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Evaluation of 10 soil moisture profile sensors using a sandbox experiment

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Abstract

Soil moisture profile sensors (SMPSs) are designed to measure the volumetric water content of soil at multiple depths simultaneously. Their vertical installation makes them particularly suitable for frequent relocation, as required for the use during cultivation of field crops. In addition to established sensor manufacturers who have been offering SMPS for some time, an increasing number of companies are now introducing new models specifically designed for agricultural applications. Beyond practical and economic factors—such as ease of installation, durability, and costs—the measurement accuracy of SMPS is a key performance criterion, yet one that end users cannot easily assess themselves. Validating sensor accuracy requires reference methods that are impractical for most users, and soil heterogeneity further complicates data interpretation. In this study, we conducted a sandbox experiment to compare the measurement accuracy of 10 SMPSs under controlled soil moisture conditions. The SMPS readings were evaluated against time-domain reflectometry reference measurements using three SMPS devices of each type. We found that most SMPSs performed with reasonable accuracy under very dry and very wet conditions. However, in the intermediate soil moisture range, strong variations were observed with respect to slope, offset, and spread of measurements for some SMPSs, which resulted in reduced accuracy. The high intra-sensor variability ($RMSE_{QB}$: 0.7–3.1 vol. %) and varying measurement accuracy ($RMSE_{QB}$: 3.1–8.3 vol. %) highlight the importance of selecting a suitable SMPS, especially for scientific applications and precision agriculture, where accurate field data are critical for informed management decisions.

Plain Language Summary

Accurately quantifying soil water availability is essential for agricultural management and environmental research, yet it remains technically challenging. Soil moisture profile sensors (SMPSs) can measure water content at several depths and are easy to move between fields, but their accuracy is not well known. We tested 10 types

Abbreviations: EM, electromagnetic; SMPS, soil moisture profile sensor; VWC, volumetric water content.

of these sensors in a controlled experiment and compared their readings to a reliable reference method. Most sensors worked well when the soil was very dry or very wet, but their accuracy dropped in moderate moisture conditions. We also found large differences between sensors of the same type. These results show that while SMPSs can be useful tools, their performance varies widely. Choosing the right sensor is especially important for research and precision agriculture, where accurate soil data are needed for good management decisions.

1 | INTRODUCTION

The increasing frequency and severity of summer droughts due to climate change is expected to significantly increase the demand for irrigation in many regions worldwide (Minoli et al., 2019; Rosa, 2022). Many farmers already use low-cost weather stations to adjust their irrigation scheduling accordingly (Villa-Henriksen et al., 2020). However, precipitation measurements alone are not sufficient to predict plant stress, as plant-available water can rapidly decline due to lateral water flow (often accelerated by drainage systems), deep percolation, and evapotranspiration losses (Vereecken et al., 2022). Therefore, real-time soil moisture monitoring along the root zone holds significant potential for smart irrigation management, improving crop productivity and quality while conserving limited freshwater resources (Bogena et al., 2022; Navarro et al., 2020). By leveraging Internet of Things (IoT) technology, soil moisture measurements can be integrated into mechanistic, stochastic, or machine learning models to forecast crop water availability based on numerical weather predictions (Giorgio et al., 2022; Jamal et al., 2023; Tace et al., 2022; Togneri et al., 2022).

To realize this potential, various sensor technologies have been developed to measure the root zone soil moisture. Neutron probes, introduced in the 1950s, allowed soil moisture measurements at depth but were limited by radiation risks and lack of automation (Schmugge et al., 1980). Electromagnetic (EM) sensors, available since the 1980s, provide automated measurements with high temporal resolution (Roth et al., 1990; Topp et al., 1980). They exploit the strong contrast in dielectric permittivity between air, minerals, and water (Birchak et al., 1974), where water (∼80) greatly exceeds that of soil minerals (∼3–5) and air (∼1). While EM sensors are typically inserted or buried in the soil to measure soil moisture at a certain depth, access tube-compatible EM sensors have been introduced for measuring soil profile water content (Mazahrih et al., 2008). These sensors measure soil moisture through the wall of the tube, so any air gap between the tube and the surrounding soil, for example, due to poor installation, settlement, or shrinkage, can interfere with the EM signal and lead to inaccurate readings (Evett et al., 2009). Additionally, the widespread use of invasive soil moisture sensors is challenging because the sensors need to be placed within the cropped soil shortly after sowing and need to be removed before harvesting and tillage.

More recently, soil moisture profile sensors (SMPSs) have been developed that are not dependent on access tubes, enabling continuous and more consistent measurements. SMPSs usually consist of a single probe with several sensor elements arranged at fixed intervals along their length. Each sensor element measures soil moisture at a specific depth range using technologies such as capacitance measurements, frequency domain reflectometry (FDR), time-domain reflectometry (TDR), or, less commonly, resistance sensors and tensiometers. Since the terms capacitance and FDR are often used interchangeably, they are briefly explained here. For FDR technology, an alternating EM signal is applied to the probe, and the LC (inductor-capacitor) circuit of the sensor oscillates at a resonant frequency that shifts depending on the surrounding soil's dielectric permittivity (Schwank et al., 2006). For capacitance technology, the sensor applies an alternating voltage at a single frequency (typically in the MHz range) to the sensors' probes. The soil permittivity is then determined by measuring the time required for the sensor to charge from a starting voltage to a specified voltage under the applied voltage (Bogena et al., 2007). Like access tube sensors, SMPS can be easily deployed from above ground, typically following pre-drilling of a narrow hole. The high potential of SMPS for precision agriculture has motivated many established sensor manufacturers to produce their own SMPS (Figure 1). In recent years, new companies have also entered this sensor market, often offering SMPS devices specifically designed or marketed for agricultural use, sometimes with integrated data transmission capabilities and mobile app integration. While practical and economic considerations are important purchasing factors, measurement accuracy is equally critical. However, customers typically lack the means to easily and independently evaluate the accuracy of these sensors.

In this study, we evaluated the accuracy of 10 EM-based SMPSs for soil water content estimation. However, EM properties of soil are influenced by several factors, including the

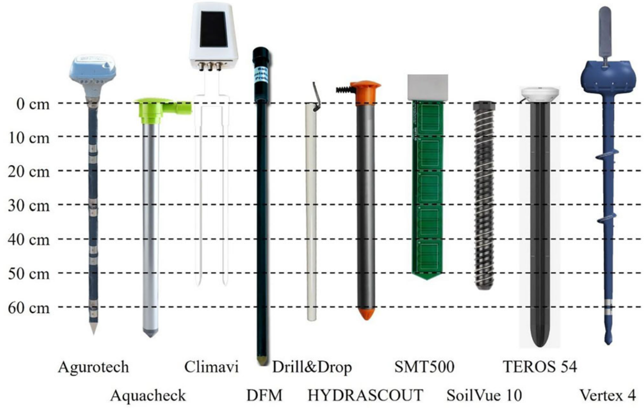

FIGURE 1 Overview of the tested soil moisture profile sensors (SMPSs).

temperature dependency of the dielectric permittivity (Roth et al., 1990), its electrical conductivity (Schwartz et al., 2013), and the sensor operating frequency (Loewer et al., 2017), among others. All these confounding factors are known to affect the measurement accuracy of EM-based soil water content sensors. Therefore, several testbed studies have been performed to evaluate the performance of specific SMPS devices (Bello et al., 2019; Dietrich & Steidl, 2021; Kibirige & Dobos, 2021; Mazahrih et al., 2008; Segovia-Cardozo et al., 2022; Wilson et al., 2023). Most of these studies were performed in natural soils, which makes it difficult to discriminate between small-scale soil heterogeneity and sensor response (Jackisch et al., 2020).

To address these challenges, we designed a repeatable, easy-to-use experimental setup, which we refer to as the sandbox. The sandbox is a 2 m × 2 m × 1.5 m sand body, which is equipped with TDR reference measurements. The sandbox is sealed watertight to all sides, and the water level can be controlled through piezometer tubes to generate repeatable soil water content profiles. A key advantage of the sandbox design is its ability to facilitate simultaneous and repeated testing of multiple sensor types. This ensures high reproducibility of results and provides potential users of SMPS with the ability to compare the performance of different sensor variants in controlled conditions. Ultimately, sandbox tests are dynamic experiments, unlike the static tests that are typically used for sensor calibration (Campora et al., 2020; Gardner et al., 1998). Thus, the sandbox approach also reflects the ability of the tested SMPS to respond to dynamic changes in the soil water profile.

