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From Points to Field Scale: A Decade of Soil-Moisture Monitoring in a German Deciduous Forest (2014–2024)

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ABSTRACT

Long-term, spatially representative soil-moisture records are critical for characterising ecosystem responses to water availability. We present a decade-long (2014–2024) dataset of continuous soil-moisture observations from distributed in situ networks and cosmic-ray neutron sensing (CRNS) across a 1 ha temperate deciduous forest in Germany. Spatial sensor coverage varied over time and challenged the derivation of a consistent spatial average due to the persistence of soil moisture patterns. We therefore implemented a semi-automatic workflow that (i) identifies reference periods via a bootstrap-based minimum required number of sensors (MRNS) and (ii) maps point measurements to the field-scale distribution using empirical CDF transformation. The resulting record provides a coherent long-term signal suitable for ecohydrological analyses and validation of remote-sensing products. Since any decade-scale monitoring will encounter sensor losses and replacements, we emphasise the critical role of robust data integration techniques to ensure the reliability of extended soil moisture datasets.

1 | Introduction

Accurate soil moisture measurements are crucial for assessing ecosystem responses to water availability. Soil moisture influences plant growth, microbial activity, carbon and nutrient cycling, and even local climate conditions (Vereecken et al. 2008; Humphrey et al. 2018, 2021; Green et al. 2019). In situ techniques, which involve direct contact with the soil using instruments such as soil moisture probes or sensors, can provide the required data. Sensors offer the advantage of continuous, near-real-time monitoring, making them ideal for capturing temporal dynamics of soil moisture over long periods. However, the complexity of installing and operating sensors in the ground means that only selected locations can be monitored. In addition to in situ monitoring, soil moisture can be obtained from proximal sensing approaches such as cosmic-ray neutron sensing (CRNS) or from satellite or airborne remote sensing. These methods enable observations over larger spatial domains but ultimately depend on in situ measurements for calibration and validation (Colliander et al. 2017; Schrön et al. 2017).

To validate spatial soil moisture information, it is necessary to bridge the "support gap" between reference measurements from sensors (point scale) and the target product (spatial scales from metres to kilometres), that is, to transfer information from the scale where measurements are obtained to, for example, the ecosystem level or the grid scale of the target product (Pachepsky and Hill 2017). Multiple measurements are required to reliably estimate the spatial mean soil water content, depending on the heterogeneity of the area of interest. Due to the strong influence of local factors on soil water content and dynamics, single sensor measurements are usually not representative for the whole area (Brocca et al. 2009; Heathman et al. 2012; Zhu et al. 2018). Based on a literature review, Crow et al. (2012) concluded that for an area of about 800 m^2 on average 10–20 sensors are required to obtain the field mean with an accuracy of 2 vol. % (1σ) in the top layer. Depending on site-specific characteristics such as topography, vegetation or climate, the actual number of sensors required can range from 1 to 12 sensors (Hupet and Vanclooster 2002) to 42 sensors (Wang et al. 2008) in extreme cases. On the other hand, soil water content measurements at the point scale can show a high level of redundancy in time (Vachaud et al. 1985; Mälicke et al. 2020), a property that can be used for quality assurance in long-term soil moisture time series based on a limited number of sensors (Pachepsky et al. 2005).

Here, we present a dataset consisting of more than 10 years of spatially distributed in situ as well as remotely sensed soil moisture measurements from a CRNS setup in a deciduous forest in Germany. The study site was established in 2013 within the framework of the TERENO project as part of the Central German Lowland Observatory (Wollschläger et al. 2016) and offers a wide range of ecohydrological research opportunities. Data gathered at the research site has been used to study, for example, species composition of mycorrhizal fungi (Marañón-Jiménez et al. 2021), the relationship between climate and litter decomposition (Djukic et al. 2018), validation of soil moisture simulations (Boeing et al. 2022), impact of an extreme drought event on carbon uptake (Pohl et al. 2023) or leaf-out dates of different tree compositions (Delpierre et al. 2024).

In addition to the description of the data, special attention is given to the derivation of a consistent and long-term spatial mean. Due to sensor failures and required re-installation of new sensors, it was necessary to develop a workflow that provides a temporally consistent spatial average soil moisture, for example, one that is faithful to the actual climatic temporal trends despite the presence of spatially and temporally irregular data gaps. Due to the temporal persistence of soil moisture patterns (Vachaud et al. 1985), averaging the remaining data runs the risk of introducing artificial trends in the time series (Vachaud et al. 1985; Pachepsky et al. 2005). Permanent sensor loss also leads to gaps in the time series that traditional gap-filling approaches cannot address (Kornelsen and Coulibaly 2014). Therefore, we present a semi-automated workflow that enables us to account for temporal shifts as a result of the different sensors contributing to the calculation of the spatial average. This approach may also be helpful for other research groups that are facing similar problems when it comes to aligning multiple sensor setups or replacing soil moisture sensors in situations where there are few soil moisture sensors installed overall, such as at eddy covariance sites. The correction is based on the philosophy proposed by Pachepsky et al. (2005), but uses an adapted correction procedure.

2 | Study Site and Design

Data are gathered within a 1 ha fenced area of the Hohes Holz forest (DE-HoH, N52°05′ E11°13′, 193 m above sea level), located in the northern part of the Bode catchment near Magdeburg in central Germany (cf. Figure 1). Since the beginning of 2019, the station has met all required instrumentation and sampling procedures according to the ICOS ecosystem standards for class 1 stations (Franz et al. 2018; Rebmann et al. 2018). Climate in the study area is subatlantic-submontane with a mean annual temperature of 9.1°C and mean annual precipitation of 563 mm (climatic period 1981–2010, station Ummendorf of the German Weather Service). The fenced area is composed of European beech (*Fagus sylvatica* L.) and sessile oak (*Quercus petraea* (Matt.) Liebl.) as dominant species (38% and 45% of total basal area, respectively) with accompanying hornbeam (*Carpinus betulus* L., 13%) with 245 trees in the enclosure.

