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ORIGINAL ARTICLE

Calculating a minimum overlap period for successful intercalibration of soil moisture sensors

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Abstract

Long-term in situ soil moisture monitoring inevitably requires sensors to be replaced. Ensuing discontinuities in the data record can be mitigated by intercalibration, however it is unclear how long the existing sensor needs to remain alongside the newly installed before there is enough overlapping data to generate a robust intercalibration. We used 154 pairs of established and newly installed sensors within the Marena, Oklahoma, In Situ Sensor Testbed to determine if there is a minimum overlap time that should be considered when planning upcoming replacements. Hourly observations of the existing sensor were linearly calibrated to those of the newly installed sensor with coefficients determined from overlap periods incremented by 30 days until a reference period of 2 years was reached. The resulting bias, root-mean-square error, and correlation coefficient for sensor pairs indicate that a minimum of 6 to 9 months of overlapping data are required to generate a successful intercalibration. Extending that to a full year before decommissioning the old sensor results in a stable intercalibration with higher confidence.

1 | INTRODUCTION

In situ networks for monitoring soil moisture are most valuable when the data are continuous and long term—capable of providing information for soil, hydrologic, and climate modeling. Ford et al. (2016) found that anywhere from 3 to 15 years of data are required, depending on the site, to compute the standardized percentiles needed to homogenize soil moisture observations and recommended a minimum of 6 years to estimate the extremes. However, in situ sensors do not have long life spans and eventually require replacement. Sensor manufacturing and technological advancements often lead to better methods for sensing soil moisture and also necessitate a change in the instrumentation; this introduces incongruity in the time series. Furthermore, the monitoring volume of an in situ sensor is difficult to exactly match from one sensor installation to the next and thus spatial variability can result in an inconsistent data record after replacement.

An example of this is found with the Illinois Climate Network, which was initially operated with neutron probe sampling every 2 weeks (Hollinger & Isard, 1994) before

Abbreviations: MOISST, Marena, Oklahoma, In Situ Sensor Testbed; RMSE, root-mean-square error.

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replacement with automated dielectric sensors. In the early 2000s, a set of Stevens Hydra Probes were deployed at the network sites and operated in tandem until the neutron probes were eventually discontinued. Coopersmith et al. (2016) developed a linear calibration for each of the network sites from overlapping observations at a depth of 5 cm which produced an root-mean-square error (RMSE) of 0.05 $m^3\ m^{-3}$. They further fit a model based on soil moisture dynamics to extend the record of the newly installed sensors and verified it against the prior years of data collection.

For the case of the simple linear adjustment, the question remains: how much overlapping data are required to produce a robust intercalibration? Coopersmith et al. (2016) utilized the entirety of available data, ranging from 1 to 5 years depending on the site, to intercalibrate sensors. We investigate this using combinations of established and newly installed sensors within the Marena, Oklahoma, In Situ Sensor Testbed (MOISST; Cosh et al. (2016)) representing multiple sites, installation depths, and soil textures.

Core Ideas

- Intercalibration mitigates discontinuities in long-term soil moisture records caused by sensor replacement.
- Sensor pairs in a testbed are intercalibrated based on the initial 1 to 24 months of overlap and then validated.
- We recommend that a year be considered the minimum overlap period for statistical and practical reasons.

2 | DATA

The MOISST was developed to provide a testbed for intercomparisons of soil moisture in situ sensors (Cosh et al., 2016). An original set of four profiles were deployed in 2010 containing a variety of in situ sensors, as well as proximal sensors like the cosmic ray neutron sensing (Zreda et al., 2012) and Global Positioning System interferometric reflectometry (Small et al., 2016). This location is also the site of an Oklahoma Mesonet site (MARE) which allows for comparisons to long-term installations (Illston et al., 2008). Additional sensors were installed within 3 m of the existing testbed sites in 2016 to add new sensor types as well as replace several faulty sensors. Figure 1 provides an example time series of overlapping data from previously established and newly installed sensors at 5 cm depth.

