Comparison of In Situ Soil Moisture Measurements: An Examination of the Neutron and Dielectric Measurements within the Illinois Climate Network

EVAN J. COOPERSMITH

Hydrology and Remote Sensing Laboratory, Agricultural Research Service, USDA, Beltsville, Maryland, and Department of Civil and Environmental Engineering, University of New Hampshire, Durham, New Hampshire

MICHAEL H. COSH

Hydrology and Remote Sensing Laboratory, Agricultural Research Service, USDA, Beltsville, Maryland

JENNIFER M. JACOBS

Department of Civil and Environmental Engineering, University of New Hampshire, Durham, New Hampshire

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ABSTRACT

The continuity of soil moisture time series data is crucial for climatic research. Yet, a common problem for continuous data series is the changing of sensors, not only as replacements are necessary, but as technologies evolve. The Illinois Climate Network has one of the longest data records of soil moisture; yet, it has a discontinuity when the primary sensor (neutron probes) was replaced with a dielectric sensor. Applying a simple model coupled with machine learning, the two time series can be merged into one continuous record by training the model on the latter dielectric model and minimizing errors against the former neutron probe dataset. The model is able to be calibrated to an accuracy of $0.050\,m^3\,m^{-3}$ and applying this to the earlier series and applying a gain and offset, an RMSE of $0.055\,m^3\,m^{-3}$ is possible. As a result of this work, there is now a singular network data record extending back to the 1980s for the state of Illinois.

1. Introduction

Soil moisture plays a pivotal role in hydrologic models. These measurements and models provide estimates of subsurface soil water storage and loss mechanisms that are crucial for drought research (Sheffield et al. 2004) and other climatic analyses (e.g., Campoy et al. 2013; Joetzjer et al. 2013). Soil moisture data are also relevant for decision support within agricultural regions in the Midwest, with one such example being the assessment of whether large equipment will damage fields or become mired (Coopersmith et al. 2014d). The previously cited study leveraged some of the data from the Illinois Climate Network (ICN), which forms the dataset for this current study.

Corresponding author address: Evan Coopersmith, Hydrology and Remote Sensing Laboratory, U.S. Department of Agriculture, 10300 Baltimore Avenue, Beltsville, MD 20705.
E-mail: ecooper2@gmail.com

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Several sparse soil moisture networks provide data throughout the continental United States. Perhaps the largest two are the U.S. Climate Reference Network (Diamond et al. 2013) and the Soil Climate Analysis Network (SCAN; Schaefer et al. 2007). In addition to these national networks, each of which provides on the order of 100 sensors, there are state-level networks that provide soil moisture time series data for climate research within their boundaries. Such networks are available in Oklahoma (Illston et al. 2008), North Carolina (Pan et al. 2012), Nebraska (Hubbard et al. 2009), and as mentioned previously, in Illinois (WARM 2014).

Previous inquiries have compared the performance of one soil moisture measurement instrument against another, but only one utilized an overlapping, multiyear time series (Cosh et al. 2016). Additionally, other research has attempted to lengthen and homogenize a data record by using one product when another was unavailable (Coopersmith et al. 2015a). In this analysis, a comparison has been performed between two soil moisture products provided by the Illinois State Water

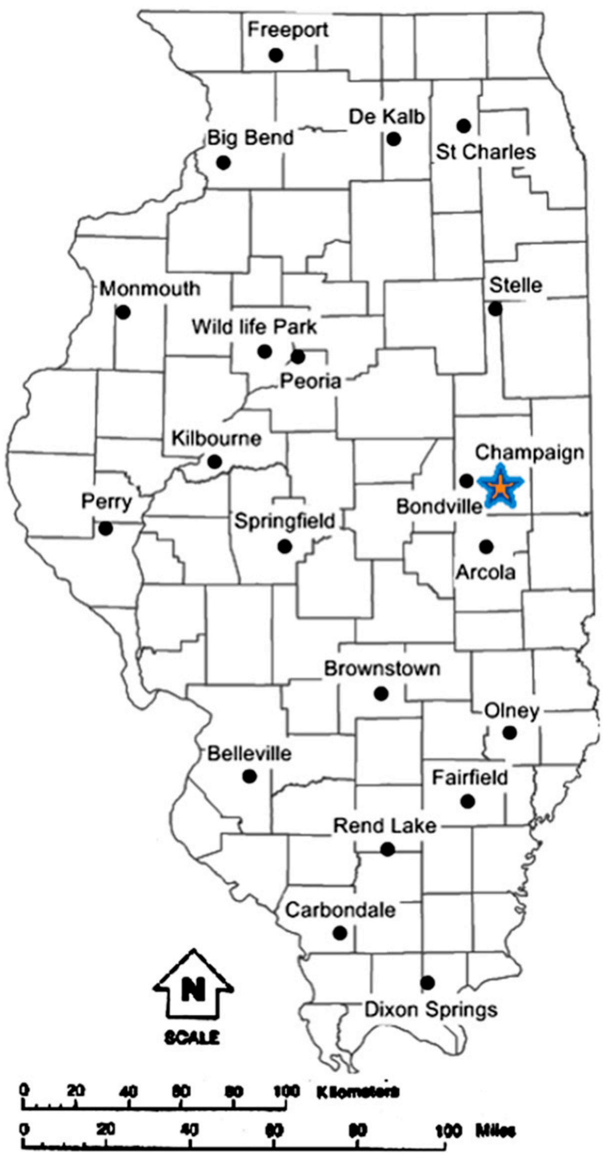

FIG. 1. Locations of the ICN.