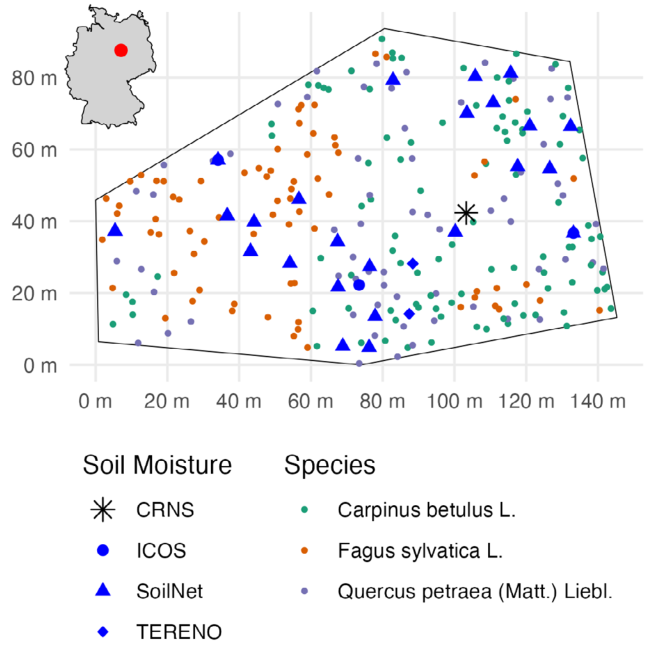

FIGURE 1 | Spatial distribution of soil moisture monitoring profiles, the location of the Cosmic-Ray Neutron Sensor (CRNS) and tree species within the study site. The inset shows the study location within Germany.

Soil water content sensors from a distributed monitoring network (SoilNet-WSN with SPADE sensors, sceme.de GmbH, Germany) (Bogena et al. 2010) were installed in April 2014 and distributed over areas with low and high tree (and thus root) density. The number of in situ sensors originally installed varied from 14 sensors at seven locations per depth at 5, 20, 40, and 50 cm, to 30 sensors at 23 locations at 30 cm, and 34 sensors at 27 locations at 10 cm, in order to better capture near-surface soil moisture dynamics. Note that sensors that worked for only a very short time or delivered erroneous data were excluded from this data release, which is why the actual number of sensors included is lower than the original setup (cf. Figure 2).

Data were collected every 10 min via the network coordinator and stored on a field computer. Soil moisture was also measured in two additional profiles using CS616 sensors (Campbell Scientific Inc., Logan, Utah, USA) to fulfil requirements for the TERENO network (Wollschläger et al. 2016). Likewise, SMT100 sensors (TRUEBNER GmbH, Germany) were additionally installed in 2017 at 4 locations to account for the sensor losses and fulfil requirements of ICOS (Rebmann et al. 2018). These data were also recorded and stored as 10 min averages by a CR1000 data logger (Campbell Scientific Inc., Logan, Utah, USA). Physically unrealistic data were removed using semi-automated procedures that check for outliers (values below zero or above the soil porosity) and spikes unrelated to precipitation using the SA/QC tool (Schmidt et al. 2023).

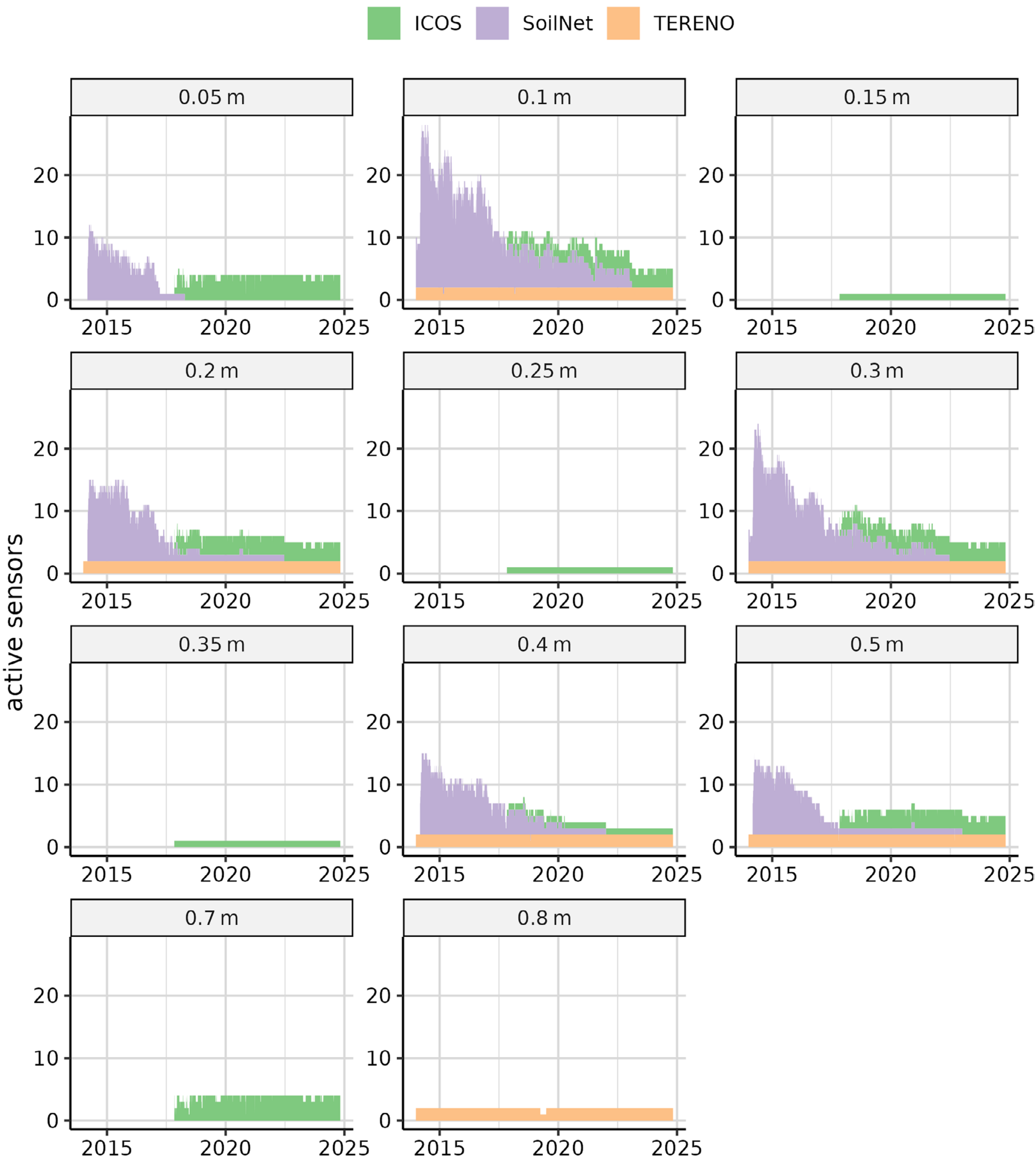

FIGURE 2 | Temporal coverage of active in situ sensors across depths (0.05 m to 0.8 m) from 2014 to 2024, colours refer to the three setups ICOS (green), SoilNet (purple), and TERENO (orange).