This region has a humid sub-tropical climate and experiences a wide range of soil moisture conditions. Figure 2 presents profiles of clay content and bulk density with depth for the four MOISST sites. The relevant installation depths for sites A, B, and D are 5, 10, 20, and 50 cm; for site C the depths are 5, 10, 20, and 30 cm. Site C has a notably lower clay content throughout the profile compared to the other three sites. Data are collected every hour in the data logger and transmitted for quality control biweekly. Repairs and maintenance are conducted as needed, though there are long spans of no data occasionally as replacement equipment or batteries needed to be ordered.

3 | METHODOLOGY

For this study, the foundation of the analysis is sensor pairs, which are defined as combinations of a previously established sensor (installed in 2010) and a newly installed sensor (installed nearby in 2016) located at the same site and installation depth. The calibration periods being tested are generated by simply subsetting the sensor pairs time series to the initial {30, 60, 90,…, 720} days (monthly duration increments

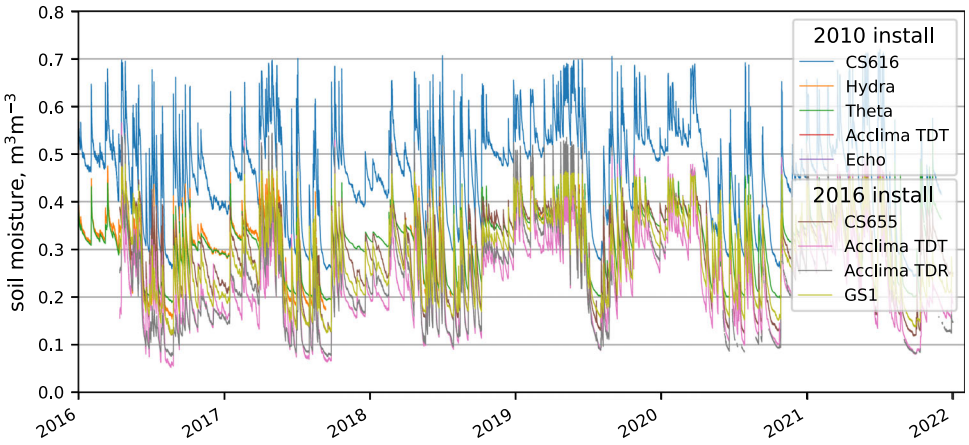

FIGURE 1 Example time series of overlapping sensor data at site D.

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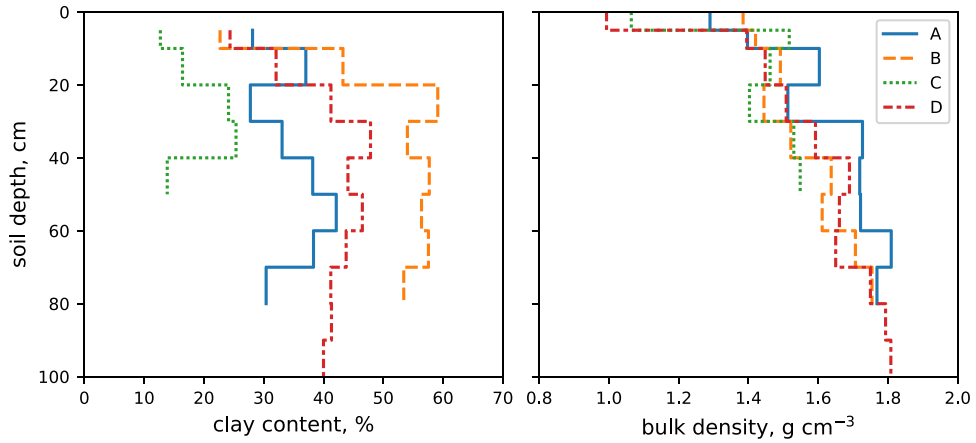

FIGURE 2 Clay content and bulk density as sampled at the four testbed sites.