In a previous study (Nieberding et al., 2023), we provided a detailed description of the experimental setup and demonstrated the capability of the sandbox system to accurately assess SMPS measurement accuracy. Building on this work, the present study expands the evaluation from 3 to 10 SMPS devices, offering a comprehensive assessment of SMPS commonly used in agricultural and broader environmental monitoring applications.

Core Ideas

- The measurement accuracy of 10 soil moisture profile sensors was evaluated using a sandbox experiment.
- The sandbox allows dynamic, quick, and repeatable adjustments of soil moisture conditions.
- The measurements of the several tested soil moisture profile sensors differed strongly in the intermediate soil moisture range.

2 | MATERIALS AND METHODS

2.1 | The sandbox design

The sandbox is a 2 m × 2 m × 1.5 m (L × W × D) pit structure filled with sand, sealed watertight on all sides with foil, and covered with a roof to prevent rainwater from entering. The sandbox is homogeneously filled with 130 cm of fine-grained, well-sieved sand (type F36) with an average particle diameter of 163 µm, resting on top of a 20-cm thick drainage layer of gravel. The sand substrate was deliberately chosen to eliminate major confounding factors that interfere with EM soil moisture measurements, that is, it contains no organic matter or clay. The electrical conductivity measured by the SoilVUE10 during the first experiment was consistently below 0.2 dS cm^{-1} (data not shown).

The sandbox is equipped with four piezometer tubes, each only filtered within the drainage layer. By pumping water into or out of the piezometers, the sand body can be homogeneously saturated or drained from below. In contrast to water addition from above, this approach eliminates the effects of preferential flow, which can lead to small-scale heterogeneities in soil moisture. The high saturated hydraulic conductivity of the fine sand (K_{sat} = 24.96 m day^{-1}) enables rapid adjustment of the soil moisture during the experiment (Bechtold, 2012). During preparation of the setup, the sand was filled in 10 cm increments. After each addition, the new layer was carefully leveled and compacted, and the surface was raked to achieve a homogeneous bulk density (~ 1.6 g cm^{-3}) and to minimize layering effects in the sandbox (Bechtold, 2012).

To evaluate the performance of the SMPS, the sandbox is equipped with 18 CS610 TDR sensors (Campbell Scientific Inc.), which were horizontally installed in triplicate in six different depths (5, 15, 25, 35, 45, and 55 cm) during the setup of the experiment. The probes were sampled consecutively using a TDR100 system via SDMX50 multiplexers and a CR1000X data logger (all from Campbell Scientific, Inc., n.d.). By relating the travel time Δt_s (s) of the EM pulse signal to the waveguide length L (m), the dielectric permittivity ε can be calculated as follows:

$$\varepsilon = \left(\frac{c\Delta t_s}{2L}\right) \tag{1}$$

where c is the velocity of light in free space (3×10^8 m s^{-1}) (Campbell Scientific, Inc., n.d.). The empirical, polynomial calibration equation proposed by Topp et al. (1980) was used to calculate the volumetric water content (VWC) (m^3 m^{-3}) from ε. A more detailed description of the full experimental setup can be found in Nieberding et al. (2023).

2.2 | Experimental procedure

The data presented in this manuscript stem from two experimental runs with the sandbox, each comprising a different set of SMPS. The first experiment took place between October 2022 and January 2023, encompassing the Drill&Drop, SMT500, and SoilVUE10 SMPSs (Nieberding et al., 2023). The second experiment in December 2024 comprised the Agurotech, Aquacheck, DFM, Climavi, HYDRASCOUT, TEROS 54, and Vertex V4 SMPSs. For both experiments, three SMPSs of each type were distributed randomly throughout the sandbox (see Figure S1). The experimental procedure differed slightly between the two runs. At the beginning of the first experiment, the sandbox was drained completely and then re-filled stepwise. Between water level adjustments, several days or even weeks passed. For the second experiment, the water table in the sandbox was adjusted in 20 steps over a period of 4 days. At least 120 min were allowed between each step to allow equilibration of the water level in the sand body.

2.3 | Tested SMPS devices

Table 1 and Figure 1 give an overview of the SMPS tested in this study. For the Aquacheck, Drill&Drop, and SoilVUE10 SMPSs, data logging and communication were performed using the SDI-12 protocol with the same CR1000X data logger (Campbell Scientific) as used to control the TDR measurements. The data acquisition interval of all sensors was set to 15 min. At the time of submission, all sensors were commercially available. However, during the experiment the SMT500 was still under development, and a near-market-ready prototype was used. While the different sensors are usually available in many different configurations (probe length, number, and placement of sensors, etc.), only the sensor configuration used in this study is presented here. Furthermore, we only provide information on the operating principle and calibration method if these aspects are sufficiently clear from the sensor information provided. In the following, we provide brief descriptions of each tested SMPS, presented in alphabetical order by model name throughout the manuscript.

2.3.1 | Agurotech

The Agurotech SMPS (Agurotech B.V.) measures soil moisture, electrical conductivity, and soil temperature at depth range centers of 15, 30, 45, and 60 cm. The Agurotech SMPS has a straight, cylindrical shape and was installed in the sandbox after pre-drilling a hole with a drill bit supplied by the manufacturer. The sensor includes an integrated data logging and communication module that transmits the data to the web and a mobile app of the manufacturer, where the measurements are visualized in near-real time and directly output as soil moisture values.

2.3.2 | AquaCheck

The AquaCheck SMPS (AquaCheck Pty Ltd.) is 60 cm long and has a diameter of 32 mm. This FDR sensor measures soil moisture and soil temperature at six depths: 10, 20, 30, 40, 50, and 60 cm. The sensor was installed into the ground after pre-drilling a hole using a drill bit with 30 mm diameter. The sensor provides a scaled frequency (SF) with values between 0 and 100 that is converted into soil moisture (θ) using a linear equation:

$$\theta = a + \mathrm{SF} \times b \tag{2}$$

with the sand-specific calibration coefficients $\boldsymbol{a} = -8.6463$ and $\boldsymbol{b} = 0.5219$.

2.3.3 | Climavi

The Climavi SMPS (Agvolution GmbH) uses capacitance technology to measure soil moisture between two parallel sensor plates spaced 5 cm apart, at depth range centers of 10, 0, and 45 cm (Maier et al., 2023). The sensor outputs a normalized capacitance (C_{norm}) that is first converted into normalized permittivity ($\varepsilon_{\mathrm{norm}}$):

$$\varepsilon_{\mathrm{norm}} = \frac{b}{1/\left(C_{\mathrm{norm}} - a\right)} \tag{3}$$

TABLE 1 Overview of the tested soil moisture profile sensors.

Model	Manufacturer	Measurement principle	Depth range centers (cm)	Net unit price (~€)
Agurotech	Agurotech	Proprietary	15, 30, 45, 60	1100
Aquacheck	Aquacheck	FDR	5, 15, 25, 35, 45, 55	650
Climavi	Agvolution	Capacitance	10, 30, 45	1080
DFM CLP5-SR80	DFM	FDR at 100 to 110 MHz	5, 15, 25, 35, 55, 75	425
Drill&Drop	Sentek	FDR	5, 15, 25, 35, 45, 55	800
HYDRASCOUT H-0606	HSTI France	FDR	5, 15, 25, 35, 45, 55	843
SMT500	TRUEBNER	TDR	5, 15, 25, 35, 45	400
SoilVue 10	Campbell Scientific	TDR	5, 10, 20, 30, 40, 50	1600
TEROS 54	Metergroup	Capacitance at 70 MHz	15, 30, 45, 60	890
Vertex V4	CropX	ADR	20, 35, 60	700

Abbreviations: ADR, amplitude domain reflectometry; FDR, frequency domain reflectometry; TDR, time-domain reflectometry.

with $a = 0.5$ and $b = 1 - a$. VWC is then calculated from $\varepsilon_{\mathrm{norm}}$ using the calibration equation presented by Gardner et al. (1998):

$$\theta = \frac{\sqrt{\varepsilon_{\mathrm{norm}}} - a - c \times \rho}{b} \tag{4}$$

with the soil-specific calibration coefficients for "Fine sand" $a = 0.23$, $b = 8.4$, $c = 0.765$, and $\rho = 2.35$. The sensor is inserted into the soil after pre-piercing with a manufacturer-supplied installation tool. For data acquisition, the sensor comes with a solar-powered datalogger using IoT technology to transmit the data directly to the manufacturer's server. Additional measurements of air temperature, humidity, and solar radiation are included in the IoT unit. A web and mobile application can be used for real-time data visualization and to download the data.