In addition to the in situ sensors, a CRS1000 cosmic-ray neutron sensor (Schrön et al. 2018) was installed at the central forest tower, about 4 m above ground level, in the summer of 2014. The neutron measurements were processed according to the methods described in (Bogena et al. 2022), assuming soil bulk density of 1.136 $\mathrm{g\,cm^{-3}}$, soil organic carbon of 0.031 g/g, soil lattice water of 0.038 g/g, and a free calibration parameter of $N_0 = 743$ cph. The final daily soil moisture product is given in volumetric percent with an uncertainty range from ± 0.5 vol. % in summer and ± 1.5 vol. % in winter. The integral measurement is representative for surface and subsurface water in an area of up to 150–200 m radius around the sensor (winter to summer) and down to 25–50 cm depth (winter to summer).

Throughout the rest of the manuscript, the term 'sensor' refers to the in situ soil moisture sensors installed below ground and the Cosmic-Ray Neutron Sensor is explicitly mentioned as 'CRNS'. An overview of all the soil moisture monitoring setups described previously is provided in Table 1.

3 | Methods

3.1 | Definition of Spatial Reference Estimates

Given a set of sensors indexed by x, let A_t be the set of sensors with valid data at time step t. For each sensor x, let T_x be the set of time steps for which x has valid data. The spatial mean at time t and the temporal mean for sensor x are

$$\bar{\theta}_t = \frac{1}{n_t} \sum_{x \in A_t} \theta_{t,x} \quad (1)$$

$$\bar{\theta}_x = \frac{1}{n_x} \sum_{t \in T_x} \theta_{t,x} \quad (2)$$

where $n_t = |A_t|$ and $n_x = |T_x|$. Here, $\theta_{t,x}$ denotes the soil-moisture reading.

We assume that the estimation error for $\bar{\theta}_t$ is small if the sample is sufficiently large, which implies that the identity of the sample (i.e., which sensors are active at time t) has little effect on the estimate of $\bar{\theta}_t$. Due to the temporal stability of soil moisture patterns, the fluctuating identity of the sample leads to different biases with increasing in situ sensor loss and increases the estimation error of $\bar{\theta}_t$ (Pachepsky et al. 2005).

In order to establish a threshold for the number of active in situ sensors needed to estimate the spatial reference averages, for each depth, we selected 50 days with the largest n_t. For each selected day and each target sample size $k \in \{k_{\min}, \ldots, n_t\}$, we drew $B = 1000$ bootstrap samples of size k and computed the spatial mean $\bar{\theta}_{t,b}^{(k)}$ for replicate b. We then summarised the variability across replicates via the coefficient of variation CV(k) and related it to k. The minimum required number of sensors (MRNS) was defined as the k at the elbow of the CV(k) curve, determined by the maximum second derivative (maximum curvature). Times with $n_t \geq$ MRNS form the reference period T_{ref}.

3.2 | Evaluation of Temporal Stability

Temporal Stability Analysis (TSA) has been widely used as a common technique to identify representative locations for spatial soil moisture patterns (Brocca et al. 2009; Vachaud et al. 1985; Jacobs 2004; Ran et al. 2017). TSA evaluates soil moisture dynamics at individual sensor locations relative to the field mean over time. Two key metrics can be considered in that sense: the mean relative difference (MRD) and the standard deviation of the relative difference (SDRD). Here and below, TSA metrics are computed only over the reference period, that is, sums run over $t \in T_x \cap T_{\text{ref}}$. For brevity, we write T_x and n_x.

MRD indicates the average deviation of the point measurement from the field mean, that is, whether a particular location is drier or wetter on average than the field mean and is defined as:

$$\text{RD}_{x,t} = \frac{\theta_{t,x} - \bar{\theta}_t}{\bar{\theta}_t} \quad (3)$$

$$\text{MRD}_x = \frac{1}{n_x} \sum_{t \in T_x} \text{RD}_{x,t} \quad (4)$$

where $\text{RD}_{x,t}$ is the relative difference of θ at the location x and observation time t, and n_x is the number of time steps for that location. Small absolute values of MRD_x indicate locations that are near the spatial average.

The standard deviation of the relative difference (SDRD) quantifies the temporal consistency, with lower values indicating high stability or temporal persistence of the soil moisture conditions at that location. SDRD is defined as:

$$\text{SDRD}_x = \sqrt{\frac{1}{n_x - 1} \sum_{t \in T_x} \left(\text{RD}_{x,t} - \text{MRD}_x\right)^2} \quad (5)$$

Jacobs (2004) defined a single metric that combines the information of MRD and SDRD that can be used to define representative locations for the target area. We follow the suggestion of (Zhao et al. 2010) and use the term index of time stability (ITS) instead of RMSE proposed by Jacobs (2004) to avoid confusion with the general RMSE. The smaller the value for ITS, the better a sensor location reflects the spatial average. ITS can be calculated as:

$$\text{ITS}_x = \sqrt{\text{MRD}_x^2 + \text{SDRD}_x^2} \quad (6)$$

3.3 | Statistical Transformation From Point to Field Scale

When the statistical distributions of two random variables are known, their cumulative distribution functions (CDFs) can be transformed from one to the other using a transfer function.

TABLE 1 | Overview of soil moisture measurement setups.