Survey (ISWS). The first is a sequence of neutron probe measurements. The probes were installed during the late 1980s and provided measurements every 2 weeks until as late as 2008 at some locations. These probes were eventually supplanted by a dielectric probe manufactured by Stevens Water (HydraProbe). The Stevens probes provided regular, automated measurements, beginning in the early 2000s and extending to the present. Figure 1 presents the locations of 19 active sensor installations within the ICN. Monitoring ceased at the Wildlife Prairie Park (Wildlife Park) site in the early 2000s, at which point Big Bend became its replacement—neither is used in the subsequent analysis. The Arcola site was utilized on a short-term basis for a research study, after which monitoring ceased—it is also excluded from further analysis. Each installation contains a collocated precipitation gauge in addition to its soil moisture sensor. The star denotes Champaign, the headquarters of ISWS. This extensive and unique data record from ICN can be improved upon by generating a singular series with similar dynamics throughout the data record. There are four main steps to this study.

First, the relationship between neutron probes and dieletric probes is analyzed during the periods for which both products are available. This analysis addresses the 5-cm (~2 in.) depth for soil moisture measurement only. Second, with precipitation data also available hourly during all periods for which the dielectric data are available, using a precipitation-driven model of soil moisture, the diagnostic soil moisture equation (Pan et al. 2003; Pan 2012) is calibrated using observed precipitation and dielectric-based soil moisture data and then used to fill gaps in the current historical soil moisture data record. Third, moving forward, future soil moisture estimation can occur if/when a sensor is removed from the network. Finally, the distributions of the soil moisture records produced by the two sensor technologies (neutron and HydraProbes) and the calibrated model are analyzed, demonstrating that similar distributions of soil moisture estimates are generated by the two in situ technologies and the model.

2. Methodology

a. In situ resources: An overview

As discussed, each of the sites within the Illinois Climate Network contained a neutron probe (typically installed from the late 1980s until roughly 2008) and a coaxial impedance dielectric reflectometry sensor (a HydraProbe, called ''dielectric'') installed in early 2003 and active thereafter. At each location's collocated precipitation gauge (which reports an hourly reading), since 2008, the ICN records total precipitation received within the previous hour. Prior to 2008, the ICN reported the total quantity of precipitation in the sensor's ''bucket,'' rather than the previous hour's collection. Data were cleaned by subtracting the readings from the previous hour from the current hour's value in these cases. Values were not permitted to fall below zero—for example, the bucket is emptied and the subsequent hour's reported value becomes *lower* than the previous hour. Though the effects of evaporation introduce potential sources of error in these pre-2008 cases, if negative differences are set to zero (i.e., in the absence of rain, the bucket reports 10 mm and then 9.9 mm the next hour) and one presumes evaporation *during* rain events to be minimal (i.e., 10 mm in hour t and 13.2 mm in hour $t + 1$ after a rain event), then the impact of this data-gathering change should be small. Moreover, the considerable majority of overlap between neutron and dielectric readings, the time for which this study's comparisons occur, takes place with the single-tipping-bucket measurement method. With respect to quality control, both precipitation and soil moisture measurements are marked with appropriate error codes when values are missing and/or estimated from data procured from surrounding stations—the latter occurring when network managers deem data unreliable and flag the values as such. Both types of flagged data are removed from this analysis.

Both neutron probes and dielectric measurements are well-established tools for delivering in situ measurements, having been discussed in the literature for several decades (e.g., Schmugge et al. 1980). Neutron probes, since their development nearly 70 years ago (Belcher et al. 1950) by detecting the presence of hydrogen atoms in the immediate proximity of the sensor via the return of slower-moving neutrons, estimate moisture within the soil (Chanasyk and Naeth 1996) at a spherical distance given by an equation from Kristensen (1973):

$$R = \frac{100}{(1.4 + 0.1W)}. \qquad (1)$$

Equation (1) estimates a radius R (cm) based on volumetric water content W (a percentage). Thus, for sensors in Illinois, where soil moisture levels are typically between 10% and 40%, the sphere of influence ranges from roughly 15 to 20 cm in wet soil to 40 cm in dry soils. Though above-surface vegetation has been shown to play a small role in neutron probe soil moisture (Coopersmith et al. 2014a), with sensitivity of neutron probes to moisture decreasing linearly with distance cubed, they serve as strong point approximations when installed at surface depths. Calibrations of dielectric soil moisture instruments suggest the soil sampled for estimation of a dielectric constant (the proxy for moisture levels) is approximately 60 cm^3, as determined by Hanson and Peters (2000). This study finds the influence of dielectric sensors to be between 1 and 4 in. (2.5–10 cm), depending on the device. Though smaller perhaps than neutron probe ranges, this implies a spatial estimate nonetheless.

b. Comparison methods

In comparing the values from the neutron probes to those produced by the dielectric probes at the same location, we began by calculating correlation and RMSE values between the neutron probe values and the calibrated dielectric probe measurements. Next, an optimal linear offset was introduced to the dielectric probe readings, a bias correction to the neutron probe values (assumed to be the most accurate; Evett and Steiner 1995). This decreases the calculated RMSE values but leaves the correlation values unchanged. Finally, an optimal gain (slope) *and* offset is introduced to dielectric probe values, thereby offering the best possible linear correction between dielectric probes and neutron probes. Once again, a lower RMSE value is obtained while the correlation values remain constant.

