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Field evaluation of portable soil water content sensors in a sandy loam

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Abstract

Ground observations are critical in the validation of soil water content (SWC) estimates from both satellites and land surface models. Portable SWC sensors provide useful information to determine the amount of SWC in the topsoil layer for various applications; however, these probes are not accurate without site-specific correction. In the present study, we examined and compared six different types of portable electromagnetic (EM) SWC sensors, including multiple sensors made by the same manufacturers, for a total of 16 EM-based SWC probes equipped with portable data loggers. All SWC probes met the target accuracy after onsite correction—the RMSD was <0.025 $m^3 m^{-3}$. Using the two-sample *t* tests, we observed that SWC data obtained from similar electrode lengths and from different manufacturers showed similar distributions over time with the same mean. Furthermore, using the maximize *R* method to combine SWC data from two different types of sensors increased the accuracy of the results. When datasets from two different types of sensors were combined, the Pearson's correlation coefficient (*R* value) and RMSD values were improved. The average *R* value improved from .930 to .945, and the RMSD decreased from 0.036 to 0.018 $m^3 m^{-3}$. These results indicate that, along with site-specific correction, synergetic use of multiple manufacturers' EM-based SWC probes can improve the *R* value and reduce systematic bias.

1 | INTRODUCTION

Portable devices are an effective tool for measuring surface soil water content (SWC). They can also serve as an alternative to gravimetric sampling, as the electromagnetic (EM) properties of soil vary according to the water content in the soil (Topp, 2003), and these devices provide reasonably accurate measurements and avoid the cumbersome collection and drying issues related to gravimetric sampling. Over the last several decades, many portable EM-based sensors have been developed to estimate volumetric water content (VWC) in porous media in an efficient manner (Birchak, Gardner, Hipp, & Victor, 1974; Lee & Fredlund, 1984; Rowlandson et al., 2013; Seyfried & Murdock, 2004; Singh et al., 2018; Topp, 2003; Vaz, Jones, Meding, & Tuller, 2013). Electromagnetic-based SWC probes have shown several advantages over

Abbreviations: DC, direct current; EC, electrical conductivity; EM, electromagnetic; GVWC, gravimetric-based volumetric water contents; OPE3, Optimizing Production Inputs for Economic and Environmental Enhancement; SMAP, Soil Moisture Active Passive; SCAN, Soil Climate Analysis Network; SWC, soil water content; TDR, time domain reflectometry; TLO, transmission line oscillation; ubRMSD, unbiased root mean square difference; VWC, volumetric water content; WCR, water content reflectometer.

other techniques; for instance, SWC probes are less invasive than gravimetric techniques, they are suitable for long-term and continuous monitoring of SWC at specific depths, they can be used in most surface conditions regardless of soil types and vegetation, and they can collect SWC data repeatedly (Abbas, Fares, & Fares, 2011; Blonquist, Jones, & Robinson, 2005; Evett, Tolk, & Howell, 2006; Vaz et al., 2013).

However, SWC probes must be calibrated for farmland management and for validation of remotely sensed SWC retrievals (Cosh, Jackson, Bindlish, Famiglietti, & Ryu, 2005; Robinson, Jones, Wraith, Or, & Friedman, 2003) and for different soil types, as soil properties affect EM-based SWC measurement (Leib, Jabro, & Matthews, 2003; Malicki, Plagge, & Roth, 1996; Ponizovsky, Chudinova, & Pachepsky, 1999). Thus, soil-specific correction is recommended for SWC probes before application, even though factory-determined calibration options are generally used due to their simplicity. Many previous studies have described EM sensor applications in different soils and have compared SWC probes in laboratory settings (Blonquist et al., 2005; Chow, Xing, Rees, Meng, & Monteith, 2009; Evett et al., 2006; Vaz et al., 2013; Walker, Willgoose, & Kalma, 2004). However, few studies have compared the performance of portable EM-based SWC probes made by different manufacturers, and even fewer studies have combined two different EM-based SWC datasets with the aim of improving the accuracy of SWC measurement at field scales.

In the present study, we focus on the evaluation, correction, and combination of six types of portable SWC probes in a portable configuration with handheld data loggers. We chose the following probes because they have been widely used both by farmers and by scientists in various research fields of study. We used the ThetaProbe soil moisture sensor (hereafter ML3), the HydraProbe soil moisture sensor (hereafter HydraProbe), the Spectrum TDR100 soil moisture meter (hereafter FS100), the SM150 soil moisture sensor (hereafter SM150), the HydroSense II portable system (hereafter HS2), and the TRIME-PICO64 probe (hereafter PICO64). An analysis of the performance of these probes is necessary for a variety of applications, as some projects cannot support the deployment of in situ loggers. Spatial assessments of SWC are more efficiently performed with portable sensors, as is the case with the following major soil moisture field experiments: the Soil Moisture Experiments (SMEX; Bosch, Lakshmi, Jackson, Choi, & Jacobs, 2006), Soil Moisture Active Passive Validation Experiments (SMAPVEX; Jackson et al., 2014), the National Airborne Field Experiment (NAFE; Mladenova et al., 2011), and the Canadian Experiment for Soil Moisture (CANEX; Magagi et al., 2013). Individual assessments of the sensors used in these campaigns have been performed, but this is the first cumulative assessment of all common sensors examined for a single soil type as a common basis of comparison. To investigate the accuracy of these six SWC probes, the data were collected in sandy loam soil at a research site in Maryland (USA) in summer 2019. The present research seeks to answer the following questions:

Core Ideas

- Six portable soil moisture probes performed accurately after site-specific correction.
- Soil moisture data from similar electrode length probes showed a similar distribution.
- Synergetic use of two different sensor types can improve the correlation coefficient.
- Synergetic use of two different sensor types can reduce systematic bias.

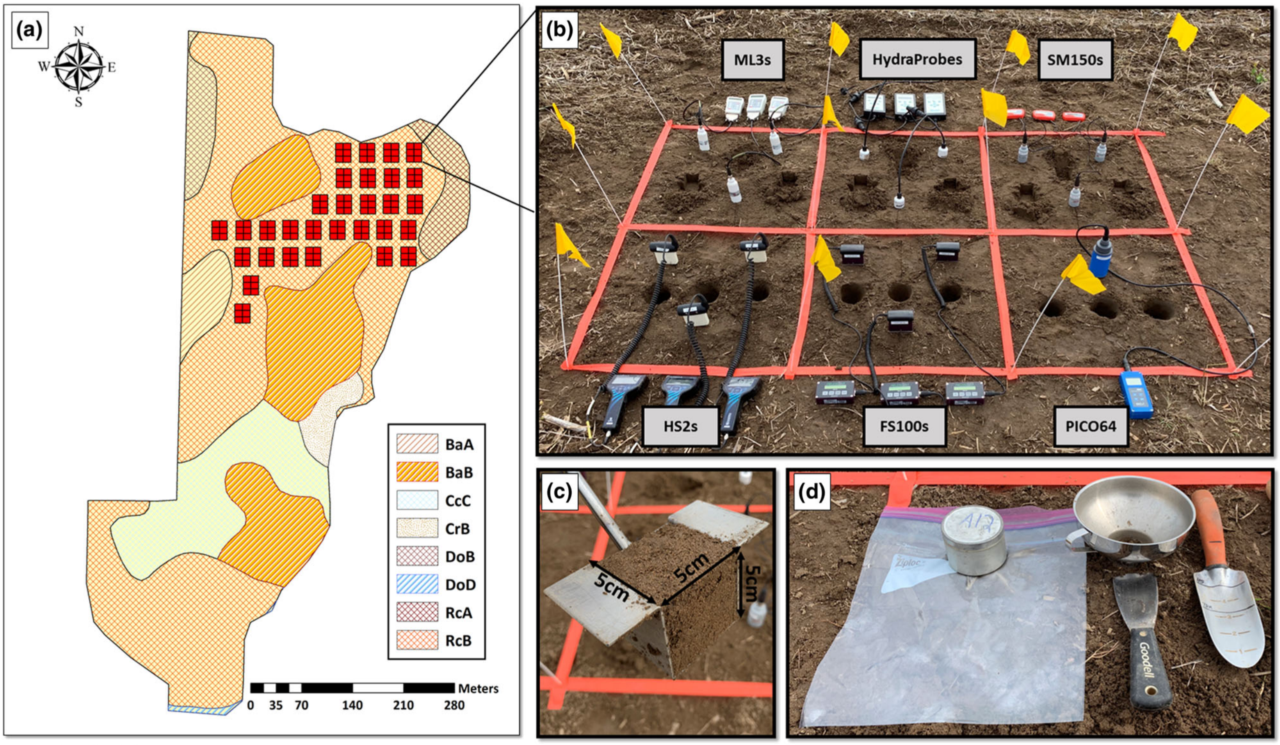
1. What are the measurement uncertainties of various commercially available portable SWC sensors?
2. Do different types of SWC probes, or several probes of the same type, show statistically different performance in comparison with reference data?
3. Can we improve the performance of SWC sensors by combining data from different type of sensors?

