Corrected Real Dielectric Constant is between 75 and 85.*
2. *The Imaginary Dielectric Constant is less than 5.*
3. *The temperature error is within ±0.6 °C for the analog Hydra Probe and ±0.3 °C for the Hydra Probe II.*
4. *The response to the SDI-12 sensor onboard verification command 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.



Mesonet

Certificate of Calibration

Sensor Serial No	**21977**
Test Type	**As Left**
Sensor Type	229-L30
Test Facility	Tenney CEVO-2021
Mount Location	7
Test Date	**20230213**
Reference Sensor	Fluke 5615 933427
Thermocouple Reference	

Prob Desc / Comment:

Full Range Statistics

Max Reference Temperature (°C)	59.64
Min Reference Temperature (°C)	-20.08
Mean Error (°C)	0.11
Min Error (°C)	0.00
Max Error (°C)	0.24
RMS Error (°C)	0.13
Total % of Obs w/in ± 0.5°C	100.0%

Range Specific Statistics

Range (°C)	#Obs	Mean	Min	Max	% w/in ± 0.5°C
-30 to -20	5	0.09	0.09	0.10	100
-20 to -10	0	NA	NA	NA	NA
-10 to 0	5	0.04	0.04	0.04	100
0 to 10	5	0.00	0.00	0.01	100
10 to 20	5	0.03	0.02	0.03	100
20 to 30	5	0.06	0.06	0.07	100
30 to 40	5	0.10	0.09	0.10	100
40 to 50	5	0.16	0.16	0.17	100
50 to 60	10	0.24	0.23	0.24	100

Methodology: The sensor was compared to a NIST traceable reference thermistor in a stirred air volume over the range of -20° to +60°C. The comparison takes place in a Tenney Environmental C-EVO C10C chamber with soak points at 10° increments.

Traceability: The Fluke Model 5615 PRT Reference Serial No. 933427 was calibrated on Feb 15 2022 by Fluke Calibration compliant to ISO/IEC 17025:2017 outlined in Calibration Report No. 4500009895. Fluke Calibration is accredited under NVLAP Lab Code 200348-0.

Py 1.0 Calibrated by: E. Becker

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 calibration[8]. 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 cm^3, 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 Areal 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.

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

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:

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

Anomaly Correlation Coefficient (Rd)

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 errors[9]. 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).

CHAPTER 7

QUALITY CONTROL AND QUALITY ASSURANCE OF SOIL MOISTURE DATA

Mike Cosh, Ed Ayres, Todd Caldwell, Vinit Sehgal, Zamir Libohova, Nandita Gaur

Learning Outcomes

Properly identifying and flagging data errors helps to ensure the quality of a dataset and support viability of data use.

Quality assurance (QA) (Campbell et al., 2013) of soil moisture data refers to the set of processes that are employed to improve confidence and decrease errors in the production of soil moisture data. Quality control (QC) processes are measures taken after data are collected to improve or remove data points so that the final product is of high quality.

QUALITY ASSURANCE

Pre-requisites of a well-functioning soil moisture sensor include proper installation of the sensor at the correct depth and use under conditions that the sensor is designed for. Proper installation methods can be accessed in Caldwell et al. (2022), and recommendations for siting methods, sensor calibration, and other important installation processes have been discussed in Chapters 2-6 of this document. This chapter describes methods to identify data errors, trace their origins, and report or fix them.

CATEGORIES OF DATA ERRORS

There are two primary types of errors (described below) that can be flagged. Type I errors can be easily flagged using automated tests during QC, but Type II errors require manual verification and are often detected during QA activities. Type II errors should not be considered errors until proper manual inspection of each erroneous data point is conducted.

The International Vocabulary of Basic and General Terms in Meteorology (VIM) also provides a classification system for identifying Uncertainty in Measurement (GUM): Type A (systematic) and Type B (random) data errors (VIM International Vocabulary of Metrology – Basic and General Concepts and Associated Terms, 2006). In this Soil Moisture Data Quality Guidance document, a different approach than the GUM approach is used to categorize data errors. In this document, error type is based on the skill set necessary to identify and address potential data errors: Type I (errors that can be identified via a simple automated algorithm) and Type II (errors that require additional skillsets to identify and address).

Visually Observable, Easy-to-Identify Errors (Type I)

Visually observable Type I errors are relatively straightforward to detect. QA tests that detect sensor failure, recorder failure, or disruptive environmental events can be discovered and corrected by automated methods since they leave distinctly identifiable signatures in the data (Campbell et al., 2013; Dorigo et al., 2013; Dorigo et al., 2021). These tests can be easily automated and should be used for flagging. Examples of Type I errors in data are shown in Figure 7, taken from Caldwell et al. (2022).

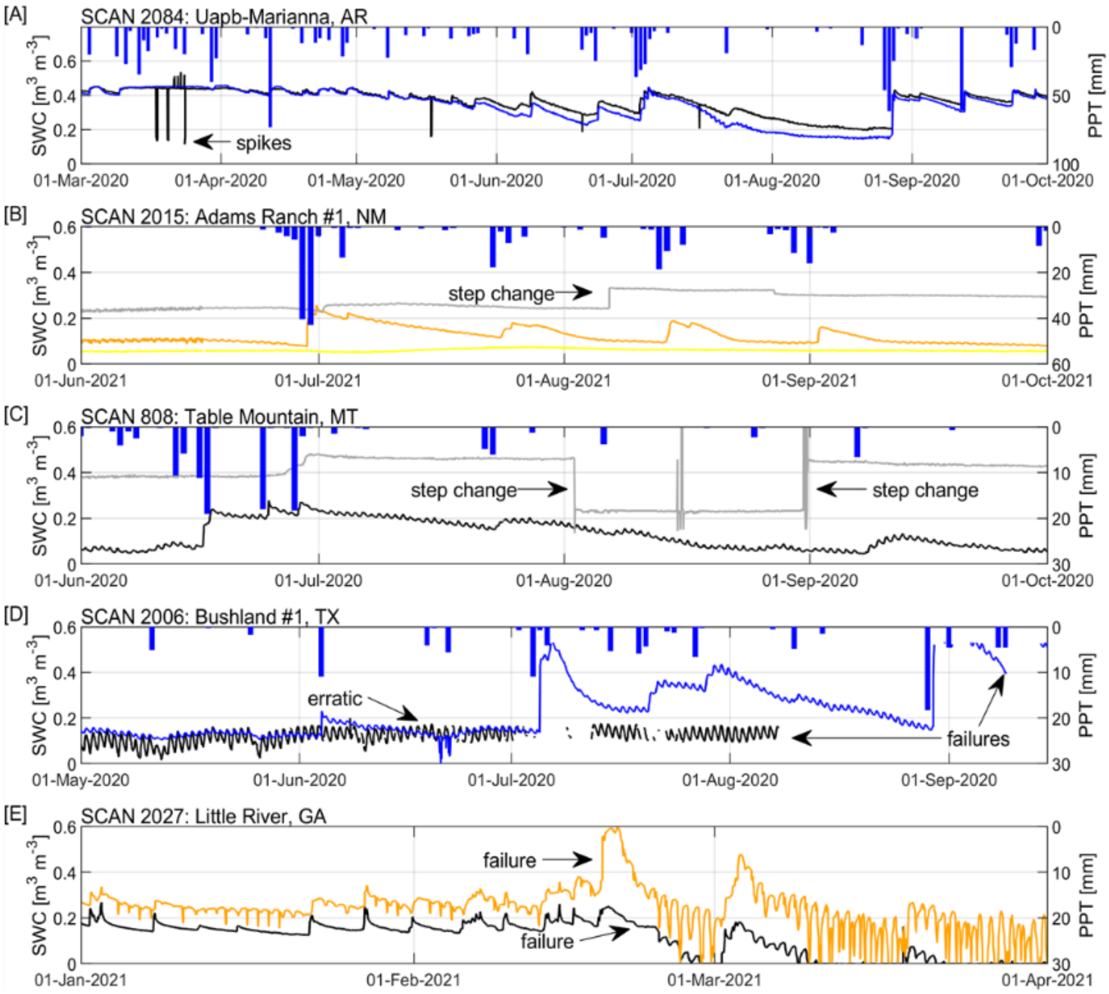


Figure 7. Examples of Type I errors in data. Data from (A) SCAN 2084, Uapb-Marianna, Arkansas, that shows periodic dips at 5 cm. (B) SCAN 2015, Adams Ranch #1, New Mexico, shows a positive step change at 50 cm depth without changes in the upper depths. (C) SCAN 808, Table Mountain, Montana, with a downward step change, spikes, and even recovery at 50 cm depth that does not correspond to rainfall events. (D) SCAN 2006, Bushland #1, Texas, showing no response to precipitation events at the 5 or 10 cm sensor, with some recovery of the 10 cm sensor followed by the eminent failure of both. (E) SCAN 2027, Little River, Georgia, with a glitching sensor at 20 cm and failure at both the 5 and 20 cm depths. Sensor depths are denoted as 5 cm (black), 10 cm (blue), 20 cm (orange), 50 cm (dark gray), and 100 cm (yellow). Abbreviations: SWC = soil water content; PPT = precipitation. Figure Credit: Caldwell et al., 2022.

Ideally, automated QA tests should be performed at the native sensor sampling frequency. A list of automated tests (Hubbard et al., 2005) that are used by existing networks and projects to flag soil water content data include:

1. **Range test or high/low range limit test:** The range test (sometimes called the high/low range limit or “upper and lower” threshold test) checks whether each soil moisture value is less than the porosity of the soil and more than 0 (or the lower measurement limit of the sensor). One occurrence of an off value would need to be flagged as an individual point in the dataset, but repeated or periodic observations of such values will require flagging of the sensor itself. Under such conditions, the sensor(s) will need manual inspection and may require replacement or additional tests before data can be reported.

2. **Constant value test:** A failed sensor may often report a constant value. While in some cases (for example, saturated conditions or very dry conditions) constant values may be legitimate, an unexplained constant value of soil moisture over an extended period must be flagged and manually examined.
3. **Spike test:** A spike test pertains to observing spikes (Figure 7c) in the data. Spikes in soil moisture must only correspond with rainfall or snowmelt events, and typically the spikes will be observed first in the near surface soil moisture and subdued replicas of the spikes may be observed after a lag in the subsequent depths. It is possible to observe a spike in the deeper soil before the sensors above in cases of shrink-swell clay soils. A spike in data that is not occurring concurrently with rainfall must be automatically flagged and subject to manual testing of the sensor since it may imply a failed or temporarily failing sensor.
4. **Break test:** Breaks in soil moisture measurements must be flagged as missing data.
5. **Temperature test:** Most soil moisture sensors are built to function within specific temperature ranges and cannot detect frozen soil moisture. If the soil temperature at any depth falls outside of that range or below 0 °C, the data must be flagged and not reported until a manual verification is performed.

Complex and Hard-to-Identify Errors (Type II)

Type II errors are more challenging to detect as the data might seem plausible at first glance, but the underlying dynamics do not align with the expected patterns of moisture redistribution or unsaturated flow processes. Addressing these errors requires a higher level of investigation, and they are better identified using QA procedures described later in this chapter. Any flags assigned to Type II errors should be verified by an expert. Some of the hydrologic principles that can be employed to assess inconsistencies include:

1. **Correlations in temporal relationship of soil moisture with ancillary variables**: It is expected that changes in soil moisture values will correlate to changes in other ancillary variables, such as rain events or some changes in air and soil temperature. Data errors wherein these relationships are not present can be identified by utilizing known rainfall-runoff-storage-soil moisture redistribution relationships that correspond to the specific soil, geomorphic, and cover conditions. Soil moisture values that do not conform to long-established relationships can be temporarily flagged and investigated during QA activities to ensure that the variability in the relationships is a true data error and not driven by changes in the landscape that justify the deviation in correlative relationships. Advanced multiscale signal-processing techniques, like Wavelet Transform and Empirical Mode Decomposition, can be used to assess the temporal variability in the soil moisture observations across multiple time scales and to detect potential anomalies and outliers (Mallat and Hwang, 1992; Geng et al., 2011; Thill et al., 2017).
2. **Moisture redistribution in unsaturated flow process:** This data quality test relies on assessing the consistency of time series data to determine if moisture redistribution patterns align with expected unsaturated flow processes. These include verifying that profile soil moisture sensors respond in order by depth to rainfall, with those nearest to the soil surface responding first. These checks would need to be investigated after immediate flagging, since in cases of preferential flow, some sensors below may respond

earlier than those above them. Such types of evaluation may require developing site-specific tools.