#	Sensor type	Referred to as	Year installed	No. of locations	Depth (m)	References
1	SPADE	SoilNet	2014	7–27	0.05, 0.1, 0.2, 0.3, 0.4, 0.5	Bogena et al. (2010)
2	SMT100	ICOS	2017	4	0.03, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.5, 0.7	Rebmann et al. (2018)
3	CS616	TERENO	2014	2	0.1, 0.2, 0.3, 0.4, 0.5, 0.8	Wollschläger et al. (2016)
4	CRS1000	CRNS	2014	1	Integral volume up to 0.25 m (winter), 0.50 m (summer)	Schrön et al. (2018)

This technique is widely used, for example, to bias-correct model outputs against observations in climate simulations (Thrasher et al. 2012; Maraun 2013; Cannon et al. 2015), to downscale remote sensing products (Xu and Cheng 2021), to estimate subsurface soil moisture from surface measurements (Gao et al. 2019; Tian et al. 2020; Zhuang et al. 2020), or to upscale profile soil measurements to field averages (De Lannoy et al. 2007; Han et al. 2012). This approach is referred to in the literature as CDF matching, quantile mapping, quantile–quantile transformation, observation operators, and other terms. In this study, we adopt the term statistical transformation, following (Gudmundsson et al. 2012). We map point-scale measurements to the field scale via an empirical CDF transformation:

$$\theta_{\mathrm{sp},x,t} = h_x\left(\theta_{t,x}\right) = F_{\mathrm{sp}}^{-1}\left(F_x\left(\theta_{t,x}\right)\right) \tag{7}$$

where F_x and F_{sp} denote the empirical CDFs computed over the overlapping calibration period $\mathcal{T}_x \cap \mathcal{T}_{\mathrm{ref}}$ for sensor x and the spatial mean $\overline{\theta}_t$, respectively. Between empirical quantiles we apply linear interpolation. Outside the observed range, values are not extrapolated but instead mapped to the nearest bound of the empirical CDF (minimum or maximum). Linear extrapolation of the outermost segment would in principle be possible, but was not applied in this release because it occasionally produced implausible values.

4 | Data

The dataset consists of soil moisture measurements collected over a decade from multiple in situ monitoring systems and Cosmic Ray Neutron Sensing (CRNS) at the study site. Due to sensor failures, replacements, and varying depths of measurement, the number of available observations fluctuates over time. To provide a comprehensive overview, Figure 2 shows the temporal coverage of active soil moisture sensors at different depths, ranging from 0.05 m to 0.8 m, for three monitoring systems: ICOS (green), SoilNet (purple) and TERENO (orange).

The SoilNet setup had been in operation since mid-2014 and initially accounted for most of the spatially distributed measurements. Depending on the depth, up to 34 sensors were installed, but due to sensor loss and erroneous data, the number of spatially distributed measurements decreased over time. In addition, two other profiles have been established to meet the requirements of TERENO and have been in operation since 2014. These are the only profiles covering the 80 cm depth. In 2018, a new set of four profiles was established as part of the ICOS certification, some of which replaced the previous SoilNet profiles. One of these profiles also covers depths of 15, 25 and 35 cm. As of 2024, between 1 and 4 sensors are still active per depth.

Figure 3 shows time series of daily mean air temperature (at 49 m at the top of the eddy-covariance tower), precipitation sums, and soil moisture time series per sensor at selected depths, as well as from the Cosmic Ray Neutron Sensing (CRNS). Sensor-based soil moisture values are presented as daily means, but original sensor data with 10–15 min resolution are available in the data release.

Strong seasonal trends in soil moisture are evident in all layers, with values peaking during the winter period and declining sharply after the onset of the vegetation active period in May, following an increase in temperature and hence evapotranspiration. With increasing depth, the seasonal variations are attenuated due to the buffering effect of deeper soil layers against surface climatic variability. For example, at 10 cm depth the TERENO profiles show differences of ~30 percentage points in volumetric soil water content between the rainy periods of winter 2017/2018 and the extremely hot and dry summer of 2018, while the difference at 80 cm is only about ~15 percentage points during the same period. Similarly, the spatial variability decreases with depth, but the different number of sensors per layer and over time makes an accurate comparison difficult. In 2015 and 2017, the influence of increased precipitation events in summer can be seen, which led to a lower annual variation in soil moisture and higher spatial variability compared to the other years.

5 | Strategies to Derive Field Scale Estimates

In addition to individual profile measurements, soil moisture information representative of the entire study site is essential for validating remote sensing products, comparison with CRNS measurements, and supporting eddy covariance flux interpretations. However, deriving consistent spatial averages from distributed sensor networks presents significant challenges, particularly when sensor coverage varies over time due to failures and replacements. The temporal persistence of soil moisture patterns means that simply averaging available sensors can introduce artificial biases if the remaining sensors are not representative of the full spatial distribution.

5.1 | Minimum Required Number of Sensors (MRNS)

To understand how sensor failure affects the reliability of the spatial mean, we bootstrapped the spatial average of soil moisture measurements on the days with the highest data availability and then artificially reduced the sample size. The resulting coefficient of variation (CV) of the mean is shown in Figure 4 for five soil depths (0.1 to 0.5 m).

The coefficient of variation (CV) increases non-linearly as the number of active sensors decreases, with the steepest changes occurring below five sensors across all depths. While this pattern and rate of change are consistent across layers, the absolute CV values vary significantly with depth. At 0.1 and 0.2 m depths, CV exceeds 20% with only 1–2 sensors and remains above 10% even with 5 sensors. Deeper layers (0.3–0.5 m) show lower overall CV values which stay below 10% with 3 to 5 or more active sensors due to a more uniform spatial moisture distribution at greater depth. The 0.4 m layer notably shows the lowest CV values across all sensor configurations.

