A selection of different soil moisture sensors. Credit: Tyson Ochsner

CHAPTER 4

CONSIDERATIONS IN SOIL MOISTURE NETWORK DESIGN

4.1 DESIGN GOALS AND ASSUMPTIONS

The purpose of this chapter is to identify and review key design considerations for soil moisture networks that may be developed or expanded in the future. Most networks are operated on a local to state level, and as new networks are proposed and developed, it is valuable for the NCSMMN community to provide some background and guidance on network design and to share lessons learned with newer network entrants. Much of this discussion however is applicable to national-scale networks and the NCSMMN as a whole as well. To begin, a clear conception is needed of the design goals and assumptions related to the specific network. Possible design goals include:

1. Quantifying the amount and vertical distribution of water in the root zone;
2. Quantifying the spatial distribution of soil moisture related to weather patterns, topography, vegetation types, land use, and soil types;
3. Documenting the occurrence of natural hazards related to deficit or excess of soil moisture (e.g., drought, flooding);
4. Incorporating data from existing Federal and state monitoring networks;
5. Providing coverage of the United States and its territories;
6. Supporting drought and flood monitoring, water supply forecasting, and fire danger ratings,
7. with many other uses expected;
8. Supporting the creation of gridded national soil moisture maps; and
9. Supporting decisions about Federal drought assistance and other related forms of disaster aid, while minimizing operational cost.

Given the importance of working towards a coordinated national system, this chapter makes three key assumptions about initial network structure. First, this chapter assumes that only permanent monitoring stations will be considered as part of the NCSMMN. Stations which are expected to remain operational in one location for <10 years would not be included because the length of the data record would not justify the time and effort required to include the station in a nationwide system. Stations in which some or all of the sensors are expected to be periodically removed and reinstalled would likewise not be included in the network, regardless of the expected period of record. Such removal and reinstallation are commonly needed, for example, in cropped fields, and the resulting disturbance introduces increased probabilities for discontinuities in the data record. Replacement of failed sensors is necessary for long-term monitoring networks and would not be considered disqualifying.

This chapter also assumes that only automated monitoring stations will be included in the NCSMMN. Monitoring sites that require a person to be present in order to collect data, such as with a neutron probe, hand-held sensors, or by soil sampling, are not likely to be suitable for this network because of the high, long-term labor cost and the inadequate frequency of measurement. Opportunities for non-automated monitoring, such as through citizen science, are one of the recommended areas of future research by the NCSMMN.

Finally, this chapter assumes that the majority of the network will be non-irrigated monitoring sites, but in the future a separate data product from NCSMMN would be produced which specifically addresses data collection from irrigated regions. Irrigated cropland and turf are important land uses, and soil moisture monitoring in these landscapes is a key strategy for improved water management and conservation. Irrigation landscapes are frequently monitored as part of a managed agricultural landscape, operated by the private sector. Irrigated soil moisture stations are also frequently temporary in nature, thus requiring more quality control and human interaction for incorporation into the main data products of the NCSMMN. For these reasons, it is necessary to conduct future research on how soil moisture data from irrigated sites can be used effectively within the NCSMMN framework.

4.2 KEY NETWORK DESIGN DECISIONS

When designing a soil moisture network, there are some key design decisions to be made, including:

1. Where should new stations be added?
2. What depths should be monitored?
3. What types of sensors should be used?

Each of these questions will be considered in turn.

4.2.1 Where should new stations be added?

To determine where new stations are needed, there are several plausible approaches, each with its own pros and cons. The first approach would be based simply on political boundaries. For example, the OKM, one of the oldest automated soil moisture monitoring networks, was designed to have at least one station in each of the state's 77 counties (Brock et al., 1995). The National Research Council has recommended the creation of a nationwide soil moisture and soil temperature observing network with "approximately 3,000 sites" (National Research Council 2009), and while the locations of these sites was unspecified, the total number is similar to the ~3,200 counties and county equivalents (i.e., independent cities, parishes, and boroughs) in the United States.

One benefit of this approach is that it may facilitate linkages with Federal disaster aid payments that have county-based eligibility, such as the Livestock Forage Disaster Program,[12] which provides assistance to livestock producers in counties suffering from drought. One drawback is that counties vary widely in areal extent, from <50 km^2 to >50,000 km^2. Counties in western states are often substantially larger than those in eastern states. From the total of 3,233 counties across all U.S. states and territories, about 22% (725 counties) have a spatial extent greater than 2,500 km^2 and about 4% (126 counties) have an area greater than 10,000 km^2. To observe soil moisture spatial patterns at a mesoscale of about 10,000 km2 (i.e., 100 km x 100 km) using political boundaries, 126 counties would need to be equipped with more than one monitoring station (Figure 4.1, *next page*). At a finer spatial resolution of 2,500 km^2 (i.e. 50 km x 50 km), it would require

[12] *https://www.fsa.usda.gov/programs-and-services/disaster-assistance-program/livestock-forage/index*

a substantially higher investment in infrastructure, since more than 700 counties would require more than one (Figure 4.2, *middle right*).

Another drawback of using county boundaries is that they may vary vastly in size within a single state or region. The Gini coefficient (Dorfman 1979) was used to quantify the inequality of county sizes within each state. Arkansas, Ohio, and Iowa have the most even county area distribution with Gini coefficients of about 0.1 (Figure 4.3, *bottom right*). California, Maine, and Oregon have the most uneven county area distributions with Gini coefficients of 0.49, 0.47, and 0.45, respectively. Alaska has the highest level with a Gini coefficient of 0.62. Thus, in states with unevenly sized counties, observations of soil moisture might be skewed to the conditions of the smaller counties. For example, the State of Virginia is divided into 95 counties and 38 county-equivalent "independent cities." These independent cities have a small area compared to the counties, resulting in the computation of a large Gini coefficient. Locating stations based on political boundaries could result in an undesirable distribution of stations in this case.

A second approach would be based on spatial gaps in the existing networks. For example, the Kansas Mesonet has adopted a geometric method to select the location of future monitoring stations. The geometric approach consists of finding the largest unmonitored circular area across the network. The centroid of the largest unmonitored circle

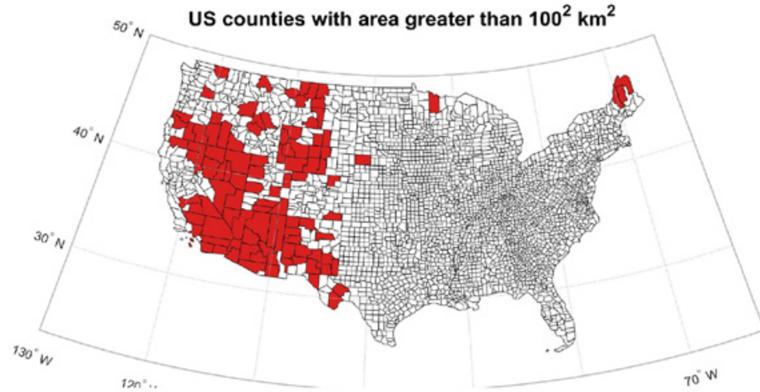

Figure 4.1: Counties in the contiguous United States with an area greater than 1,002 km^2 (or 10,000 km^2).