3. **Calibration shift or sensor fouling:** Sensors may change in the accuracy of their readings over time. A slow drift in a sensor is often also very hard to detect. Identifying drift of this type would require careful evaluation of the data and recalibration of the sensor (Wagner et al., 2006). One way of observing this may be to identify the ultimate minimum soil moisture value after a significantly long drydown (> 60 days). It is reasonable to assume that two periods of 60 days of drying would end at the same number if there were a similarity in the temperature or season. Consistency of readings is not as readily observed at maximum soil moistures because the salinity of the soil can change more easily with rainfall/overland flow, and salinity may be a dominant portion of the dielectric constant, if a dielectric based probe is being used.

Correcting Source of Data Errors

Upon error detection, the cause of errors in the data should be identified and corrected. Random Type I errors in data can occur as a result of voltage fluctuations, inappropriate temperature conditions, or other random or natural occurrences beyond the operator's control, but systematically occurring errors must be corrected. Errors of either type can occur as a result of four causes.

1. **Instrument malfunction:** Instrument malfunction will typically lead to Type I errors and can be corrected by repair or replacement of the sensor.
2. **Personnel errors**: Personnel errors may include incorrect metadata for error detection (for example, incorrect upper and lower limits for the range test). Such errors will also be a systematic and can be corrected by training personnel or establishing protocols that do not leave scope for errors.
3. **Transmission errors**: Transmission errors will typically lead to increased latency in data and so are easily detected. Correcting the source of these types of errors would require expert inspection.
4. **Data processing errors**: Data processing errors can be Type I or II. Once identified, these must be corrected by updating algorithms or incorporating additional manual verification.

Considerations for Automating Soil Moisture Data Quality Checks

Automated QA tests are often the most effective way to identify suspect data for large networks and/or long-term projects where the quantity of data is typically too large relative to staffing resources to allow effective manual data reviewing and flagging[10]. One advantage of automated tests is that they can usually be run shortly after data collection, facilitating near-real-time provisionally QA data availability. Other advantages of automated tests include their consistency and reliability. QA checks performed by humans are more prone to biases, person-to-person variability, competing time commitments, variable focus, and other disruptions. However, there are also disadvantages to automated QA tests, including the large upfront development effort and

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[10] Resources for automating soil moisture data flags, include discussion of this topic in a paper from the International Soil Moisture Network (ISMN) (Dorigo et al., 2021, Section 3.1) and a GitHub repository managed by the Group on Earth Observations (GEO): https://github.com/TUW-GEO/flagit.

ongoing code and database maintenance, as well as the effort involved in optimizing test thresholds for a range of sites and measurement depths. Moreover, automated tests are typically designed within the context of recent historical data under "normal" operating conditions, which may result in inappropriate flagging when real but unusual or unprecedented events occur (e.g., extreme rain events, burrowing animals), likely requiring human intervention in data flagging for these edge cases.

Previous work has developed broadly applicable automated QA tests that can be applied to a wide range of sensors, including soil water content sensors (e.g., Hubbard et al., 2005), but soil water content sensors also require some sensor-specific tests due to their measurement principle. In particular, most, if not all, moisture sensors are unable to detect frozen water, and sensors typically output very low water contents under frozen conditions, regardless of the actual soil water content. **As a result, flagging data as unreliable when the soil is frozen or close to freezing is an important QA procedure for soil moisture sensors in most temperate, polar, and high elevation regions.**

Since any given data point may pass, fail, or be unassessed (e.g., due to missing thresholds and/or missing data) by any combination of the automated QA tests, it can be useful to synthesize the results into an all-encompassing final quality flag at the published data's resolution (i.e., averaging interval) so that users have the option to quickly filter for valid data without having to inspect the results of each test. For example, some networks, such as NEON, assign a final quality flag of 0 (i.e., good). For NEON, this flag is applied when less than 10% of data points fail any QA tests and the tests are performed on more than 80% of data points are within the averaging interval (Smith et al., 2014).

Types of Flags and Flagging Frequency

Type I errors should be flagged in near real time, while data must be assessed for Type II errors at least once a year and flagged accordingly. A note should be made on the public-interfacing website describing the type of flags and flagging frequency for each flag.

QUALITY CONTROL

QC may include comparisons or correlations with existing data sources or water balance studies including: (1) correlations or relationships with ancillary data (like temperature, humidity, etc.) and soil properties (like porosity), (2) comparisons with other measured or modelled soil moisture data, (3) checking for expected trends based on long-term temporal analysis of data, and (4) checking for expected relationships between neighboring soil moisture stations (time stability analysis). Each of the four methods could be used in isolation but when used in combination will create the best quality soil moisture data.

QA is especially necessary to identify Type II errors. These can be identified in several ways described below.

Triple Collocation

Triple collocation is a method to understand the ability of a location to provide a representative soil moisture estimate. Three independent methods of estimating soil moisture (usually remote sensing, modelling, and in situ monitoring) are needed to determine the random error of estimation (Chen et al., 2016). Random error estimation is a means of comparing multiple estimates of the same metric to determine if the values match or differ from one another[11]. With a well-functioning sensor, random errors should be low. Random error estimation from in situ monitoring has been estimated as low as 0.01 m^3/m^3, although it is more often in the range of 0.02-0.05 m^3/m^3 for sensors with a soil-specific calibration (Table 5, Chapter 6). There are challenges related to the differences in observation scale because there is a significant difference between the multiple data series; however, this is still a useful tool for estimating error budgets.

Correlations with Ancillary Data and Soil Properties

Various ancillary data can be measured along with soil moisture to assess its quality. These datasets include soil temperature, soil permittivity, potential or actual evapotranspiration, and precipitation. Expected correlations between soil moisture and these variables will often vary by pedon and be hydro-climate specific. Hence, they cannot be borrowed from neighboring stations. Correlations between soil moisture and ancillary data are best developed by long-term data from the same site or by recommendations from an expert. Additionally, all possible response variables measured by a soil moisture sensor like bulk electrical conductivity (BEC), temperature, voltage ratios etc. must be recorded. This ancillary sensor-based information can be used during manual verification of errors in times of uncertainty. Examples of comparisons of soil moisture data with ancillary data (e.g., normalized difference vegetation index [NDVI], evapotranspiration, and temperature) can be found in Zhang et al. (2018), Engstrom et al. (2008), Wang et al. (2007), Dong et al. (2022), and Ford and Quiring (2014).

Comparison with Satellite/Remote Sensing

Remote sensing calibration and validation rely upon ground truth data from in situ stations that monitor the near surface, as this depth is the limit of current soil moisture sensing from L and C band radiometers/radars. Therefore, very often the critical installation depth for a point sensor is at 5 cm, with a sensing volume that can be calibrated to the top 5 cm, the approximate monitoring depth of L-band radiometry. Examples of remote sensing data that can be used for comparisons include Zhang et al. (2017), Colliander et al. (2017), Li et al. (2022), and Wang et al. (2021).

Examples of Datasets for Performing QC Activities

Open-source hydrological, meteorological or vegetation datasets can be accessed through cloud and web-based platforms that provide reference datasets for QA of soil moisture observations. One such application, Application for Extracting and Exploring Analysis Ready Samples (AppEEARS), developed by NASA, provides a convenient on-demand extraction tool for point and area samples. A survey of some relevant datasets available through AppEEARS is given in Table 7.

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[11] 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).

Table 7. A brief sampling of hydrometeorological and vegetation indices products accessible through the AppEEARS platform for point-based comparison with network sensors.

Suite	Full Name	Identifier	Variable	Resolution	Source
MODIS	MODIS/Aqua Vegetation Indices Monthly L3 Global 1 km SIN Grid	MYD13A3	NDVI	1 km, monthly	Satellite
	MODIS/Aqua Vegetation Indices 16-Day L3 Global 250 m SIN Grid	MYD13Q1	NDVI	250 m, 16-day	Satellite
	MODIS/Aqua Net Evapotranspiration Gap-Filled 8-Day L4 Global 500 m SIN Grid	MYD16A2GF	Total ET Total PET	500 m, 8-day	Satellite
DAYMET	Daily Surface Weather Data on a 1-km Grid for North America, Version 4 R1	Daymet_v4	Precipitation Air temp Shortwave radiation	1 km, daily	Ground-based observations and statistical interpolating/extrapolating
SMAP	SMAP Enhanced L3 Radiometer Global and Polar Grid Daily 9 km EASE-Grid Soil Moisture, Version 5	SPL3SMP_E v005	Soil moisture descending (6 AM) and ascending (6 PM)	9 km, daily	Satellite
	SMAP L3 Radiometer Global Daily 36 km EASE-Grid Soil Moisture, Version 8	SPL3SMP v008	Soil moisture descending (6 AM) and ascending (6 PM)	36 km, daily	Satellite
	SMAP L4 Global 3-hourly 9 km EASE-Grid Surface and Root Zone Soil Moisture Geophysical Data, Version 6	SPL4SMGP v006	Rootzone (0-100) soil moisture Top layer (0-5cm) soil moisture	9 km, 3-hour	Land surface model with satellite data assimilation

Comparison with AI/Machine Learning (AI/ML) Driven Tools

Spatial estimation of soil moisture can be accomplished with artificial intelligence (AI) combined with hydrologic modeling. AI is ideal for this task because of the complex nature of the relationships between different processes and variables. However, this methodology is largely driven by training data. While it is possible to forecast outside of the observed training domain, the artificial intelligence will rely upon the mechanisms that are observed within the training domain. This can be a particular challenge for extreme or rare events. Drought and flood events are often the most important features that a soil moisture network needs to detect/forecast, but many statistics are not optimized for performance at these extremes.

Gap Filling for Missing Values of Soil Moisture Continuous Data

Gap filling of missing soil moisture data involves following scientific procedures to estimate soil moisture values during times of periodic sensor failure. It is often an important exercise for several stakeholders but, if attempted, must be done with caution. This is especially true if gap filling is conducted over long time periods. Care must be taken to closely follow literature and adhere to all mentioned conditions before incorporating gap filling into a network's protocol. **Gap filled data must also be flagged**.

Many hydrological models require high temporal resolution of inputs such as weather data (precipitation, temperature, wind, solar radiation, etc.). Because high temporal resolution data are rare, many methods have been developed to fill in the gaps with values from other sources, when available, or by different interpolation techniques of the actual incomplete data (Waichler and Wigmosta, 2022; Libohova et al., 2024; Owens et al., 2024). Missing data (gaps) from soil moisture sensors are not uncommon and can happen for many reasons (instrument failure, low battery, accidental damage, funding, etc.). This may in turn result in time series gaps spanning from few hours to days depending on the sensors setting.

Simple techniques, such as linear interpolation, or more complex techniques, such as random forest and other machine learning techniques, can be used successfully to fill in gaps or intervals with missing data. The selection of the techniques depends on the temporal resolution of the sensor and width of the gaps. For example, gaps of a few hours can be filled in through linear interpolation or by calculating the rolling average from the five-hour period centered on the missing time point, across all years. Random forest can be used to fill in wider gaps consisting of multiple days or weeks. Similar techniques can be used to increase or decrease the temporal resolution (timestep) of the moisture data. The coarsening, or decrease, in the temporal resolution is usually more accurate than the opposite, although often finer temporal resolutions are preferred. Data from different sensors can be combined to create a complete dataset, and factors such as sensors type, depth, location, soils, or landscape position need to be considered for pairing the correct appropriate sensors.

In Figure 8, sensors within the watershed boundaries have gaps in data that can be filled out with data from sensors outside of the watershed boundaries. However, sensors need to be grouped based on slope positions (Summit; sideslope (SS); toeslope (TS)); by the stream). For example, the sensor with missing data located on a summit within the watershed (26) needs to be paired with sensors located in the same or similar slope position outside the watershed boundaries (12, 18, 21, and 29). Plotting the moisture data grouped by slope position (Figure 9) shows the gaps and provides the first visual assessment of the potential to fill in the gaps for the sensors within the watershed using sensors outside of the watershed boundaries. However, not all the gaps can be filled: some gaps might be too large, and any approach would not yield accurate results (Figure 10).