The minimum required number of sensors (MRNS) for the reference period was defined as the point of maximum curvature in the non-linear relationship between sample size and the coefficient of variation (CV). This analysis indicated a threshold of at least six

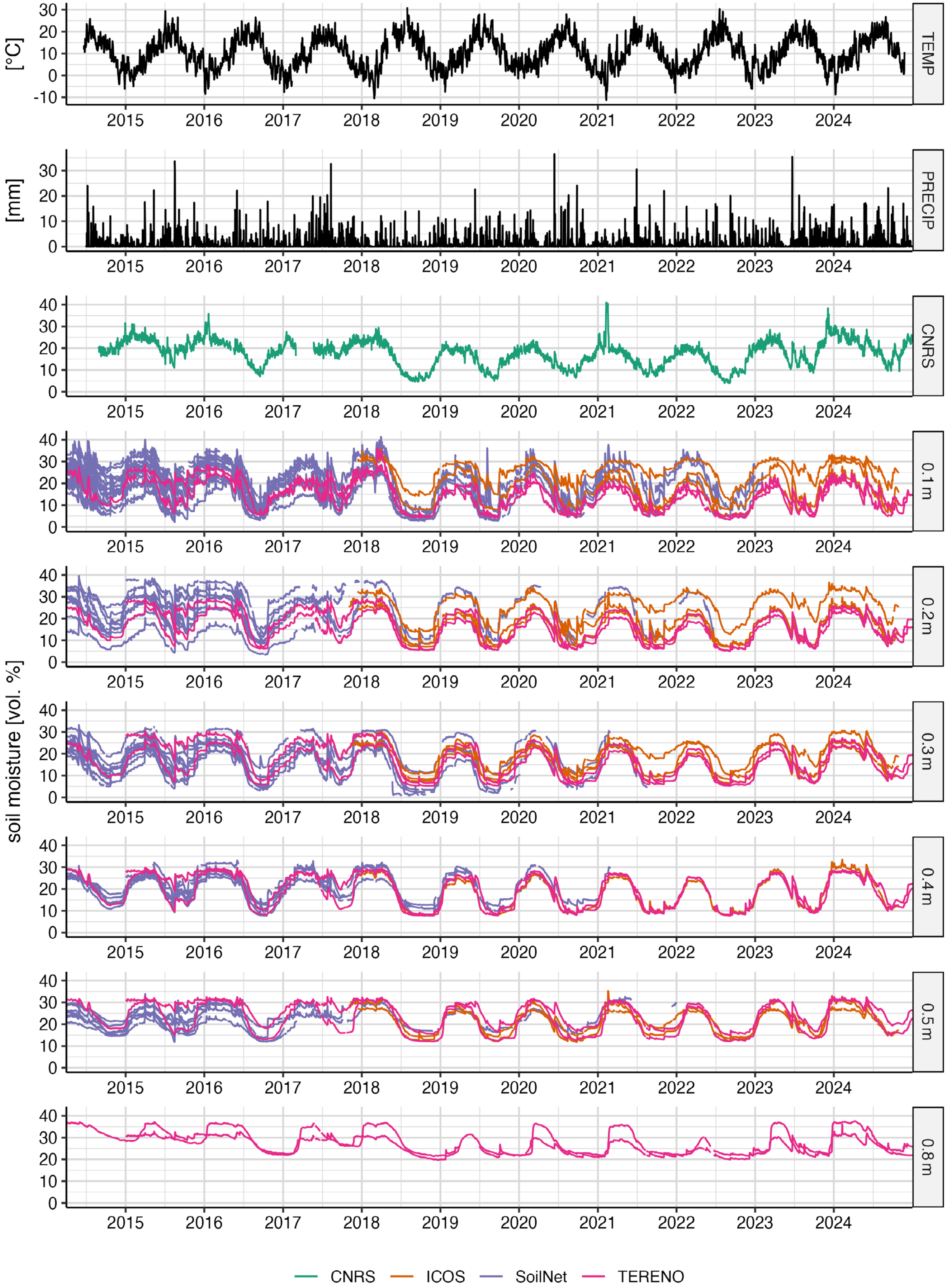

FIGURE 3 | Legend on next page.

FIGURE 3 | Time series of daily mean air temperature at 49 m height, daily precipitation sums and daily mean soil moisture (volumetric water content, %) at different depths (0.1 to 0.8 m) from 2014 to 2024, measured by the ICOS (orange), SoilNet (purple), TERENO (red) and CRNS (green) setups.

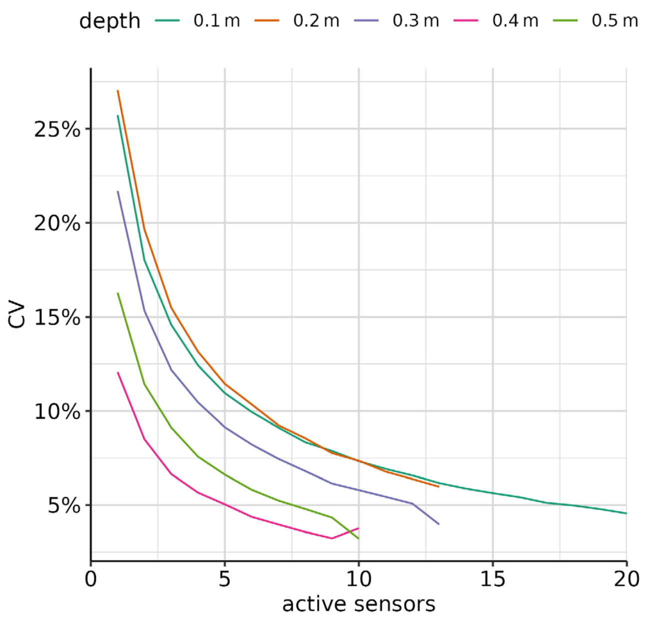

FIGURE 4 | Bootstrapped coefficient of variation (CV) of the arithmetic mean of soil moisture measurements as a function of the number of active sensors, sampled at 50 days with maximum data coverage. Results are stratified by soil depth.

active sensors for the 10 and 20 cm layers, five for the 30 cm layer, and four for the 40 and 50 cm layers. However, a visual inspection of the reference period revealed that the reference period for the two deepest layers extended into a phase where the spatial mean was likely to be biased due to sensor losses (a sudden shift in field capacity in winter). To account for this potential artificial shift, we adopted a more conservative threshold of five active sensors for these layers instead of the four suggested by the maximum-curvature method.

5.2 | Temporal Stability Analysis

We show the results of the TSA exemplarily for two depths, 0.1 and 0.5 m in Figure 5. Sensors are ranked by their MRD (shown as filled circles), with error bars indicating SDRD. Additionally, the index of temporal stability (ITS) is represented by the dashed line. ITS combines MRD and SDRD into a single metric, providing an integrated assessment of both proximity to the field mean and temporal stability. The colour gradient of the data points reflects the number of days with available measurements.