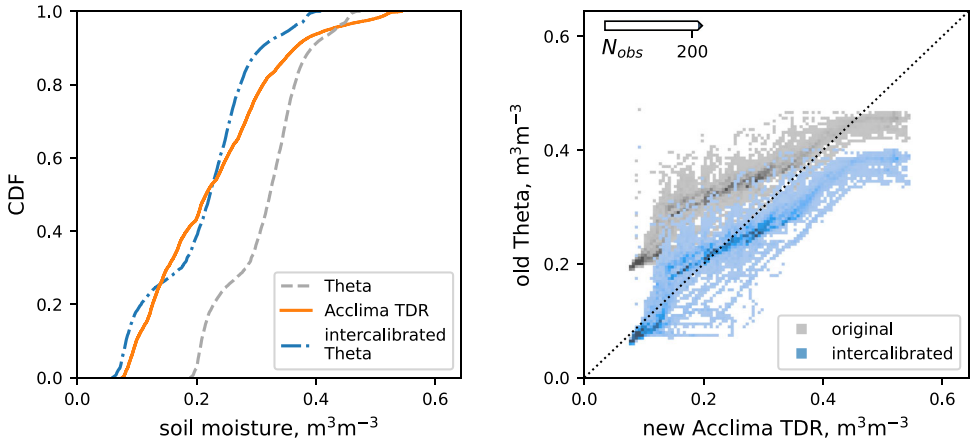

FIGURE 3 Example of initial-year intercalibration applied to 5 years of hourly observations as illustrated by cumulative distribution functions [left] and bivariate histograms with a bin width of 0.005 m^3 m^{-3} [right].

between 1 month and 2 years) of overlapping data for a total of 24 sets per sensor pair. The start dates of each period are fixed to when the newly installed sensor began reporting to mimic what a network replacing sensors would experience. Intercalibration occurs via linear regression by fitting the equation $SM_{new} = m \times SM_{old} + b$ and applying the subsequent coefficients to the entirety of the old sensor's time series. This creates a record for the previously established sensor which best matches that produced by the newly installed given the ingested calibration data. The process is repeated per pair for all of the tested calibration sets. Figure 3 illustrates the difference between 5 years of hourly observations for a random sensor pair (site D, 5 cm, Acclima TDR and Theta) before and after intercalibration with the initial year of overlap.

Intercalibration quality is estimated by the bias (+ indicates that the newly installed sensor is wetter than the previously established), RMSE, and Pearson correlation coefficient (Pearson-R). The combination of varying the duration of the calibration period and the inconsistent length of record for sensors (from either temporary data outages or permanent failures) makes it difficult to chose a single best validation period. We aim to provide a consistent length of time for validation while still taking advantage of the longer records available for many of the pairs. For each pair's tested calibration sets, a synthetic 2-year validation is produced by generating intercalibrated time series for all possible 24-month subsets, computing validation metrics for each, and aggregating. Potential subsets are discarded if they contain any of the calibration data or have an hourly data availability of less than 75%. For example, a 6-month intercalibration for a hypothetical sensor pair whose overlapping data begins in April 2016 and ends due to a sensor failure in March 2021 would require the initial 6 months of data to be set aside for calibration. The bias, RMSE, and Pearson-R would be computed for each allowable 24-month period (i.e., {Oct 2016 – Sep 2018, Nov 2016 – Oct 2018,…, Apr 2019 – Mar 2021}) subset from the remaining four and a half years and then aggregated (mean and standard deviation) into a single 2-year validation.