Having completed three comparisons (unaltered, with an optimal offset, with an optimal gain and optimal offset), the residuals are analyzed between the raw values of the neutron probes and dielectric probes. Neutron probes have been shown to ''count'' moisture stored in vegetation in addition to the moisture stored in the soil that they are intended to measure. Corrections have been introduced to Cosmic-Ray Soil Moisture Observing System (COSMOS) rovers (first introduced by Zreda et al. 2008), whose area estimates have been shown to be influenced by proximal vegetation (Coopersmith et al. 2014a). For this reason, we observed whether the passage of the growing season seemed to alter the residuals obtained between the neutron probe and dielectric probe measurements. All measurements are compared with the model product during periods when all three products are available.

This analysis focuses upon soil moisture estimates produced by the two relevant technologies at the 5-cm depth. This depth reflects the focus of studies performed within other sparse and dense networks alike (e.g., Stillman et al. 2014). Soil moisture at the surface level also becomes a key parameter to be estimated with remotely sensed estimates from land surface satellites (AMSR-E, SMOS, SMAP, etc.). Soil moisture estimates used to calibrate and validate those satellites are those taken at the 5-cm depth from dense and sparse networks.

c. Model calibration

The diagnostic soil moisture equation is a simple lumped bucket model developed by Pan et al. (2003) and updated by Pan (2012) to better facilitate its calibration. This model calculates a modified antecedent precipitation index, convoluting a series of decaying temporal weights with a time series of antecedent precipitation. Integrating these weights with estimated losses from deep drainage or evapotranspiration, which are assumed to be fully specified by a sinusoidal function with a period of one year, a precipitation time series is converted to a soil moisture time series by a model containing six calibrated parameters. The diagnostic soil moisture equation is defined as

$$\theta_{\text{est}} = \theta_{\text{re}} + (\phi_e - \theta_{\text{re}})(1 - e^{-c_4\beta}). \quad (2)$$

Originally designed as a model with which to estimate the average daily soil moisture, the model can be updated to produce hourly estimates (represented by θ_{est}). In Eq. (2), ϕ_e and θ_{re} denote the maximum and minimum possible modeled values for soil moisture (porosity and residual soil moisture, respectively, both measured in $\text{m}^3\,\text{m}^{-3}$), while c_4 indicates the rate at which soil dries, as a function of both conductivity and drainage. Note that for infinitesimal values of c_4, the soil is presumed to dry infinitely rapidly. The term θ_{est} remains anchored to its lowest possible value, θ_{re}. In contrast, if c_4 grows large, then the soil will be unable to dry, remaining pinned to ϕ_e, its highest possible value. The dimensionless β series appears below:

$$\beta = \sum_{i=2}^{i=n-1}\left[\frac{P_i}{\eta_i}\left(1 - e^{-\frac{\eta_i}{z}}\right)e^{-\sum_{j=1}^{j=i-1}\left(\frac{\eta_j}{z}\right)}\right] + \frac{P_1}{\eta_1}\left(1 - e^{-\frac{\eta_1}{z}}\right). \quad (3)$$

Within the β series, the convolution occurs, combining a precipitation series (values of P_i) running backward by hour i. Rainfall from the previous hour therefore carries a larger weight than rainfall from the previous day, week, month, etc., until n historical hours have been reached (the weights eventually decay to trivial values). The depth of the model estimate is denoted by z. The values of η_i, the eta series, connote the estimated losses due to deep drainage or evapotranspiration at hour i, which is assumed to be part of a sinusoidal function defined by three parameters (the fourth, period, is assumed to be equal to one year). The three parameters of the sinusoid, then the three parameters (ϕ_e, θ_{re}, and c_4) in Eq. (2) are fit via a pair of real-coded genetic algorithms, for which more detail is available in Coopersmith et al. (2014c). Each ISWS location is fit with a distinct set of six parameters (the three parameters of the sinusoid, and ϕ_e, θ_{re}, and c_4) along with a historical window to consider, n.

d. *Determining model validity, choosing viable sites*

The calibration–validation process of model development can be deployed as a filter, allowing us to exclude sites for which a model cannot be calibrated and validated successfully. This approach was used in Coopersmith et al. (2015a) to choose 91 sites from within the U.S. Climate Reference Network (USCRN; 114 sensors in total) whose historical data records could be extended by employing the diagnostic soil moisture equation. This approach also distilled the most reliable and consistent sites from SCAN. In turn, with these works having demonstrated that this model can be calibrated successfully at 100+ locations scattered throughout the CONUS, if a site in Illinois cannot be calibrated in this manner, it is reasonable to assume that the time series data may contain some irregularities that would disqualify them from use in this work.