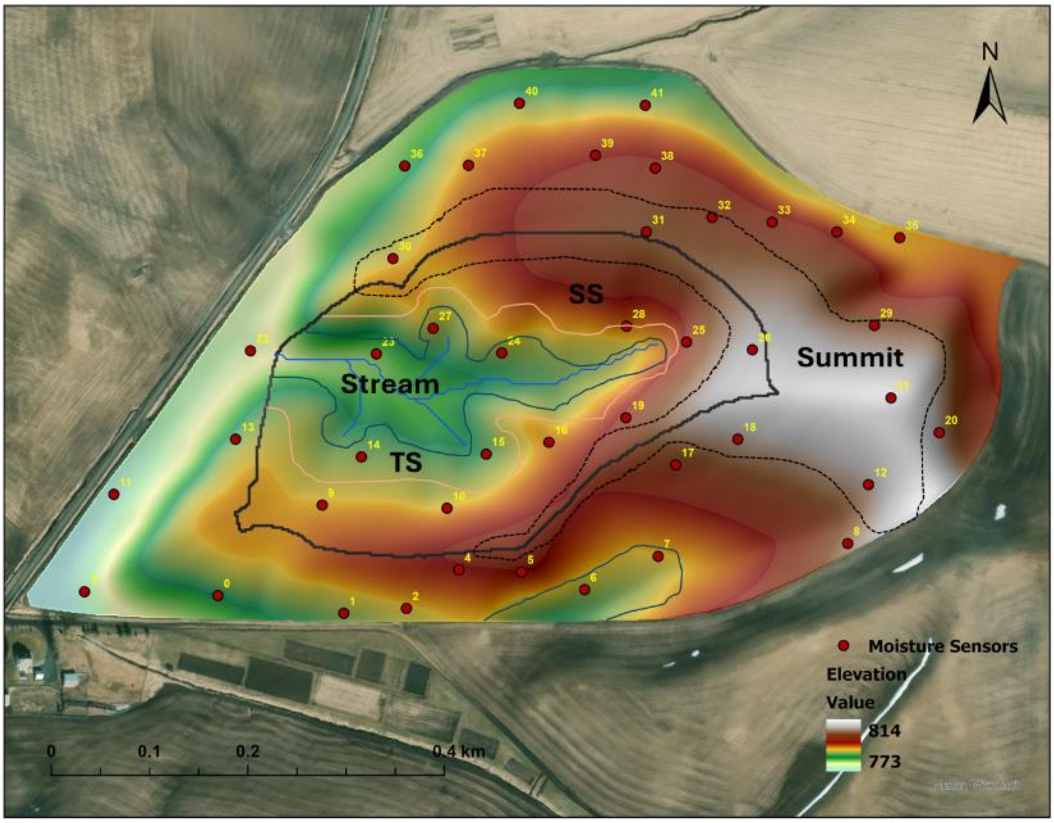

Figure 8. Layout of soil moisture sensors within and outside watershed boundaries and grouped by slope position (Summit; SS – sideslope; TS – toeslope; by the stream). Figure Credit: The Long-Term Agroecosystem Research (LTER) Network site of USDA-ARS Northwest Sustainable Agroecosystems Research, at Cook Farm, Washington State University, Department of Crop and Soil Sciences, Pullman, Washington.

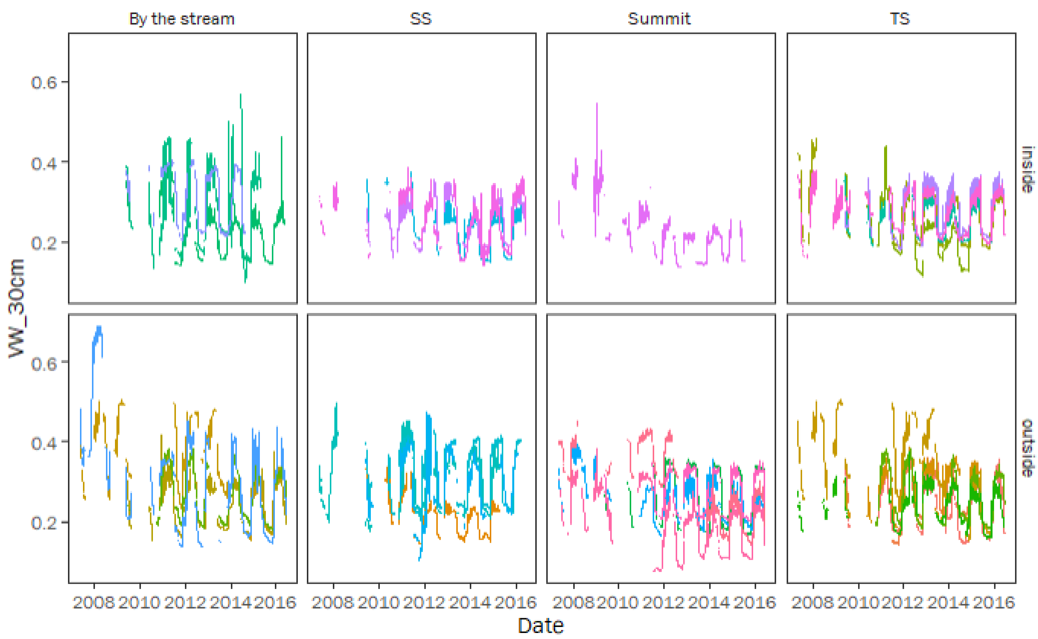

Figure 9. Soil moisture data plotted over time for sensors inside and outside of the watershed grouped by slope position (Summit; SS – sideslope; TS – toeslope: and by the stream). Colors indicate different sensors. Figure Credit: USDA-ARS Northwest Sustainable Agroecosystems Research, at Cook Farm, Washington State University, Department of Crop and Soil Sciences, Pullman, Washington Cook Farm. Data compiled by Caley Gasch, under supervision of David Brown, Department of Crop and Soil Sciences, Washington State University, Pullman, Washington.

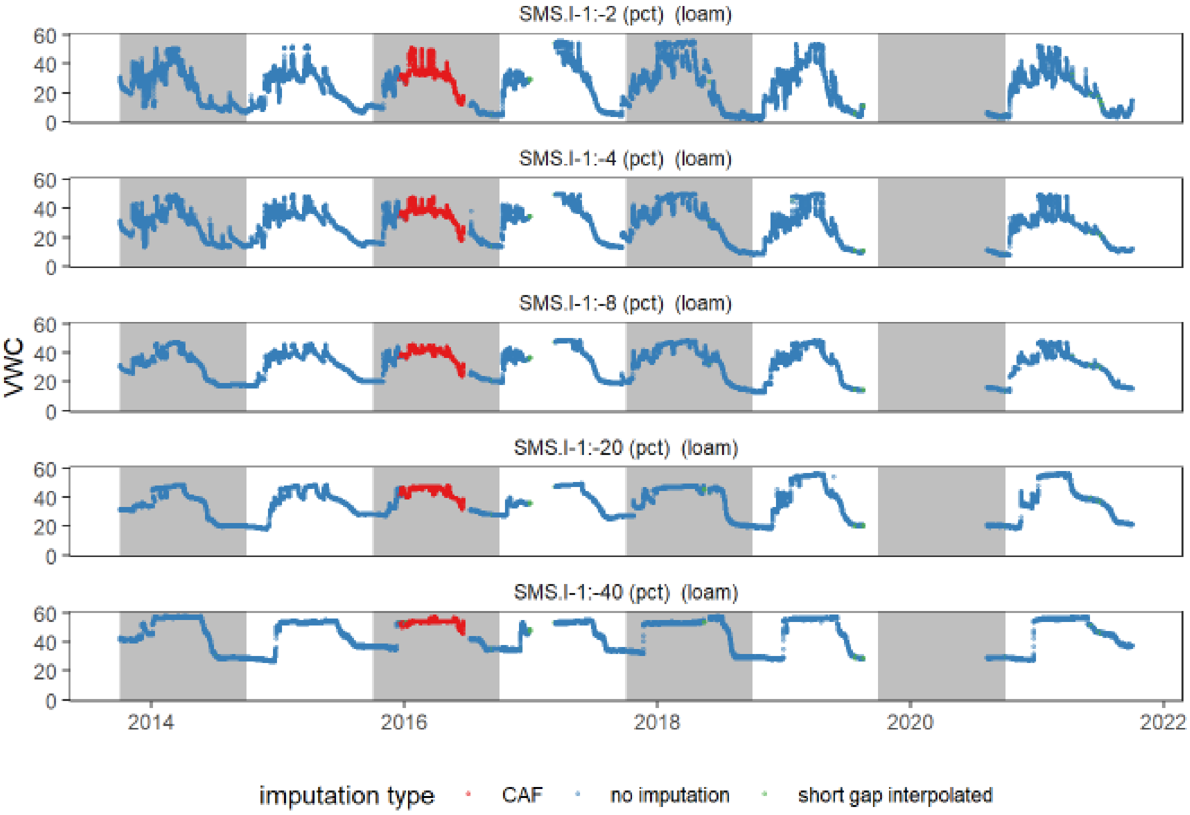

Figure 10. A soil moisture sensor filled in with data from different techniques as described earlier. The red line represents filled in gaps. Figure Credit: USDA-ARS Northwest Sustainable Agroecosystems Research, at Cook Farm, Washington State University, Department of Crop and Soil Sciences, Pullman, Washington Cook Farm. Data compiled by Caley Gasch, under supervision of David Brown, Department of Crop and Soil Sciences, Washington State University, Pullman, Washington.

CHAPTER 8

DATA QUALITY TIERS OF SOIL MOISTURE DATA

Mike Cosh, Nandita Gaur

> **Learning Outcomes**
>
> The data quality tiering system described below can be used to categorize soil moisture data being produced by different networks, at a network or individual station level.
>
> This tiering system provides an aspirational framework for network operators looking to improve data quality and a short-hand approach for data users to quickly assess whether a dataset's quality is likely to be appropriate for their intended use.

Networks benefit from setting goals and criteria for the products they produce. While networks may have individual goals and criteria outlined for themselves, standardized goals across networks can help coalesce soil moisture data from different networks in a more efficient way for stakeholders. This chapter outlines a tiering system for data quality self-assessment.

The approach described in this chapter for categorizing soil moisture networks into three tiers parallels a proposed tiering method for meteorological networks more broadly described by the World Meteorological Organization's Global Climate Observing System (WMO GCOS)[12]. Similar to the classification system described in this document, the WMO GCOS concept of a three-tiered structure is intended to support user guidance when selecting a dataset and is centered around data quality, data assurance, and documentation[13]. The network tiering approach described in this document differs in that it provides a set of guidelines or goals specific to soil moisture networks.

This chapter describes a method for soil moisture data quality tier assignment, which can be self-assessed for (1) a time series of soil moisture data from a certain sensor that is continually collecting long-term data, (2) a long-term station, and (3) a long-term network.

Broadly, the quality of soil moisture data and its utility to stakeholders can depend upon:

1. the numerical accuracy of the soil moisture dataset,
2. its spatial representativeness,
3. data latency,
4. ancillary information about the site, and
5. depth of soils that are represented.

There are a large variety of applications and purposes for network deployment, each with specific criteria and features. Based on available resources and purpose of the network, data quality objectives can vary greatly based on the five factors mentioned above. Any tiering system must

[12] Proposal for formalization and standardization of tiered network approach across domains and observing system programs. 2022. https://gcos.wmo.int/sites/default/files/2.3_c_concept_note_tiered_networks_v5_0.pdf?48eYWrX00RFgPm7j87Cle.PdX8grWXLo

[13] The tiers for the WMO GCOS networks are "Reference, Baseline, or Additional" networks. The GCOS proposed tiering approach was endorsed by the WMO in 2022, and specific criteria associated with the tiers are still in development as of 2024.

thus be comprehensive in defining the critical and common characteristics for networks, while also being flexible and applicable to the variety of conditions found among the many networks deployed in the past, present, and future. A system is therefore proposed with three criteria for determining the tier of a dataset: Error Analysis, Data Stream Density, and Metadata. Error analysis incorporates both errors arising due to choice of sensor and calibration (pre-data collection) and errors due to QA and QC issues (post data collection). Data stream density broadly refers to the spatial (depth-based) and temporal frequency of data collection and reporting. Metadata refers to the amount of standardized information per the Metadata Guidance document that the network provides. These criteria have been selected after discussions with network operators and data users that identified factors in selecting data and products for use. Broadly, each of these criteria will be evaluated for having 'None', 'Some', or 'All of the Ideal Criteria'.

THREE-TIER SYSTEM FOR DATA QUALITY

A three-tier system to categorize the quality of soil moisture data is provided in Table 8. The tiering system can be applied to a network, a station, or an individual time series of soil moisture data produced by a sensor within a station. It can vary over specific time spans for a specific station as well, because it is possible to have the quality of a station improve or degrade over time. For instance, stations in mountainous regions may have high latency in winter months because of access and data transmission logistics. Such a station could be classified as Tier I during the growing season or summer months, and Tier III during the winter. This will help users of the data understand the limitations of the network and data streams.