In the shallow layer, considerable spatial variability in soil moisture patterns can be found, with deviations from the field mean ranging from −52% to 36% in extreme cases. Sensors with small standard deviation values are mostly closer to the field mean, but exceptions exist. At 0.5 m depth, the range of the MRD is much narrower, ranging between −24% and 17%.

Ideally, representative sensors should be selected whose index of temporal stability (ITS) is close to zero (i.e., both MRD and SDRD are close to zero), but with the available data these sensors cover only a fraction of the total measurement period. Alternatively, sensors with low SDRD are preferable, as a low value here indicates high temporal stability relative to the spatial mean, as the correct temporal dynamics may be more important than the absolute values. In addition, a sensor with high temporal stability enables the offset to be easily corrected to the spatial mean, as a simple linear transformation may be sufficient here.

5.3 | Upscaling of Sensor Measurements

If no suitable sensor can be identified as representative of the spatial mean, or if the selected sensor has an offset to the spatial mean, the sensor measurements can be scaled up. This requires that the relationship between the sensor and the spatial mean is known or can be estimated. Here we used the spatial mean of the sensor readings over time with sufficient coverage, as explored by the bootstrapping analysis, to estimate the empirical CDF of the field mean. Alternatively, other references such as remote sensing products or model outputs could be used, but this would require knowledge of their accuracy before using them as a reference. Data from the Cosmic Ray Neutron Sensing (CRNS), also included in this data release, could be a promising reference for area- and depth-average soil moisture, which remains to be examined in future studies.

To check the accuracy of the upscaled sensor data, we compared it to spatial reference estimates derived from all active sensors. Figure 6 shows a scatter plot of the upscaled sensor data against the spatial reference estimates, where the colour gradient indicates the number of data points (count). The results show a strong correlation ($R^2 = 0.90$) between the upscaled data and the reference estimates and a root mean square error (RMSE) of 2.12 vol. % by volume. Most of the data points are grouped along the 1:1 line (dashed), reflecting a close correspondence between the upscaled values and the spatial reference. However, the number of data points for which there is good agreement between the upscaled and reference value decreases at the low and high ends of the soil moisture range, where variability is typically higher due to soil heterogeneity or sensor limitations.

Figure 7 shows the time series of the upscaled soil moisture data (black) and the corresponding temporal median (red line) for five depths ranging from 0.1 m to 0.5 m. Highlighted in blue are periods which were identified as reference periods based on a minimum number of active sensors and used to estimate parameters for the sensor transformation. Using the upscaled data instead of raw sensor readings to calculate the spatial mean is particularly beneficial during dry and wet periods. This ensures the time series consistently reflects the true hydrological signal

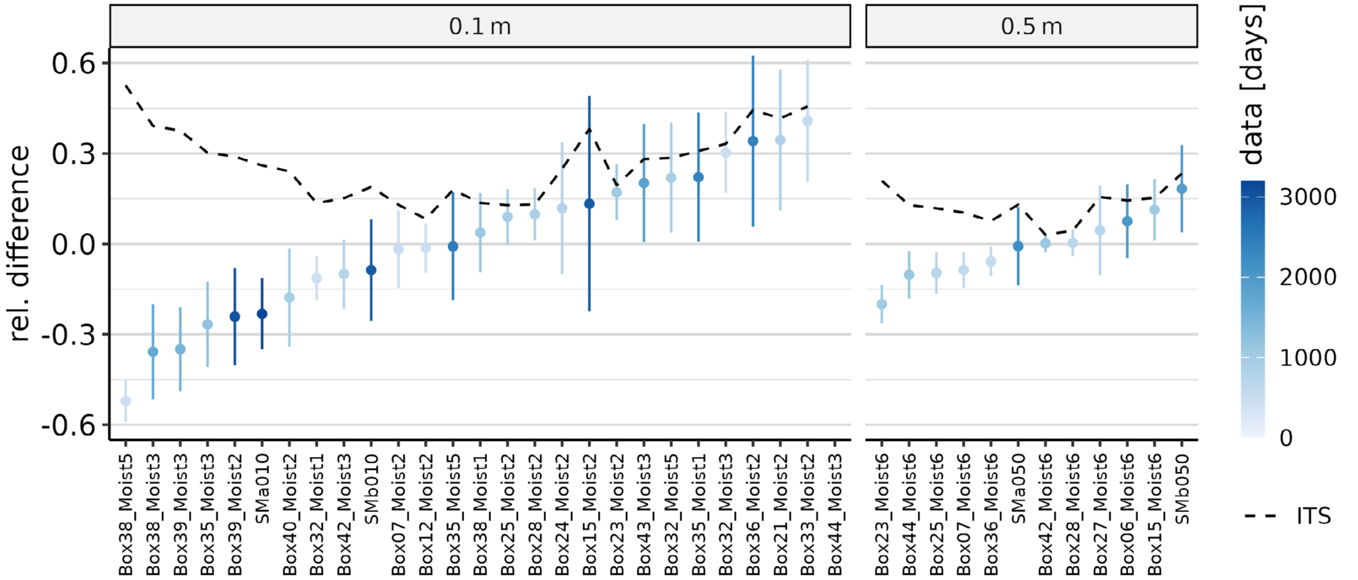

FIGURE 5 | Temporal stability analysis for two depths (0.1 and 0.5 m). Sensors are ranked by their mean relative difference (MRD), and error bars represent the standard deviation of the relative difference (SDRD). The dashed line is the index of time stability (ITS). Data point colour represents the number of measurement days, with darker colours indicating longer measurement periods.