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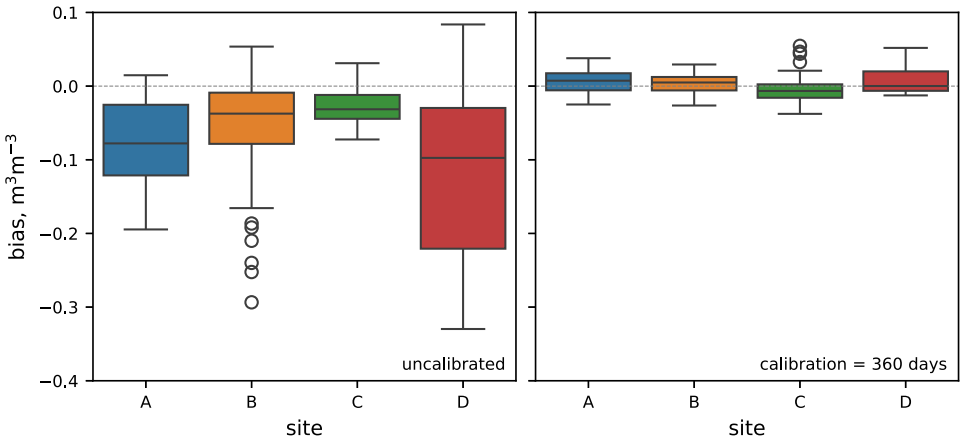

FIGURE 4 Bias (− indicates that the newly installed sensor is drier) between the 154 sensor pairs as grouped by site prior to intercalibration [left] and after a calibration period of 360 days [right].

Applying the aforementioned validation requirements reduces the total number of suitable pairs from the 224 with a minimum overlap of 2 years to 154. This leaves 39 pairs each at sites A and B, 48 at site C, and 28 at site D. Intercalibration performance is assessed both per site and as binned by clay content (bins = {<20%, 20%–30%, 30%–40%, >40%}). At these sites, clay content generally increases with installation depth (Figure 2) and thus it is difficult to disentangle effects of the two on intercalibration performance. However, Ford and Quiring (2019) previously found no significant connection between installation depth and relative error variance.

4 | RESULTS

The expected result of intercalibration via linear regression is that the bias between sensors should approach zero during validation as the amount of data used for calibration is extended. Figure 4 illustrates both the dramatically different soil moistures that different sensors at the same depth and similar location report and how that bias is minimized when the initial year of overlapping data are used for calibration. The biases between uncalibrated sensor pairs are strongly negative (i.e., the newly installed sensor is much drier than the previously established sensor) for sites A, B, and D. This is due to the long-lived CS616s overestimating soil moisture across sites and depths with high clay content (see the time series in Figure 1 for an example at site D).

Table 1 provides the mean and standard deviation of the bias, RMSE, and Pearson correlation coefficient across all intercalibrated pairs during validation. The observed biases for the entire set of tested calibration periods are grouped per site in Figure 5. While the initial magnitudes differ, all four sites follow similar patterns of minimizing biases between intercalibrated pairs somewhere between 6 months and a year of calibration. Variability in the bias across pairs stabilizes after 3 months of calibration. There appears to be little additional benefit when the calibration period is extended from 1 to 2 years.

TABLE 1 Validation period bias, root-mean-square error (RMSE), and Pearson correlation coefficient between intercalibrated sensors for selected calibration periods.

	Bias (m^3 m^{-3})		RMSE (m^3 m^{-3})		Pearson-R	
Days	**Mean**	**St.dev.**	**Mean**	**St.dev.**	**Mean**	**St.dev.**
30	−0.011	0.037	0.049	0.039	0.84	0.12
60	−0.024	0.026	0.047	0.024	0.84	0.12
90	−0.019	0.021	0.039	0.015	0.84	0.12
120	−0.016	0.020	0.037	0.014	0.84	0.12
180	−0.006	0.021	0.035	0.014	0.84	0.12
270	+0.003	0.020	0.034	0.015	0.85	0.12
360	+0.003	0.017	0.033	0.014	0.85	0.13
540	+0.006	0.016	0.032	0.014	0.84	0.13
720	+0.006	0.016	0.032	0.013	0.85	0.13

Discrepancies between sensors in an intercalibrated pair reflect physical differences between nearby (but not identical) soil volumes as well as any technological differences between the two sensors. Successful intercalibration will not reduce the RMSE to zero, but, assuming both sensors have repeatable responses to changes in soil moisture, it should reach a minima after the full range of soil moisture for the site is observed. Figure 6 illustrates the improvement in RMSE after calibration with a year of data; at this point the bias, which mathematically affects RMSE, has minimized for those sensors which could be successfully intercalibrated. The dotted line in Figure 6 is a visual reference for the 0.04 m^3 m^{-3} accuracy goal of satellite soil moisture retrievals (e.g., Colliander et al., 2017), which in situ observations must also meet if they are to be utilized for evaluation of such products.