Answering these questions will provide us with new insights into the characteristics, limitations, and uncertainties of different SWC probes with portable devices.

2 | MATERIALS AND METHODS

2.1 | Study site

The Optimizing Production Inputs for Economic and Environmental Enhancement (OPE3) site is located in Prince George's County, Maryland (39.03° lat., −76.84° long.). Since 1998, >90 scientists from several U.S. federal agencies, universities, and private industry have conducted research at this location (De Lannoy, Verhoest, Houser, Gish, & Van Meirvenne, 2006; Srivastava et al., 2015). This site is listed in the Soil Climate Analysis Network (SCAN) as Powder Mill (https://www.wcc.nrcs.usda.gov/scan/). The soil texture at the OPE3 site is sandy loam with 56% of the site classified as the Russett (fine-loamy, mixed, semiactive, mesic Aquic Hapludults)–Christian (fine, mixed, semiactive, mesic Typic Hapludults) complex. The field texture of the soil was determined based on particle-size distribution analysis. Further information regarding the soil texture of the OPE3 site is shown in Figure 1a and Table 1. The thirty locations from which soil samples were taken are marked with red boxes (Figure 1a). More detailed descriptions of each sampling



BaA Beltsville silt loam, 0 to 2 percent slopes
BaB Beltsville silt loam, 2 to 5 percent slopes
CcC Christiana-Downer complex, 5 to 10 percent slopes
CrB Croom gravelly sandy loam, 2 to 5 percent slopes
DoB Downer-Hammonton complex, 2 to 5 percent slopes
DoD Downer-Hammonton complex, 10 to 15 percent slopes
RcA Russett-Christiana complex, 0 to 2 percent slopes
RcB Russett-Christiana complex, 2 to 5 percent slopes

FIGURE 1 (a) The soil map of the Optimizing Production Inputs for Economic and Environmental Enhancement (OPE3) site: the 30 red boxes indicate sampling locations. The actual sampling boundary was about 2.1 by 1.4 m, and a gap of at least 2 m from the center of each sampling point was ensured between different soil types in order to collect only sandy loam soil. (b) One of the sampling locations at the OPE3 site. (c) The scoop tool (5 × 5 × 5 cm) and funnel (inset picture) used to sample 0- to 5-cm soils. (d) Can, bag, funnel, spatula, and depth-marked hand shovel. Note: the shovel was used to sample soil depths >5 cm

TABLE 1 Summary of the soil texture at the Optimizing Production Inputs for Economic and Environmental Enhancement (OPE3) site

Depth	Texture	Clay	Silt	Sand
cm		———	%	———
0–14	Sandy loam	5.7	23.9	70.4
14–29		6.3	25.9	67.8
29–46		6.2	30.8	63.0

Note. Source: https://ncsslabdatamart.sc.egov.usda.gov/.

location are shown in Figure 1b, and further information on the process used to obtain the soil samples is provided in Section 2.3.

2.2 | Datasets

The relative permittivity of soil is dependent primarily on water content and secondarily on temperature, bulk electrical conductivity (EC), clay content and type, and EM frequency (Logsdon, Green, Seyfried, Evett, & Bonta, 2010; Robinson et al., 2003; Seyfried, Grant, Du, & Humes, 2005). The relative permittivity is defined as the ratio of the dielectric of the material to that of the voids. The real part of the soil dielectric describes its ability to store energy in an applied electric field, whereas the imaginary part relates to energy loss (Bosch, 2004; Topp, Davis, & Annan, 1980). Estimates of the real component of the dielectric are often described as the apparent dielectric (K_a), as estimates neglect the energy loss components (Bosch, 2004). The effective frequency range for measuring SWC is based on the dielectric number of the saturated soil known to lie approximately between 50 and 10,000 MHz (Vaz et al., 2013). If the frequency is below 100 MHz, the relative permittivity of moist soil depends greatly on soil type (Smith-Rose, 1935), and if the frequency is above 10,000 MHz, the relative permittivity of moist soil falls off due to water relaxation (Hoekstra & Delaney, 1974; Roth, Schulin, Flühler, & Attinger, 1990). Many impedance

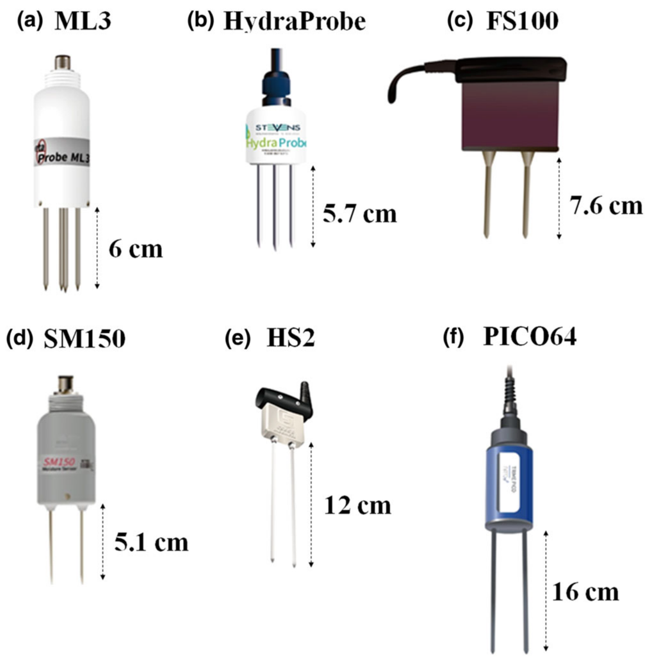


FIGURE 2 Six portable electromagnetic sensors and electrode lengths. The probes used are as follows: (a) three ML3s, (b) three HydraProbes, (c) three FS100s, (d) three SM150s, (e) three HS2s, and (f) one PICO64

and capacitance sensors operate at lower frequencies between 20 and 300 MHz (Bosch, 2004), and time domain reflectometry (TDR), time-domain transmissometry (TDT), and transmission line oscillation (TLO) operate within the frequency range of 100–10,000 MHz (Cassel, Kachanoski, & Topp, 1994; Heimovaara, de Winter, van Loon, & Esveld, 1996; Topp et al., 1980; Vaz et al., 2013).

In this study, we investigated six different portable EM-based SWC probes with portable data loggers (Figure 2), using multiple sensors of the same type and testing 16 SWC probes in all. It is worth noting that although this study tested probes equipped with portable data loggers, the performance results of the probes will be analogous to an in situ installation. The total number of sensors included three ML3 ThetaProbe soil moisture sensors (Delta-T Devices; Section 2.2.1), three HydraProbe soil moisture sensors (Stevens Water Monitoring Systems; Section 2.2.2), three FS100 (Spectrum) sensors (Spectrum Technologies; Section 2.2.3), three SM150 soil moisture sensors (Delta-T Devices; Section 2.2.4), three HydroSense II sensors (Campbell Scientific; Section 2.2.5), and one TRIME-PICO64 sensor (IMKO; Section 2.2.6). All 16 sensors were tested at the OPE3 site in Maryland,. Model numbers, manufacturers, and descriptive information for all sensors are presented in Table 2.

All sensor electrodes were inserted perpendicularly into the soil surface until the electrodes were fully covered by soil. Then, factory-determined VWC values were taken by reading values shown in the datalogger display.