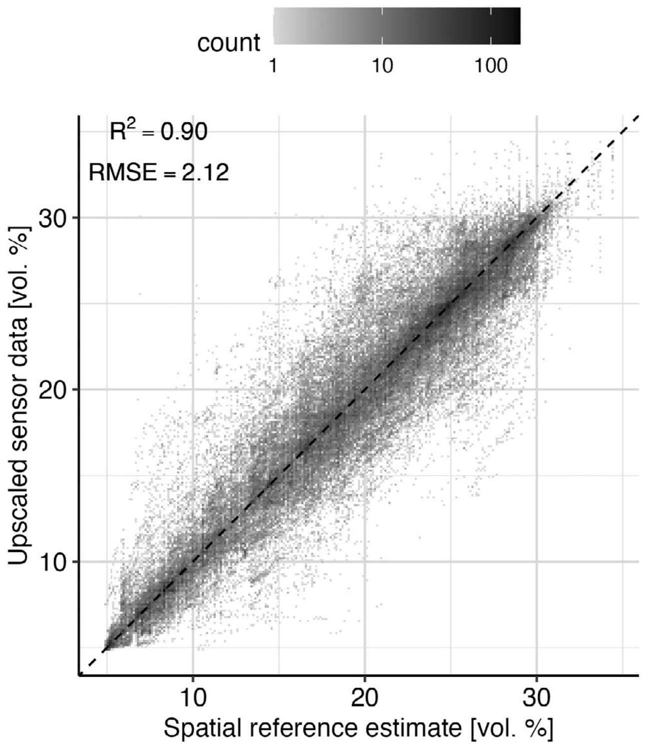

FIGURE 6 | Comparison of upscaled sensor data with spatial reference estimates of soil moisture [vol. %]. The scatter density plot highlights the agreement between the upscaled data and reference values.

of the spatial mean rather than being shifted by sensor failure or dropout.

The spatial average of the upscaled in situ sensors has been compared with the field-scale CRNS data in the center of the area (Figure 8). Since the measured neutrons are more sensitive to shallow soil horizons and to the near-field area around the station, an equal average of all in situ data in the area across their depth and distance would not result in a fair comparison. For this reason, the in situ data has undergone a horizontally weighted averaging and a vertically weighted averaging according to CRNS sensitivity expressed by (Schrön et al. 2017). Figure 8 shows both averaging approaches which demonstrate a very good agreement between the two measurement techniques. Despite the expected better performance of the weighted averaging approach, the CRNS shows decent performance also in representing the equally weighted average soil moisture of the area. This result indicates that the spatial soil moisture pattern at the site is relatively homogeneous. A perfect match between CRNS and the in situ measurements cannot be expected, since CRNS is sensitive to water in the vegetation, litter layer, and uppermost soil layers, which is invisible to the in situ sensors (Bogena et al. 2013).

6 | Discussion

The spatial soil moisture characteristics of the study site are highly heterogeneous, with differences of up to ~20 percentage points (vol. %) between sensors at the same time. This is comparable to other studies in similar forest and climate types (Lv et al. 2016; Wei et al. 2017; Zhu et al. 2021), indicating that such scatter is expected at these sites. A systematic issue arises when averaging the remaining measurements if sensor availability changes along the dry–wet gradient: because missingness is not random (e.g., failures cluster in drier or wetter locations within the research area), a changing set of active sensors can bias the field-scale mean time series (Pachepsky et al. 2005; Guber et al. 2008). For example, if more sensors fail in drier locations, the spatial average computed via Equation (1) will tend to shift toward wetter conditions and no longer reflect the full area.

We suspect this issue is common in aggregated soil-moisture products from in situ sensors, as missing data, failures, replacements, and new installations are typical at long-term observatories.

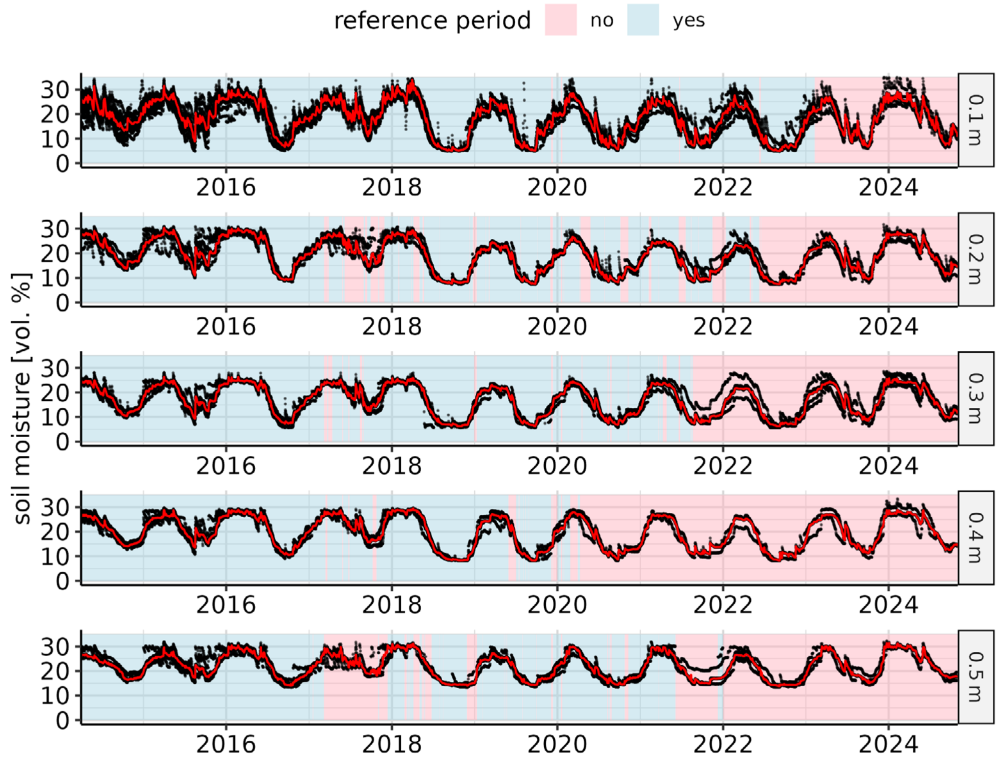

FIGURE 7 | Time series of upscaled soil moisture data (black) and its temporal median (red line) across five depths (0.1 to 0.5 m). Blue shading indicates the reference periods with sufficient sensor coverage.