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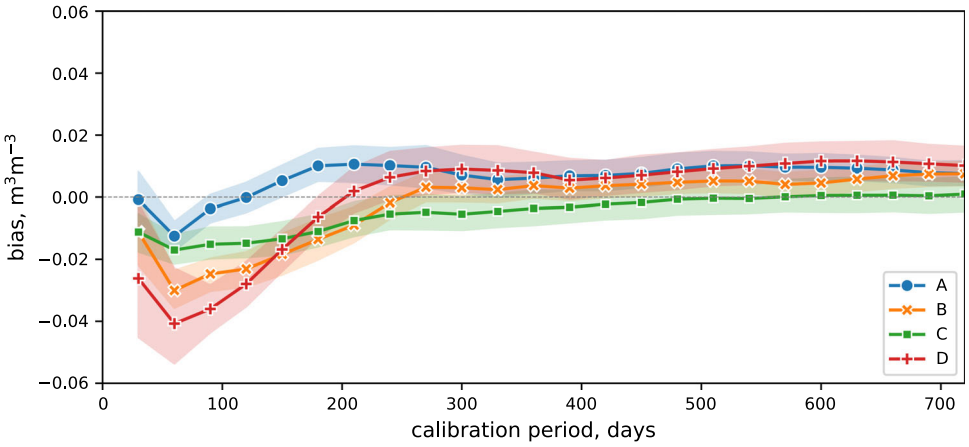

FIGURE 5 Bias (95% CI) between intercalibrated sensor pairs averaged by site for calibration periods up to 2 years.

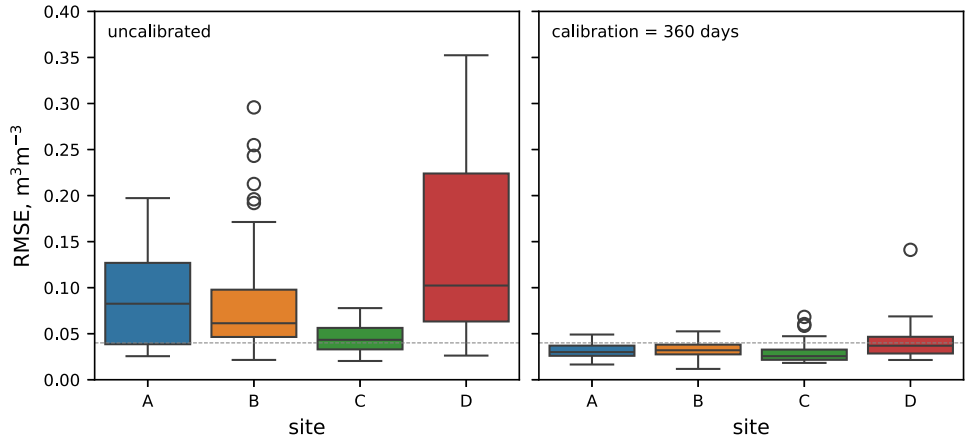

FIGURE 6 Root-mean-square error between sensor pairs averaged by site prior to intercalibration [left] and after a calibration period of 360 days [right].