2.3.4 | DFM CLP5-SR80

The DFM CLP5-SR80 SMPS (DFM Technologies Pty Ltd.) uses an FDR approach in the 100–110 MHz range to measure soil moisture (Myeni et al., 2021). Following the instructions from the manufacturer, the sensor outputs the soil water content in mm (θ_{mm}) that is converted to volumetric soil water content (θ) by multiplying the frequency scaled fraction ($\theta_{\mathrm{mm}}/90$) with the porosity ($\phi = 0.392$) of the soil:

$$\theta = \phi \times \theta_{\mathrm{mm}}/90. \tag{5}$$

The 80-cm long DFM CLP5-SR80 sensor measures soil moisture and soil temperature at six depth centers of 10, 20, 30, 40, 60, and 80 cm. The sensor has a diameter of 25 mm and was installed in the sandbox after pre-drilling a hole with a slim auger. The measurements were recorded internally every 15 min and retrieved using a hand-held device.

2.3.5 | Drill&Drop

The 60 cm long Drill&Drop SMPS (Sentek Pty Ltd.) measures soil moisture using FDR technology, as well as soil temperature and electrical conductivity (optionally) at six different depth range centers of 5, 15, 25, 35, 45, and 55 cm. The sensor outputs an SF that is converted to soil water content (θ) using the generic calibration coefficients $a = 0.232$, $b = 0.410$, and $c = -0.021$:

$$\theta = \left(\frac{\mathrm{SF} - c}{a}\right)^{1/b}. \tag{6}$$

The Drill&Drop sensor has a slightly tapered shape, with a 30 mm outer diameter at the top and 27.5 mm at the bottom, and is inserted into the soil after pre-drilling a hole using a manufacturer-supplied drill bit matching the sensor's conical shape. This design aims to provide better soil contact than a straight cylindrical shape.

2.3.6 | HYDRASCOUT H-0606

The HYDRASCOUT H-0606 SMPS (HSTI) uses FDR technology to measure soil moisture and soil temperature at six different depth range centers of 10, 20, 30, 40, 50 and 60 cm (Bello et al., 2019). The sensor output is a SF that is converted to VWC (θ) using the following calibration equation:

$$\theta = \alpha \times e^{\beta \mathrm{SF}} \tag{7}$$

with the sand-specific calibration coefficients $\alpha = 3.21$ and $\beta = 0.033$. The sensor has a straight cylindrical shape with a shaft diameter of 50 mm. The tested sensors were installed in the sandbox after pre-drilling a hole using an Edelman auger with 48 mm diameter. The tested sensors were installed with an offset of -5 cm to match exactly with the measurement depths of the TDR reference sensors (5, 15, 25, 35, 45, and 55 cm). The sensor was operated using the manufacturer-supplied IoT device.

2.3.7 | SMT500

The SMT500 sensor (TRUEBNER GmbH) determines the volumetric soil water content of the surrounding soil using the TDR principle. With its slim, plate-like shape (50 cm × 9 cm × 0.2 cm), the SMT500 can be installed directly into the soil, ensuring optimal soil contact. In harder soils, the soil may need to be pre-pierced with a simple installation tool provided by the manufacturer. The sensor determines the time (t) it takes an EM signal to travel along a circuit board and reach a certain voltage level, thereby integrating the signal across depth ranges of 0–10, 10–20, 20–30, 30–40, 40–50 cm. By subtracting the travel time measured in air (t_a), the volumetric soil water content (θ) can be calculated using a second order polynomial:

$$\theta = a \times \left(t - t_a\right)^2 + b \times \left(t - t_a\right) + \boldsymbol{c} \tag{8}$$

with the calibration coefficients a = 1.08686, b = 2.30166, and c = −2.27044.

2.3.8 | SoilVue 10

The SoilVue 10 sensor (Campbell Scientific Inc.) uses TDR technology to measure the travel time along helical waveguides at depth range centers of 5, 10, 20, 30, 40 and 50 cm (Wilson et al., 2023). The embedded waveguides extend ± 2.5 cm above and below the depth range centers, thereby defining the vertical sensing dimensions. The 50-cm long sensor has a threaded design with 52 mm diameter without the threads and 58 mm diameter including the threads. With the threaded design, the manufacturer aims for good soil contact and minimization of preferential flow along the sensor. The SoilVue 10 sensor uses the same equation as the TDR reference sensor (Equation 1) to convert the EM signal travel time along the embedded waveguides into dielectric permittivity. The volumetric soil water content is then calculated using a mixing model that accounts for the low permittivity of the plastic core (https://www.campbellsci.com/SoilVue 10). After pre-drilling a hole with an Edelman auger with 50 mm diameter, the sensor was installed by threading it into place.

2.3.9 | TEROS 54

The TEROS 54 SMPS (METER Group Inc.) is a capacitance sensor that determines the dielectric permittivity of the surrounding medium via a 70 MHz EM wave that responds to the material's dielectric properties. The TEROS 54 provides a raw value (RAW) corresponding to the soil dielectric permittivity, which is then converted to VWC using a third-order polynomial:

$$\theta = a \times \mathrm{RAW}^3 + b \times \mathrm{RAW}^2 + c \times \mathrm{RAW} + d \tag{9}$$

with the generic calibration coefficients for mineral soils $a = 1.8543 \times 10^{-9}$, $b = -4.1231 \times 10^{-5}$, $c = 3.1015 \times 10^{-2}$, and $d = -7.7224$. The 75-cm long sensor has a cross-shaped design with 6 cm diameter and measurement range centers at 15-, 30-, 45-, and 60-cm depth. Using the manufacturer-provided tools, the sensor was installed by first preparing a hole with a slim auger and then hammering it in with a falling weight mounted along a pole on the sensor head. In the experiment, the TEROS 54 sensors were operated using a SoilNet V5 NB-IoT data logging unit (Bogena, 2025) via SDI-12 communication.

2.3.10 | Vertex V4

The Vertex V4 SMPS (CropX) is an impedance sensor that measures soil moisture by determining the amplitude of a high-frequency signal amplitude domain reflectometry applied to the soil at three different depth range centers (20, 40, and 66 cm). The amplitude measurements are converted to VWC using a proprietary self-calibration method (CropX, 2025). For this study, the Vertex V4 sensors were installed with a 5 cm elevation offset, resulting in measurement depth range centers of 15, 35, and ~60 cm (Figure 1). The sensor features a threaded design and was installed according to manufacturer guidelines after pre-drilling a hole with the provided drill bit. For data acquisition, the sensor features a built-in IoT datalogger to transmit data directly to the manufacturer's server, and a web or mobile application enables real-time visualization and data download.

2.4 | Data homogenization

Several calibration equations exist for the different sensors. To ensure comparability between the different sensors, we used the best fitting calibration relationship if multiple options were available. Most manufacturers provided a sand-specific calibration equation (Aquacheck, Agurotech, DFM, Drill&Drop, HYDRASCOUT, and Climavi). When no sand-specific calibration was provided, we show the data with the default calibration equation (Agurotech, SMT500, SoilVue 10, TEROS 54, and Vertex V4). For the Drill&Drop sensor, the default calibration equation produced a higher correlation with the reference measurements than the sand-specific calibration. Therefore, the default calibration was used.

Because the different SMPSs were operated using different data loggers, the sensor acquisition times differed between the systems. Hence, it was not possible to synchronize all measurements to the exact same timestep. To maintain comparability between the sensor readings, only data acquired during the last 15 min before each soil moisture adjustment was used for sensor evaluation. An additional time difference may have been introduced due to the serial TDR data acquisition using multiplexers. However, the first and last of the 18 TDR readings only showed a small time difference of about 30 s.