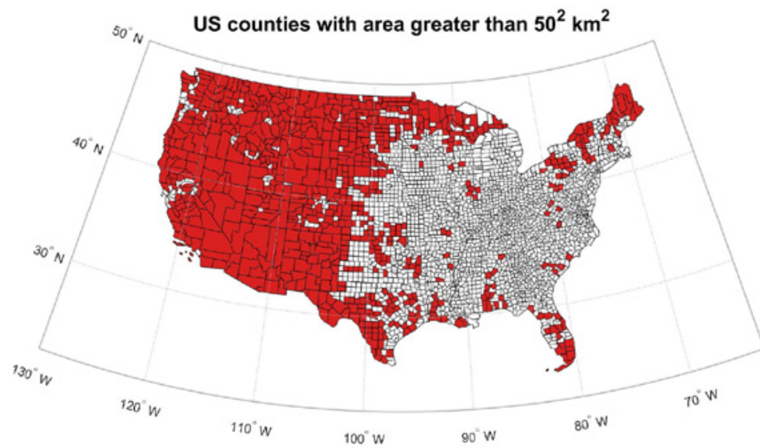

Figure 4.2: Counties in the contiguous United States with an area greater than 502 km^2 (or 2,500 km^2).

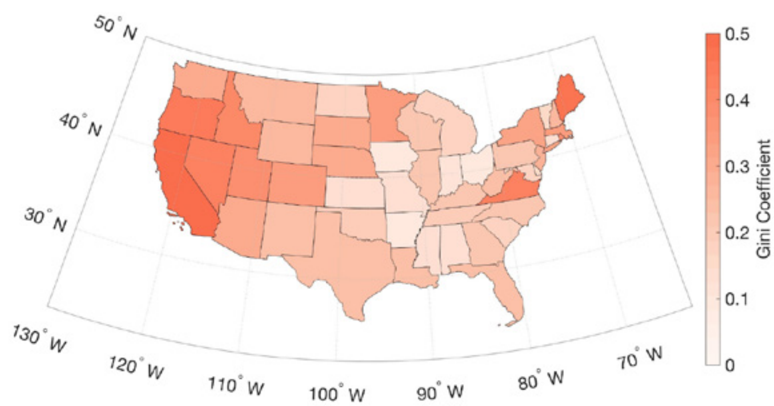

Figure 4.3: Inequality in the county size distribution within each of the 48 contiguous U.S. states. The Gini coefficient was used to represent the degree of inequality in county sizes. The Gini coefficient ranges between zero and one, where zero represents uniformly sized counties and higher values indicate greater inequality of county sizes.

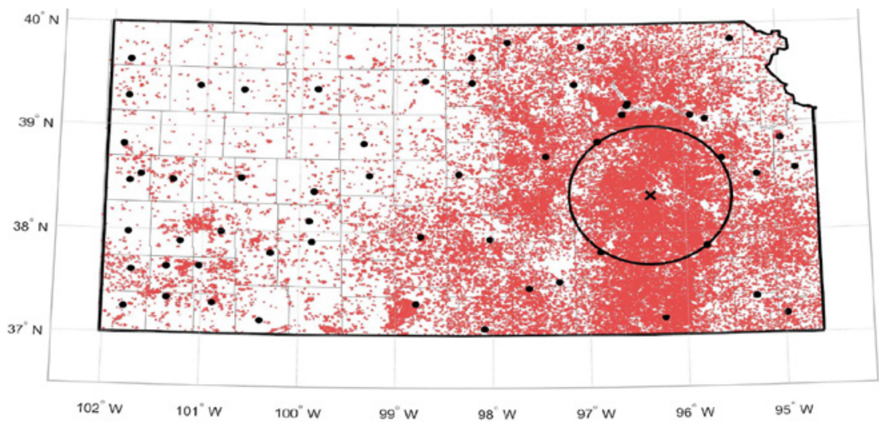

Figure 4.4: Locations of existing monitoring stations in the Kansas Mesonet (*black dots*), the largest unmonitored area (*circle*), and the proposed location of the next additional monitoring station (x). The locations of wildland fires (2000–2018) are shown in red and highlight the potential value of the proposed station for fire danger ratings.

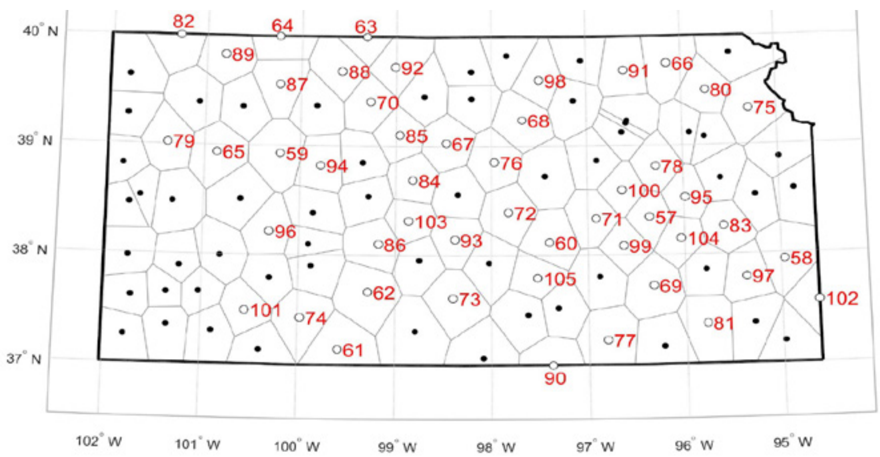

Figure 4.5: Sequence of future monitoring stations for the Kansas Mesonet generated by recursively applying the geometric method. At the time the analysis was run the network had 56 stations represented by the black circles. Thus, the open circle markers represent the locations and sequence of stations 57 to 105. The polygons are Thiessen polygons where every location inside the polygon is closer to the station in that polygon than to any other station.

represents the tentative location for the next future station (Figure 4.4, *above*).

This geometric approach has three main advantages. First, it is simple and only requires the geographic coordinates of the stations and the boundary of the network's domain. This is also an advantage in data-sparse regions places where the spatial structure of soil moisture or rainfall is unknown. Second, it can be easily integrated with the spatial occurrence of natural hazards such as droughts, flooding events, or wildland fires. Figure 4.4 (*above*) represents the largest unmonitored areas with the largest count of wildland fires (prescribed and accidental) in Kansas. Deploying a new soil moisture monitoring station in the selected location has the potential to improve the accuracy of wildfire danger rating systems. Third, the method can be applied recursively to generate a roadmap for future stations, assisting network managers with long-term planning and management of limited resources (Figure 4.5, *above*).