Table 8. Tiers of data quality

Element	Tier I	Tier II	Tier III	Uncategorized
1: Error analysis				
Sensor calibration	Soil-specific calibration with at least one post-deployment calibration activity.	Point scale and soil-specific calibration (Laboratory based)	Factory calibrated	Not defined
Quality assurance & quality control	Wide range of tests and data quality flags for Type I and Type II data errors[14]	Tests for Type I errors*	none	none
2: Data Stream Density				
Measurement frequency	Hourly	Hourly	> Hourly	>daily
Depths	3 depths or more	2 depths	1 depth	-
Temporal resolution	Near-real time	Daily	> Daily	Uncertain
Available data per quarter-year[15]	Reports 90% data/quarter	75%	50%	< 50%
3: Metadata	**Tier I**	**≥Tier II**	**≥ Tier III**	**No metadata**
Site characterization	Expert soil characterization	Map based estimates	Lat/Long	
Maintenance	Multiple times per year	Annual	Less than annual	

TIERS OF DATA QUALITY

A full description of metrics for tier classification can be found in the Appendices to this document. Summary descriptions of each category are provided below and in Table 8.

UNCATEGORIZED

The network or program collects data inconsistently or is lacking many parameters of quality assurance and control. An examples of soil moisture data that might be classified as "uncategorized" could be citizen science data that are collected on an irregular basis.

- Error analysis:
  - Sensor calibration is not defined by the network or is non-existent.
  - Data quality assurance and control protocols do not exist. Data are not flagged or quality checked following collection.
- Data stream density:
  - Data are collected on a less frequent basis than daily. Data collection may be sporadic.
  - Soil moisture is collected only at one depth or at different depths during different data collection events.

[14] *See Chapter 7 of this document for further information of Type I and Type II Data errors
[15] Under current operative conditions this may not possible; this element is currently only a recommendation.

    - Temporal resolution is not defined or irregular.
    - No more than 50% of the data collected within a 3-month time period are valid data (Chapter 7). Note: there may be some exceptions to this rule, for example, when frozen soils reduce sensor performance for a known, seasonal period.
- Metadata
    - No metadata are available.

Tier III Data (Basic/Low Quality)

- Sensor calibration:
    - Only factory calibration has taken place. No soil-specific calibrations or in-lab tests have been conducted by the network operators.
    - No QA or QC is applied to data post-collection. Data are not flagged or checked.
- Data stream density:
    - Data are collected less frequently than on an hourly basis. Data may be collected only once daily.
    - Soil moisture and relevant parameters are measured at one or more depth per site.
    - Data are made available on a daily or less frequent basis.
    - At least 50% of the data collected within a 3-month time period are valid data (Chapter 7). Note: there may be some exceptions to this rule, for example, when frozen soils reduce sensor performance for a known, seasonal period.
- Metadata: (See NSCMMN Metadata Recommendations Guide for Tier Selection)
    - Latitude and longitude are provided (See NSCMMN Guidelines).
    - Soil and landscape characterization are not present or are incomplete (See NSCMMN Guidelines).
    - Maintenance does not occur on an annual basis or more frequently. Maintenance is sporadic.

Tier II Data (Moderate Quality)

- Error analysis:
    - Soil specific calibration in laboratory is complete for all installation locations for all deployed sensor makes and models (Chapter 2, 4).
    - Point scale calibration has taken place
    - Data-processing includes testing for and flagging Type I (visually observable) data errors (Chapter 7).
- Data Stream Density:
    - Data are collected at least hourly or more frequently.
    - Soil moisture and companion parameters are measured at two or more depths within the same soil column.
    - Temporal resolution is at least daily.
    - At least 75% of the data collected within a 3-month time period are valid data (Chapter 7). Note: there may be some exceptions to this rule, for example, when frozen soils reduce sensor performance for a known, seasonal period.

- Metadata: (See Metadata Guidance document for metadata criteria)
    - Site characterization (landscape cover, soil type, etc.) is conducted using estimates based on maps or is only partially available (Metadata Guidance document).
    - Latitude, longitude, and elevation are provided to a high degree of accuracy (Metadata Guidance document).
    - Site maintenance occurs annually (Chapter 5).

TIER I DATA (HIGH QUALITY)

- Error analysis:
    - Soil specific calibration in laboratory must be complete for all installation locations for all deployed sensor makes and models (Chapter 2, 4).
    - At least one post-deployment field calibration or validation activity must have been completed for each sensor deployment location (Chapter 6).
    - Data post-processing includes a wide range of tests and associated flags for both Type I (visually observable) and Type II (complex) data errors (Chapter 7). A key is provided for all error flags.
- Data stream density:
    - Measurements are taken least hourly, if not more frequently.
    - Soil moisture and accompanying parameters are measured at three or more depths within the same soil pit/trench.
    - Temporal resolution is near real time. (Data are transmitted multiple times daily.)
    - At least 90% of the data collected within a 3-month time period are valid data (Chapter 7). Note: there may be some exceptions to this rule, for example, when frozen soils reduce sensor performance for a known, seasonal period.
- Metadata: (See Metadata Guidance document for metadata classifications)
    - Soil characteristics, including soil texture, salinity, pore size, etc., have been characterized by a soils expert.
    - Latitude, longitude, and elevation are provided to a high degree of accuracy
    - Site description (landscape type, slope, etc.) are collected in-person.
    - Station maintenance is conducted multiple times per year (Chapter 5).

OTHER TIERING CONSIDERATIONS

For representing soil moisture in certain units other than volumetric soil moisture, Tier I metadata is a pre-requisite. These include fraction available water and % field capacity. Hence, to support some stakeholder uses it may be beneficial to maintain Tier I *metadata* (per the Metadata Guidance document) even if the other parameters do not conform to that tiering.

To address seasonal impacts to data collection and data quality, data availability should be measured per 3-month period. It is possible that a station or network meet different tier criteria during different seasons of the year: therefore, data users might choose to utilize the network for only the growing season, or some other time frame.

A network, station, or time series under consideration will be classified based on the lowest tier it conforms to, based on all three elements of data tiering (error analysis, data stream density, and metadata). A few examples are provided below.

1. For determining the tier for a network of 10 stations, if eight stations are Tier I while two stations are Tier II, the classification of the network would be Tier II. However, this network can advertise that 80% of their stations conform to Tier I while 20% correspond to Tier II.
2. For determining the tier for a station with five soil moisture sensors, if two sensors are Tier II but the remaining are Tier II, the station tier would be classified as a Tier III.
3. For a time-series of soil moisture data from a sensor, if the measurements correspond to Tier I for two elements per Table 8 but Tier III for the remaining element, the time series will be classified as a Tier III.

WHO WILL DETERMINE THE TIERING LEVEL OF A STATION OR NETWORK?

These elements are intended for network self-evaluation but may also be subject to peer review, as usually occurs in scientific reviews and publications. Generally, a station would be classified only as high as their lowest tier class among metrics for evaluation. However, there may be some situations, such as performance during periods of frozen soils, where temporal caveats are reasonable.

WHY SHOULD YOU PARTICIPATE IN THE TIERING EXERCISE?

There are various reasons for using the tiering system.

1. The system is designed with both network operators and stakeholders in mind.
2. It enables better integration of soil moisture data from different sources and networks, which can increase the large-scale usability of soil moisture data as is often required by stakeholders.
3. At a network level, it provides a standardized baseline for different networks to compare themselves with other networks. This information can be used to identify areas of improvement for the network and identify areas that require investment of additional resources.
4. Finally, a network may use the tiering to support its intra-network management decision-making. For example, if a network characterizes themselves as having 80% Tier I stations and 20% Tier II stations, that information might be used to create aspirations for station improvements and selective investment of resources.
5. The tiering system is transparent and allows stakeholders to identify the tier of data they require. As such, stakeholders can quickly identify networks that provide data that is of interest to them, while network operators can identify additional stakeholders for their dataset creating the potential for additional sources of funding for maintenance.

CHAPTER 9

CONCLUSION

This *Soil Moisture Data Quality Guidance* document provides recommendations to network operators on collecting and reporting accurate soil moisture data. It is designed to standardize long-term soil moisture data being collected by diverse networks, using different kinds of soil moisture sensors and operating across varied landscapes. The document was developed based on a review of existing literature and in consultation with network operators, data users, and soil moisture experts. The document introduces a Data Quality Tiering system that quantifies the quality of soil moisture data produced by different networks using measurable parameters. The tiering system standardizes data reported by different networks and can be applied by existing, as well as new networks. It can also be used by different stakeholders to determine the tier of data that works for them.

It should be stressed that this document attempts to describe current best practices in the context of a field that is continuing to evolve and mature. The intention is to provide an initial path forward to harmonize existing and upcoming in situ soil moisture datasets. These are intended to be “living guidelines” and the NCSMMN community will continue review and update the document as necessary over time.

APPENDIX A

CHECKLIST FOR INSTALLING A NEW SENSOR NETWORK

PRE-INSTALLATION

- ☐ Determine the tier of network/stations you are aspiring for. (Table 8, Chapter 8)
- ☐ Identify local soil experts if you aspire to be Tier II or above. This includes staff at a local National Resources Conservation Service (NRCS) office, university, or a private company. You can also reach out to the National Coordinated Soil Moisture Monitoring Network (NCSMMN) at soil.moisture@noaa.gov and the AASC Mesonet community for recommendations.
- ☐ Complete macro and micro site selection if setting up a brand-new network. If soil moisture sensors are being added to previously installed weather networks, refer only to micro-site selection. (Chapter 4)
- ☐ Ensure long-term access to the site. (Chapter 2)
- ☐ Select soil sensors appropriate for the specific soil conditions at network sites. Refer to Appendix B1 for a quick guide or Tables 3 and 4 for more detail (Chapter 5). If possible, consult with other soil moisture sensor users in the region to verify sensor choice for your soil type.
- ☐ If soil-specific calibration is intended at any time (a requirement for Tier II classification), prepare to collect at least two full shovels of soil from each site at each depth. Note that each soil type will need to be collected separately, and consequently you will require a separate container for each depth at which a sensor will be installed. Soil types will be determined by the soil scientist on site or through laboratory testing at an experienced facility.

DURING INSTALLATION

- ☐ Follow the installation protocol for sensor installation. Directions can be found at: www.drought.gov/drought-research/installation-protocol-situ-soil-moisture-data-collection
- ☐ Request soil characterization from local soil expert for the sensor installation borehole or pit.
- ☐ Provide the list of parameters defined in the metadata document (per the tier your network is aspiring for) to the soil expert to ensure all information is recorded and soil samples necessary for the listed measurements are collected (Metadata Guidance document).
- ☐ Include any additional ancillary data required by both current and potential stakeholders (Chapter 3, Table 2).
- ☐ If the network aims to produce a Tier I dataset, then a general site characterization of the surrounding area must also be requested from the soil scientist to identify similar soil series in the area. Note that this can also be done post installation at any time.

- ☐ Collect soils for soil-specific calibration. Label with site ID and date and store under refrigerated conditions to avoid microbial activity.

POST- INSTALLATION

- ☐ Establish site maintenance routine and frequency. Document <u>all</u> activities performed onsite.
- ☐ Establish and document QA and QC practices. Refer to Appendix C for a quick guide. Maintain a log of QA/QC activities.
- ☐ Evaluate the tier of data quality for each station each quarter or at least yearly (Chapter 8).

APPENDIX B

SENSOR GUIDELINES

APPENDIX B1: SENSOR SELECTION UNDER LIMITING CONDITIONS

The following table provides a quick guide for recommendations under common limiting conditions. For a full list of limiting conditions, refer to Table 4.

Limiting Condition	Recommendation	Unwanted outcome
High clay content/Bulk electrical conductivity (BEC)	• Use high frequency >1GHz sensors and smaller waveguides • Sensors should measure BEC • Conduct soil-specific calibration • Do not use TDR if Bulk Electrical Conductivity (BEC) is high	
Pre-installed sensors	• Conduct post-deployment activities or externally calibrate sensor in lab at an estimated bulk density with similar soil type estimated from SSURGO	• Uncertain improvement in accuracy • An independent validation through a higher-level research endeavor (modeling or other activities) may be required
Space constraints (cannot dig pit to horizontally install sensors)	• Use soil VUE TDR/Watermark sensors	• Lower accuracy
Volcanic soils	• Conduct soil-specific calibration	

APPENDIX B2: SENSOR CALIBRATION GUIDELINES

When Should Sensors Be Calibrated?

Sensors must be calibrated according to their respective data quality/assurance tier guidelines. Sensor calibration must be performed per the following recommendations.