The diagnostic soil moisture equation was calibrated and validated during the growing season only. This was achieved by utilizing only data from days 100 to 300 of a calendar year, and thereby avoiding issues of freeze–thaw for which the diagnostic soil moisture equation is not appropriately constructed. The calibration period was chosen to be the data from the installation of the dielectric probes and precipitation gauges (in 2003 or 2004) through the conclusion of the 2011 growing season. Three additional growing seasons (2012, 2013, and 2014) were retained for validation of the parameters calibrated on the historical datasets. It is worth noting that the dynamic range of soil moisture values present in Illinois is larger than most locations throughout the CONUS. Within these data, soil moisture values frequently exceed 0.4 or even $0.5\,\text{m}^3\,\text{m}^{-3}$ while still falling to values below $0.1\,\text{m}^3\,\text{m}^{-3}$ during dry-down events. For this reason, root-mean-square error (RMSE) values in the 0.05–$0.07\,\text{m}^3\,\text{m}^{-3}$ range are probably reasonable model performances (where, say, in an arid region where soil moisture rarely exceeds $0.15\,\text{m}^3\,\text{m}^{-3}$, they would not be). In these cases, a site will be deemed viable if, during the validation period, an RMSE value below $0.07\,\text{m}^3\,\text{m}^{-3}$ is achieved in concert with a correlation (Pearson's ρ) > 0.7 (this roughly corresponds to $r^2 > 0.5$, meaning more variance is explained by the model than not). The standard has been selected due to the challenges of modeling soil moisture in the Upper Midwest, where anthropogenic influences (tillage, irrigation, tile drainage, etc.) are significant. Analyses for which soil moisture models are calibrated in the Upper Midwest (e.g., Coopersmith et al. 2015a,b,c) often produce validation correlations in the 0.7–0.85 range. Other hydrologic process models fail altogether in this region (e.g., Ye et al. 2012). To ensure that model performance is not compromised by flooded sensors immediately following rain events and/or sensors that have not yet received the infiltrated rainfall, the 4 h immediately following a rain event are removed. This 4-h removal has been deployed in other similar comparisons of soil moisture products to ensure consistency. (Coopersmith et al. 2015a,b,c).

As this model is highly dependent upon the accuracy and reliability of precipitation data, steps were taken during the calibration and validation periods to ensure

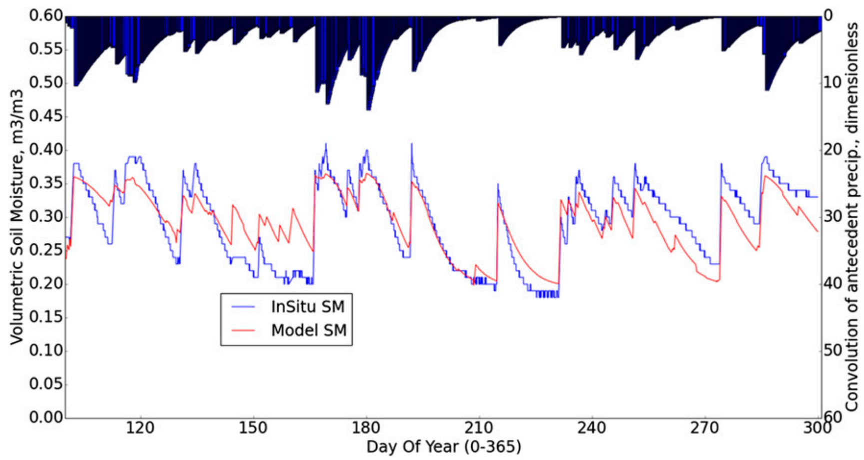

FIG. 2. Freeport 2014. Model vs dielectric probe in situ.

defensible machine learning approaches over imperfect datasets. For this reason, the flagged precipitation data points and/or those with missing values are set to zero but ignored in terms of calculating the fitness functions within the genetic algorithms used for calibration; that is, those time stamps are not used to determine the accuracy of a model when attempting to calibrate optimal parameters, and subsequently, in validation, whether or not it meets appropriate thresholds.

Having used a model to ascertain the consistency and reliability of a given site's dielectric probe and precipitation time series at that location, an additional constraint is imposed, requiring that neutron data are available at times overlapping the dielectric probe measurements. At this point 11 sites remained, containing between 9 and 45 neutron probe measurements during the period in which dielectric probe measurements were gathered. These sites included Belleville, Brownstown, Carbondale, Champaign, Dixon Springs, Fairfield, Freeport, Monmouth, Olney, Springfield, and Stelle (see Fig. 1).

e. *Verification of similar distributions*

In comparing neutron probe estimates to those generated with dielectric probes, it is illustrative to calculate the first two moments of the distribution of those estimates during periods where both products exist. In so doing, we can understand how "different" the values produced by neutron and dialectric probes are on a statistical level, and to what extent the variability generated by the model approximates the variability of measurements produced by dielectric and neutron probes.