The tested SMPS differ in measured volume, vertical integration, as well as the number and depth ranges of the soil moisture measurements. To allow an intercomparison between the SMPS and TDR sensors, we compared measurements from the same "depth range center." Depth mismatches of up to 5 cm between SMPS and TDR sensors were addressed by linear interpolation among the measurement depths.

At the beginning of Experiment 1 (i.e., before October 26, 2022, 10:00 a.m.), the operation of the TDR measurements through multiplexers caused some spikes in the measured time series that were removed by filtering. In addition, implausibly high values >0.41 $m^3\ m^{-3}$ were also removed throughout the measurement period.

2.5 | Data processing

For the comparison of the inter- and intra-sensor performance, the root mean squared error (RMSE) and R^2 are reported as basic performance metrics. Because the sand used (type F36) has a steep soil water retention curve, under equilibrium conditions only a thin soil layer exhibits intermediate soil moisture conditions. Consequently, intermediate soil moisture is measured only by few sensor segments while most sensor segments experience dry or wet conditions, resulting in a bimodal soil moisture sample distribution. To reduce this dominance of dry and wet states when calculating RMSE, we additionally calculated the quantile-balanced RMSE ($RMSE_{QB}$) as follows: First, the reference soil moisture values (TDR) were binned into five quantile ranges (Q_j) based on their empirical distribution. Next, the RMSE was computed separately for each quantile range Q_j as

$$\mathrm{RMSE}_j = \sqrt{\frac{1}{n_j}\sum_{i\in Q_j}(y_i - x_i)^2} \tag{10}$$

where y_i and x_i denote reference and SMPS soil moisture values, respectively, and n_j is the number of observations within each quantile j. Finally, the overall $RMSE_{QB}$ was calculated for each SMPS, with equal weight across all J quantiles:

$$\mathrm{RMSE}_{\mathrm{QB}} = \sqrt{\frac{1}{J}\sum_{j=1}^{J}\mathrm{RMSE}_j^2} \tag{11}$$

This approach allows a more balanced evaluation of sensor performance across the full soil-moisture range while preserving the interpretability of RMSE.

The total error between SMPS and TDR measurements was decomposed into an inter-sensor and intra-sensor component (SMPS and TDR). Assuming independence of both error sources, the total error variances ($RMSE^2_{total}$) were computed as the quadratic sum of inter- and intra-sensor RMSE:

$$\mathrm{RMSE}^2_{\mathrm{total}} = \mathrm{RMSE}^2_{\mathrm{inter}} + \mathrm{RMSE}^2_{\mathrm{SMPS,intra}} + \mathrm{RMSE}^2_{\mathrm{TDR,intra}} \tag{12}$$

This decomposition allows a direct assessment of whether observed discrepancies are dominated by sensor-specific biases or by sensor-to-sensor variability.

All data homogenization and processing were performed using Python and R software for statistical computing (R Core Team, 2025). The data and code are freely available and can be obtained from a repository.

3 | RESULTS

3.1 | Time series of SMPS measurements

As demonstrated in Figure 2, all SMPS provided plausible and consistent measurements during Experiment 1. Some differences can be observed in intra-sensor variability, that is, the consistency between sensor replicates. Most sensors exhibited a low sensor-to-sensor variability during Experiment 1, whereas higher variability was observed for the SoilVue 10 SMPS. During the extended period of Experiment 1, the TDR sensors exhibited some random noise, probably caused by the algorithm used to estimate dielectric permittivity.

Experiment 2 (see Figure 3) revealed notable differences between the different sensors. For instance, the DFM sensor captured the same general pattern as the TDR sensors but with reduced variability. Additionally, the measurements from the Agurotech and Vertex V4 SMPSs diverged notably from the other sensors, particularly at greater depths. Higher intra-sensor variability was observed for the Vertex V4 SMPS.

3.2 | Intra-sensor variability

As described in Section 2.4, it was not possible to synchronize all SMPS measurements to the exact same timestamp.

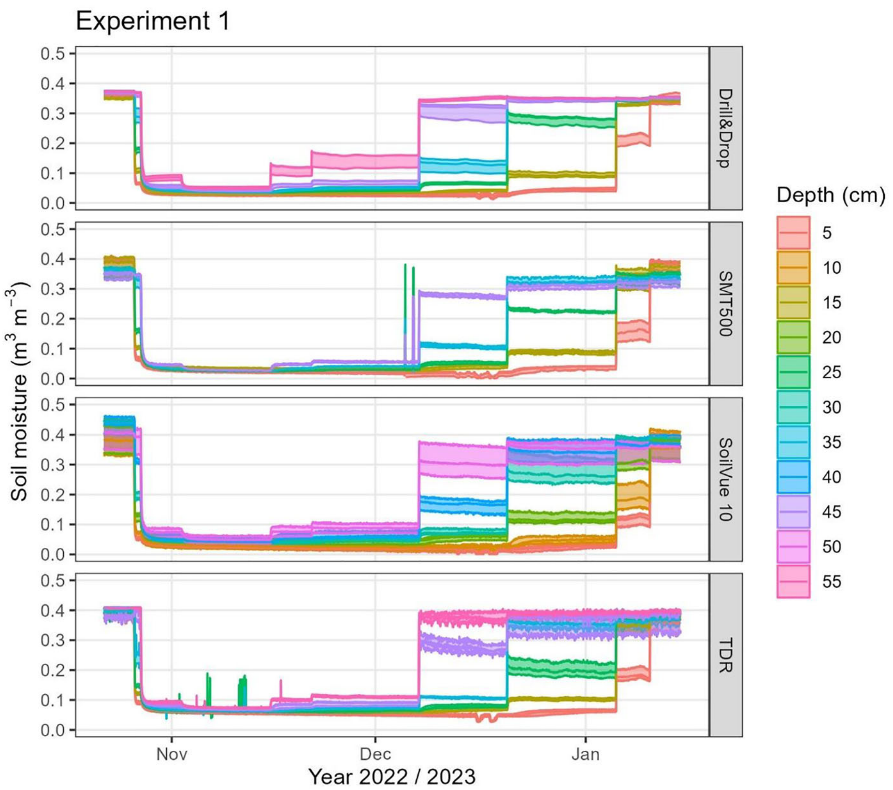

FIGURE 2 Time series of the soil moisture profile sensor (SMPS) and reference soil moisture measurements during the first experiment as presented in Nieberding et al. (2023). The central lines depict the median and the shaded areas the maximum and minimum soil moisture measurements in the respective depths. TDR, time-domain reflectometry.

To ensure comparability of the measurements, only the last measurement before each water table adjustment (i.e., at equilibrium) was used for the following analyses. To further evaluate the intra-sensor variability (i.e., the variability between sensor replicates from the same manufacturer), the RMSE and $\mathrm{RMSE_{QB}}$ between the mean and each of the three replicate measurements were calculated for each time step, providing a measure for the variability between the three replicate measurements (Figure 4). The $\mathrm{RMSE_{QB}}$ was always higher than the RMSE, indicating that the sampling imbalance indeed masks the intra-sensor variability when using the conventional RMSE to some extent. Most sensors exhibited low intra-sensor variability, except for the Vertex V4 ($\mathrm{RMSE_{QB}}$ = 0.031 m^3 m^{-3}) and SoilVue 10 ($\mathrm{RMSE_{QB}}$ = 0.025 m^3 m^{-3}) sensors. Interestingly, both sensors use a threaded design intended to improve soil contact and reduce variability due to installation. Very low intra-sensor variability was observed for the Aquacheck ($\mathrm{RMSE_{QB}}$ = 0.007 m^3 m^{-3}) and DFM ($\mathrm{RMSE_{QB}}$ = 0.007 m^3 m^{-3}) sensors. Intermediate variability was found for the Agurotech ($\mathrm{RMSE_{QB}}$ = 0.009 m^3 m^{-3}), Drill&Drop ($\mathrm{RMSE_{QB}}$ = 0.010 m^3 m^{-3}), TEROS 54 ($\mathrm{RMSE_{QB}}$ = 0.012 m^3 m^{-3}), SMT500 ($RMSE_{QB}$ = 0.014), Climavi ($\mathrm{RMSE_{QB}}$ = 0.014 m^3 m^{-3}), and Hydrascout ($\mathrm{RMSE_{QB}}$ = 0.015 m^3 m^{-3}) sensors. The 3 × 6 horizontally installed TDR sensors exhibited an overall $\mathrm{RMSE_{QB}}$ of 0.014 m^3 m^{-3}. While $\mathrm{RMSE_{QB}}$ was below 0.010 m^3 m^{-3} at 15-, 35-, and 55-cm depth, measurements at 5-, 25-, and 45-cm depth showed a higher spread (data not shown), resulting in a moderate overall sensor-to-sensor variability. For the evaluation of the SMPS performance, the larger intra-sensor variability of the TDR measurements will be explicitly addressed in Section 3.4.