- **New installation**: Whenever a new site or station is planned.
- **Relocation of existing site**: If an existing station is moved and all sensors are relocated to a new borehole, the borehole must be characterized again by a soil scientist.
    - If the borehole is characterized differently from the first borehole that they were installed in, calibrations pertaining to Tiers I and II must be repeated (Chapter 8).
    - If the borehole is characterized as the same soil series, but the station is moved to a different landscape location, vegetation type, or cover, only calibration pertaining to Tier I must be repeated. A Tier II classification can be retained from the previous site.
    - If the borehole is characterized as the same soil series and the station is not moved far from the original location, no re-calibration is required.
- **Sensor relocation**: If a new sensor is installed close to an existing station to replace a failed sensor with similar soil type and bulk density, the existing calibration equations that were developed for the previous sensor can be used. However, if the sensor make and model is changed, a new calibration equation must be developed.

  *Information on sensor calibration can be found in Chapter 6 of this document.

Calibration Guidelines

Tiers categories for calibration are listed from least to most rigorous.

Tier III

- Sensors should be factory calibrated. No additional calibration required.

Tier II

- Factory calibrations must be replaced with soil-specific calibration for each soil type and soil bulk density sensors will be installed in. This step can only be conducted post site characterization by a soil scientist and should be done for each sensor type-soil type combination at specific dry bulk densities.

Tier I

At least one post-validation activity must be performed in addition to soil-specific calibration performed in the lab. While most post-validation activities require modeling or expert involvement, field-based measurements offer an alternative post-validation activity that can be performed by network operators is described below. Note that any other post-deployment activity can also be performed in lieu of this process.

- Factory calibrations must be replaced with soil-specific calibrations.
- Post-validation calibration must be conducted.
    - Soil samples must be collected from several locations (at least 5) in the area surrounding the site (i.e., no variability in meteorological conditions).

- These locations must have the same soil series as the site of sensors installation.
- Samples must be collected under different wetness conditions (~ 6-10 time points total) that are preferably spread across different seasons from all depths that the sensors are installed in.
- Soil samples should be of a known volume to ensure bulk density and volumetric soil moisture can be calculated as explained in Appendix D.
- 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 document for soil/point-specific calibration (here). 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.

Note that several companies offer calibration services for a fee, and sensor calibration can be outsourced. If performing calibration in-house, follow instructions provided by Meter Group: https://metergroup.com/expertise-library/video-how-to-calibrate-meter-soil-moisture-sensors/. *Both video and text instructions are provided. While this methods example refers to one particular sensor model, the procedure remains the same for many other makes and models*.

NOTE: A POORLY DONE CALIBRATION CAN MAKE SENSORS PERFORM WORSE THAN A FACTORY CALIBRATED SENSOR.

APPENDIX C

QUALITY ASSESSMENT & QUALITY CONTROL PROCESS

FLAGGING TYPE AND FREQUENCY

1. Identify the tier your dataset complies with. Flag the dataset for each error that needs to be tested for in that tier. Flags should be categorized in two categories: Type I flags (for Type I errors) and Type II flags (for Type II errors). (Chapter 7)
2. Type I flags must be assigned in near-real time with an automated QC process while Type II flags must be updated at least once a year.
3. A clear description of flagging type and frequency must be provided on the public facing website.

TIER III

No QA/QC required. Report data directly measured by the sensor.

TIER II

QA/QC has been carried out using the following tests. Details of each test are provided within this document in Chapter 5.

1. Range test or high/low range limit test
2. Constant value test
3. Spike test
4. Break test
5. Temperature test

TIER I

The following tests must be performed <u>in addition to Tier II tests</u> and should be conducted once a year. This exercise can coincide with the time of evaluating the data quality for a tier assignment. Details of each test are provided within this document in Chapter 7.

1. Correlations in temporal relationship of soil moisture with ancillary variables
2. Moisture redistribution in unsaturated flow process
3. Calibration shift or sensor fouling

Common causes of data errors:

- Instrument malfunction
- Personnel errors
- Transmission errors
- Data processing errors

Take appropriate corrective actions for flagged data as described in Chapter 7. Note that some data processing errors that pertain to producing Tier I datasets will require the services of a soil moisture data expert. You can reach out to the program coordinator NCSMMN for recommendations on soil moisture data experts (soil.moisture@noaa.gov).

APPENDIX D

SOIL MOISTURE UNIT CONVERSIONS

Soil moisture sensors measure volumetric water content (SWC). Often, conversion of soil moisture to other units will be required. Some common conversions are provided below. * Note: θ_{WP}, θ_{FC}, and bulk density can be measured as per NRCS recommended standards and methods.

Measurement units	Conversion units	Conversion formula	Examples of conditions necessitating conversion
Volumetric soil moisture (SWC), θ $\frac{cm^3}{cm^3}$	Fraction available water content (FAW)	$FAW = \frac{\theta - \theta_{WP}}{\theta_{FC} - \theta_{WP}}$ $\theta_{WP} = SWC\ at\ wilting\ point$ $\theta_{FC} = SWC\ at\ field\ capacity$	Stakeholder requirements (see Table 2, Chapter 3)
Gravimetric soil moisture, θ_g $(\frac{g}{g})$	SWC, θ $\frac{cm^3}{cm^3}$	$\theta = \theta_g x bulk\ density$	Field calibration or lab calibration exercise
Volumetric soil moisture (SWC), θ $\frac{cm^3}{cm^3}$	Equivalent water depth, D cm	$D = \theta x thickness\ of\ representative\ soil\ layer$	Stakeholder requirements (see Table 2, Chapter 3)
Volumetric soil moisture (SWC), θ $\frac{cm^3}{cm^3}$	Plant Available Water, PAW, cm	$PAW = (\theta_{FC} - \theta_{WP})\ x thickness\ of\ representative\ soil\ layer$	Stakeholder requirements (see Table 2, Chapter 3)

Example conversions between different soil moisture units are provided in the following below for two different soil types in Georgia in Tables D1 and D2. The corresponding soil moisture graphs are shown in Figure 10, Appendix D.

Table D1. Water retention information for the upper 100 cm of a Cecil soil in the Georgia Piedmont

Depth or represented soil increment cm	Thickness cm	Centered depth of soil core cm	Bulk Density (g cm^{-3})	GravFC (kg kg^{-3})	GravWP (kg kg^{-3})	ThetaFC %	ThetaWP %	PAW	Equivalent Depth of Water, D (cm)	AWHC in upper 100 cm (cm)
			Mass Oven-dry soil/Volume of sample	Mass water at FC/Oven-dry soil mass	Mass water at WP/Oven-dry soil mass	GravFC*BD	GravWP*BD	ThetaFC - ThetaWP	PAW* Thickness	Sum of Water thickness
0-6	6	5	1.35	0.13	0.04	0.17	0.05	0.12	0.72	11.67
6-15	9	10	1.46	0.12	0.03	0.18	0.05	0.13	1.13	
15-30	15	20	1.51	0.12	0.05	0.18	0.08	0.10	1.54	
30-75	45	50	1.56	0.12	0.05	0.19	0.08	0.11	5.11	
75-100	25	96	1.52	0.23	0.14	0.35	0.22	0.13	3.18	

Table D2. Water retention information for the upper 100 cm of a Tifton soil in the Georgia Coastal Plain

Depth or represent-ed soil increment cm	Thickness cm	Centered depth of soil core cm	BD (g cm^{-3})	GravFC (kg kg^{-3})	GravWP (kg kg^{-3})	ThetaFC %	ThetaWP %	PAW	Equivalent Depth of Water, D (cm)	AWHC in upper 100 cm (cm)
			Mass Oven-dry soil/Volume of sample	Mass water at FC/Oven-dry soil mass	Mass water at WP/Oven-dry soil mass	GravFC*BD	GravWP*BD	ThetaFC - ThetaWP	PAW*Thick-ness	Sum of Water thickness
0-6	6	5	1.41	0.14	0.05	0.20	0.07	0.14	0.82	9.47
6-15	9	10	1.57	0.12	0.03	0.18	0.05	0.13	1.20	
15-30	15	20	1.65	0.10	0.03	0.16	0.05	0.11	1.72	
30-75	45	50	1.70	0.14	0.09	0.23	0.15	0.09	3.93	
75-100	25	100	1.55	0.15	0.11	0.24	0.17	0.07	1.79	

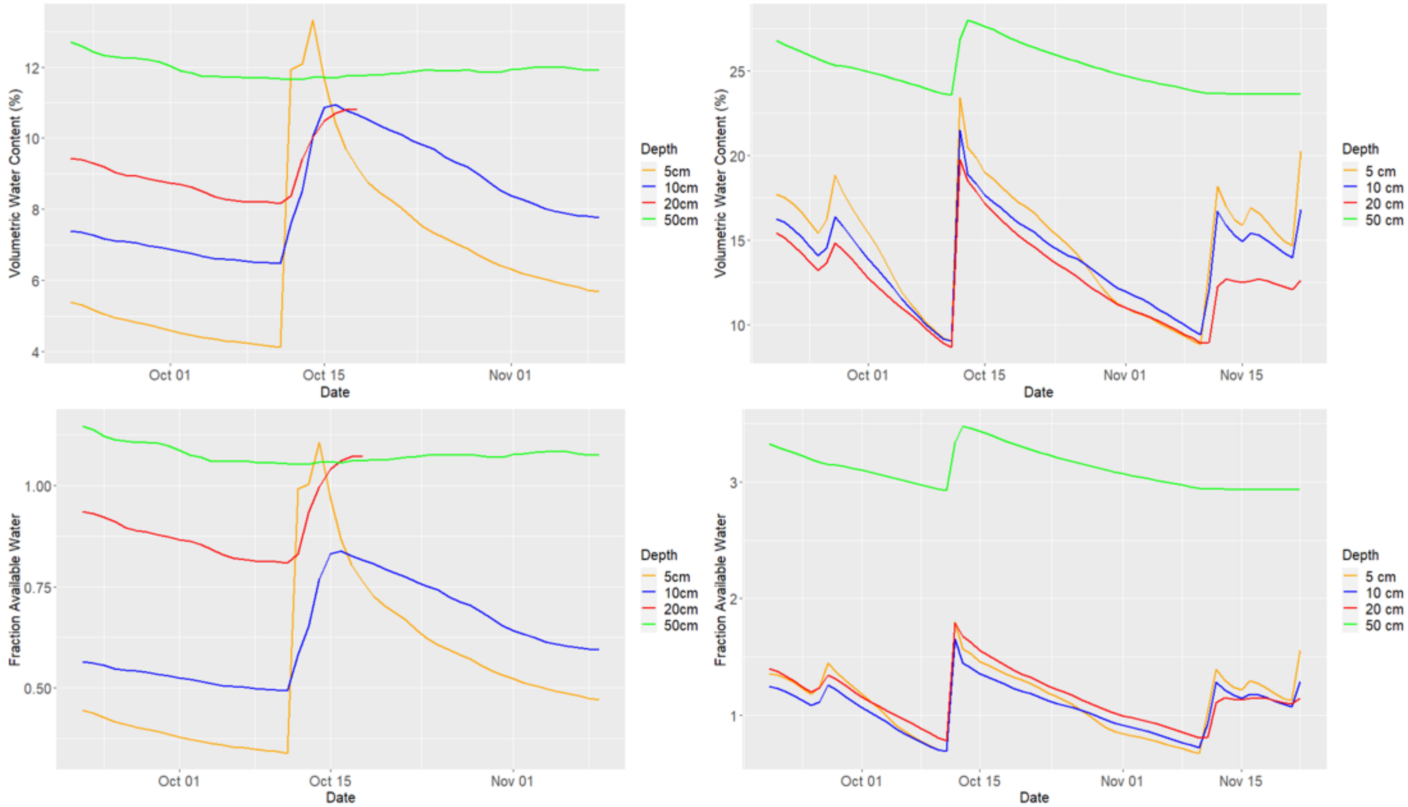

Figure D1. Volumetric water content and fraction available water (FAW) for four depths for a Cecil soil (left panel) and Tifton soil (right panel) in the Georgia Piedmont. Image Credit: Matthew Levi.

APPENDIX E

GUIDELINES FOR EXISTING NETWORK OPERATORS

Most pre-existing networks will likely easily fit in the Tier III category with minor updates. See below for how to upgrade the networks/stations to more rigorous tiers.

NETWORKS WITH PRE-INSTALLED SOIL MOISTURE SENSORS

TIER III

- Verify sensor(s) is(are) factory calibrated and report accuracy. This information can be sourced from the sensor manual or by contacting the company.
- Ensure compliance with allowable missing data values per Table 8, Chapter 8.
- Report metadata as per Tier III requirements (Metadata Guidance document). Besides basic information on site location, you will need access to the soil series classification per NRCS SSURGO. You can identify the soil series from this link by searching for latitude and longitude of your site (https://casoilresource.lawr.ucdavis.edu/gmap/).