3. Results

Figure 2 presents a time series at the Freeport site (see Fig. 1) during validation—in this case during the growing season of 2014. The blue line illustrates the dielectric probe values as measured hourly. The red line represents the model's approximation thereof. Finally, the blue bands atop the image convey the values of the dimensionless values of the β series, the antecedent precipitation convolution.

This is a model that performs well, achieving a correlation of 0.839 and an RMSE value of 0.045 $m^3 m^{-3}$ despite historical values ranging from 0.12 to 0.45 $m^3 m^{-3}$. As discussed during the methodology section, correlations above 0.7 and RMSE values below 0.07 $m^3 m^{-3}$ are the thresholds to consider. This allows our analysis to continue consideration of Freeport results hereafter.

Table 1 presents the overall findings of our analysis at each site, providing the aggregate performance of the comparisons and model performances.

Table 1 presents results comparing neutron and dielectric measurements, beginning with every site for which there is a period where both neutron and dielectric measurements exist. Rows 2–4 improve the results by eliminating sites for which a model cannot be successfully calibrated, then introducing the optimal

TABLE 1. Performance of dielectric probes and calibrated models against neutron probes.

Subset	RMSE ($m^3 m^{-3}$)
All sites containing overlapping neutron/dielectric probe data	0.084
After elimination of sites for which the model performed poorly	0.073
After including optimal offsets	0.056
After including optimal gains and offsets	0.050
Model estimates (calibrated by dielectric probes) against neutron probes	0.080
Model estimates with optimal gain/offset, against neutron probes	0.055

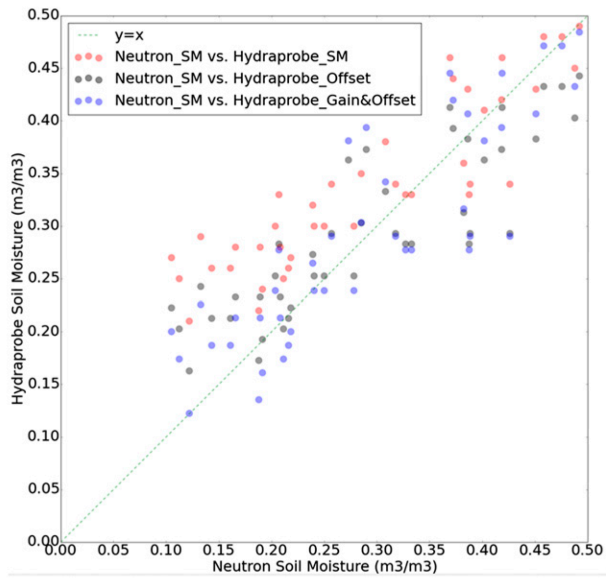

FIG. 3. Fairfield 2003–08. Dielectric probe vs neutron probe comparisons.

linear offset (bias correction) to the remaining sites, and then introducing an optimal offset and gain. The final two rows illustrate the performance of the model against neutron probes with and without the introduction of the optimal gain and offset. In all cases, the RMSE column represents the average root-mean-square error for all of the comparisons performed for that row.

These results suggest that an optimally offset time series of dielectric probe data and an optimally offset model calibrated with dielectric probe data perform comparably against neutron probe data, both falling between 0.050 and 0.055 $m^3 m^{-3}$. Additionally, the elimination of sites at which the model performs poorly does offer a substantial benefit to dielectric probe performance against neutron probes (0.084 vs 0.073 $m^3 m^{-3}$). It is appropriate to note that, in Coopersmith et al. (2016), it was discovered that the random error associated with soil moisture measurement in the Upper Midwest via dielectric probes is 0.02–0.03 $m^3 m^{-3}$ in many locations and as such, even a perfect model would encounter a *minimum* of this level of error.

Figure 3 presents a scatterplot, at the Fairfield site (see Fig. 1), presenting an *X–Y* comparison of neutron and dielectric probes (during the times at which neutron probe measurements were gathered in concert with dielectric probe values, from 2003 to 2008). The pink dots denote the unaltered dielectric probe readings, the gray dots illustrate the same readings following the introduction of an optimal offset, and the blue dots signify the results once an optimal gain and offset have been introduced. For clarity, a green dashed line with a slope of unity is offered to better illustrate the relationship between the two data sources. It is evident that, with the introduction of an appropriate gain and offset, a relationship that appears close to 1:1 can be achieved.

Figure 4 presents an annual time series (2005) from the Carbondale site. The dark blue line presents the dielectric probe time series values before the introduction of an optimal offset (dark blue dashed line). Finally, after the introduction of an optimal gain and offset, the light blue dashed line illustrates the optimally adjusted time series. These are compared with the pink dots, the values of the neutron probe measurements. In Fig. 4 specifically, it is evident that the neutron probe senses more moisture than do the dielectric probes. As a result, the optimal offset shifts the dark blue line upward. From there, the addition of an optimal gain results in a smaller alteration, which approximates the values of the pink dots much more closely. The nature of the remaining errors becomes the topic of the next set of results.