3.3 | Comparison between tested SMPS

Figures 5 and 6 visualize the correlations between all tested SMPSs installed in parallel during the two experiments following the approach of Jackisch et al. (2020). Because of the different number and depths of the individual measurements along the SMPS, only measurements and interpolated values between 15 and 45 cm were used for the comparison. Although it does not cover the entire root zone, this approach provides a fair comparison between all SMPSs.

During the first experiment (Figure 5), most sensor combinations showed high consistency as indicated by low RMSE and $\mathrm{RMSE_{QB}}$ and high R^2. The slope and offset were also low, indicating high overall agreement between the measurements. In the second experiment (Figure 6), more pronounced deviations between the SMPS were observed. Most sensor

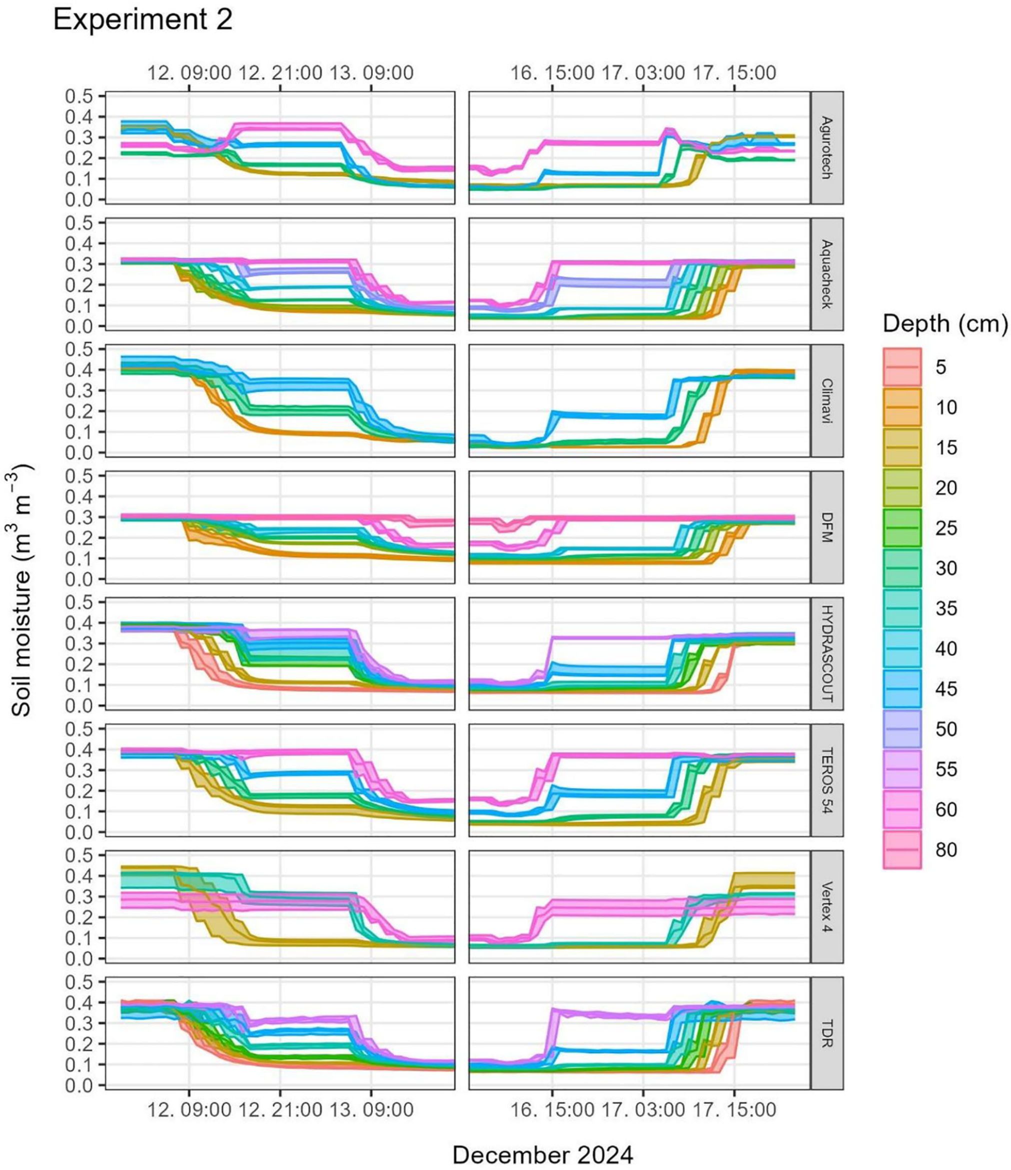

FIGURE 3 Time series of the soil moisture profile sensor (SMPS) and reference soil moisture measurements during the second experiment in 2024. The central lines depict the median and the shaded areas the maximum and minimum soil moisture measurements in the respective depths. TDR, time-domain reflectometry.

combinations exhibited low offset values ±0.05 m^3 m^{-3}, indicating good agreement at low soil moisture conditions. The DFM sensor showed particularly large offsets of up to −0.127 m^3 m^{-3}, for example, when compared with the TEROS 54. Overall, the DFM sensor also exhibited the largest deviations in slope, followed by the Agurotech and Vertex V4 sensors. As indicated by the orange boxes, the DFM-TEROS 54 combination is also among the group of sensor pairs with $RMSE_{QB}$ ≤ 0.05 m^3 m^{-3} and R^2 ≥ 0.95, indicating low variability between their measurements. The pronounced difference in slope and offset, combined with a high R^2 suggests that appropriate sensor calibration could substantially reduce the slope and offset of some sensor combinations. This is also true for the other sensor combinations Aquacheck–TEROS 54, Aquacheck–TDR, Climavi–DFM, Climavi–HYDRASCOUT, Climavi–TEROS 54, DFM–TEROS 54, and TEROS 54–TDR, which are marked by orange boxes.

Figures S2 and S3 in the supporting information present the same data but averaged over available measurements between 5 and 45 cm (i.e., without any interpolation). This allows for a comparison of the sensors' ability to represent root zone-soil moisture, independent of the available measurement depths of the individual sensors. By comparing the vertically averaged soil moisture measurements, the data points are more evenly distributed and show less pronounced bimodality than when comparing individual segments (Figures 5 and 6). Albeit

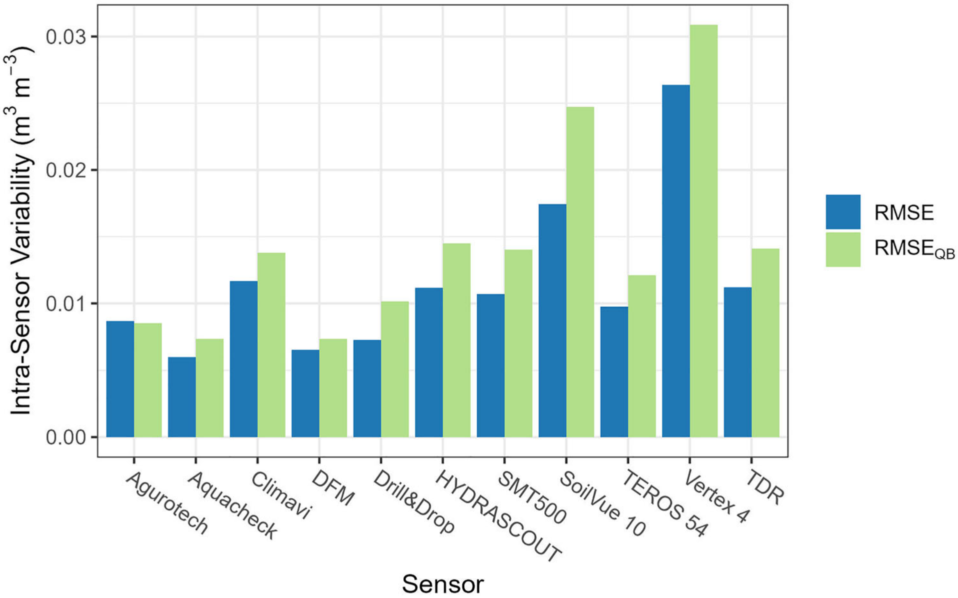

FIGURE 4 Bar plot showing intra-sensor variability of the soil moisture profile sensor (SMPS) expressed as the RMSE and $RMSE_{QB}$ between replicate soil moisture measurements and the mean of the replicates. TDR, time-domain reflectometry.