TIER II

- ***Installing additional sensors***: If additional sensors need to be installed to upgrade the tier of a station:
  - Do not remove or disturb pre-existing sensors.
  - Reach out to local NRCS offices or soil science departments in land-grant universities to request help with site characterization.
  - With the help of a soil scientist, follow guidelines for micro-site selection and install the new set of sensors in a new borehole. It is recommended to install new sensors at all depths even if the pre-installed sensors are already measuring data at that depth.
  - Collect soils for calibration as described in Appendix A and apply calibration to both sets of sensors.
  - Report data from both sets of sensors.
- ***No additional sensors required***: If the pre-installed sensors satisfy the depth requirements of Tier II:
  - Reach out to local NRCS offices or soil science departments in land-grant universities to request help with site characterization. Site characterization can be performed anywhere near the installed site as recommended by the soil scientist. Ensure that you are at least one foot away from the installed sub-surface sensors' extremities. You can also reach out to the National Coordinated Soil Moisture Monitoring Network (NCSMMN) at soil.moisture@noaa.gov and the AASC Mesonet community for recommendations.
    - Upgrade metadata as required. Tier II metadata will require assistance from a soil scientist.

- Ensure compliance with parameters described in 'Data Stream Density' per Table 8, Chapter 8.
- Ensure all QA/QC procedures are in place (Chapter 7).

Tier I

- In addition to activities described for Tier II data, perform post-validation for all installed sensors.

GUIDELINES FOR REPLACING FAILED SENSORS

When a new sensor(s) is(are) to be added to replace an existing failed sensor "close" to the existing site, then it must be installed along the same contour such that neither the new sensor or existing sensors impede water flow above the ground where either of them are installed.

NETWORKS WITH NO PRE-EXISTING SOIL MOISTURE SENSORS

Follow Appendix A.

REFERENCES

AASC. (2019.) *Recommendations and Best Practices for Mesonets, Version 1.* American Association of State Climatologists. https://stateclimate.org/docs/AASC%20Recommendations%20and%20Best%20Practices%20for%20Mesonets%20-%20Final,%20Ver%201;%20approved%2026%20Jun%2019.pdf

A Strategy for the National Coordinated Soil Moisture Monitoring Network. (2021.) Report prepared for the NOAA's National Integrated Drought Information System (NIDIS) by the Executive Committee of the National Coordinated Soil Moisture Monitoring Network. https://www.drought.gov/documents/strategy-national-coordinated-soil-moisture-monitoring-network

Albertson, J. D., & Montaldo, N. (2003.) Temporal Dynamics of Soil moisture Variability: 1. Theoretical basis. *Water Resources Research*, 3(10): 1274, doi:10.1029/2002WR001616.

Baldoncini, M., Albéri, M., Chiarelli, E., Giulia Cristina Raptisa, K., Strati, V., Mantovani, F. (2018.) Investigating the Potentialities of Monte Carlo Simulation for Assessing Soil Water Content via Proximal Gamma-Ray Spectroscopy. *Journal of Environmental Radioactivity*, 192: 105–116. https://doi.org/10.1016/j.jenvrad.2018.06.001

Behroozmand, A. A., K. Keating, & E. Auken. (2015.) A Review of the Principles and Applications of the NMR Technique for Near-Surface Characterization. *Surveys in Geophysics, 36*: 27-85, doi:10.1007/s10712-014-9304-0.

McMichael, B., & Lascano, R.J. (2003.) Laboratory Evaluation of a Commercial Dielectric Soil Water Sensor. *Vadose Zone Journal*, *2*(4): 650–654. doi: https://doi.org/10.2113/2.4.650

Burns, T. T., Adams, J. R., & Berg, A. A. (2014.) Laboratory Calibration Procedures of the Hydra Probe Soil moisture Sensor: Infiltration Wet-up vs. Dry-down. *Vadose Zone Journal*, *13*(12): vzj2014-07. https://doi.org/10.2136/vzj2014.07.0081

Caldwell, T.G., Bongiovanni, T., Cosh, M.H., Halley, C., & Young, M.H. (2018.) Field and Laboratory Evaluation of the CS655 Soil Water Content Sensor. *Vadose Zone Journal*, 17(1): 1-16. https://doi.org/10.2136/vzj2017.12.0214.

Caldwell, T.G., Bongiovanni, T., Cosh, M.H., Jackson, T.J., Colliander, A., Abolt, C.J., Casteel, R., Larson, T., Scanlon, B.R. & Young, M.H. (2019.) The Texas Soil Observation Network: A Comprehensive Soil Moisture Dataset for Remote Sensing and Land Surface Model Validation. *Vadose Zone Journal*, *18*:100034, doi:10.2136/vzj2019.04.0034.

Chandler, D., Seyfried, M., Murdock, M., & McNamara, J.P. (2004.) Field Calibration of Water Content Reflectometers. *Soil Science Society of America Journal*, *68*(5). doi:10.2136/sssja2004.1501

Caldwell, T.G., Cosh, M.H., Evett, S.R., Edwards, N., Hofman, H., Illston, B.G., Meyers, T., Skumanich, M., & Sutcliffe, K. (2022.) In situ Soil Moisture Sensors in Undisturbed Soils. *Journal of Visualized Experiments*, *189*: e64498. doi:10.3791/64498.

Campbell, J.L., Rustad, L.E., Porter, J.H., Taylor, J.R., Dereszynski, E.W., Shanley, J.B., Gries, C., Henshaw, D.L., Martin, M.E., Sheldon, W.M., & Boorse, E.R. (2013.) Quantity is Nothing Without Quality: Automated QA/QC for Streaming Environmental Sensor Data. *Bioscience, 63*(7): 574–585. https://doi.org/10.1525/bio.2013.63.7.10

Chatterjee, S. (2021.) A New Coefficient of Correlation. *J. Am. Stat. Assoc, 116*: 2009–2022. https://doi.org/10.1080/01621459.2020.1758115

Chen, F., Crow, W.T., Colliander, A., Cosh, M.H., Jackson, T.J., Bindlish, R., Reichle, R.H., Chan, S.K., Bosch, D.D., Starks, P.J., & Goodrich, D.C. (2016.) Application of Triple Collocation in Ground-Based Validation of Soil Moisture Active/Passive (SMAP) Level 2 Data Products. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *10*(2): 489-502. https://doi.org/10.1109/JSTARS.2016.2569998

Chen, F., Crow, W. T., Bindlish, R., Colliander, A., Burgin, M. S., Asanuma, J., & Aida, K. (2018.) Global-scale Evaluation of SMAP, SMOS and ASCAT Soil Moisture Products Using Triple Collocation. *Remote Sensing of Environment, 214*: 1–13. https://doi.org/https://doi.org/10.1016/j.rse.2018.05.008.

Colliander, A., Chan, S., Kim, S-B. Das, N., Yueh, S., Cosh, M., Bindlish, R., Jackson, T., & Njoku, E. (2012.) Long Term Analysis of PALS Soil Moisture Campaign Measurements for Global Soil Moisture Algorithm Development. *Remote Sensing of the Environment*, *121*: 309-322. https://doi.org/10.1016/j.rse.2012.02.002

Colliander, A., Jackson, T.J., Bindlish, R., Chan, S., Das, N., Kim, S.B., Cosh, M.H., Dunbar, R.S., Dang, L., Pashaian, L., & Asanuma, J. (2017.) Validation of SMAP Surface Soil Moisture Products with Core Validation Sites. *Remote Sensing of Environment*, *191*: 215-231. https://doi.org/10.1016/j.rse.2017.01.021

Coopersmith, E. J., Cosh, M. H., Bell, J. E., Kelly, V., Hall, M., Palecki, M. A., & Temimi, M. (2016.) Deploying Temporary Networks for Upscaling of Sparse Network Stations. *International Journal of Applied Earth Observation and Geoinformation*, *52*. https://doi.org/10.1016/j.jag.2016.07.013.

Coopersmith, E., Cosh, M. H., & Daughtry, C. S. T. (2014.) Field-Scale Moisture Estimates Using COSMOS Sensors: A Validation Study with Temporary Networks and Leaf Area Indices. *Journal of Hydrology*, *519*(A): 637-643. https://doi.org/doi:10/1016/j.jhydrol.2014.07.060

Coopersmith, E.J., Cosh, M.H., Starks, P.J., Bosch, D.D., Holifield Collins, C., Seyfried, M., Livingston, S., & Prueger, J. (2021.) Understanding Temporal Stability: A Long-term Analysis of USDA ARS Watersheds. *International Journal of Digital Earth, 14*(10): 1243-1254. https://doi.org/10.1080/17538947.2021.1943550

Cosh, M.H., Jackson, T.J., Bindlish, R., Famiglietti, J.S., & Ryu, D. (2005.) Calibration of an Impedance Probe for Estimation of Surface Soil Water Content Over Large Regions. *Journal of Hydrology*, *311*(1-4): 49-58. https://doi.org/10.1016/j.jhydrol.2005.01.003

Cosh, M. H., Jackson, T. J., Starks, P., & Heathman, G. (2006.) Temporal Stability of Surface Soil Moisture in the Little Washita River Watershed and Its Applications in Satellite Soil Moisture Product Validation. *Journal of Hydrology, 323*(1-4). https://doi.org/10.1016/j.jhydrol.2005.08.020

Cosh, M. H., Jackson, T. J., Moran, S., & Bindlish, R. (2008.) Temporal Persistence and Stability of Surface Soil Moisture in a Semi-Arid Watershed. *Remote Sensing of Environment*, *112*(2): 304-313. https://doi.org/10.1016/j.rse.2007.07.001

Cosh, M. H., Jackson, T. J., Smith, C., Toth, B., & Berg, A. A. (2013.) Validating the BERMS in situ Soil Water Content Data Record with a Large-Scale Temporary Network. *Vadose Zone Journal*, *12(*2). https://doi.org/10.2136/vzj2012.0151

Cosh, M.H., Ochsner, T.E., McKee, L., Dong, J., Basara, J.B., Evett, S.R., Hatch, C.E., Small, E.E., Steele-Dunner, S.C., Zreda, M., & Sayde, C. (2016.) The Soil Moisture Active Passive Marena, Oklahoma in situ Sensor Testbed (SMAP-MOISST): Testbed Design and Evaluation of in situ Sensors. *Vadose Zone Journal*, *15*(4):1-11. https://doi.org/10.2136/vzj2015.09.0122

Datta S, Taghvaeian S, Ochsner TE, Moriasi D, Gowda P, Steiner JL. (2018.) Performance Assessment of Five Different Soil Moisture Sensors under Irrigated Field Conditions in Oklahoma. *Sensors*, *18(*11): 3786. https://doi.org/10.3390/s18113786

Dong, J., & Ochsner, T. E. (2018.) Soil Texture Often Exerts a Stronger Influence Than Precipitation on Mesoscale Soil Moisture Patterns. *Water Resources Research*, *54*: 2199–2211. https://doi.org/10.1002/2017WR021692

Dong, J., Akbar, R., Short Gianotti, D.J., Feldman, A.F., Crow, W.T., & Entekhabi, D. (2022.) Can Surface Soil Moisture Information Identify Evapotranspiration Regime Transitions? *Geophysical Research Letters*, *49*(7): e2021GL097697.

Dong, J., Ochsner, T. E., Zreda, M., Cosh, M. H., & Zou, C. B. (2014.) Calibration and Validation of the COSMOS Rover for Surface Soil Moisture. *Vadose Zone Journal*, *13*(4). https://doi.org/10.2136/vzj2013.08.0148

Dorigo, W.A., Xaver, A., Vreugdenhil, M., Gruber, A., Hegyiová, A., Sanchis-Dufau, A.D., Zamojski, D., Cordes, C., Wagner, W., & Drusch, M. (2013.) Global Automated Quality Control of in situ Soil Moisture Data from the International Soil Moisture Network. *Vadose Zone Journal*, *12.* doi:10.2136/vzj2012.0097.