There are significant reductions to both the mean and standard deviation of the RMSE (Table 1) with just 3 months of calibration data. Figure 7 provides RMSE for intercalibrated sensor pairs, grouped by site and clay content, as the calibration period progresses through the first year. Site D, noted earlier to have fewer sensor pairs under consideration than the other sites, has both a larger and more variable RMSE, particularly when the calibration period is less than 4 months. This corresponds with site D exhibiting a larger bias than other sites when smaller overlaps are assumed (Figure 5). The RMSE of specific sensor pairings (across all sites and depths) which occur five or more times is given in Figure 8 for the case of the 1 year calibration period. The combination of previously established CS616 and newly installed Acclima TDT, which occurs eight times, is the only such pairing which has a notably higher RMSE.

Neither the mean Pearson correlation coefficient nor its variability amongst the sensor pairs varies significantly with calibration period (Table 1). Figure 9 presents the relationship between Pearson-R and clay content as aggregated over all valid pairs assuming a 1 year calibration. Unsurprisingly, sites with higher clay contents exhibit lower Pearson-R values between sensor pairs. Figure 10 provides the mean Pearson-R for paired sensor models at the poorly correlated site D; those containing the CS616 are notably degraded. Unfortunately, the CS616 is the only type of the previously established sensors at site D with enough data for validation at all four depths and as such is in 15 of the 28 valid sensor pairs.

5 | DISCUSSION

From Figures 5 and 7, it is evident that a sufficient length of overlap for sensor intercomparison and cross calibration can be as little as 6 to 9 months, though for both statistical as well as practical reasons, one full year should be considered a minimum overlap period. One year of overlap would include a full annual weather cycle although there may be some data loss due to frozen soil. This conclusion is based on the assumption that the sensors being considered in the overlap measure

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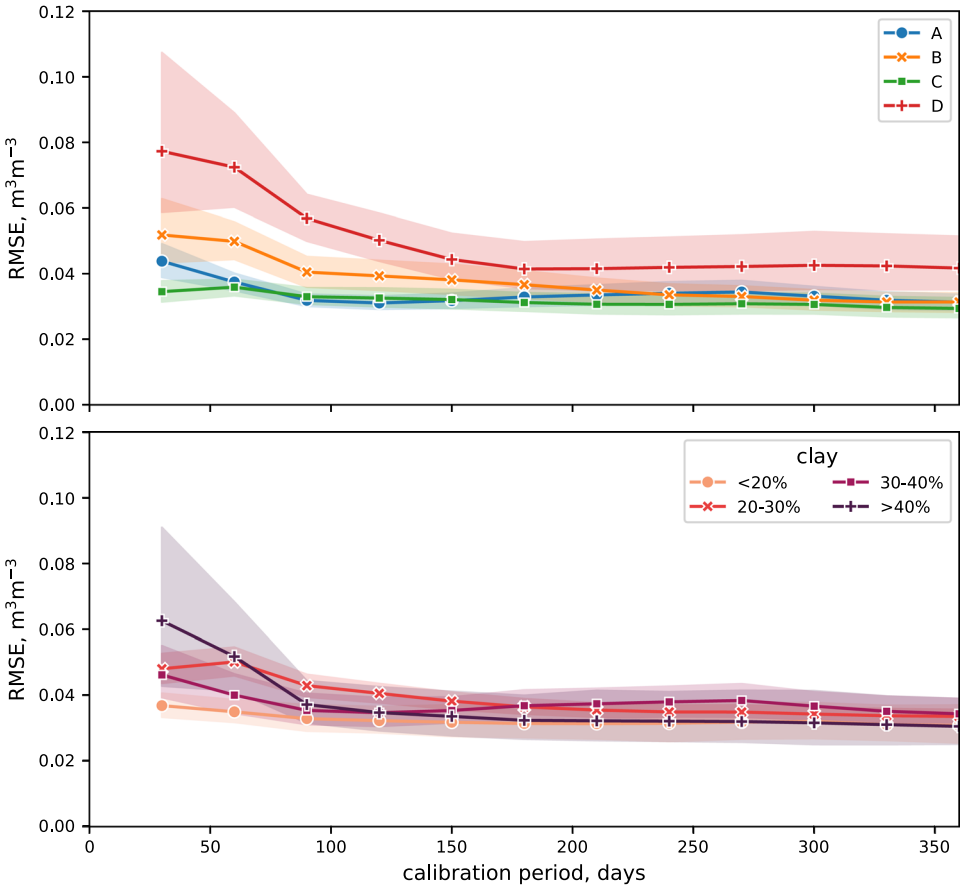

FIGURE 7 Root-mean-square error (95% CI) between intercalibrated sensor pairs averaged by site [top] and clay content [bottom] for calibration periods up to a year.