One main drawback of this approach is that it does not consider the spatial structure of soil moisture. The geometric approach may be better suited for multifunctional mesoscale networks that monitor multiple environmental variables with different spatial correlation structures. For application-specific networks that monitor only a few variables, such as soil moisture and rainfall, geostatistical approaches that focus on the minimization of the spatial variance will likely result in more representative locations.

A third approach is based on identifying regions of similarly expected soil behavior. This approach identifies regions of similar soil, climate, and vegetation characteristics that could be expected to produce similar soil moisture dynamics (Coopersmith et al., 2014; Chaney et al., 2015). These regions would be referred to as soil hydrological response units (SHRU).[13] After identification of SHRUs, the adequacy of existing monitoring stations to represent the different types of SHRUs could be assessed, and the locations of necessary additional monitoring stations could be determined. Given the expected monetary or logistic limitations for the number of sites that can be installed and maintained, one strategy could be to allocate sites between different SHRUs such that the number of sites within each type of SHRU is proportional to the area covered by that type of SHRU across the United States. For example, if a given type of SHRU occupies 4% of the land area and 1000 total sites can be included in the network, then 40 sites should be installed in that type of SHRU.

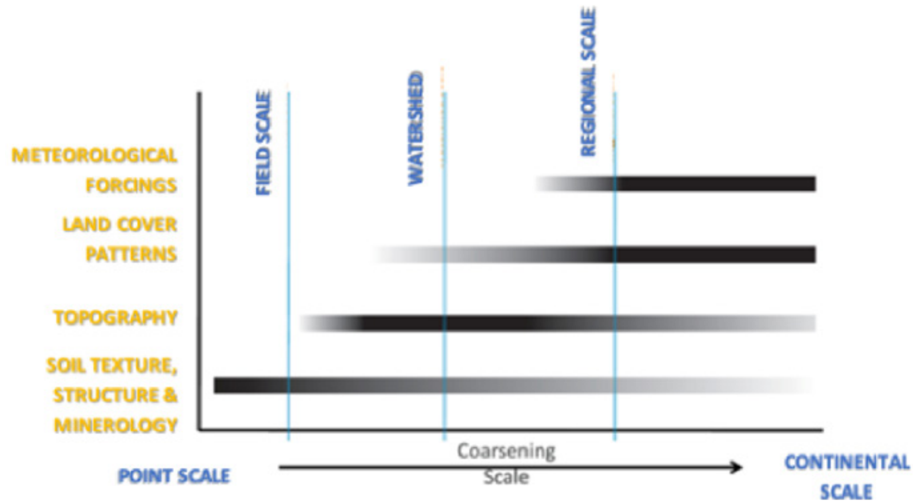

Figure 4.6: Factors controlling soil moisture spatial distribution. Adapted from Jana, 2010

SHRUs can be identified based on existing information about similarities in hydrologically-relevant attributes such as meteorological conditions, land-cover/vegetation, topography/terrain, and soil type; each of which control soil moisture variability at different spatial scales (Figure 4.6, *above*).

At the continental scale, soil moisture variability may be associated with different hydro-climates which represent the precipitation and temperature patterns of a region. They can be identified using the Koppen classification system (Figure 4.7, *next page*). These hydro-climates may provide a first step towards defining SHRUs for a coordinated National Coordinated Soil Moisture Monitoring Network.

Further refinement in SHRUs can be achieved by incorporating soils, topography and land-use information. SHRU refinement can be done using spatial clustering methods. For example, SHRUs were recently identified in support of a soil moisture monitoring strategy to inform water resources management in California (Curtis et al., 2019; Figure 4.8, *page 39*).

This method identifies SHRUs using principal component analysis and unsupervised K-means clustering. Key input variables include characteristics of the soil (texture, porosity, depth, available water capacity), climate (average annual precipitation, snow water equivalent on April 1, potential evapotranspiration, and climatic water deficit), hydrology (average annual recharge and runoff), vegetation (seasonally integrated NDVI), topography (digital elevation model), and land use (National Land Cover Database).

The main advantages of SHRU based methods are that: 1) they explicitly consider known factors that influence the spatial and temporal patterns of soil moisture; and 2) they can be applied using existing information. A disadvantage of such methods is that they do not explicitly consider the end users of the data. Also, these methods are data intensive and the results will likely vary with the quality of ancillary data available. This method is conceptually appealing but has not yet been used to design and implement a large-scale soil moisture monitoring network, so its real-world effectiveness remains to be seen.

[13] Other physical characteristics could also be used as the basis of siting decisions. For example, one option for forestry and ecological applications would be to use ecologically-based land classifications, such as the U.S. Forest Service's Terrestrial Ecological Unit Inventory (TEUI) system. Another option is to use Hydrologic Unit Codes (HUCs).