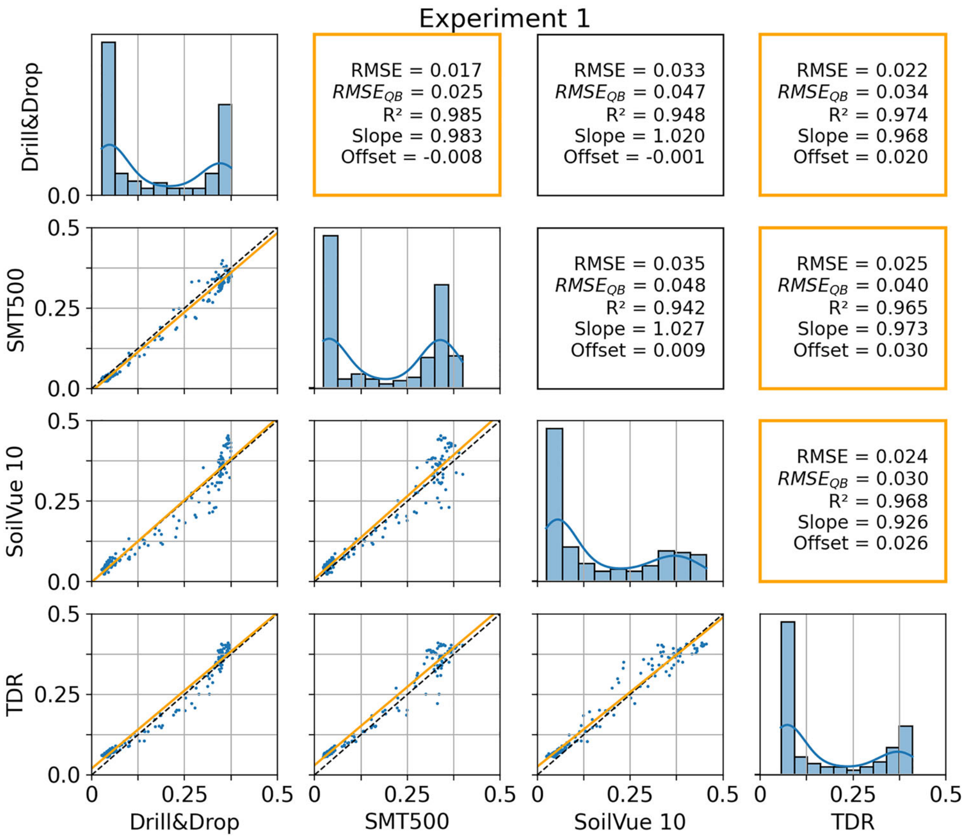

FIGURE 5 Correlation visualization for Experiment 1, showing measured and interpolated volumetric water content (VWC) values between 15- and 45-cm depth. The lower left panels show scatter plots between sensors, with the linear correlation indicated by the yellow line. The central histograms show the number of observations distributed across 10 bins each, while the top right panels indicate key error metrics: RMSE, $RMSE_{QB}$, R^2, slope, and offset from the 1:1 line. Sensor combinations with $RMSE_{QB} \leq 0.05$ m^3 m^{-3} and $R^2 \geq 0.95$ are indicated by orange boxes. TDR, time-domain reflectometry.

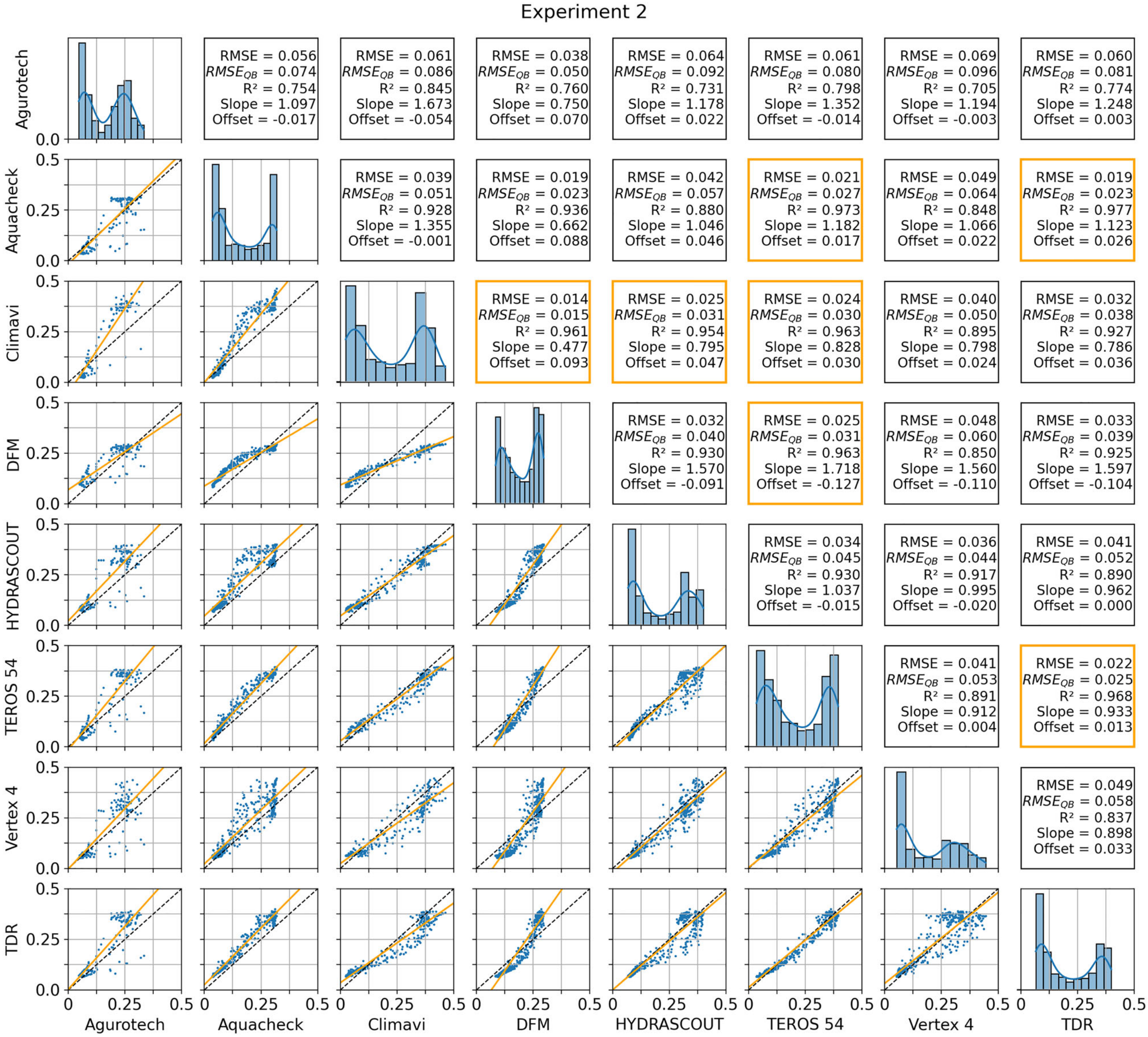

FIGURE 6 Correlation visualization for Experiment 2 across interpolated and measured volumetric water content (VWC) values between 15- and 45-cm depth. The lower-left panels show scatter plots between sensors, with the linear correlation indicated by the yellow line. The central histograms show the number of observations distributed across 10 bins each, while the top right panels indicate key error metrics: RMSE, $\mathrm{RMSE_{QB}}$, R^2, slope, and offset from the 1:1 line. Sensor combinations with $\mathrm{RMSE_{QB}} \le 0.05\ \mathrm{m^3\ m^{-3}}$ and $R^2 \ge 0.95$ are indicated by orange boxes. TDR, time-domain reflectometry.

with the much smaller number of data points, the results of the two data integration techniques (interpolated vs. averaged) are largely consistent, corroborating the adequacy of the interpolation technique.