Figures 5 and 6 present the residual plots at Brownstown and Freeport during the entirety of the overlapping period between dielectric probe and neutron probe measurements. The values of these residuals are plotted against the day of the year (0–365) in which they occur. In Brownstown (Fig. 5), it is evident that the values of the residuals increase as the growing season elapses. As the residuals are the difference between the neutron probe values and the Hydprobe measurements (the former responds to moisture stored in vegetation, the latter does not), it seems plausible that, at Brownstown, the growth of vegetation covering the sensory installation affects one measurement product but not the other. In contrast, at Freeport (Fig. 6), no such trend is observed. Additionally, while all ICN measurements are made under sod, between the two stations utilized as examples (Brownstown and Freeport), the former is located in a lower-lying area that can, potentially, become mired.

Table 2 presents the summary statistics of the distributions of the three soil moisture products (neutron, dielectric, model) at each of the 11 well-performing locations, during those time stamps where the records of all three products overlap.

In Table 2, μ_N, μ_D, and μ_M represent the mean soil moisture at each location for the neutron probes, dielectric probes, and model estimates, respectively. The σ_N, σ_D, and σ_M values denote the standard deviations of those respective distributions, respectively. It is evident that neutron probes report slightly higher soil moisture values than their dielectric counterparts, as found by Coopersmith et al. (2014a). The average μ_N value, 0.291 $m^3 m^{-3}$, exceeds the average μ_D value, 0.253 $m^3 m^{-3}$.

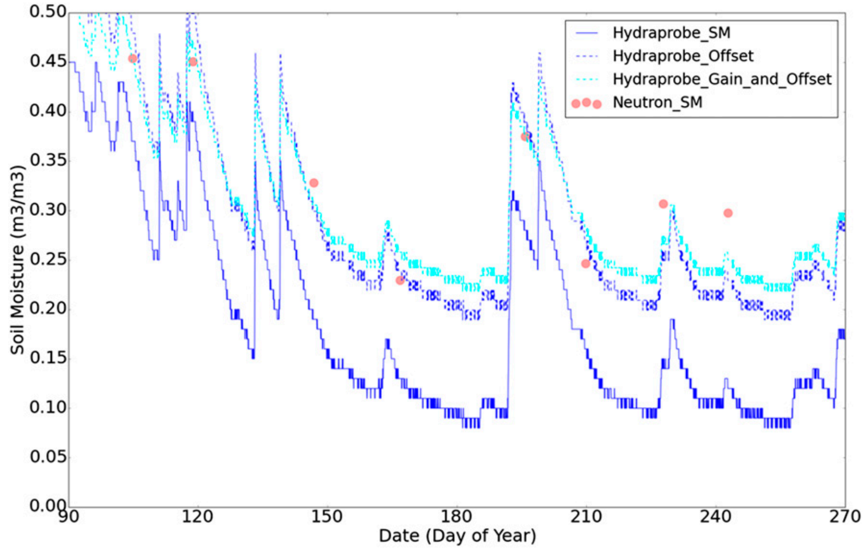

FIG. 4. Carbondale 2005. Illustration of adjusted dielectric probe data to approach neutron probe measurement values.

The model, calibrated using dielectric probes, nonetheless, generates values that fall between the two, as the average value of μ_M, 0.270 $m^3 m^{-3}$.

It is also worth noting that the variability of the neutron and dielectric probe measurements are comparable, with the average values of σ_N and σ_D at 0.100 and 0.090 $m^3 m^{-3}$, respectively. The model's estimates display somewhat diminished variabilities, as they are calibrated via the dielectric estimates (that do not respond to the vegetation-bound soil moisture of the neutron probes), ignoring hours during and immediately following rain events—this smooths the estimates such a model generates.

Table 3 presents the results from two-tailed, paired, heteroscedastic t tests to compare the means of the distributions of soil moisture estimates generated by the neutron probes, their dielectric replacements, and the model. Additionally, the results of F tests assessing the significance of the differences in standard deviations associated with the three products are calculated. The

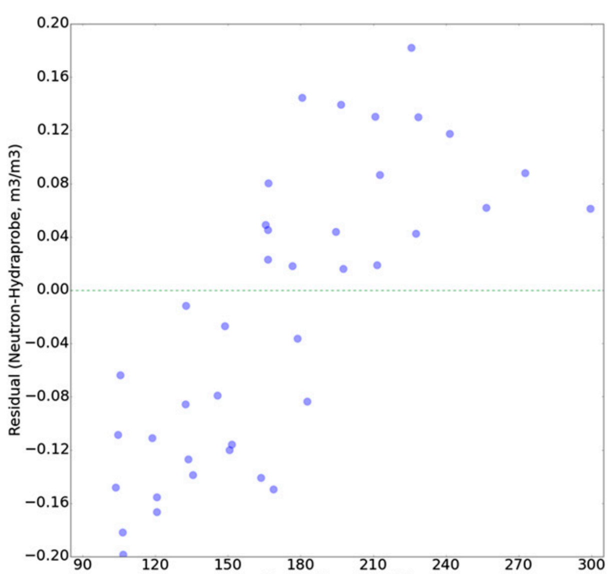

FIG. 5. Brownstown 2003–08. Residual plot with notable trend.