2.2.1 | The ThetaProbe soil moisture sensor (ML3)

The ML3 ThetaProbe (Delta-T Devices) is an impedance-type sensor designed to measure the relative permittivity of soil (Figure 2a). ML3 sensors have been used both as portable sensors and as in situ sensors buried in the soil for long-term studies. Four electrodes are attached to the sealed plastic body, and these electrodes are inserted directly into the soil to measure voltage (mV). The manufacturer's specification of the sensing volume is >95% influence within a 40-mm-diam. cylinder, 60 mm long, around the central rod. In this study, the linearization table was set to the "mineral" type of soil.

TABLE 2 Summarization of specs and related websites for each sensor

Sensor	Abbreviation	Manufacturer	Type	f	Manufacturer's estimated accuracy	Length of sensing rods
				MHz		cm
ThetaProbe soil moisture sensor	ML3	Delta-T	I	100	±1% (VWC) over 0–50% and 0–40 °C	6.0
HydraProbe soil moisture sensor	HydraProbe	Stevens	I	50	3% (WFV) and ±0.3% (WFV precision)	5.7
TDR100 soil moisture meter	FS100	Spectrum Tech.	TLO	N/A	±1% (VWC) with electrical conductivity < 2 dS m^{-1}	7.6
SM150 soil moisture sensor	SM150	Delta-T	C	100	±3% (VWC) over 0–70% VWC and 0–60 °C	5.1
HydroSense II portable system	HS2	Campbell	TLO	175	±3% (VWC)	12.0
TRIME-PICO64 probe	PICO64	IMKO	TLO	1,000	±2% (VWC) over 0–40% VWC and ±3% VWC over 40–70% VWC	16.0

Note. f, frequency; TDR, time-domain reflectometry; TLO, transmission line oscillation; I, impedance; C, capacitance; N/A, not available; VWC, volumetric water content; WFV, water fraction by volume. The effective frequency is not provided by manufacturers.

Further details regarding the ML3 sensor are provided in the supplemental material.

2.2.2 | The HydraProbe soil moisture sensor (HydraProbe)

The Stevens HydraProbe soil moisture sensor (Stevens Water Monitoring Systems) is an electrical impedance sensor designed to determine the relative permittivity of soil using EM waves at a frequency of 50 MHz (Figure 2b). It has proven to be robust under various field conditions (Seyfried & Murdock, 2004) and has been used both as a portable sensor and as part of in in situ SWC networks; for example, SCAN in the United States and REMEDHUS in Spain have adopted the HydraProbe for long-term SWC monitoring (Lievens et al., 2015; Sanchez, Martinez-Fernandez, Scaini, & Perez-Gutierrez, 2012). The sensors were buried for periods of several months to years to assess sensor performance (Bosch et al., 2006; Cosh et al., 2016) or for application in various research fields (Cosh, Jackson, Moran, & Bindlish, 2008; Dumedah, Walker, & Merlin, 2015; Hottenstein, Ponce-Campos, Moguel-Yanes, & Moran, 2015; Kelleners & Norto, 2012). The manufacturer's specification of the sensing volume is within a 30-mm-diam. cylinder, 57 mm long, around a central rod. In this study, we used the Stevens Hydra data reader: three HydraProbes were logged into three Stevens Hydra data readers. The Hydra data reader provides four user-selectable soil texture settings: sand, silt, clay, and loam. The soil type was set to sand, as is common for the OPE3 field. Further details regarding the HydraProbe sensor are provided in the supplemental material.

2.2.3 | The Fieldscout TDR100 soil moisture meter (FS100)

The Fieldscout TDR100 (Spectrum Technologies) is a water content reflectometer (WCR) based on the TLO principle (Figure 2c). The name "TDR100" would lead the reader to assume that the unit uses TDR, but in reality, it does not. Despite its name, the TDR100 is a WCR-type device (Benor, Levy, Mishael, & Nadler, 2013; Kargas & Kerkides, 2008). The K_a is related to the period of applied voltage, which is measured from the WCR. For more details regarding the WCR, please refer to Chandler, Seyfried, Murdock, and McNamara (2004). The FS100 technique is similar to that of the Campbell CS616: it uses a quadratic equation related to a period average to calculate SWC (Singh et al., 2018). Very few studies are publicly available regarding comparative research of the FS100 sensors with other SWC probes, performance assessment over various soils, or performance assessment over soils having different physicochemical characteristics. The FS100 is suitable for these purposes, as it was originally designed for use with portable devices for periodic monitoring and recording of SWC, rather than for use in continuous monitoring of SWC in situ networks. The manufacturer's specification of the sensing volume is an elliptical cylinder extending ∼10 mm around the rods. In this study, we used three FS100 sensors (7.6-cm rods) with the VWC setting of "standard mode." Further details regarding the FS100 sensor are provided in the supplemental material.

2.2.4 | The SM150 soil moisture sensor (SM150)

The SM150 soil moisture sensor (Delta-T Devices) is a capacitance sensor designed to estimate SWC from a differential analog direct current (DC) voltage (Figure 2d). SM150 sensors have been used both as portable sensors and as sensors buried in the ground. These sensors have been buried for periods of several days to years in order to collect SWC data for application in various fields of research (Roets, Cronje, Schoeman, Murovhi, & Ratlapane, 2013; Veeramanikandasamy, Sambath, Rajendran, & Sangeetha, 2014); however, no performance assessment has been conducted involving the use of the SM150 as a portable sensor. The manufacturer's specification of the sensing volume for best results is an elliptical cylinder extending ∼25 mm around the rods. In this study, we used three SM150 SWC probes with three HH150 data loggers manufactured by Delta-T Devices. The HH150 meter provides five default soil texture settings: mineral, peat mix, coir, mineral wool, and perlite. The soil type was set to mineral. Further details regarding the SM150 sensor are provided in the supplemental material.

2.2.5 | The HydroSense II portable system with CS659 (HS2)

The CS659 water content sensor for HydroSense II (Campbell Scientific) is a 12-cm electrode version of the CS65x (e.g., CS650/655), and all CS65x are new versions of the original CS615 WCR (Figure 2e; Caldwell, Bongiovanni, Cosh, Halley, & Young, 2018). It is worth noting that all the new CSI TLO are referred to as "CS65x." The CS65x has been used in various research fields that require ground-based SWC measurements; for instance, it was used in optimizing satellite-based SWC data (Bai, He, & Li, 2016), investigating tree establishment conditions (Morrison, Holdo, Rugemalila, Nzunda, & Anderson, 2019), and validating satellite- and model-based SWC data (Caldwell et al., 2018, 2019; Moller, Jovanovic, Garcia, Bugan, & Mazvimavi, 2018). In this study, we used the CS659 with the HydroSense II portable device. The manufacturer's specification of the sensing volume is a cylinder of ∼30-mm diam. along the full length of the rods. We used three HS2 probes. Further details regarding the CS65x sensor are provided in the supplemental material.

2.2.6 | The TRIME-PICO64 probe

The TDR with intelligent micromodule element (TRIME)-PICO64 (hereafter PICO64) sensor is WCR and determines VWC, temperature, and EC in soils (Figure 2f). The PICO64 sensor is ideal for mobile use with the portable measuring device HD2. The PICO64 sensors have been used as in situ sensors requiring burial for long periods of time; however, no performance assessment has been made regarding this sensor. In contrast with conventional TDR systems, the TRIME system does not determine transit time from the entire waveform; rather, it determines transit time from the time of reflection at a given (threshold) voltage level (amplitude) (Dettmann & Bechtold, 2018). The manufacturer's specification of the sensing volume is ∼2 mm in the vicinity of the probe rods. In this study, we logged a PICO64 sensor (IMKO) into an HD2 data logger because PICO64 requires an external 7- to 24-V DC power supply. Further details regarding the PICO64 sensor are provided in the supplemental material.