3.4 | Comparison between SMPS and TDR measurements

For the evaluation of the measurement accuracy, a comparison between the SMPS and the continuously installed TDR sensors is presented in the following. To account for different measurement depth centers, the TDR measurements were linearly interpolated between the individual depths, and the interpolated values were used for comparison with the SMPS measurements.

The analysis revealed substantial variation in measurement accuracy for the tested sensors (Figure 7), indicating that not all sensors performed equally well under the same experimental conditions. Several SMPSs closely followed the 1:1 reference line, demonstrating high accuracy and consistency with the TDR measurements. Among the sensors that demonstrated the highest measurement accuracy were the Drill&Drop (R^2 = 0.98, RMSE = 0.026 $\mathrm{m^3{\cdot}m^{-3}}$, $\mathrm{RMSE_{QB}}$= 0.0334 $\mathrm{m^3\ m^{-3}}$), SoilVue 10 (R^2 = 0.97, RMSE = 0.034 $\mathrm{m^3{\cdot}m^{-3}}$, $\mathrm{RMSE_{QB}}$= 0.046 $\mathrm{m^3\ m^{-3}}$), TEROS 54

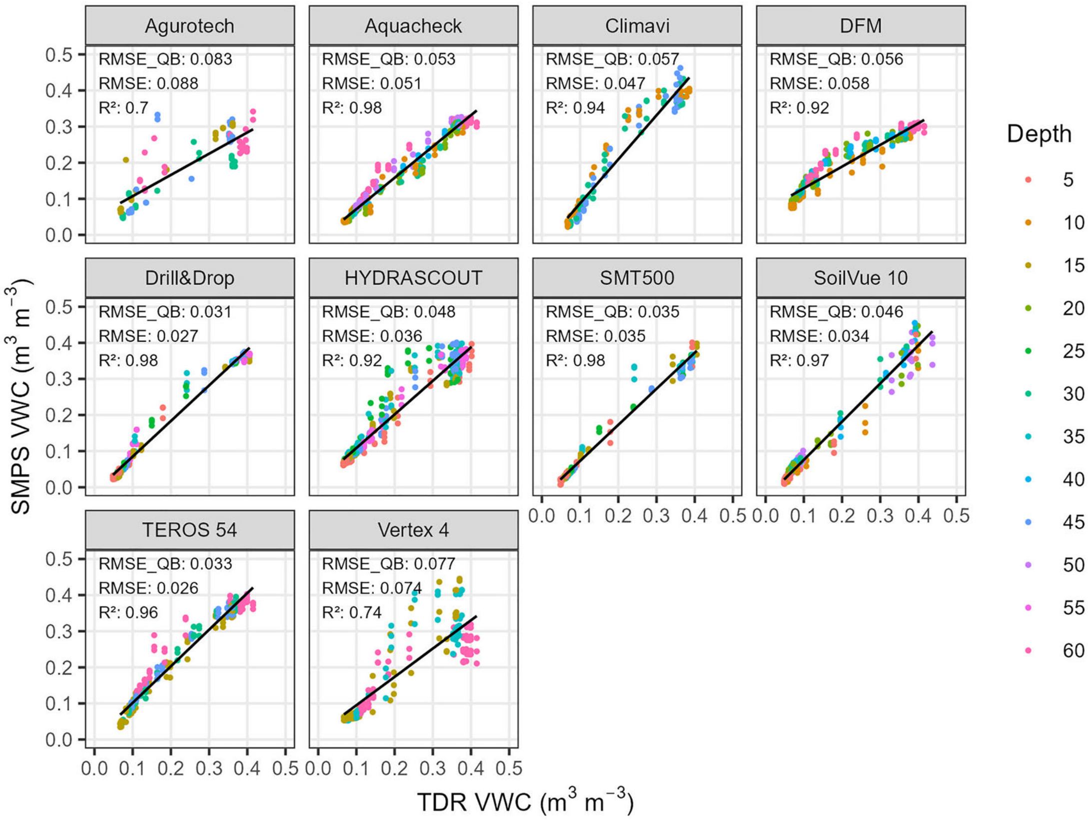

FIGURE 7 Scatter plot of soil moisture measured by all soil moisture profile sensor (SMPS) and SMT100 sensors versus time-domain reflectometry (TDR) measurements at different depths. VWC, volumetric water content.

(R^2 = 0.96, RMSE = 0.026 m^3·m^{-3}, RMSE$_{QB}$= 0.033 m^3 m^{-3}), and the SMT500 (R^2 = 0.98, RMSE = 0.035 m^3·m^{-3}, RMSE$_{QB}$= 0.0358 m^3 m^{-3}). These SMPSs showed strong linear correlations (R^2 > 0.9) with the TDR reference measurements and relatively low root mean squared errors (RMSE ≤ 0.036 m^3·m^{-3}).

For most of these sensors, RMSE$_{QB}$ was substantially higher than the conventional RMSE, indicating that a considerable fraction of the overall error originated from measurements in the intermediate soil moisture ranges, while deviations in the high and low soil moisture ranges were comparatively small. In contrast, for the Drill&Drop and SMT500 sensors, RMSE and RMSE$_{QB}$ were nearly identical, suggesting a more uniform error distribution across the investigated soil moisture range.

The Agurotech (R^2 = 0.70, RMSE = 0.088 m^3·m^{-3}, RMSE$_{QB}$= 0.083 m^3 m^{-3}) and the Vertex V4 sensor (R^2 = 0.74, RMSE = 0.074 m^3·m^{-3}, RMSE$_{QB}$= 0.077 m^3 m^{-3}) displayed stronger deviations from the reference measurements. In both cases, considerable deviations from the 1:1 line and a pronounced scatter were observed, particularly within the intermediate soil moisture range that is often critical for field-based agricultural and hydrological applications. The comparatively high RMSE$_{QB}$ values indicate that these deviations cannot be attributed solely to extreme moisture conditions but also affect the central moisture range.

A third group of sensors consisting of the Aquacheck (R^2 = 0.98, RMSE = 0.051 m^3·m^{-3}, RMSE$_{QB}$= 0.053 m^3 m^{-3}), DFM (R^2 = 0.92, RMSE = 0.058 m^3·m^{-3}, RMSE$_{QB}$= 0.05 6 m^3), Climavi (R^2 = 0.94, RMSE = 0.047 m^3·m^{-3}, RMSE$_{QB}$= 0.05m^3 m^{-3}), and HYDRASCOUT (R^2 = 0.92, RMSE = 0.036 m^3·m^{-3}, RMSE$_{QB}$= 0.048 m^3 m^{-3}) SMPSs demonstrated moderate performance. These devices generally showed an acceptable correlation with the TDR measurements (R^2 > 0.9), but their measurements showed some nonlinearity and different slope compared with the reference measurements. However, a large portion of uncertainty may have arisen from the calibration equation used to convert the raw sensor readings into soil moisture. Hence, an adequate, soil-specific recalibration would put this cohort of SMPS together with the best performing SMPS.