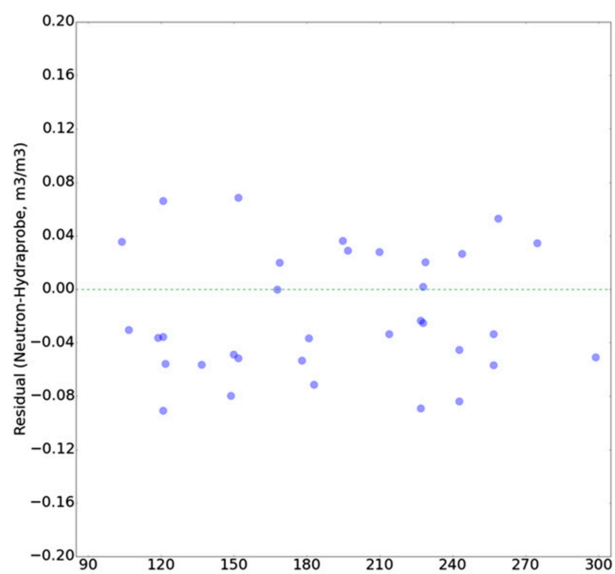

FIG. 6. Freeport 2003–08. Residual plot without a notable trend.

TABLE 2. Distributions of soil moisture values from three products.

Site	Start Year, DOY	End Year, DOY	n	μ_N	μ_D	μ_M	σ_N	σ_D	σ_M
Belleville	2003, 177	2004, 259	13	0.273	0.236	0.218	0.085	0.103	0.077
Brownstown	2003, 119	2008, 183	40	0.338	0.314	0.314	0.133	0.048	0.036
Carbondale	2003, 121	2008, 198	38	0.330	0.221	0.232	0.116	0.132	0.113
Champaign	2003, 151	2004, 210	12	0.266	0.178	0.196	0.060	0.072	0.080
Dixon Springs	2003, 150	2004, 275	12	0.292	0.252	0.306	0.132	0.110	0.073
Fairfield	2003, 149	2008, 198	45	0.301	0.348	0.349	0.120	0.083	0.064
Freeport	2003, 121	2008, 197	34	0.278	0.258	0.295	0.068	0.058	0.030
Monmouth	2003, 106	2004, 244	17	0.256	0.248	0.265	0.080	0.067	0.048
Olney	2003, 134	2004, 274	9	0.261	0.231	0.266	0.146	0.117	0.066
Springfield	2003, 105	2008, 197	40	0.276	0.231	0.262	0.084	0.083	0.056
Stelle	2003, 135	2004, 260	9	0.333	0.272	0.267	0.080	0.114	0.094

time period and sample size values are available in Table 2. All comparisons occur only using time stamps where the availability of all products overlap.

It is noteworthy that, with respect to comparisons of means, it is in the minority of cases, at any given site, that the differences in mean soil moisture reported by one product or another are significant at the $\alpha = 0.05$ level. In comparing the distributions from neutron and dielectric probes, 4 of the 11 sites display statistically significant differences in mean and only 2 display statistically significant differences in variability. With respect to the model, which was calibrated using dielectric probe data, only one site displays significant differences with respect to either of the distribution's first two moments. Encouragingly, the number of statistically significant differences noted between the two technologies exceeds the number of such differences between the model and either technology. It is worth noting that two distributions that are statistically significant in their differences may, nonetheless, be extremely similar. Namely, if one sensor technology repeatedly reported 0.001 $m^3 m^{-3}$ higher values than another, given a sufficient number of samples, the differences would become statistically significant, despite their obvious similarity. One technology would represent a fair replacement for the other, especially if the introduction of a linear offset was plausible.

Note that it is possibly inappropriate to compare the neutron probe distributions during their previous years (beginning in the 1980s) to the dielectric estimates from more recent years, as studies have demonstrated that the impacts of long-term climate change are observable on such temporal scales, specifically as it related to runoff timing in the Midwest (Coopersmith et al. 2014b). Hence, our comparisons are limited to time periods of overlapping availabilities.

4. Discussion and conclusions

It was demonstrated that dielectric probes, once an optimal gain and offset are introduced, perform relatively well in comparison with neutron probes. The RMSE value of 0.051 $m^3 m^{-3}$ is in line with other works comparing performances of soil moisture products (Coopersmith et al. 2015b). Moreover, a semiempirical model based on the dielectric probes performs almost as well (after the inclusion of a gain and offset) with an RMSE of 0.055 $m^3 m^{-3}$. It would be feasible to maintain

TABLE 3. Tests of significance—means (t tests) and standard deviations (F tests)—of neutron and dielectric probe estimates.