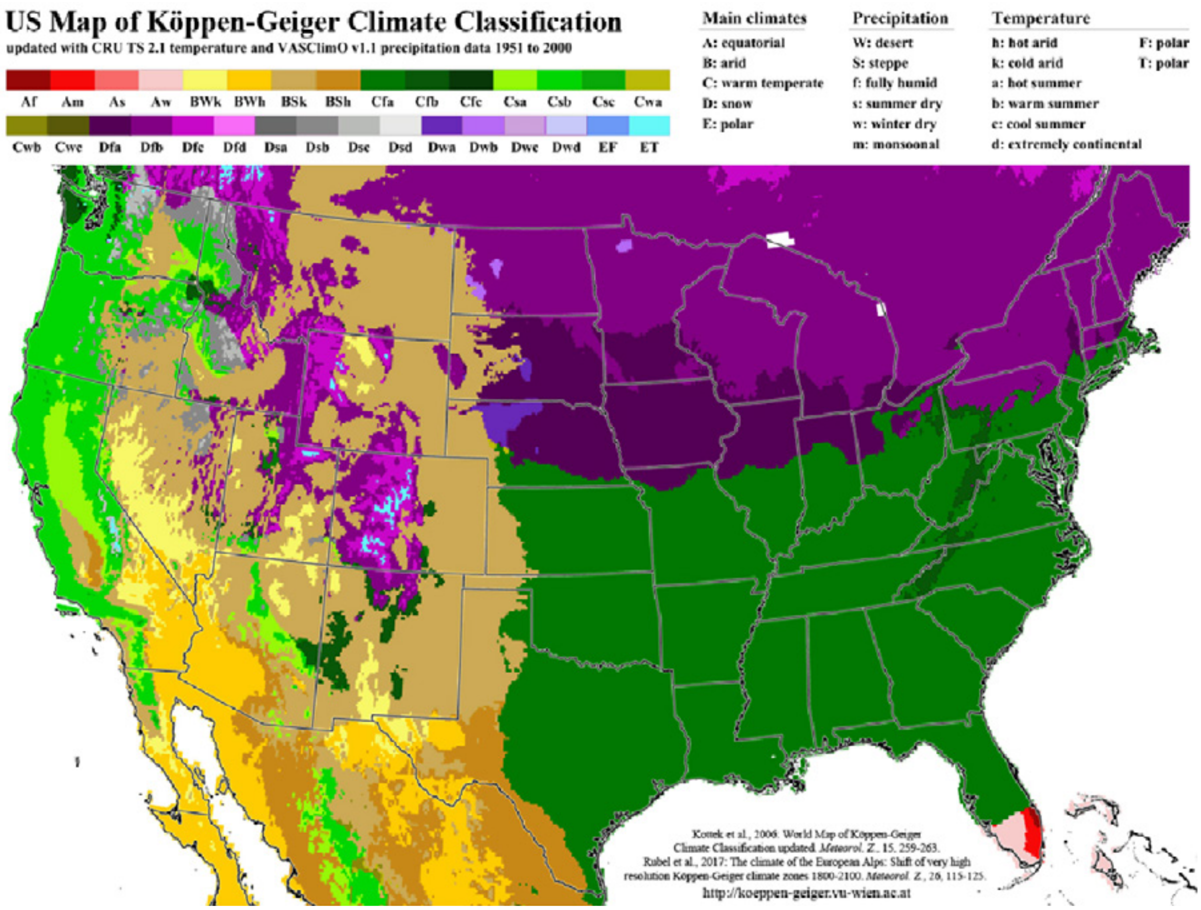

Figure 4.7: Köppen-Geiger hydro-climate map. (Source: *http://koeppen-geiger.vu-wien.ac.at/usa.htm*)

4.2.2 What depths should be monitored?

The selection of the sensor installation depths in the soil profile influences the accuracy of monitoring the soil moisture content in both individual soil horizons and the total soil water storage in the rootzone. The decision to monitor deep layers of the soil profile typically requires substantial additional hardware and labor costs. Each additional monitoring depth in a network can meaningfully impact the network's long-term budget. A key part of that added cost is the labor required for the initial installation and the removal and replacement of failed sensors at depth. Installing soil moisture sensors has traditionally involved digging a trench or pit and installing sensors into the exposed face of the soil profile followed by careful repacking of soil. With the advent of new soil profile sensors (e.g., Campbell Scientific SoilVue, Sentek Drill and Drop) and borehole installation tools (e.g., Meter Environment TEROS Borehole Installation Tool), the installation process can be less physically demanding. However, these labor-saving technologies have yet to be widely tested for long-term monitoring networks.

Another relevant point when choosing installation depths for soil moisture sensors is compatibility with existing networks. This is particularly important when deploying soil moisture sensors within the scope of a coordinated NCSMMN that will integrate observations from multiple networks. One of the most common sets of sensor depths is that adopted by the NRCS Soil Climate Analysis Network, which has sensors at 5, 10, 20, 50, and 100 cm. These depths are also used by the NOAA Climate Reference Network. Some networks, like the Kansas Mesonet, have partially adopted this layout with the exception of the sensor at 100 cm. The OKM, which initially adopted a layout with sensors at 5, 25, 60, and 75 cm depth, decommissioned the sensors at 75 cm due to maintenance costs. More recently, the OKM has added sensors at the 10 cm depth.

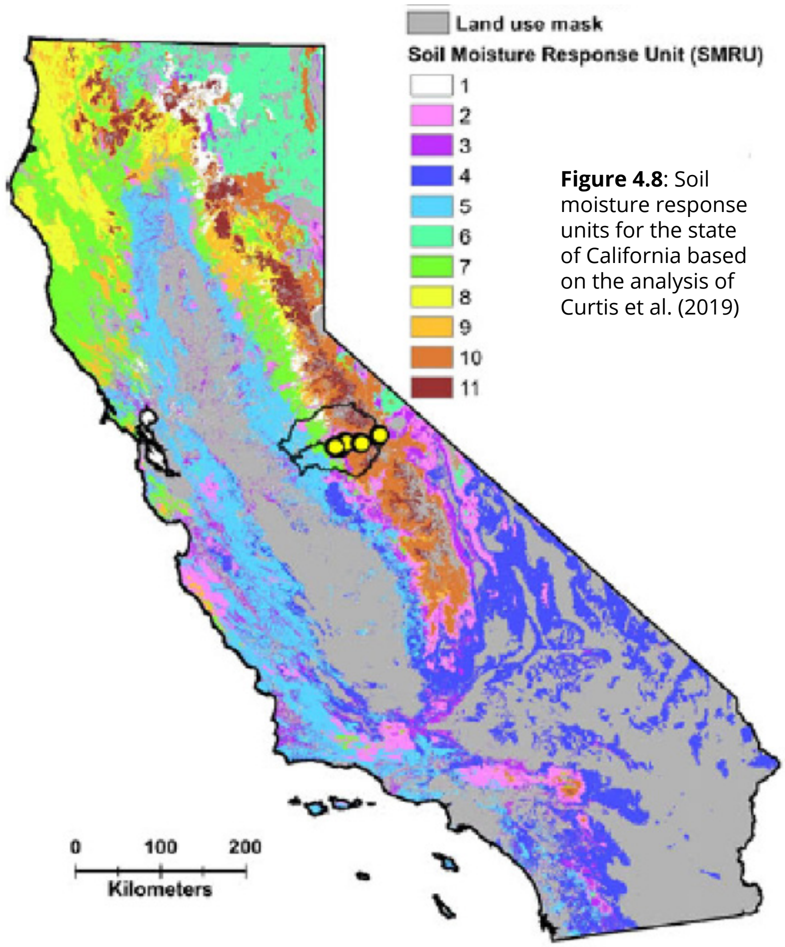

Figure 4.8: Soil moisture response units for the state of California based on the analysis of Curtis et al. (2019)

Often soil moisture measurements at discrete depths are integrated to calculate the total soil water storage in the profile. If the sensor depths are such that each sensor can be treated as measuring at the center of a soil layer, then the soil water storage of the layer is simply estimated as the value reported by the sensor times the thickness of the soil layer. This approach is the most logical approach from a hydrological and soil water balance perspective. This approach also facilitates comparisons between in situ soil moisture observations and land surface or hydrologic models, which typically simulate soil moisture for discrete soil layers, e.g. 0–10 cm. Thus, this installation approach is also well-suited for assimilation of soil moisture observations into such models. An example of a network using this approach is the OKM, where sensors deployed at 5 cm represent the 0–10 cm layer, sensors deployed at 25 cm represent the 10–40 cm layer, and sensors deployed at 60 cm represent the 40–80 cm layer.