2.3 | Methodology

2.3.1 | Gravimetric water content

In the present study, we used gravimetric water content (GWC) as the reference for SWC, since the thermogravimetric method, which consists of collecting and oven drying the soil, has been considered to produce the most reliable SWC value (Bosch, 2004; Reynolds, 1970). The collected GWC values were converted to VWC units, since the probes used in this study use the EM method to determine VWC. The GWC, which is provided in units of grams per gram, was converted to volumetric units by estimating the ratio of water volume in the soil (called the bulk density of the soil, ρ_b, in g cm^{-3}) to the ratio of the estimated soil sample volume. The GWC is converted to VWC using Equation 1:

$$\mathrm{VWC} = \mathrm{GWC}\left(\frac{b}{w}\right) \quad (1)$$

where w is the density of water. In the present study, in order to convert the gravimetric SWC values to VWC—hereafter GVWC—we used the soil scoop and coring tools to collect soil samples from the 30 different points at the OPE3 site where we tested the 16 sensors. These soil samples were also used to determine the b values for depths of 0–5, 0–10, 0–15, and 0–20 cm (Bosch, 2004; Reynolds, 1970). Figure 3 illustrates the boxplots of ρ_b values with respect to the different depths sampled at OPE3. From Figure 3, it is clear that the most accurate GVWC values can be obtained by using different ρ_b values to convert gravimetric SWC values into VWC for different soil depths. For the GVWC values used as references for the ML3s (electrode length = 6 cm), HydraProbes (electrode length = 5.7 cm), and SM150s (electrode length = 5.1 cm) sensors, we used the median values of the 0- to 5-cm ρ_b. Similarly, for the FS100s, HS2s, and PICO64, we used the median values of 0- to 10-cm, 0- to 10-cm, and 0- to 15-cm ρ_b, respectively, to convert gravimetric SWC to VWC. This conversion was necessary because the electrode lengths of these sensors are 7.6, 12, and 16 cm, respectively. For the soil depth of 0–5 cm, the scoop tool was used to determine the ρ_b value directly because this tool was specially designed to sample soil in the topsoil layer (5 × 5 × 5 cm, Figure 1c). However, in order to sample deeper soils (i.e., depths of 7.6, 12, and 16 cm), it was necessary to use the coring tool to determine ρ_b values.

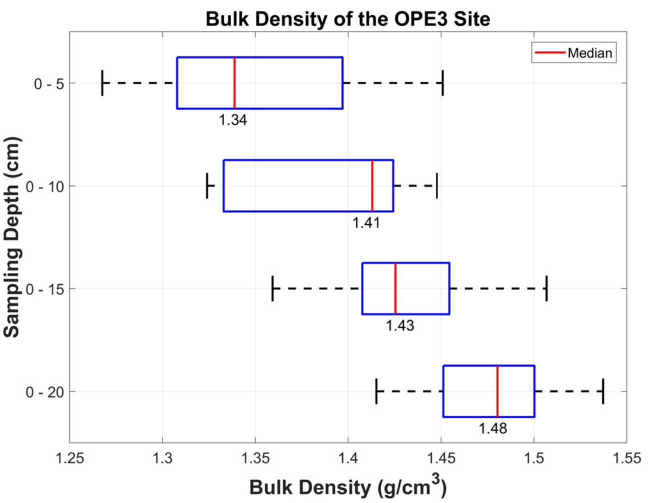


FIGURE 3 Boxplot showing the bulk density (ρ_b) values for different depths at the Optimizing Production Inputs for Economic and Environmental Enhancement (OPE3) site. The central red line indicates the median, and the left and right edges of the box represent the 25th and 75th percentiles, respectively. The whiskers extend to the farthest data points not considered as outliers

2.3.2 | Site-specific sensor correction

All sensor readings and soil samples were collected from 30 locations within the OPE3 site (Figure 1a). Each sensor was tested within a rectangular grid (70 × 70 cm), and three soil samples were taken for each sampling. For example, the VWC estimates from the ML3 (electrode length = 6 cm), HydraProbe (electrode length = 5.7 cm), and SM150

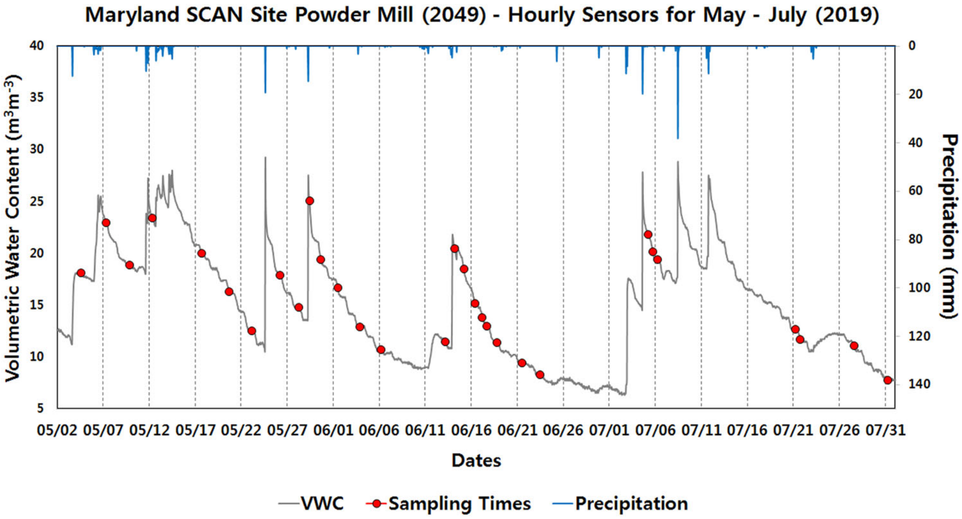


FIGURE 4 The hourly volumetric water content (VWC, at 5-cm depth) time series and hyetograph during the study period in Soil Climate Analysis Network (SCAN) site Powder Mill. The sampling dates are indicated with red dots

(electrode length = 5.1 cm) sensors were compared with the GVWC values taken from soil samples using a scoop tool with a fixed volume (the scoop tool is shown in Figure 1c). Similarly, for the FS100, HS2, and PICO64 sensors, we sampled the soil from depths of 0–8, 0–12, and 0–16 cm to obtain the GVWC (using the hand shovel shown in Figure 1d). To cross-check the sample depth against the length of the electrodes, we measured the depth of the hole after removing the sample. The GVWC sampling location was always <10 cm from the location where the probe was inserted (the location of holes and sensors can be seen in Figure 1b).

To reduce random errors, we averaged the GVWC values obtained from the three soil samples taken at each different sensor type's specific depth. Since we collected three soil samples from 30 locations for the six different types of sensors, we obtained a total of 540 soil samples (Figure 1b). In order to prevent soil drying between the time each sample was taken and the time it was first weighed, we used cans and sealable zipper storage bags (Ziploc) (Figure 1d): the weights of the can and bag were subtracted after the soil dried in order to calculate the soil weight. For the soil samples that were oven dried, the oven temperature was set to 105 °C, and the soil samples were dried for 24 h within their containers (cans or bags).

On the first day of sampling, we carefully chose locations with different SWC conditions based on the wetness of the soil. The sampling dates were also carefully chosen between May and July 2019. In order to obtain the wettest SWC value, we consistently measured SWC after storm events, using all 16 SWC probes and the wettest sampling locations. Every 1 or 2 d after a storm event, we conducted sampling at around 8:00 a.m. and 5:00 p.m. to obtain drier SWC conditions than those taken immediately after the storm event. We did not collect soil samples during storm events; all data were collected during drying cycles. Figure 4 illustrates the SCAN site Powder Mill (2049) hourly SWC time series with a hyetograph during the experiment period. The red dots indicate sampling dates. On each sampling date, several of the 30 locations shown in Figure 1a were selected for sampling based on soil wetness conditions. For instance, if a location had drier SWC values on a new sampling date than on a previous sampling date, we chose that location for sampling to ensure that we collected the drier SWC values. For a selected sampling location, all 16 probes were used to measure SWC, and soil samples were taken. Each sampling location was visited at least three times during the study period. This process allowed us to obtain the wettest to driest (or near-driest) possible ranges of SWC in the sandy loam areas of the OPE3 site.

The linear regression equations were determined by comparing the GVWC values (θ_{GVWC}), and the SWC values estimated with the sensors (θ_{sensor}). Before and after site-specific correction, the corresponding error statistics were calculated.