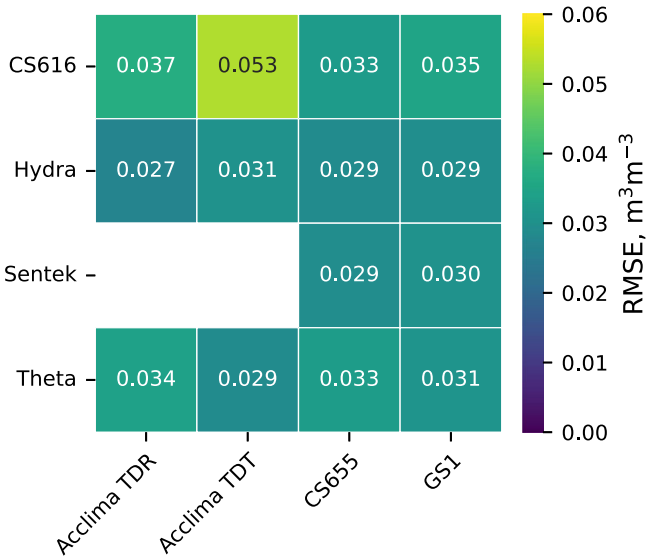

FIGURE 8 Average root-mean-square error (1 year calibration) for sensor pairings that occur five or more times across the testbed.

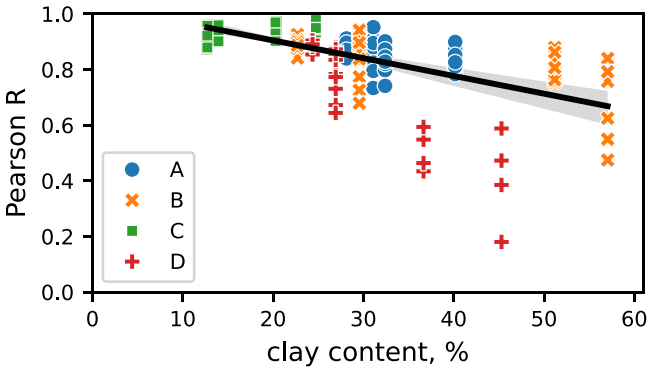

FIGURE 9 Pearson correlation coefficient between intercalibrated sensor pairs with respect to clay content given 1 year of calibration.

similar soil moisture conditions and produce estimates that are approximately linearly related. Nonlinearity may result from the interruption of one of the sensor installations, either physical or electrical in nature (e.g., a step change in the time series) which impacted the observations without registering as a sensor failure. These could be sensor drift, minor manufacturer defect, or even shrinking/swelling in the soil.

The bias, RMSE, and Pearson-R presented in this study are computed using all 154 sensor pairs that had enough

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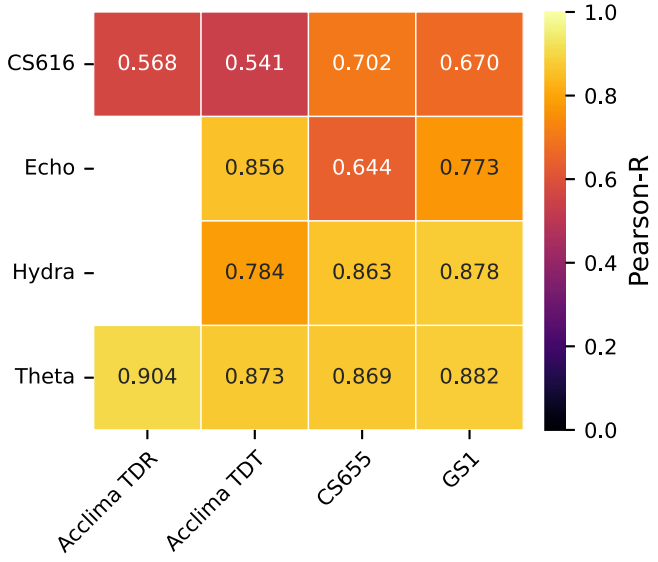