Dorigo, W., Himmelbauer, I., Aberer, D., Schremmer, L., Petrakovic, I., Zappa, L., Preimesberger, W., Xaver, A., Annor, F., Ardö, J., Baldocchi, D., Bitelli, M., Blöschl, G., Bogena, H., Brocca, L., Calvet, J.-C., Camarero, J. J., Capello, G., Choi, M., Cosh, M. C., … Sabia, R. (2021.) The International Soil Moisture Network: Serving Earth System Science for Over a Decade. *Hydrology and Earth Systems Sciences*, *25*(11): 5749-5804. https://doi.org/10.5194/hess-25-5749-2021

Du, J., Kimball, J. S., Bindlish, R., Walker, J. P., & Watts, J. D. (2022.) Local Scale (3-m) Soil Moisture Mapping Using SMAP and Planet SuperDove. *Remote Sensing*, *14*(15). https://doi.org/10.3390/rs14153812

Engstrom, R., Hope, A., Kwon, H., & Stow, D. (2008.) The Relationship Between Soil Moisture and NDVI near Barrow, Alaska. *Physical Geography, 29*(1): 38-53. https://doi.org/10.2747/0272-3646.29.1.38

Entekhabi, D., Reichle, R.H., Koster, R.D. & Crow, W.T. (2010.) Performance Metrics for Soil Moisture Retrievals and Application Requirements. *Journal of Hydrometeorology, 11*(3): 832-840. https://doi.org/10.1175/2010JHM1223.1

Entin, J. K., Robock, A., Vinnikov, K.Y., Hollinger, S.E., Liu, S.X., & Namkhai, A. (2000.) Temporal and Spatial Scales of Observed Soil Moisture Variations in the Extratropics. *Journal of Geophysical Research, 105*(D9): 11,865–11,877. https://doi.org/10.1029/2000JD900051

Evett, S.R., Schwartz, R.C., Casanova, J.J., & Heng Lee, K. (2012.) Soil Water Sensing for Water Balance ET and WUE. *Agricultural Water Management, 104*:1–9. doi:10.1016/j.agwat.2011.12.002

Evett, S.R., Schwartz, R.C., Tolk, J.A., & Howell, T.A. (2009.) Soil Profile Water Content Determination: Spatio-Temporal Variability of Electromagnetic and Neutron Probe Sensors in Access Tubes. *Vadose Zone Journal, 8*(4): 926–941. doi:10.2136/vzj2008.0146

Evett, S.R., & Steiner, J.L. (1995.) Precision of Neutron Scattering and Capacitance Type Soil Water Content Gauges from Field Calibration. *Soil Science Society of America Journal, 59*(4): 961-968. https://doi.org/10.2136/sssaj1995.03615995005900040001x

Evett, S.R., Marek, G.W., Colaizzi, P.D., Copeland, K.S., & Ruthardt, B.B. (2022.) Methods for Downhole Soil Water Sensor Calibration—Complications of Bulk Density and Water Content Variations. *Vadose Zone Journal, 21*(6): e20235. https://doi.org/10.1002/vzj2.20235

Evett, S.R., Tolk, J.A., & Howell, T.A. (2005.) Time Domain Reflectometry Laboratory Calibration in Travel Time, Bulk Electrical Conductivity, and Effective Frequency. *Vadose Zone Journal, 4*(4): 1020-1029. https://doi.org/10.2136/vzj2005.0046

Famiglietti, J.S., Ryu, D., Berg, A.A., Rodell, M., & Jackson, T.J. (2008.) Field Observations of Soil Moisture Variability Across Scales. *Water Resources Research, 44*: W01423. https://doi.org/10.1029/2006WR005804

Famiglietti, J., Devereaux, J., Laymon, C.A., Tsegaye, T., Houser, P.R., Jackson, T.J., Graham, S.T., Rodell, M., & van Oevelen, P.J. (1999.) Ground-Based Investigation of Soil Moisture Variability Within Remote Sensing Footprints During the Southern Great Plains 1997 (SGP 97) Hydrology Experiment. *Water Resources Research, 35*(6): 1839–1851. https://doi.org/10.1029/1999WR900047

Fares, A., Abbas, F., Maria, D., & Mair, A. (2011.) Improved Calibration Functions of Three Capacitance Probes for the Measurement of Soil Moisture in Tropical Soils. *Sensors, 11*(5): 4858–4874. https://doi.org/10.3390/s110504858

Ferrarezi, R.S., Nogueira, T.A.R., & Zepeda, S.G.C. (2020.) Performance of Soil Moisture Sensors in Florida Sandy Soils. *Water, 12*(2):358. https://doi.org/10.3390/w12020358

Fiebrich, C.A., Morgan, C.R., McCombs, A.G., Hall, P.K., & McPherson, R.A. (2010.) Quality Assurance Procedures for Mesoscale Meteorological Data. *Journal of Atmospheric and Oceanic Technology*, *27*: 1565-1582, doi: 10.1175/2010jtecha1433.1.

Ford, T.W., & Quiring, S.M. (2014.) In situ Soil Moisture Coupled with Extreme Temperatures: A Study Based on the Oklahoma Mesonet. *Geophysical Research Letters*, *41*(13): 4727-4734. https://doi.org/10.1002/2014GL060949

Ford, T.W., Wang, Q., & Quiring, S.M. (2016.) The Observation Record Length Necessary to Generate Robust Soil Moisture Percentiles. *Journal of Applied Meteorology and Climatology*, *55*(10): 2131-2149. https://doi.org/10.1175/JAMC-D-16-0143.1

Gardner, W., & Kirkham, D. (1952.) Determination of Soil Moisture by Neutron Scattering. *Soil Science*, *73*: 391-402.

Gaur, N., & Mohanty, B.P. (2013.) Evolution of Physical Controls for Soil Moisture in Humid and Subhumid Watersheds. *Water Resources Research, 49*: 1244–1258. https://doi.org/10.1002/wrcr.20069

Gaur, N., & Mohanty, B.P. (2016.) Land-Surface Controls on Near-Surface Soil Moisture Dynamics: Traversing Remote Sensing Footprints. *Water Resources Research*, *52*: 6365–6385. https://doi.org/10.1002/2015WR018095

Gaur, N., & Mohanty, B.P. (2019.) A Nomograph to Incorporate Geophysical Heterogeneity in Soil Moisture Downscaling. *Water Resources Research*, *55*(1): 34-54. https://doi.org/10.1029/2018WR023513

Ge, X., Ding, J., Jin, X., Wang, J., Chen, X., Li, X., Liu, J., & Xie, B. (2021.) Estimating Agricultural Soil Moisture Content through UAV-Based Hyperspectral Images in the Arid Region. *Remote Sensing*, *13*(8). https://doi.org/10.3390/rs13081562

Geng, Y., Xue, S., & Shen, Z. (2011.) Outlier Detection Based on Hilbert-Huang Transform. *2011 International Conference on Remote Sensing, Environment and Transportation Engineering*: 3311-3314. IEEE. https://doi.org/10.1109/RSETE.2011.5965020

Gruber, A., Dorigo, W.A., Zwieback, S., Xaver, A., & Wagner, W. (2013.) Characterizing Coarse-Scale Representativeness of in situ Soil Moisture Measurements from the International Soil Moisture Network. *Vadose Zone Journal*, *12*(2): 1-5. https://doi.org/10.2136/vzj2012.0170

Heathman, G.C., Cosh, M.H., Han, E., Jackson, T.J., Mckee, L.G., & McAfee, S. (2012.) Field Scale Spatiotemporal Analysis of Surface Soil Moisture for Evaluating Point-Scale in situ Networks. *Geoderma*, *170*(1): 195–205. https://doi.org/10.1016/j.geoderma.2011.11.004

Hubbard, K.G., Goddard, S., Sorensen, W.D., Wells, N., & Osugi, T.T. (2005.) Performance of Quality Assurance Procedures for an Applied Climate Information System. *Journal of Atmospheric and Oceanic Technology*, *22*(1): 105-112. https://doi.org/10.1175/JTECH-1657.1

IAEA. (2008.) *Field Estimation of Soil Water Content: A Practical Guide to Methods, Instrumentation and Sensor Technology.* International Atomic Energy Agency (IAEA), Vienna. https://www-pub.iaea.org/mtcd/publications/pdf/tcs-30_web.pdf

Illston, B.G., Basara, J.B., Fiebrich, C.A., Crawford, K.C., Hunt, E., Fisher, D.K., ... & Humes, K. (2008.) Mesoscale Monitoring of Soil Moisture Across a Statewide Network. *Journal of Atmospheric and Oceanic Technology*, *25*(2): 167-182. https://doi.org/10.1175/2007JTECHA993.1

International Soil Moisture Network. (n.d.) https://ismn.earth/en/networks/ (references within)

Joint Committee for Guides in Metorology (JCGM). (2006.) *International Vocabulary of Metrology—Basic and General Concepts and Associated Terms (VIM): 3rd Edition*. January 8, 2006. https://www.nist.gov/system/files/documents/pml/div688/grp40/International-Vocabulary-of-Metrology.pdf

Joshi, C., & Mohanty, B.P. (2010.) Physical Controls of Near-Surface Soil Moisture Across Varying Spatial Scales in an Agricultural Landscape During SMEX02. *Water Resources Research*, *46* (W12503). https://doi.org/10.1029/2010WR009152

Kelleners, T.J., Soppe, R.W.O., Robinson, D.A., Schaap, M.G., Ayars, J.E., & Skaggs, T.H. (2004.) Calibration of Capacitance Probe Sensors Using Electric Circuit Theory. *Soil Science Society of America Journal*, *68*(2):430-439. https://doi.org/10.2136/sssaj2004.4300

Kim, K.Y., Zhu, Z., Zhang, R., Fang, B., Cosh, M.H., & Russ, A.L. (2024.) Precision Soil Moisture Monitoring with Passive Microwave L-Band UAS Mapping. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *17*: 7684-7694. Doi: 10.1109/JSTARS.2024.3382045.

Leeper, R.D., Bell, J.E., & Palecki, M.A. (2019.) A Description and Evaluation of US Climate Reference Network Standardized Soil Moisture Dataset. *Journal of Applied Meteorology and Climatology, 58*(7): 1417-1428. https://doi.org/10.1175/JAMC-D-18-0269.1

Li, X., Wigneron, J.P., Fan, L., Frappart, F., Yueh, S.H., Colliander, A., Ebtehaj, A., Gao, L., Fernandez-Moran, R., Liu, X., & Wang, M. (2022.) A New SMAP Soil Moisture and Vegetation Optical Depth Product (SMAP-IB): Algorithm, Assessment and Inter-comparison. *Remote Sensing of Environment*, *271*:112921. https://doi.org/10.1016/j.rse.2022.112921

Libohova, Z., Mancini, M., H. Winzeler, H.E., Read, Q.D., Sun, N., Beaudette, D., Williams, C., Blackstock, J.,. Silva, S.H.G., Curi, N., Adhikari, K., Ashworth, A., Minai, J.O., & Owens, P.R. (2024.) Interpreting the Spatial Distribution of Soil Properties with a Physically-Based Distributed Hydrological Model. *Geoderma Regional, 39*: e00863. https://doi.org/10.1016/j.geodrs.2024.e00863

Mahmood, R., Boyles, R., Brinson, K., Fiebrich, C., Foster, S., Hubbard, K., Robinson, D., Andresen, J., & Leathers, D. (2017.) Mesonets: Mesoscale Weather and Climate

Observations for the United States. *Bulletin of the American Meteorological Society*, 98 (7): 1349-1361. https://doi.org/10.1175/BAMS-D-15-00258.1

Mallat, S., & Hwang, W.L. (1992.) Singularity Detection and Processing with Wavelets. *IEEE Transactions on Information Theory, 38*(2): 617-643. https://doi.org/10.1109/18.119727

Marshall, C. H. (2016.) *The National Mesonet Program* [Presentation]. 96th American Meteorological Society Annual Meeting, New Orleans, LA. https://ams.confex.com/ams/96Annual/videogateway.cgi/id/31841?recordingid=31841&uniqueid=Paper290349&entry_password=193017

Martinez-Fernandez, J., & Ceballos, A. (2003.) Temporal Stability of Soil Moisture in a Large-Field Experiment in Spain. *Soil Science Society of America Journal, 67*: 1647–1656. https://doi.org/10.2136/sssaj2003.1647

Mazahrih, N.T., Katbeh-Bader, N., Evett, S.R., Ayars, J.E., & Trout, T.J. (2008.) Field Calibration Accuracy and Utility of Four Down-Hole Water Content Sensors. *Vadose Zone Journal*, *7* (3): 992–1000. doi:10.2136/vzj2008.0001

Meek, D. W., & Hatfield, J.L. (1994.) Data Quality Checking for Single Station Meteorological Databases. *Agricultural and Forest Meteorology*, 69: 85-109. doi:10.1016/0168-1923(94)90083-3.