2.3.3 | Statistical metrics

For all sensors, we considered four statistical indicators: R value (Equation 2a), bias (Equation 2b), RMSD, and unbiased root mean square difference (ubRMSD, Equation 2c) (p value < .05):

$$R = \frac{\mathrm{cov}\left(\theta_{\mathrm{GWVC}}, \theta_{\mathrm{sensor}}\right)}{s^2_{\theta_{\mathrm{GVWC}}} s^2_{\theta_{\mathrm{sensor}}}} \tag{2a}$$

$$\text{bias} = \frac{\sum_{i=1}^{N}\left(\theta_{\text{sensor}_i} - \theta_{\text{GVWC}_i}\right)}{N} \tag{2b}$$

$$\text{RMSD} = \sqrt{\frac{\sum_{i=1}^{N}\left(\theta_{\text{GVWC}_i} - \theta_{\text{sensor}_i}\right)^2}{N}} \tag{2c}$$

$$\text{ubRMSD} = \sqrt{\frac{\sum_{i=1}^{N}\left[\left(\theta_{\text{GVWC}_i} - \overline{\theta_{\text{GVWC}_i}}\right) - \left(\theta_{\text{sensor}_i} - \overline{\theta_{\text{sensor}_i}}\right)\right]^2}{N}} \tag{2d}$$

where cov(•) and s^2 are covariance and standard deviation statistics and N is 30. Positive or negative bias values indicate overestimation or underestimation of SWC from SWC probes. We also considered ubRMSD, as the variability of ρ_b of the soils can cause large variance in θ_{GVWC}, thus introducing systematic errors.

2.3.4 | Two-sample *t* test and Kolmogorov–Smirnov test

In order to determine whether the different types of portable SWC sensors of similar electrode length showed similar performance, we conducted a two-sample *t* test ($\alpha = .01$). A two-sample *t* test is used to test the hypothesis of equality between two population means, assuming that the populations exhibit similar means (Kirkwood & Sterne, 2010). Prior to conducting a two-sample *t* test, the population of the dataset must be verified. The two populations are assumed to be normally distributed based on a Kolmogorov–Smirnov test ($\alpha = .01$).

2.3.5 | Maximize *R* method

The linear correction method described in Section 2.3.2 corrects for a known portion of systematic error in the data measured from the portable sensors. Thus, after site-specific correction of the data based on the linear correction method, the corrected VWC data will have no systematic errors. However, this linear correction method will not improve the *R* and ubRMSD values.

The maximize *R* method is a weighted linear combination method for combining two individual data sets; it is a physics-based data fusion method introduced by Kim, Parinussa, Liu, Johnson, and Sharma (2015). This method produces combined data from parent datasets. The combined data will have improved *R* values compared with the parent datasets. Previous research has shown that a combined product based on the maximize *R* method is superior to the combined datasets of an individual product (Baik, Liaqat, & Choi, 2018; Kim et al., 2018).

We introduced an application of the maximize *R* method, which combines the VWC data from two different types of sensors (i.e., parent datasets) to obtain improved temporal variation. Using this methodology, we produced VWC data of a higher correlation with the GVWC data. Since GVWC is the target value that EM-based probes seek to estimate, obtaining VWC data having a close temporal correlation with GVWC data is significant. As we mentioned above, the linear correction method cannot improve the *R* value, but the maximize *R* method can improve it.

Figure 5 shows a schematic step-by-step diagram of the maximize *R* method. The three steps of the detailed description are as follows:

- Step 1: Two different types of sensors must be inserted closely, either vertically (Type 1 as shown in Figure 5, Step 1) or horizontally (Type 2 as shown in Figure 5, Step 1). For vertical installation, the two sensor types must have similar electrode lengths in order to measure VWC at similar soil depths. On the other hand, for horizontal installation (Type 2), two different sensor types can have different electrode lengths because they will measure VWC at similar depths. For satellite-based SWC validation field campaigns, sensor installation normally follows Type 1, but for long-term monitoring of VWC, sensor installation normally follows Type 2.
- Step 2: It is important to collect VWC data simultaneously from two different types of sensors. For Type 1, while the probes are measuring VWC, soil samples for GVWC calculation should be taken from a depth similar to the sensors' electrode lengths. For Type 2, while the probes are measuring VWC, soil samples for GVWC calculation should be taken from the same depths where the two sensors are buried. This GVWC data are the target data that we want to estimate from two different types of sensors.
- Step 3: After collecting sufficient data from Step 2, we can combine the VWC measured from two different types of sensors using Equations 3a–3d, shown below.
  In the present study, all EM-based SWC probes inserted perpendicularly into the soil surface (described as Type 1), as is shown in Figure 5, Step 1. Thus, only the VWC measured in the similar depth of soil (top 5–6 cm) by the ML3, HydraProbe, and SM150 sensors in similar depths of soil (top 5–6 cm) were considered for the maximize *R* method for in this study.

Two sets of VWC measurements from two different types of sensors were combined into VWC values (θ_C) by applying a weighting factor (w) with a constrained range of 0–1 as follows:

$$\theta_{C(\text{sensor1, sensor2})} = w\theta_{\text{sensor}_1} + (1-w)\,\theta_{\text{sensor}_2} (0 \le w \le 1) \tag{3a}$$

In order to determine the optimum w value that maximizes the R value between θ_C and θ_{GVWC}, it is necessary to express the R value as a function of θ_C and θ_{GVWC} as follows:

$$R = f(w) = \frac{E\left[\left(\theta_C - \overline{\theta_C}\right)\left(\theta_{GVWC} - \overline{\theta_{GVWC}}\right)\right]}{s^2_{\theta_C}\, s^2_{\theta_{GVWC}}} \tag{3b}$$

where $\bar{\theta}$ stands for the average, and s^2 stands for the standard deviation of each datum. Before combining the two different SWC measurements in Equation 3a, the systematic differences between θ_{GVWC} and each VWC dataset measured by an EM-based SWC probe must be removed. Previously, Draper, Reichle, De Lannoy, and Liu (2012) suggested a method to normalize each VWC measurement against the reference data (e.g., GVWC) using Equation 3c:

$$\theta_{NORM} = \left(\theta_{\text{sensor}} - \overline{\theta_{\text{sensor}}}\right) \times \frac{s^2_{\theta_{GVWC}}}{s^2_{\theta_{\text{sensor}}}} + \overline{\theta_{GVWC}} \tag{3c}$$

Equation 3b can be differentiated with regard to w, and the resulting w value should theoretically maximize the R value between θ_C and θ_{Gvwc}. After the differentiation of Equation 3b, w is expressed as a function of the R values between VWC measured from each EM-based SWC probe and GVWC dataset as follows:

$$w = \frac{R_{\text{sensor}_1\cdot GVWC} - R_{\text{sensor}_1\cdot\text{sensor}_2} \times R_{\text{sensor}_2\cdot GVWC}}{\left[\begin{array}{l}\left(R_{\text{sensor}_2\cdot GVWC} - R_{\text{sensor}_1\cdot\text{sensor}_2} \times R_{\text{sensor}_1\cdot GVWC}\right) \\ +\left(R_{\text{sensor}_1 \times GVWC} - R_{\text{sensor}_1\cdot\text{sensor}_2} \times R_{\text{sensor}_2\cdot GVWC}\right)\end{array}\right]} \tag{3d}$$

where $R_{x\bullet y}$ is the R value between two individual measurements after removing systematic differences, according to Equation 3c.

In order to obtain an unbiased w factor, VWC data of all possible ranges within the area of interest should be collected. In addition, to determine the w factors, a large enough sample size of GVWC and VWC from two different types of sensors is required to calculate the robust statistics shown in Equations 3a–3d.