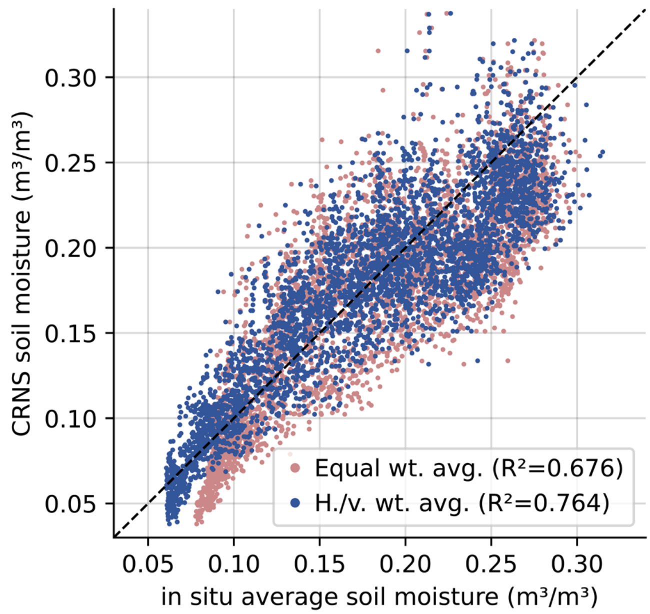

FIGURE 8 | Comparison of the spatial average of the upscaled in situ sensors with CRNS field-average soil moisture. In situ sensor data has been weighted equally over depth and distance (red) and non-linearly in horizontal and vertical space following the nature of neutron transport (blue).

Likewise, Vanderlinden et al. (2012) reported that 29% of datasets examined showed bias in mean relative differences, likely due to incomplete observations. Numerous statistical and data-driven methods have been used to fill gaps in soil-moisture time series (Kornelsen and Coulibaly 2014; Bárdossy et al. 2005; Dumedah and Coulibaly 2011; Shao et al. 2017), ranging from monthly-mean replacement to k-nearest neighbours, variance-reduction techniques, neural networks, and evolutionary polynomial regression. While performance varies by site and method, these approaches are generally suited to relatively short gaps (hours to a few days) (Kornelsen and Coulibaly 2014) and do not by themselves resolve long-term representativeness when sensor availability changes.

With this data release, we propose a strategy to derive long-term consistent spatial averages from in situ measurements even under sensor attrition. Prior work shows that only a limited number of active sensors is needed to estimate the spatial mean reliably (Crow et al. 2012; Brocca et al. 2010; Gao et al. 2013; Lv et al. 2020). Our MRNS analysis operationalises this idea by identifying periods with sufficient coverage to define a reference for calibration (Section 5.1).

Upscaling before averaging helps maintain the spatial mean within the empirical range during the reference period because the CDF transformation maps point measurements to the distribution of the site mean (Section 3.3). In this data release, values falling below or above the observed range were not extrapolated. Instead, we truncated them to the minimum or maximum of the reference CDF because linear extrapolation of the outermost segment sometimes yielded implausible values. Theoretically, linear extrapolation of the outermost local segment can be attempted, but we consider it only in exceptional cases and with explicit uncertainty checks. Although CDF mapping can reduce biases between point sensors and the site mean, errors tend to increase near the distribution tails where empirical support is sparse.

A key open question is the impact of the length and representativeness of the reference period for a stable transformation. Currently, the minimum length of the calibration window required for reliable upscaling is unknown and is likely to depend on the site, depth, and climate regime. Future work should quantify how mapping error varies with calibration window length (e.g., via cross-validation across windows) and in relation to specific site conditions.

Moreover, the point–field relationship is likely to be non-stationary on a seasonal basis. Winter recharge, spring transitions and summer dry-down differ in terms of variance, spatial patterns and the dominant processes involved, such as infiltration events, root water uptake and hydraulic redistribution. Pooling all months into a single empirical cumulative distribution function (ECDF) can obscure these regimes and bias the transformation. Where records are sufficiently long and seasonal coverage meets the MRNS within each regime, however, seasonal ECDFs or moving-window transformations may better capture regime-specific behaviour. This approach does require more data per season, though.

In our data, no single sensor was able to perfectly replace the reference. While a carefully chosen "representative" sensor can capture substantial variance (e.g., via a low ITS), a semi-automatic workflow that upscales all available sensors and then aggregates them with a robust estimator (e.g., the median across upscaled sensors at each time) produces a more reliable site-mean series. This choice prioritises temporal dynamics and reduces sensitivity to individual sensor offsets, though the optimal approach will depend on site characteristics and network design.

Overall, long-term soil-moisture observatories are inevitably subject to sensor attrition and technological change. To our knowledge, there is no universally accepted protocol for harmonising successive instruments at a single site. Projects therefore need to develop transfer functions, overlap campaigns, or statistical homogenisation tailored to their networks. In order for soil-moisture archives to underpin climate-trend analyses and cross-sensor syntheses over the next few decades, it will be essential to advance shared standards, including the transparent reporting of coverage thresholds (e.g., MRNS), calibration periods, and transformation/aggregation choices.

7 | Dataset Access

The data is publicly available at Zenodo (DOI: 10.5281/zenodo.17121123) and is organised into three files: one containing all available sensor data, one containing pre-filtered sensor data as presented in Sections 4 and 5 and one containing the spatial average of the research site, using both the original and the upscaled data. An additional file contains the data from the Cosmic-Ray Neutron Sensor (CRNS); for more information on its content we refer to the original data release (Bogena et al. 2022).

The pre-filtered sensor data file is in long format and includes the measurement date, sensor identifier, installation depth, volumetric soil water content (SWC), the corresponding upscaled value for that sensor, geographic coordinates and the data source. An additional column (Tref) indicates whether the record falls within the designated reference period used for calculating temporal stability and scaling. This dataset preserves the full spatial detail and is suited to sensor-level analysis and cross-comparisons.

The file containing the daily, plot-level averages includes the spatial mean of the original soil water content (SWC) data and the median of the upscaled sensor data for each depth and day. It also provides details of the number of active sensors that contributed valid data on each day and the MRNS (minimum required number of sensors) threshold that had to be met to obtain a value that is representative of the whole area. The Tref column again marks entries belonging to the reference period. For general use of the spatially averaged soil water content at the research site, the median of the upscaled SWC is recommended.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in ZENODO at https://doi.org/10.5281/zenodo.17121123.

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