As indicated in Section 3.2, the intra-sensor variability of the SMPS and TDR sensors can be considerable. When comparing different SMPSs against the TDR sensors, it is thus necessary to account for the combined inter- and intra-sensor variability of the tested and reference measurements. Figure 8 shows which portion of the error variance (RMSE^2) between SMPS and TDR sensors can be attributed to the intra-

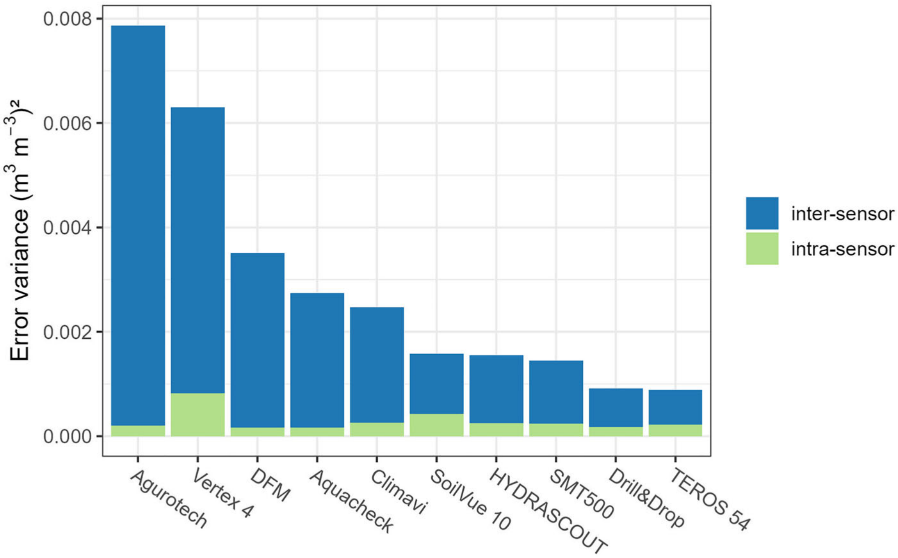

FIGURE 8 Comparison of inter- and intra-sensor error variance (RMSE^2) between the tested soil moisture profile sensor (SMPS) and time-domain reflectometry (TDR) measurements.

sensor variability (Equation 12). Corroborating the previous findings, the Vertex V4 sensor has the highest combined variance. Generally, the relative importance of the intra-sensor variability is low but increases with decreasing inter-sensor variability. The TEROS 54 and Drill&Drop sensors exhibit the lowest combined error variance. These findings corroborate the high accuracy of these sensors. Only the SoilVue 10 and Vertex V4 sensors exhibit slightly increased intra-sensor variance, indicating that for the SoilVue 10, an even better measurement accuracy could probably be achieved with optimal sensor installation.

4 | DISCUSSION

Comparative evaluations of soil moisture sensors have a long tradition, but most studies focus on either single-point sensors or single manufacturers, often under controlled laboratory conditions or uncontrolled field conditions (Adla et al., 2020; Blonquist et al., 2005; Leib et al., 2003). To our knowledge, we present the first extensive intercomparison evaluation of SMPS under varying yet consistent boundary conditions.

For this study, individually installed TDR probes were used as reference sensors due to their physically based measurement principle and large, well-defined sampling volume (Sheng et al., 2024). Under the experimental conditions (i.e., homogeneous fine sand and low electrical conductivity), the assumptions underlying the dielectric mixing models employed for TDR measurements are well fulfilled (Roth et al., 1990; Topp et al., 1980). Although carried out carefully, the horizontal installation of the individual TDR probes may have led to the observed moderate intra-sensor variability. Even small variations in measurement depth could be amplified by the steep soil water retention characteristics of the F36 sand. Determining the reference soil moisture using a more direct measurement approach, such as gravimetric soil sampling could potentially provide greater accuracy but was not feasible during the experiment due to its destructive nature.

Importantly, the explicit quantification of intra-sensor variability allows disentangling inter-sensor variability from measurement and installation uncertainty inherent to both sensor systems. This study found that sensor-to-sensor variability was relatively high and sometimes of the same magnitude as the variability between different sensor types. Our findings are consistent with the open-field comparison by Jackisch et al. (2020), who evaluated a wide range of soil moisture and matric potential sensors across different technologies and manufacturers. Their study highlighted that even sensors based on similar dielectric methods can show substantial differences in accuracy and variability. Comparable conclusions have also been drawn in other multi-sensor evaluations, where installation effects, calibration strategy, and sensing geometry were shown to be as influential as the underlying measurement principle (Mazahrih et al., 2008).

The experiments were conducted using fine sand, which was chosen for its high hydraulic conductivity and minimal confounding factors, such as organic matter and clay content. However, this choice also introduced some limitations. For this study, the allowed times to reach equilibrium differed strongly from several weeks during Experiment 1 down to 120 min during Experiment 2. For the sandy substrate used, a slightly longer waiting time of maximum 24 h would have been beneficial. Additionally, the soil water retention curve of the used sand is very steep, making it challenging to obtain soil moisture measurements in the intermediate soil moisture range with the sandbox experiment. In contrast, finer textured soils, such as loamy sand, exhibit smoother retention curves, potentially alleviating this challenge. However, such soils would also have a lower hydraulic conductivity, resulting in significantly longer equilibrium times during the sandbox experiment. This trade-off should be considered when designing calibration or validation experiments.

One potential solution is to use mixed soil-like substrates that combine adequate hydraulic conductivity with a broad plant-available water range (Wang et al., 2017). This could be achieved using two-component mixtures (Willaredt & Nehls, 2021), for example, by adding silt material to the F36 sand. However, de-mixing effects may occur during preparation of the soil pit using two substrates with narrow particle size distributions. Furthermore, it must be considered that the ability to reach dry conditions is limited by the vertical dimensions of the sandbox. Hence, a material must be selected that drains completely at the maximum reachable suction, which is 130 hPa in case of the sandbox.

Among the tested SMPS, not all sensors measured at the same depths as the TDR reference sensors. Furthermore, measurement uncertainties may arise from differences in measurement volumes and vertical integration characteristics of the various SMPSs. For example, the SoilVue 10 measures along the helical waveguides, which expand about ±2.5 cm in vertical direction from the measurement centers (Wilson et al., 2023). In contrast, the SMT500 integrates the signal over a full 10-cm vertical segment (Nieberding et al., 2023). Because not all manufacturers provided detailed information about the sensors' sampling volumes, we compared the SMPS and TDR measurements at the same depth range center. However, this approach may have introduced additional uncertainty in the sensor comparison, particularly under conditions with steep soil moisture gradients. Greater transparency from manufacturers regarding sensor sampling volumes would enable more accurate and meaningful sensor evaluations. A standardized approach should be used to evaluate the horizontal and vertical dimensions around the sensor (e.g., Sheng et al., 2024).

In this study, a sandy substrate was used to focus on sensor performance without the influence of confounding factors that could complicate comparisons. To generalize sensor performance across broad field conditions, further studies are required. For instance, soil-packing approaches, albeit laborious, are suitable for evaluating sensor performance across different soil textures (e.g., Payero et al., 2017). Additionally, lysimeter systems with packed sand can be used to investigate the effects of confounding factors on SMPS performance, such as temperature effects under saturated conditions (e.g., Nieberding et al., 2023). Alternatively, dielectric liquid tests offer a standardized, soil-independent method to assess sensor response under varying salinity or temperature conditions (Blonquist et al., 2005). For instance, Schwank et al. (2006) developed a dedicated, solvent-resistant measurement container filled with dioxane–water mixtures to investigate temperature effects on an access-tube-based capacitance soil moisture sensor.

5 | CONCLUSIONS

In this study, we evaluated the accuracy of 10 commercially available SMPSs for estimating water availability in the root zone. Under controlled moisture conditions in sandy soil, we observed substantial variability in the measurement accuracy among the tested SMPS. Several sensors, including Drill&Drop, TEROS 54, SMT500, SoilVue 10, and HYDRASCOUT, showed high agreement with the TDR reference measurements ($\mathrm{RMSE_{QB}} \leq 0.050$ $\mathrm{m^3 m^{-3}}$). Other sensors exhibited systematic offsets, increased scatter, or nonlinear behavior. The sensor evaluation conducted in a homogeneous sandy soil represents a simplified measurement scenario due to the absence of confounding factors. On the downside, the steep water retention characteristics of the sand material used in our experiments made it challenging to obtain stable soil moisture in the intermediate range and probably led to higher than expected intra-sensor variability of the TDR reference measurements ($\mathrm{RMSE_{QB}} = 0.014$ $\mathrm{m^3\ m^{-3}}$). To comprehensively assess sensor accuracy, further testing across diverse soil textures, salinity levels, and temperature regimes is recommended, employing standardized methods such as soil packing or dielectric reference liquids.

AUTHOR CONTRIBUTIONS

Felix Nieberding: Data curation; formal analysis; investigation; methodology; software; visualization; writing—original draft; writing—review and editing. **Johan Alexander Huisman**: Conceptualization; methodology; supervision; validation; writing—original draft; writing—review and editing. **Heye Reemt Bogena**: Conceptualization; funding acquisition; methodology; project administration; resources; supervision; validation; writing—original draft; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The raw data and processing scripts used to generate the presented figures can be downloaded from Jülich DATA repository: https://doi.org/10.26165/JUELICH-DATA/L3IWWM.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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