3 | RESULTS AND DISCUSSION

3.1 | Results of site-specific correction

The results of default factory-calibration SWC data are illustrated in Figure 6 using linear regression. All statistical numbers, including the bias (m^3 m^{-3}), RSMD (m^3 m^{-3}), ubRMSD (m^3 m^{-3}), R value, and constants in linear regression (i.e., m and n) lines, are shown in Table 3. Since the target accuracy of the Soil Moisture Active Passive (SMAP)

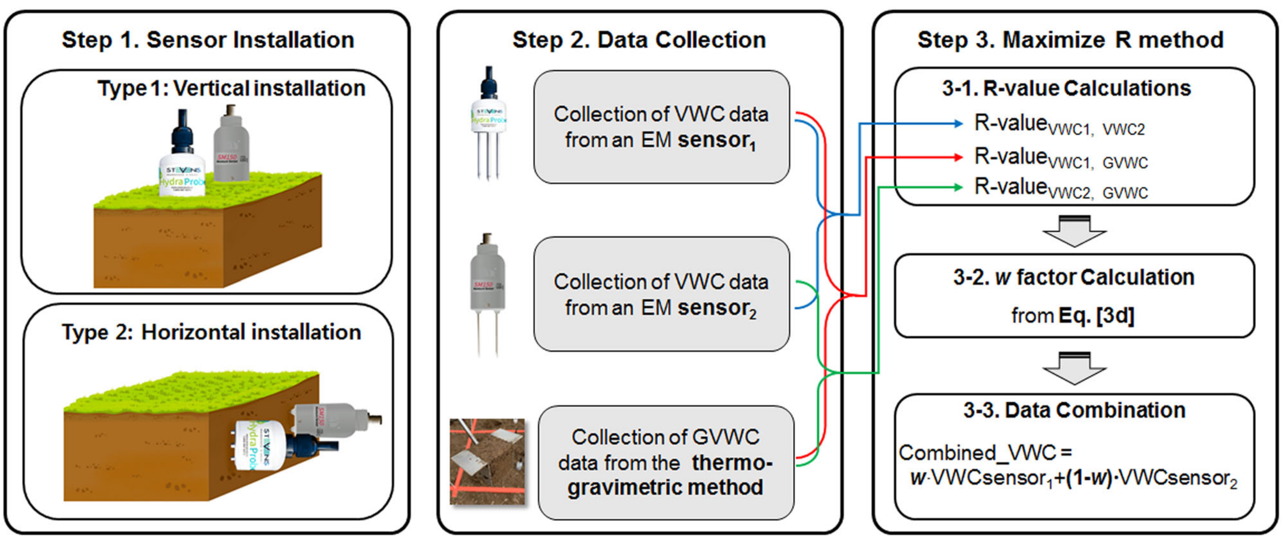


FIGURE 5 A step-by-step schematic diagram of the maximize R method. Volumetric water content (VWC) data are measured from two different types of sensors by inserting them vertically or horizontally (Step 1). The VWC data should be collected simultaneously from two different types of sensors and from the thermogravimetric method (Step 2). These collected data are then used to calculate the weighting (w) factor, which will be used to combine the VWC data collected from two different types of sensors (Step 3). EM, electromagnetic; GVWC, gravimetric-based volumetric water contents

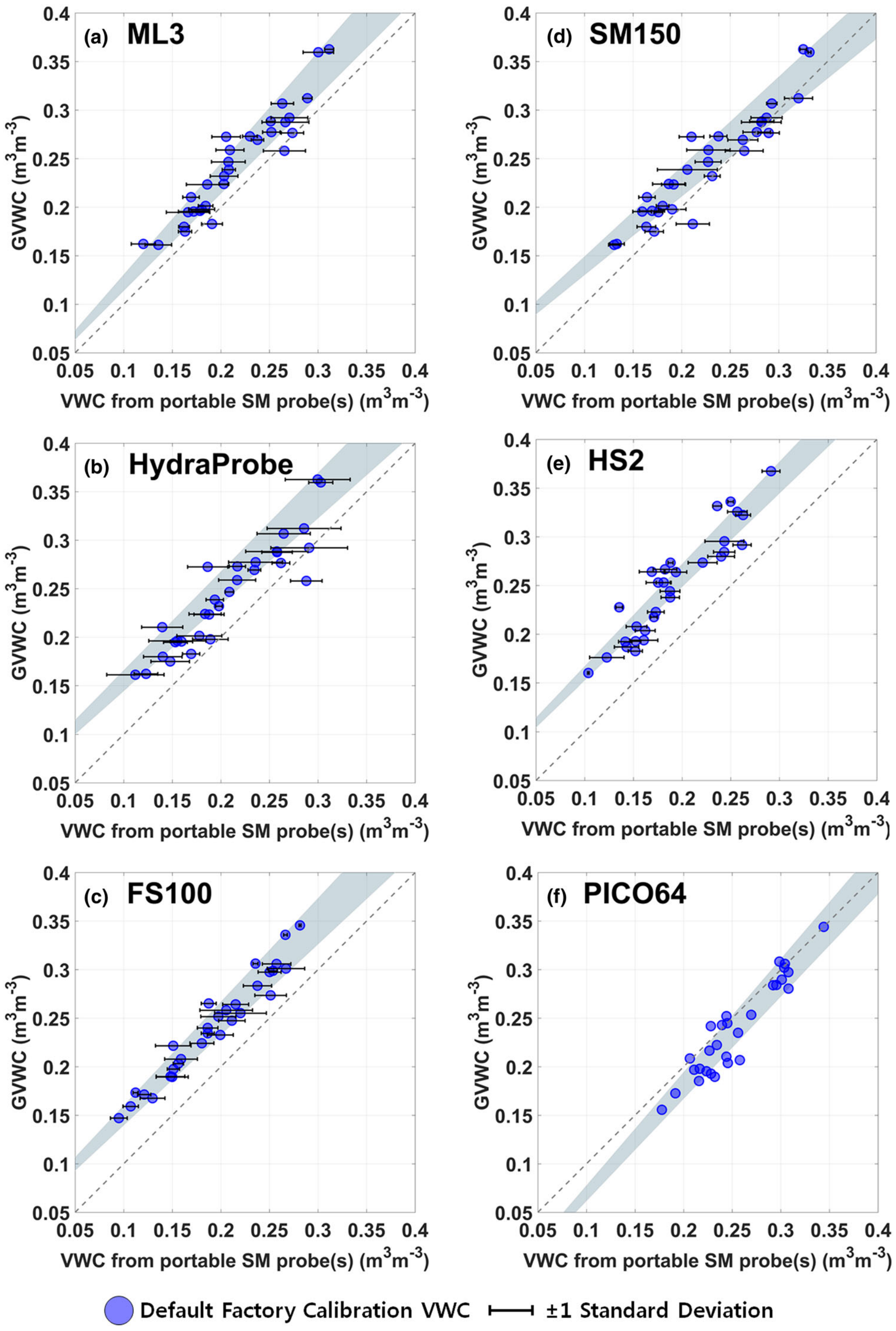


FIGURE 6 Factory calibrated volumetric water content (VWC) from physical sampling versus the paired mean of three sensors for (a) ML3, (b) HydraProbe, (c) FS100, (d) SM150, and (e) HS2 and one sensor value for (f) PICO64. The gray shaded areas in the scatterplots are the possible correction lines from different bulk density (ρ_b) values of 0- to 5-cm depth at the Optimizing Production Inputs for Economic and Environmental Enhancement (OPE3) site and horizontal error bars indicate the standard deviation of paired datasets. GVWC, gravimetric-based volumetric water contents; SM, soil moisture

satellite mission is ± 0.04 m^3 m^{-3} (Entekhabi et al., 2010), the ubRMSD of the SWC probes should be at or below this magnitude to validate the satellite-based SWC estimates. In Figure 6 and Table 3, with SWC data estimated using the manufacturer's calibration, some SWC probes had RMSD values >0.04 m^3 m^{-3}; however, all three ML3s, HydraProbe(B), all three SM150s, and the PICO64 had RMSD values <0.04 m^3 m^{-3}.