In contrast, if the sensor depths are such that each sensor can be treated as measuring at the boundary between two layers, then estimating the soil water storage requires a numerical integration procedure. An example would be any network using depths such as 5, 10, 20, 50, and 100 cm. The soil water storage in the soil layer between each pair of successively deeper sensors (e.g., 5 and 10 cm) could be estimated as the average of the soil moisture values from the two sensors times the thickness of the soil layer. Some extrapolation procedure is needed to estimate the soil water storage for the 0–5 cm layer. A third approach, seldom used, consists of deploying sensors at site-specific depths dictated by the different soil horizons. While this approach respects the morphology of the soil, it creates varying sensor depths across the network, complicating maintenance and end-user applications.

Sensors at 5-cm depth are present in most existing networks. This sensor depth has often been used in the calibration and validation of remotely-sensed soil moisture products. Although shallower placements might provide a better match with the sensing depths of many microwave-based remote sensing techniques, sensors placed at depths shallower than 5 cm can be easily exposed due to soil erosion. Also, the accuracy of soil moisture sensors may be negatively influenced by the soil–air interface if placed at depths <5 cm. The World Meteorological Organization (2014) recommends 10-cm as the standard depth for soil temperature measurement. Recommendations for some agricultural management decisions, such as when to plant warm-season crops, have traditionally been based on soil temperature measurements at the 10-cm depth under bare soil. However, because a limited number of sensors are typically available for monitoring soil moisture throughout the root zone, placing two of those sensors only 5 cm apart (at 5 and 10 cm) is not optimal. New approaches are needed to strategically coordinate soil moisture and soil temperature observation systems for maximum efficiency under resource constraints. Other common depths among existing networks in the United States are sensors at 20 or 25 cm depth, 50 or 60 cm depth, and 100 cm depth (Zhang et al., 2017).

Another approach to choosing sensor depths and numbers is to fit the vertical distribution of sensors to the known or expected extent of the active root zone, defined by the soil thickness and the predominant vegetation in the area. In grasslands or annual croplands, this could lead to sensors more closely spaced near the surface and extending down to approximately 100 cm. In woodlands or perennial crops, this could lead to much deeper sensor profiles. If NCSMMN data were used to assess the severity of hydrologic drought, then soil water contents down to 200 cm or more might be warranted. Additional data-driven approaches, such as a robust decision-making approach (Clutter and Ferre, 2019), can further help identify the specific depths of value to a decision process. A broader understanding of the applications intending to use the NCSMMN is necessary to help narrow the scope of depth selection as well as other parameters. This requires a consensus from both the scientific community and the local stakeholders within each network.

4.2.3 What sensors should be used?

4.2.3.1 Available sensor types

There are a number of sensor options, operating at various depths, ranges and spatial-scales, with which to monitor soil moisture within a network. Most technologies rely on electromagnetic (EM) techniques (see Robison et al., 2008) that use various travel-time, capacitance and impedance-based approaches for sensing volumetric soil water content. Options we focus on here come in the form of: i) commonly deployed point-scale insertable sensors; ii) bore-hole sensors; iii) larger-scale neutron-based sensors; and iv) sensing capabilities using global positioning satellite systems.

The seminal work of Topp, Davis and Anaan (Topp, Davis, and Annan 1980) demonstrated the amazing potential of time domain reflectometry (TDR) for nondestructive, nonradioactive determination of soil moisture. Since then electromagnetic (EM)-based sensor designs that take advantage of various travel-time and impedance-based approaches for sensing volumetric water content are continuing to be developed. Decades of research have shown that measurement frequency (i.e., between MHz and GHz), is a significant factor affecting the accuracy of EM-based water content sensors. There is substantial evidence showing low frequency measurements are more susceptible to secondary effects (e.g., from temperature, salinity, polarization, relaxation, etc.) on dielectric permittivity determination than are measurements made at higher frequency. Correcting for these secondary effects can be challenging given the complexity and variety of circuit designs and the compounding of these environmental effects in materials being measured (Bogena et al., 2007). Low frequency devices (e.g., <100 MHz) were initially built due to their simpler design and low cost, however in the past decade cellular technology has lowered the cost of higher frequency components, resulting in competitively priced GHz frequency devices, which are less susceptible to these secondary effects (Chen and Or 2006). Dozens of commercially-available, EM-based soil moisture sensor designs can now be found worldwide with more being conceived of and developed every year (Figure 4.9, *next page*).

For developers or consumers of EM sensors, there is currently little information available that provides standardized sensor performance measures or evaluation criteria. Most of the literature on EM sensor comparison has focused on comparing several EM sensors in one or more porous media, generally in soils of varied texture. Some of the misinformation generated from such studies arise when evaluators are not aware of, or ignore, characteristics such as the sensor sampling volume. Standard testing criteria are needed to better inform developers and consumers. Jones et al. (2005) proposed standardized testing in liquids to characterize and compare EM sensing systems. Ideal standard liquids would be globally available and provide a homogeneous background as opposed to heterogeneous natural materials. The frequency dependent permittivity of the material under test (i.e., soil) can be used to estimate the apparent measurement frequency of a given sensor (Robinson et al., 2003). This can also be an indicator of the sensor measurement quality given the tendency of higher frequency measurements to be less sensitive to phase configuration, salinity and other secondary effects on permittivity.

Figure 4.9: Array of electromagnetic-based bore-hole (left) and insertable soil water content sensors.

Nonetheless, the plethora of sensor evaluations in the literature lead to some conclusions about the existing fundamental sensor technologies (e.g., Evett and Parkin, 2005; Evett et al., 2012). As pointed out by Evett et al. (2012) most of the existing EM sensor technologies use one of two physical approaches to sensing. One approach, and the most common one due to its relevant simplicity and lower cost, is to measure the resonant frequency of an oscillating electrical circuit composed of capacitors, inductors, resistors and a power source. In this approach, the EM field of one of the capacitors is coupled with the soil matrix either by inserting electrodes of the capacitive element into the soil or by placing the capacitive element in a plastic tube inserted into the soil. In the latter case the fringing EM field of the capacitive element pass through the tube wall and into the soil surrounding the tube. The various sensors based on capacitance principles relate the soil water content to some function of the resonant frequency. The geometry of the sensor's electromagnetic field strongly determines the value of capacitance and, therefore, the resonant frequency. Unfortunately, the geometric factor is not well defined for some capacitance-based soil water sensors, leading to both bias and scatter in the soil water data (Evett et al., 2005, 2008, 2012, etc.).