METER Group. (n.d.) *Soil-Specific Calibrations for METER Soil Moisture Sensors.* https://publications.metergroup.com/Sales%20and%20Support/METER%20Environment/Website%20Articles/how-calibrate-soil-moisture-sensors.pdf

Mittelbach, H., Lehner, I., & Seneviratne, S.I. (2012.) Comparison of Four Soil Moisture Sensor Types Under Field Conditions in Switzerland. *Journal of Hydrology, 430*: 39–49. https://doi.org/10.1016/j.jhydrol.2012.01.041

Mohanty, B. P., & Skaggs, T.H. (2001.) Spatio-Temporal Evolution and Time-Stable Characteristics of Soil Moisture within Remote Sensing Footprints with Varying Soil, Slope, and Vegetation. *Advances in Water Resources, 24*: 1051–1067. https://doi.org/10.1016/S0309-1708(01)00034-3

Mohanty, B. P., Famiglietti, J. S., & Skaggs, T. H. (2000.) Evolution of Soil Moisture Spatial Structure in a Mixed Vegetation Pixel During the Southern Great Plains 1997 (SGP97) Hydrology Experiment. *Water Resources Research, 36*(12): 3675–3686. https://doi.org/10.1029/2000WR900258

Multistate In-situ Sensor Testbeds. (n.d.) https://soilwater.github.io/mist/ (resources within)

Nash, J.E., & Sutcliffe, J.V. (1970.) River Flow Forecasting through Conceptual Model. Part 1—A Discussion of Principles. *Journal of Hydrology, 10*: 282-290. http://dx.doi.org/10.1016/0022-1694(70)90255-6

McPherson, R.A., Fiebrich, C., Crawford, K.C., Kilby, J.R., Grimsley, D.L., Martinez, J.E., Basara, J.B., Illston, B.G., Morris, D.A., Kloesel, K.A., Melvin, A.D., Shrivastava, H., Wolfinbarger, J.M., Bostic, J.P., Demko, D.B., Elliott, R.L., Stadler, S.J., Carlson, J.D., & Sutherland, A.J. (2007.) Statewide Monitoring of the Mesoscale Environment: A

Technical Update on the Oklahoma Mesonet. *Journal of Atmospheric and Oceanic Technology, 24*: 301–321. https://doi.org/10.1175/JTECH1976.1

Onyutha, C. (2021.) A Hydrological Model Skill Score and Revised R-Squared. *Hydrology Research, 53*: 51–64. https://doi.org/10.2166/nh.2021.071

Owens, P.R., Mancini, M., Winzeler, H.E., Quentin, D.R., Sun, N., Blackstock, J., & Libohova, Z.* (corresponding). (2024.) Simulating Water Dynamics Related to Pedogenesis Across Space and Time: Implications for Four-Dimensional Digital Soil Mapping. *Geoderma, 447*. https://doi.org/10.1016/j.geoderma.2024.116911

Patrignani, A., Ochsner, T.E., Feng, L., Dyer, D., & Rossini, P.R. (2022.) Calibration and Validation of Soil Water Reflectometers. *Vadose Zone Journal*, 21(3). https://doi.org/10.1002/vzj2.20190

Robinson, D.A., Jones, S.B, Wraith, J. M., Or, D., & Friedman, S.P. (2003.) A Review of Advances in Dielectric and Electrical Conductivity Measurement in Soils Using Time Domain Reflectometry. *Vadose Zone Journal, 2* (4): 444–475. doi: https://doi.org/10.2113/2.4.444

Rodriguez-Iturbe, I., Vogel, G. K., Rigon, R., Entekhabi, D., Castelli, F., & Rinaldo, A. (1995.) On the Spatial Organization of Soil Moisture Fields. *Geophysical Research Letters*, *22*(20): 2757–2760. https://doi.org/10.1029/95GL02779

Rowlandson, T.L., Berg, A.A., Bullock, P.R., Ojo, E.R., McNairn, H., Wiseman, G., & Cosh, M.H. (2013.) Evaluation of Several Calibration Procedures for a Portable Soil Moisture Sensor. *Journal of Hydrology, 498*: 335-344. https://doi.org/10.1016/j.jhydrol.2013.05.021

Ryu, D., & Famiglietti, J.S. (2006.) Multi-Scale Spatial Correlation and Scaling Behavior of Surface Soil Moisture. *Geophysical Research Letters, 33* (L08404). https://doi.org/10.1029/2006GL025831

Seyfried, M.S., Grant, L.E., Du, E., & Humes, K. (2005.) Dielectric Loss and Calibration of the Hyrda Probe Soil Water Sensor. *Vadose Zone Journal, 4*(4): 1070-1079. https://doi.org/10.2136/vzj2004.0148

Seyfried, M.S., & Grant, L.E. (2007.) Temperature Effects on Soil Dielectric Properties Measured at 50 MHz. *Vadose Zone Journal, 6*(4): 759-765. https://doi.org.10.2136/vzj2006.0188

Smith, D.E., Metzger, S., & Taylor, J.R. (2014.) A Transparent and Transferable Framework for Tracking Quality Information in Large Datasets. *PLoS One, 9*(11): e112249. https://doi.org/10.1371/journal.pone.0112249

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. *Soil Survey Geographic (SSURGO) Database. Retrieved* November 8, 2024. https://sdmdataaccess.sc.egov.usda.gov

Sturtevant, C., DeRego, E., Metzger, S., Ayres, E., Allen, D., Burlingame, T., Catolico, N., Cawley, K., Csavina, J., Durden, D., Florian, C., Frost, S., Gaddie, R., Knapp, E., Laney, C., Lee, R., Lenz, D., Litt, G., Luo, H. … SanClements, M. (2022.) A Process Approach to Quality Management Doubles NEON Sensor Data Quality. *Methods in Ecology and Evolution, 13*(9): 1849-1865. https://doi.org/10.1111/2041-210X.13943

Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., Rippey, B., Tinker, R., Palecki, M., Stooksbury, D., Miskus, D., & Stephens, S. (2002.) The Drought Monitor. *Bulletin of the American Meteorological Society, 83*(8): 1181-1190. https://doi.org/10.1175/1520-0477-83.8.1181

Tavakol, A., McDonough, K. R., Rahmani, V., Hutchinson, S. L., & Hutchinson, J. S. (2021.) The Soil Moisture Data Bank: The Ground-Based, Model-Based, and Satellite-Based Soil Moisture Data. *Remote Sensing Applications: Society and Environment*, *24*: 100649. https://doi.org/10.1016/j.rsase.2021.100649

Teuling, A.J., & Troch, P.A. (2005.) Improved Understanding of Soil Moisture Variability Dynamics. *Geophysical Research Letters, 32*: L05404, doi:10.1029/2004GL021935.

Thill, M., Konen, W., & Bäck, T. (2017.) Time Series Anomaly Detection with Discrete Wavelet Transforms and Maximum Likelihood Estimation. In *International Conference on Time Series and Forecasting (ITISE)*, Vol. 2: 11-23.

Topp, G.C., Davis, J.L., & Annan, A.P. (1980.) Electromagnetic Determination of Soil Water Content: Measurements in Coaxial Transmission Lines. *Water Resources Research, 16*(3): 574-582. https://doi.org/10.1029/WR016i003p00574

Topp, G.C., & Ferre, P. A. (Eds.) (2002.) The Soil Solution Phase. In *Methods of Soil Analysis: Part 4* (pp. 417-1074). Wiley.

Vachaud, G., Passerat De Silans, A., Balabanis, P., & Vauclin, M. (1985.) Temporal Stability of Spatially Measured Soil Water Probability Density Function. *Soil Science Society of America Journal*, *49*: 822–828. https://doi.org/10.2136/sssaj1985.03615995004900040006x

Vanderlinden, K., Vereecken, H., Hardelauf, H., Herbst, M., Martínez, G., Cosh, M.H., & Pachepsky, Y.A. (2012.) Temporal Stability of Soil Water Contents: A Review of Data and Analyses. *Vadose Zone Journal, 11*(4). https://doi.org/10.2136/vzj2011.0178

Vaz, C.M.P., Jones, S., Meding, M., & Tuller, M. (2013.) Evaluation of Standard Calibration Functions for Eight Electromagnetic Soil Moisture Sensors. *Vadose Zone Journal, 12*(2). doi:10.2136/vzj2012.0160.

Vergopolan, N., Chaney, N.W., Beck, H.E., Pan, M., Sheffield, J., Chan, S., & Wood, E.F. (2020.) Combining Hyper-Resolution Land Surface Modeling with SMAP Brightness Temperatures to Obtain 30-m Soil Moisture Estimates. *Remote Sensing of Environment, 242* (March): 111740. https://doi.org/10.1016/j.rse.2020.111740

Wagner, R.J., Boulger, R.W., Oblinger, C.J., & Smith, B.A. (2006.) *Guidelines and Standard Procedures for Continuous Water-Quality Monitors: Station Operation, Record Computation, and Data Reporting.* U.S. Geological Survey Techniques and Methods. https://doi.org/10.3133/tm1D3

Waichler, S.R., & Wigmosta, M.E. (2002.) Development of Hourly Meteorological Values from Daily Data and Significance to Hydrological Modeling at H. J. Andrews Experimental Forest. *Journal of Hydrometeorology, 4* (2): 251-263. https://doi.org/10.1175/1525-7541(2003)4<251:DOHMVF>2.0.CO;2

Wang, X., Lü, H., Crow, W.T., Zhu, Y., Wang, Q., Su, J., Zheng, J., & Gou, Q. (2021.) Assessment of SMOS and SMAP Soil Moisture Products Against New Estimates Combining Physical Model, a Statistical Model, and in-situ Observations: A Case Study Over the Huai River Basin, China. *Journal of Hydrology, 598*: 126468. https://doi.org/10.1016/j.jhydrol.2021.126468

Wang, X., Xie, H., Guan, H., & Zhou, X. (2007.) Different Responses of MODIS-derived NDVI to Root-Zone Soil Moisture in Semi-Arid and Humid Regions. *Journal of Hydrology, 340*(1-2):12-24. https://doi.org/10.1016/j.jhydrol.2007.03.022

Western, A.W., & Blöschl, G. (1999.) On the Spatial Scaling of Soil Moisture. *Journal of Hydrology, 217*(3–4): 203–224. https://doi.org/10.1016/S0022-1694(98)00232-7

Western, A.W., Zhou, S.L., Grayson, R.B., McMahon, T.A., Blöschl, G., & Wilson, D.J. (2004.) Spatial Correlation of Soil Moisture in Small Catchments and Its Relationship to Dominant Spatial Hydrological Processes. *Journal of Hydrology*, *286*(1–4): 113–134. https://doi.org/10.1016/j.jhydrol.2003.09.014

Wilson. T.B., Diamond, H.J., Kochendorfer, J., Meyers, T.P., Hall, M., Casey, N.W., Baker, C.B., Leeper, R., & Palecki, M.A. (2020.) Evaluating Time Domain Reflectometry and Coaxial Impedance Sensors for Soil Observations by the U.S. Climate Reference Network. *Vadose Zone Journal, 19*(1). https://doi.org/10.1002/vzj2.20013

Wilson, T.B., Kochendorfer, J., Diamond, H.J., Meyers, T.P., Hall, M., French, B., Myles, L., & Saylor, R.D. (2023.) Field Evaluation of the SoilVUE10 Soil Moisture Sensor. *Vadose Zone Journal*, *22*(2). https://doi.org/10.1002/vzj2.20241

Wyseure, G., Mojid, M., & Malik, M. (1997.) Measurement of Volumetric Water Content by TDR in Saline Soils. *European Journal of Soil Science, 48*(2): 347–354. https://doi.org/10.1111/j.1365-2389.1997.tb00555.x

Zhang, H., Chang, J., Zhang, L., Wang, Y., Li, Y., & Wang, X. (2018.) NDVI Dynamic Changes and Their Relationship with Meteorological Factors and Soil Moisture. *Environmental Earth Sciences, 77*:1-11. https://doi.org/10.1007/s12665-018-7759-x

Zhang, X., Zhang, T., Zhou, P., Shao, Y., & Gao, S. (2017.) Validation Analysis of SMAP and AMSR2 Soil Moisture Products over the United States Using Ground-Based Measurements. *Remote Sensing, 9*(2):104. https://doi.org/10.3390/rs9020104

Zreda, M., Shuttleworth, W.J., Zeng, X., Zweck, C., Desilets, D., Franz, T., & Rosolem, R. (2012.) COSMOS: The COsmic-ray Soil Moisture Observing System. *Hydrology and Earth System Sciences, 16*: 4079–4099. https://doi.org/10.5194/hess-16-4079-2012