TABLE 3 Summary statistics for the default factory calibration and site-specific correction of each soil water content (SWC) probe

Probe	Default factory calibration		Site-specific correction				Correction equation	
	Bias	RMSD	Bias	RMSD	ubRMSD[a]	*R* value	Slope *m*	*y* intercept *n*
ML3(A)	−0.026	0.033	0.000	0.022	0.021	.920	0.976	0.031
ML3(B)	−0.033	0.039	0.000	0.021	0.020	.926	0.960	0.042
ML3(C)	−0.027	0.033	0.000	0.019	0.018	.941	1.058	0.015
Avg.	−0.029	0.035	0.000	0.021	0.020	.929		
HydraProbe(A)	−0.042	0.050	0.000	0.026	0.025	.883	0.812	0.080
HydraProbe(B)	−0.019	0.030	0.000	0.022	0.021	.917	0.843	0.054
HydraProbe(C)	−0.047	0.052	0.000	0.022	0.021	.918	0.940	0.059
Avg.	−0.036	0.044	0.000	0.023	0.023	.906		
SM150(A)	−0.018	0.028	0.000	0.019	0.019	.937	0.850	0.052
SM150(B)	−0.016	0.028	0.000	0.022	0.022	.916	0.839	0.053
SM150(C)	−0.019	0.030	0.000	0.021	0.021	.923	0.855	0.052
Avg.	−0.018	0.028	0.000	0.021	0.020	.926		
HS2(A)	−0.058	0.063	0.000	0.025	0.025	.887	0.972	0.063
HS2(B)	−0.049	0.054	0.000	0.023	0.022	.914	1.070	0.035
HS2(C)	−0.058	0.062	0.000	0.023	0.022	.913	1.002	0.058
Avg.	−0.055	0.059	0.000	0.024	0.023	.905		
FS100(A)	−0.044	0.047	0.000	0.018	0.017	.947	0.927	0.058
FS100(B)	−0.058	0.059	0.000	0.012	0.011	.977	0.966	0.064
FS100(C)	−0.046	0.049	0.000	0.017	0.016	.952	0.985	0.049
Avg.	−0.049	0.052	0.000	0.015	0.015	.959		
PICO64	0.014	0.022	0.000	0.017	0.016	.942	1.105	−0.041

[a]ubRMSD, unbiased RMSD.

Huang, Akinremi, Sri Rajan, and Bullock (2004) also reported RMSD values of 0.037 m^3 m^{-3} for ML3s and concluded that ML3s were more accurate than other soil water instruments (Watermark, Aquaterr, and Aqua-Tel sensors) in sandy loam soil and required no correction under laboratory conditions. Furthermore, under laboratory conditions, ML3 RMSD values of 0.020–0.040 m^3 m^{-3} were reported in other literature (Fares, Abbas, Maria, & Mair, 2011; Vaz et al., 2013). Finally, in our study, the ML3 ubRMSD values obtained in field conditions were close to the reported laboratory accuracy of 0.020 m^3 m^{-3} (Vaz et al., 2013). The HydraProbe showed an average RMSD value of 0.044 m^3 m^{-3}, but HydraProbe(A) and HydraPorbe(C) showed higher RMSD values (0.050 and 0.052 m^3 m^{-3}). Seyfried and Murdock (2004) noted that for the HydraProbe, the factory calibration function for a generic soil has an RMSD of 0.330 m^3 m^{-3} due to the limited dielectric range imposed by the unrealistic shape of its calibration function. Considering that 10% of our GVWC data are >0.330 m^3 m^{-3}, the relatively high RMSD might be caused by an SWC range that was >0.330 m^3 m^{-3} during the study period. Furthermore, the RMSD and ubRMSD of the SM150 sensors are lower than those of all other sensors except the PICO64. In terms of RMSD, the SM150 using the factory default calibration performs better than other sensors of similar sensing depths (the ML3 and HydraProbe, Table 3). The average RMSD values for the default factory and site-specific correction measurements were 0.028 and 0.021 m^3 m^{-3}, respectively. Furthermore, Zhu, Irmak, Jhala, Vuran, and Diotto (2019) reported that the SM150 produced the highest accuracy of all TLO- and frequency domain reflectometry (FDR)-type sensors in silt loam. However, the permittivity of the soil could cause an anomaly in the transmitted EM field, since the EM field is affected by other soil properties. Therefore, in other soil conditions, the performance of SM150 may vary.

After site-specific correction, the ubRMSD values from three probes of similar sensing depths—the ML3s, HydraProbes, and SM150s—were almost identical: 0.020, 0.023, and 0.020 m^3 m^{-3}, respectively. For ML3 sensors, after site-specific correction, the average RMSD value decreased from 0.035 to 0.021 m^3 m^{-3}. However, Cosh et al. (2005) reported that after field-specific correction for soil type of sandy loam–sand (0–25% sand and 50–70% clay), ML2 sensors used in measuring 21 field samples returned an RMSD of 0.043 m^3 m^{-3}. Since Vaz et al. (2013) reported a lower performance of ML3 sensors in soil with high fractions of clay than in sandy soils, the lower RMSE results produced by the current research may be the result of the soil type, which were composed mostly of sandy loam. Fares et al. (2011) reported a RMSE value of 0.043 m^3 m^{-3} after applying the calibration function to the ML2 laboratory calibration equations. These results indicate that for collecting SWC data at shallow soil depths (0–5 cm) for remotely sensed SWC data, the ML3, HydraProbe, and SM150—along with portable devices—are suitable for sandy loam soil conditions after site-specific correction.

Of all the sensors studied, the PICO64, which is based on the principle of TLO, showed excellent performance both before and after site-specific correction: the RMSD values were 0.022 m^3 m^{-3} before site-specific correction and 0.017 m^3 m^{-3} after site-specific correction. The PICO64 probe is less susceptible to interference from EC because it operates at a high frequency (1,000 MHz) than capacitance probes (Robinson et al., 2008). High frequencies, such as 1,000 MHz, can carry out an exact partition of moisture and conductivity, unlike capacitive probes with lower frequencies. This difference in performance is due to the fact that capacitance probes are affected by the EC properties of soil. Of all the sensors, the FS100 showed the greatest improvement. The average statistics from all the FS100s showed the highest R value (average = 0.959) and the lowest ubRMSD (average = 0.015 m^3 m^{-3}) after site-specific correction. There appeared to be a large improvement (0.037 m^3 m^{-3}) in the RMSD of the FS100s after correction, dropping from 0.052 m^3 m^{-3} before correction to 0.015 m^3 m^{-3} afterward. Site-specific correction decreased RMSD errors of all FS100 sensors to <0.02 m^3 m^{-3} with negligible bias. This result indicates that after proper correction, all portable sensors tested in the present work can be used to validate satellite-based SWC estimates with good accuracy (better than ±0.04 m^3 m^{-3}). However, site-specific correction is always recommended before beginning a validation effort or a field campaign. This result also indicates that several separate correction efforts may be required to accurately represent satellite-based SWC estimates over large areas (i.e., several kilometers) with multiple soil types.

3.2 | Results of two-sample *t* test

The null hypothesis of the two-sample *t* test is that the data in a pair of SWC measurements from sensors come from normal distributions with the same mean. A *p* value with a significance level of <1% rejects the null hypothesis. Supplemental Figure S1 shows the *p* value results of two-sample *t* test for sensors of similar electrode lengths (5–6 cm), including ML3s, HydraProbes, and SM150s. We did not perform two-sample *t* test on variances pairing the CS659 and the FS100 with other sensors because the CS659 and FS100's electrode lengths are quite different from those of the ML3s, HydraProbes, FS100s, and PICO64.

In Supplemental Figure S1, it is observed when the manufacturer's calibration is used to estimate SWC sensors having similar electrode lengths (e.g., ML3 vs. HS, ML3 vs. SM150, and HS vs. SM150) the null hypothesis of the two-sample *t* test was not rejected. This is because the SWC measurements from sensors of similar electrode lengths were statistically similar without site-specific correction.

3.3 | Results of combined volumetric water content data calculated from two different types of electromagnetic-based probes

Table 4 shows the improvement in R value after combining two different types of sensors for the 0- to 5-cm SWC estimations (ML3, HydraProbe, and SM150). The results show that the R value is always higher after combining data from two different types of sensors. The maximum improvements in R value were found when the HydraProbe sensors were used with ML3 sensors. Specifically, the R value for single-sensor use of HydraProbe(A) improved from .883 to .941 when HydraProbe(A) was combined with ML3(C) (Table 4). On average, when any two sensors were combined, the R value increased by ∼1.9%, and the maximum improvement in R value was ∼2.8% ("Improvement in R value" column in Table 4). The average R value improved from .930 to .959.

Table 5 shows the w factor for each pair of sensors for 0- to 5-cm depths of SWC data. The largest w factor is shown in the SM150(A) [0.775, the SM150(A) row and the "Avg." column in Table 5], and the average w factor for all SM150 sensors was 0.661 ("Same sensor type avg." column in Table 5). This result indicates that the SM150 sensor is the major contributor in improving the R value of data combinations measuring 0- to 5-cm SWC.