The other major electromagnetic approach to soil water sensing is time domain reflectometry or TDR. In the TDR approach, the travel time of an electronic pulse in a waveguide surrounded by soil (i.e., electrodes inserted into the soil) is related to the apparent relative permittivity of the soil. Although the electromagnetic field in the soil surrounding the TDR electrodes is subject to the same factors that influence the electromagnetic field of a capacitance sensor, there is no geometric factor in the equations, and the travel time is not influenced by the geometry of the electromagnetic field. Therefore, data from TDR sensors is often more accurate and less influenced by the small-scale soil structure, water content, and bulk electrical conductivity variations than the data from sensors based on capacitance principles.

Beyond the EM-based sensors commonly used in weather stations and sensor networks, there are newer, noninvasive technologies providing larger footprint estimates of soil moisture (Bogena et al., 2015). Among these is the cosmic ray neutron probe (CRNP, Figure 4.10, *next page*), which is a noninvasive technique to sense the areal averaged soil moisture with an effective depth typically between 10 and 50 centimeters and a circular footprint with a radius on the order of 200 hundred meters (M. Zreda et al., 2012; Marek Zreda et al., 2008; Köhli et al., 2015). Cosmic rays interact with nuclei of atoms in the atmosphere, water, vegetation and soil, leading to the emission of fast neutrons in the atmosphere, and those fast neutrons are mainly slowed or moderated by hydrogen atoms. The probe, typically

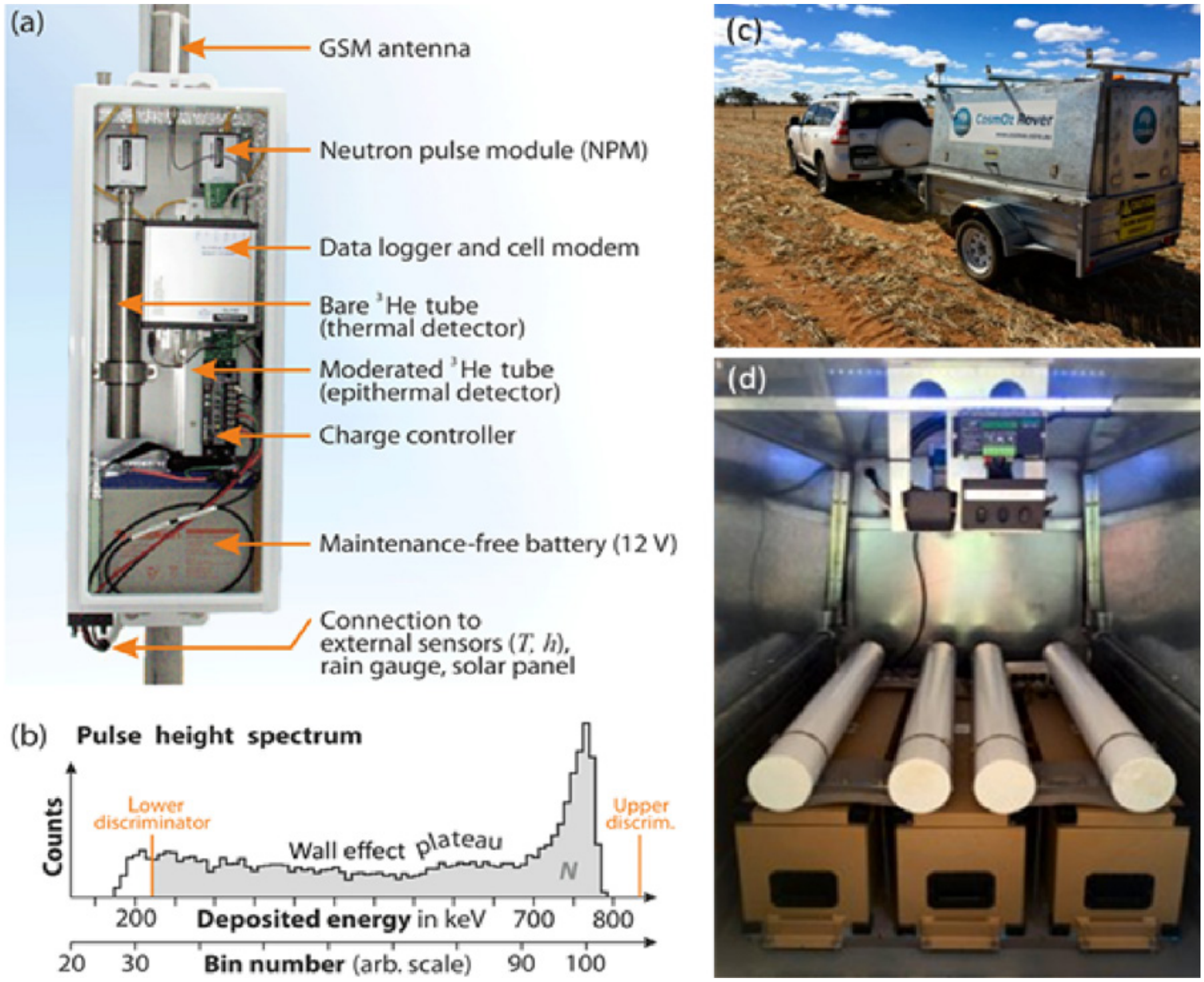

Figure 4.10: (*a*) Cosmic-ray neutron sensor system illustrating the basic components, (*b*) A typical, measured pulse height spectrum shows the deposited energy in the gas tube (Schrön et al., 2018b), (*c*) Mobile CRNP Rover, and (*d*) sensor array used for spatial mapping of soil moisture (CosmOz, 2019, October 21).

installed ~1 meter above the land surface, determines the count rate of these fast neutrons, and that count rate is inversely correlated with the soil water content. Several studies have characterized the response of the CRNP to soil moisture determined by direct sampling and by networks of soil water sensors installed at various depths. These studies have led to advances in the modeling of the neutron scattering and attenuation processes (Köhli et al., 2016), to improved understanding of spatial sensitivity (Martin Schrön et al., 2017) as well as better understanding of the influence of nonsoil constituents, such as vegetation (Lv et al., 2014; Baatz et al., 2015), roadways (M. Schrön et al., 2018a), etc. Networks of CRNPs are growing worldwide, with the original COSMOS network in the United States (COSMOS, 2019, October 23) and with Europe, the UK, China, and other countries building additional networks.

Another relatively new and noninvasive soil moisture sensing capability comes from Global Navigation Satellite System (GNSS) reflectometry. In this approach, near-surface soil water content can be estimated based on the interference pattern observed by a GNSS receiver positioned a few meters above the ground. Early work using the GNSS sensors showed promising relationships between this interference pattern and the soil moisture of the surrounding area on the order of 300 m2 (Larson et al., 2008). The GNSS interference reflectometry approach can potentially take advantage of existing GNSS receiver networks at sites where there are no trees or other verticals obstacles in close proximity to the receiver. For example, the National Geodetic

Survey (NGS), an office of NOAA's National Ocean Service, manages a Continuously Operating Reference Stations (CORS) network that provide GNSS data in support of three-dimensional positioning, meteorology, space weather, and geophysical applications throughout the United States. The CORS network is a multipurpose cooperative endeavor involving over 230 government, academic, and private organizations managing sites that are independently owned and operated. Each agency shares their data with NGS who in turn analyze and distribute the data free of charge. The CORS network provides data from more than 2,000 active sites as of August 2018.