FIGURE 10 Average Pearson-R (1 year calibration) for sensor pairings at site D.

overlapping data to meet the validation requirements. Some of those did not have a sufficiently linear relationship for successful intercalibration. Only 9 of the 154 pairs (1 at site B, 3 at site C, and 5 at site D) were unable to obtain a validation RMSE ≤ 0.05 m^3 m^{-3} based on the first year of overlapping data. The failed pairs at sites B and C included a GS1 as the newly installed sensor; at site D it was either an Acclima TDT or TDR. Of these nine pairs all but two had CS616s as the previously installed sensor. Slightly constricting the criteria for success to a validation RMSE ≤ 0.04 increases the number of unsuccessful pairs to 32 (8 at site A, 6 each at sites B and C, and 12 at site D). Extending the calibration to 2 years does not significantly affect the number of pairs able to meet these thresholds.

Manufacturers often list the accuracy of soil moisture sensors as less than 0.01 m^3 m^{-3} (Cosh et al., 2016). Focusing just on the US Climate Reference Network, in which sensors are installed in triplicate, Coopersmith et al. (2016) found that triple collocation errors across the network's Hydra probes averaged 0.01 m^3 m^{-3}. However, these errors, akin to the random error of monitoring soil moisture, had a strong geographic distribution; stations in the Midwest commonly had triple collocation errors of 0.02 to 0.03 m^3 m^{-3}. In Coopersmith et al. (2016), the intercalibration of Hydra probes and neutron probes had an RMSE of 0.05 m^3 m^{-3} after the elimination of poor performing sites. Our study finds an average RMSE between successfully intercalibrated sensor pairs of 0.03 m^3 m^{-3}.

Ultimately, the results of this study support a recommendation of at least 1 year of overlap in sensor time series for in situ networks when sensor technology needs to be replaced. Long time series of soil moisture data are critical to understanding land surface processes and climate dynamics. Collecting these inevitably requires replacing or upgrading sensors as all technology ages and breakage occurs. This study will help transition planning and network evolution as new sensors are developed and deployed in long-term monitoring networks. There are limitations to this study as there is limited soil texture variety among the test sites. Land cover is limited to grassland/pasture, though for most in situ network installations the soil surface is often locally managed as short grassland. It will be challenging to develop testbeds that allow for every landscape and soil texture combination, but it is expected that the results of this study will provide valuable guidance for network operators who must make reasonable but efficient decisions on resources to best serve the needs of the stakeholders for their network. The soils at Marena were considered to be more challenging for soil moisture study as they have significant clay content and some shrink–swell phenomenon has been observed. The landscape was selected to be typical of station locations, with the goal of studies developed here to be applicable to most network operations.

The findings of this study can aid network operations in the planning of network updates and sensor re-deployment. Often networks will operate with one common sensor across all sites, but eventually technology improves to the point that a new sensor is desired to be deployed, whether to improve accuracy, reduce failures, or because an initial sensor selection was determined to be insufficient for stakeholder needs. When these changes are known or anticipated, network managers can establish overlap periods so that time series continuity can be established. This is a common question among environmental managers and this study will inform decisions on soil moisture sensor overlap.

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AUTHOR CONTRIBUTIONS

Victoria A. Walker: Conceptualization; formal analysis; writing—original draft; writing—review and editing. **Michael H. Cosh**: Conceptualization; data curation; funding acquisition; writing—review and editing. **Tyson E. Ochsner**: Conceptualization; data curation; funding acquisition; writing—review and editing.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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