Before combining of two different SWC measurements from Equation 3a, the systematic differences between θ_{GVWC} and each parent product were removed. Thus, the RMSD from a single sensor measurement decreased dramatically. Table 6 shows the results of RSMD before and after the two different types of sensors were paired. The greatest improvement in RMSD was shown when the HydraProbe was combined with the ML3. On average, when a sensor of one type was combined with a sensor of another type, the RMSD decreased by ∼44.8% of the original error. The average maximum decrease in RMSD was 47.5% ("Improvement in RMSD" column in Table 6). The average RMSD decreased from 0.036 to 0.018 m^3 m^{-3}.

In this study, we proposed combining two different types of EM-based SWC probes to improve the quality of SWC data. However, it is worth noting that the currently determined w factors shown in this study are not applicable to other soil properties because these values were determined only for sandy loam and only for one specific depth of soil (0–5 cm).

TABLE 4 *R* values for ML3, HydraProbe, and SM150 sensors' 0- to 5-cm soil water content (SWC) data when combined with a different type of sensor to create sensor paired data

Sensor	Single-sensor *R* value	Two-sensor combined *R* value: With ML3(A)	With ML3(B)	With ML3(C)	With Hydra Probe(A)	With Hydra Probe(B)	With Hydra Probe(C)	With SM150(A)	With SM150(B)	With M150(C)	Improvement in *R* value: Avg.	Max.	Same sensor type avg.
											%		
ML3(A)	.920	–	–	–	.921	.933	.934	.943	.939	.941	1.6	2.4	
ML3(B)	.926	–	–	–	.927	.938	.938	.947	.932	.939	1.2	2.3	1.8 (ML3)
ML3(C)	.941	–	–	–	.941	.946	.947	.948	.942	.945	0.4	0.7	
Hydra Probe(A)	.883	.921	.927	.941	–	–	–	.937	.919	.926	5.2	6.6	
Hydra Probe(B)	.917	.933	.938	.946	–	–	–	.944	.934	.943	2.5	3.2	4.9 (HydraProbe)
Hydra Probe(C)	.918	.934	.938	.947	–	–	–	.944	.932	.932	2.2	3.1	
SM150(A)	.937	.943	.947	.948	.937	.944	.944	–	–	–	0.7	1.2	
SM150(B)	.916	.939	.932	.942	.919	.934	.932	–	–	–	1.9	2.9	2.1 (SM150)
SM150(C)	.923	.941	.939	.945	.926	.943	.932	–	–	–	1.6	2.3	
Avg.											1.9	2.8	

TABLE 5 ML3, HydraProbe, and SM150 weighting factor (w) to combine different pairs of SWC measurements for 0- to 5-cm depth

Data_1	Optimized weighting factor (w) [combined_data = $w \times$ Data_1+ (w –1) $\times$ Data_2]										
	Data_2										
Sensor	With ML3(A)	With ML3(B)	With ML3(C)	With Hydra Probe(A)	With Hydra Probe(B)	With Hydra Probe(C)	With SM150(A)	With SM150(B)	With SM150(C)	Avg.	Same sensor type avg.
ML3(A)	–	–	–	0.892	0.531	0.520	0.334	0.527	0.482	0.548	
ML3(B)	–	–	–	0.832	0.565	0.560	0.403	0.611	0.521	0.582	0.625 (ML3)
ML3(C)	–	–	–	0.993	0.699	0.692	0.553	0.833	0.709	0.747	
HydraProbe(A)	0.108	0.168	0.007	–	–	–	0.002	0.233	0.216	0.150	
HydraProbe(B)	0.469	0.435	0.301	–	–	–	0.334	0.506	0.465	0.435	0.339 (HydraProbe)
HydraProbe(C)	0.480	0.440	0.308	–	–	–	0.337	0.516	0.441	0.432	
SM150(A)	0.666	0.597	0.447	0.998	0.666	0.663	–	–	–	0.775	
SM150(B)	0.473	0.389	0.167	0.767	0.494	0.484	–	–	–	0.582	0.661 (SM150)
SM150(C)	0.518	0.479	0.291	0.784	0.535	0.559	–	–	–	0.626	

TABLE 6 ML3, HydraProbe, and SM150 RMSD after combining different pairs of SWC measurements for the 0- to 5-cm depth

Sensor	Single-sensor RMSD	Two sensors combined RMSD									Improvement in RMSD		
		With L3(A)	With L3(B)	With L3(C)	With ydra Probe(A)	With ydra Probe(B)	With Hydra Probe(C)	With SM150(A)	With SM150(B)	With SM150(C)	Avg.	Max.	Same sensor type avg.
	$m^3\ m^{-3}$										%		
ML3(A)	0.033	–	–	–	0.021	0.020	0.019	0.018	0.019	0.018	−42.3	−36.0	
ML3(B)	0.039	–	–	–	0.020	0.019	0.019	0.017	0.020	0.019	−51.3	−47.6	−42.4 (ML3)
ML3(C)	0.033	–	–	–	0.018	0.017	0.017	0.017	0.018	0.018	−45.7	−43.6	
HydraProbe(A)	0.050	0.021	0.020	0.018	–	–	–	0.019	0.021	0.020	−59.9	−63.3	
HydraProbe(B)	0.030	0.020	0.019	0.017	–	–	–	0.018	0.019	0.018	−37.9	−43.8	−53.6 (HydraProbe)
HydraProbe(C)	0.052	0.019	0.019	0.017	–	–	–	0.018	0.020	0.020	−63.7	−65.4	
SM150(A)	0.027	0.018	0.017	0.017	0.019	0.018	0.018	–	–	–	−34.9	−44.3	
SM150(B)	0.028	0.019	0.020	0.018	0.021	0.019	0.020	–	–	–	−30.9	−39.3	−42.5 (SM150)
SM150(C)	0.030	0.018	0.019	0.018	0.020	0.018	0.020	–	–	–	−36.3	−43.9	
Avg.											−44.8	−47.5	

Although the proposed method can improve *R* and ubRMSD statistics, for practical application, *w* factors should be determined for each study area of interest.

4 | CONCLUSION

We compared, calibrated, and combined six commonly used and/or newly available portable EM-based SWC probes equipped with portable data loggers. Our first finding was that without site-specific correction, some of the portable EM-based SWC probes, including the HydraProbe, HS2, and FS100 sensors, showed RMSD values >0.040 $m^3\ m^{-3}$ (accuracy required by SMAP soil moisture products). In other words, they demonstrated unsatisfactory accuracy for validating remotely sensed SWC data in sandy loam soils. However, after site-specific correction, the RMSD for all sensors decreased to <0.025 $m^3\ m^{-3}$. These results indicate that SWC probes with portable devices are suitable for validating large-scale SWC estimates in a sandy loam soil, after implementation of site-specific correction. Use of portable EM-based SWC probes presents a quick and easy way to take multiple observations within various satellite pixels—either at the original resolution (e.g., ∼36-km products from SMAP product) or at the downscaled resolution of SWC product (e.g., 1-km products from SMAP/Sentinel). The accuracy of the portable EM-based SWC probes is greater than the requirements for satellite soil moisture retrievals, which makes these probes a very attractive option for future validation studies. However, it should be noted that we have undertaken this evaluation at the OPE3 site with sandy loam soils. Therefore, results shown in this study are only valid for similar soil properties because capacitance and quasi-TDR sensors are influenced by EC and soil texture and cannot be generalized to other locations with soil types other than sandy loam.

Second, we conducted a two-sample *t* test to determine whether VWC data measured from the different types of sensors showed significantly similar performance. The two-sample *t* test results showed that VWC measurements from EM-based SWC probes of similar electrode lengths were statistically similar without site-specific correction.

Third, using the maximize *R* method, we combined VWC data from different pairs of VWC sensors. Data combination improved the *R* values and decreased the ubRMSD. These results suggest that, in addition to performing site-specific correction, EM-based SWC probes can be used in pairs to produce more accurate VWC data and reduce the systematic bias of VWC sensors.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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SUPPORTING INFORMATION

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