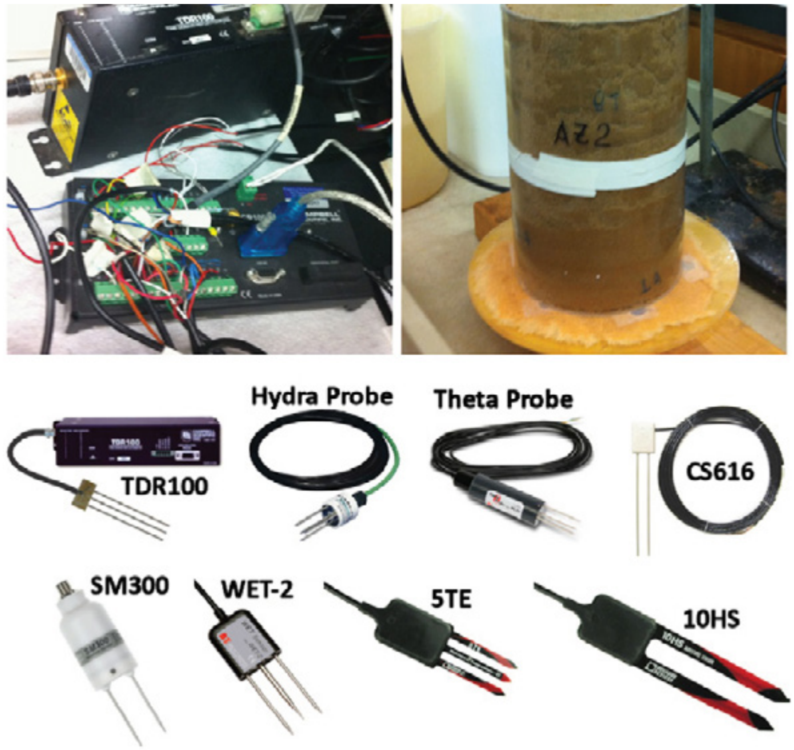

Figure 4.11: Eight electromagnetic soil moisture sensors evaluated by Vaz et al. (2013)

4.2.3.2 Approaches to sensor selection

Three possible approaches to sensor selection are: 1) precedent-based; 2) performance-based; and 3) feature-based approaches. Networks may also utilize some combination of these various approaches to guide sensor selection.

A precedent-based approach means that when a new network is established, the sensor is chosen to match the sensors in pre-existing networks. This has the obvious advantage of facilitating similarity across networks and consistency over time. A disadvantage is that it creates a bias against newer, and possibly better performing technologies. For example, USDA Agricultural Research Service (ARS) researchers in Durant, OK, evaluated commercially available sensors for long-term, automated soil moisture and temperature monitoring in the Little Washita River Watershed in 1994, and selected a heat dissipation sensor (CS-229, Campbell Scientific) as the best available option (Schneider et al., 2003). Soon thereafter, the OKM and the U.S. Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) Program's Southern Great Plains Cloud and Radiation Testbed (CART) site followed this precedent and selected the same sensor for their networks. The OKM has used these heat dissipation sensors continuously since 1996, which is also the year in which the first peer-reviewed paper describing their performance was published (Reece, 1996).

Separate from these developments in Oklahoma, USDA NRCS staff in multiple states began to collaborate on a Soil Moisture and Soil Temperature Pilot Project in 1991 (NRCS, 2004). Soil moisture measurements were initially made using granular matrix sensors (Watermark, Irrometer), but the sensors were changed to impedance-based sensors (HydraProbe, Vitel) beginning in 1994. These sensors were developed based on the approach of Campbell (1990), and the first peer-reviewed papers including HydraProbe measurements appeared in 1998 (e.g., Nelson et al., 1998; Miller et al., 1998). Based on the Soil Moisture and Soil Temperature Pilot Project, the NRCS Soil Climate Analysis Network was established in 1999 and the HydraProbe sensors were selected for this first nationwide network. Based on this precedent, HydraProbes and the second generation HydraProbe II have subsequently been selected for use in other networks such as the NRCS SNOTEL network, the

Table 4.1: Soil water content accuracies provided by sensor manufacturers and root mean squared difference (RMSD) obtained by Vaz et al. (2013) for mineral soils with factory-supplied and soil-specific calibrations.

Sensor	θ accuracy, UM†		θ-RMSD‡	
	Factory	Soil specific	Factory	Soil specific§
	$m^3 m^{-3}$			
Wet2	±0.050	±0.030	0.034	0.025
5TE	±0.030	< ±0.020	0.040	0.026
10HS	±0.030	±0.020	0.073	0.013
SM300	±0.025	_	0.037	0.014
Theta Probe	±0.050	< ±0.020	0.029	0.015
Hydra Probe	±0.030	_	0.048	0.028
CS616	±0.025	_	0.129	0.025
TDR100	±0.030	±0.020	0.023	0.022

† UM: from user manuals.
‡ From this study for mineral soils AZ2, AZ6, AZ9, AZ11, and AZ18.
§ Average soil-specific calibrations obtained for the mineral soils in this study (Table 6).

NOAA USCRN,[14] multiple USDA ARS experimental watersheds, and multiple state Mesonets.

A performance-based approach selects a soil moisture sensor based on evidence of its acceptable performance, where performance may include factors such as accuracy, precision, and durability. Sensor performance may be evaluated through laboratory testing in standard test media (Jones et al., 2005; Blonquist et al., 2005) or natural soils. Less commonly, sensor performance may be evaluated through testing in the field. Laboratory evaluation of soil moisture sensor performance is exemplified by the work of Vaz et al. (2013) who evaluated eight types of commercially-available electromagnetic soil moisture sensors (Figure 4.11, *previous page*). Such laboratory studies facilitate sensor evaluations in diverse soil types in a controlled environment and sensor accuracy can be summarized by statistical measures such as the root mean squared difference (RMSD) between the estimated and known soil moisture values (Table 4.1, *above*).

Field evaluations and inter-comparisons provide another valuable way of assessing soil moisture sensor performance. A benefit of field evaluations is that they provide better opportunities than lab experiments to learn about between-sensor differences in ease of installation, site disturbance, and durability. Sensors in field evaluations are also confronted with the real-world challenges of structured soil, soils with coarse fragments, and the inherent spatial variability of soil in situ. These challenges are a benefit in terms of providing a rigorous test, and they are also a drawback because they make it more difficult to know the true value of soil moisture for the sake of quantifying sensor errors. One such field evaluation is the Marena, OK, In Situ Sensor Testbed (MOISST) site (Cosh et al., 2016). Twelve different types of soil moisture sensing technologies have been intercompared at this field site, with seven of the sensor types replicated in four profiles installed in different soils (Figure 4.12, *next page*). As with laboratory evaluations, field evaluations like this also allow quantification of sensor accuracy when soil moisture can be independently determined by some standard method, typically by soil sampling and oven drying (Table 4.2, *next page*).

A third approach to sensor selection is feature-based in which a sensor type is selected because it inherently possesses a certain feature deemed necessary to the objectives of the measurements. For example, in 2004, during the planning phase for the National Ecological Observatory Network (NEON), it was decided that the soil moisture sensors must be "... retrievable to allow for regular calibration and maintenance" (Roberti et al., 2018). At the time, the only commercially-available, automatable sensors that offered this feature were tube-type capacitance sensors (e.g., EnviroSCAN, Sentek Pty.). This sensor type was then selected for deployment across NEON; however, subsequent laboratory testing showed an unacceptable root mean square error (RMSE) at 33 sites of 0.123 $cm^3\ cm^{-3}$, necessitating the development of unique calibration functions for each site and depth (Roberti et al., 2018). Another example of feature-based sensor selection is the increasing

[14] USCRN has now switched to Acclima TDR-315 for new installations.

use of CRNPs selected for monitoring networks such as the COSMOS network in the United States (Zreda et al., 2012) and the CosmOz network in Australia (Hawdon et al., 2014). Yet, there are no perfect sensors, and the CRNPs have a sensing depth that varies substantially with soil moisture, complicating interpretation of the data.

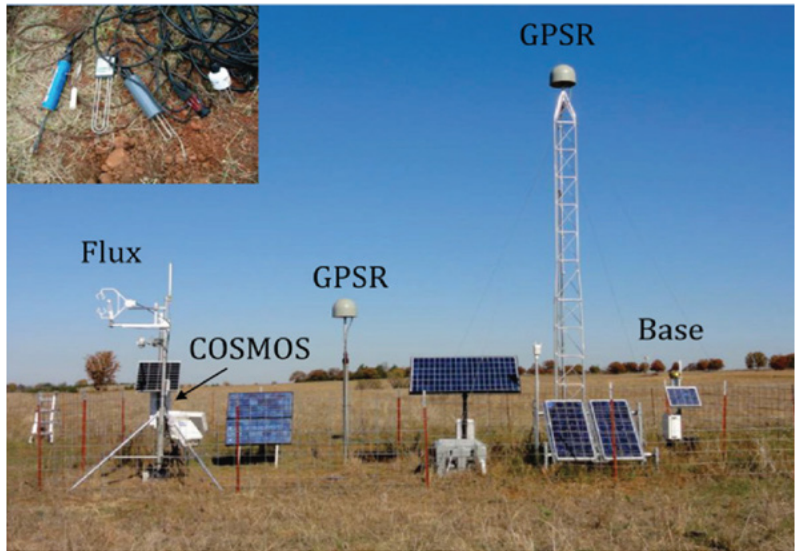

Figure 4.12: One of four sensor installation sites in the Marena, OK, In Situ Sensor Testbed (MOISST). The inset in the upper left shows several of the types of soil moisture sensors evaluated. Labeled in the main photograph are an eddy covariance system (Flux), a cosmic-ray neutron detector (COSMOS), and an antenna used for GPS reflectometry (GPSR), and one of four base stations to which the below-ground sensors are connected (Base).

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

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

Table 4.2: Bias and root mean squared error (RMSE) for soil moisture estimated using factory calibrations and RMSE values for soil-specific calibrations for soil moisture sensors at the MOISST site (Cosh et al., 2016).

4.3 ENGAGING USERS IN NETWORK DESIGN

In designing a network, there are often trade-offs because it is difficult to develop a network which meets all objectives efficiently. The design criteria detailed in the previous sections are based on the approach of providing a robust observation set that can generically define the amount of water in the soil. In addition to this approach, it may also be worth considering application-specific network designs. These approaches consider the expected value of observations at certain spatial, depth, and temporal resolution to support specific anticipated decisions.

The first step to designing a monitoring network to support current and anticipated uses of soil moisture data is to review current uses of available soil moisture observations. Key user groups at the national level include the authors of the U.S. Drought Monitor and other USDA and NOAA (and non-Federal) entities responsible for producing conditions reports and forecasts. Key user groups to consult with at the state level include agricultural agencies, water resource managers, and other natural resource decision-makers. More details on the user community are provided in Chapter 6.

Ideally, users would be polled to determine the locations and depths of soil moisture information that have been found to be most useful to inform their decisions. Data may be used directly, as for drought monitoring, or indirectly by constraining a model that informs anticipated wildfire activity, explores biological activity, or that projects the impacts of climate change on groundwater availability. A similar exercise could be completed to ask those whose decisions are most affected by soil moisture data to identify gaps in data that would best support their decision-making process. Finally, it is worth considering how to identify and survey key potential data users. One example is foresters, who currently do not often consider soil moisture in their assessments.

A survey of current and anticipated soil moisture data needs may uncover that some proposed observation locations or depths will be highly valued by an already-identified user group. This should imply prioritizing these elements within the network design. The survey may also indicate that the user groups do not foresee the value of some proposed soil moisture observations. This should guide network designers to carefully consider their rationale for including such observations. More likely the user group will identify needs for more station locations or measurement depths than are planned in the initial design. This may include higher spatial and/or temporal resolution, seasonal observations, or episodic observations.

In the likely event that users request more information than can be supported by the monitoring budget, a formal analysis can be completed to identify the most broadly useful subset of observations. These analyses can be based on reducing redundancy by, for example, replacing some generic elements (e.g., a single observation at a location) with a higher resolution local network (e.g., a set of observations designed to answer a question that requires high resolution near-surface observations). Similarly, regularly timed observations can be included as part of short duration surveys with higher temporal resolution. This redundancy reduction can serve both the regular data stream and question-specific data needs.

Even after forming a hybrid regular/focused network, it is likely that the number of observations will not be economically viable and fewer stations than desired will be available for deployment. At this stage, an approach like robust decision-making under uncertainty (RDM) can be applied. These approaches essentially require soil moisture data users to consider second and third best options for data to support their decision-making (Clutter and Ferré 2019). The full data set, comprised of all requested observations, forms the full set of hypothetically available observations. Users are tasked with describing how their selected alternative data subsets could be used to support their analyses and with predicting the impact of using these alternative data on the quality and/or costs of their decisions. RDM or similar approaches can then be used to explore the data space to describe the cost of measurement subsets. Ultimately, the network design will represent a trade-off decision that attempts to equitably provide sub-optimal data to all users with the greatest utility under given budgetary restrictions.