Site	Neutron vs dielectric (t test)	Neutron vs model (t test)	Dielectric vs model (t test)	Neutron vs dielectric (F test)	Neutron vs model (F test)	Dielectric vs model (F test)
Belleville	0.333	0.099	0.618	0.085	0.103	0.077
Brownstown	0.270	0.278	0.919	0.133	0.048	0.036
Carbondale	0.000	0.000	0.688	0.116	0.132	0.113
Champaign	0.004	0.026	0.565	0.060	0.072	0.080
Dixon Springs	0.426	0.751	0.170	0.132	0.110	0.073
Fairfield	0.033	0.019	0.927	0.120	0.083	0.064
Freeport	0.201	0.193	0.002	0.068	0.058	0.030
Monmouth	0.776	0.683	0.411	0.080	0.067	0.048
Olney	0.634	0.939	0.454	0.146	0.117	0.066
Springfield	0.017	0.369	0.054	0.084	0.083	0.056
Stelle	0.212	0.129	0.913	0.080	0.114	0.094

this soil moisture record into the future with a loss of dielectric probes, as long as precipitation data are available. Both of these methods adjust the current soil moisture record to mimic the dynamics of the earlier neutron probe network. It would be just as simple to reverse the regression and replace the neutron probe data record to be consistent with the modern dielectric probe network. Last, it seems plausible that one could generate a quality-control system that employs such a calibrated model to fill the gaps in the dielectric probe data record where needed. Extending this particular line of thought, future work could incorporate a model to increase the continuous data record of ICN, specifically at moments for which precipitation data are available but when soil moisture data are not. In this vein, ICN can obtain, without the installation of additional sensory resources, a more robust and continuous data record.

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REFERENCES

Belcher, D. J., T. R. Cuykendall, and H. S. Sack, 1950: The measurement of soil moisture and density by neutron and gamma-ray scattering. Tech. Development Rep. 127, Technical Development and Evaluation Center, Civil Aeronautics Administration, 20 pp.

Campoy, A., A. Ducharne, F. Cheruy, F. Hourdin, J. Polcher, and J. C. Dupont, 2013: Response of land surface fluxes and precipitation to different soil bottom hydrological conditions in a general circulation model. *J. Geophys. Res. Atmos.*, **118**, 10 725–10 739, doi:10.1002/jgrd.50627.

Chanasyk, D. S., and M. A. Naeth, 1996: Field measurement of soil moisture using neutron probes. *Can. J. Soil Sci.*, **76**, 317–323, doi:10.4141/cjss96-038.

Coopersmith, E. J., M. H. Cosh, and C. S. T. Daughtry, 2014a: Field-scale moisture estimates using COSMOS sensors: A validation study with temporary networks and Leaf-Area-Indices. *J. Hydrol.*, **519**, 637–643, doi:10.1016/j.jhydrol.2014.07.060.

——, B. S. Minsker, and M. Sivapalan, 2014b: Patterns of regional hydroclimatic shifts: An analysis of changing hydrologic regimes. *Water Resour. Res.*, **50**, 1960–1983, doi:10.1002/2012WR013320.

——, ——, and ——, 2014c: Using similarity of soil texture and hydroclimate to enhance soil moisture estimation. *Hydrol. Earth Syst. Sci.*, **18**, 3095–3107, doi:10.5194/hess-18-3095-2014.

——, ——, C. E. Wenzel, and B. J. Gilmore, 2014d: Machine learning assessments of soil drying for agricultural planning. *Comput. Electron. Agric.*, **104**, 93–104, doi:10.1016/j.compag.2014.04.004.

——, M. H. Cosh, and J. E. Bell, 2015a: Extending the soil moisture data record of the U.S. Climate Reference Network (CRN) and Soil Climate Analysis Network (SCAN). *Adv. Water Resour.*, **79**, 80–90, doi:10.1016/j.advwatres.2015.02.006.

——, ——, R. Bindlish, and J. E. Bell, 2015b: Comparing AMSR-E soil moisture estimates to the extended record of the U.S. Climate Reference Network (USCRN). *Adv. Water Resour.*, **85**, 79–85, doi:10.1016/j.advwatres.2015.09.003.

——, ——, W. Petersen, J. Prueger, and J. J. Niemeier, 2015c: Full access soil moisture model calibration and validation: An ARS watershed on the South Fork Iowa River. *J. Hydrometeor.*, **16**, 1087–1101, doi:10.1175/JHM-D-14-0145.1.

——, ——, J. E. Bell, and W. T. Crow, 2016: Multi-profile analysis of soil moisture within the US Climate Reference Network (USCRN). *Vadose Zone J.*, **15** (1), doi:10.2136/vzj2015.01.0016.

Cosh, M. H., and Coauthors, 2016: The Soil Moisture Active Passive Marena, Oklahoma, In Situ Sensor Testbed (SMAP-MOISST): Testbed design and evaluation of in situ sensors. *Vadose Zone J.*, **15** (4), doi:10.2136/vzj2015.09.0122.

Diamond, H. J., and Coauthors, 2013: U.S. Climate Reference Network after one decade of observations: Status and assessment. *Bull. Amer. Meteor. Soc.*, **94**, 485–498, doi:10.1175/BAMDS-D-12-00170.1.

Evett, S. R., and J. L. Steiner, 1995: Precision of neutron scattering and capacitance type soil water content gauges from field calibration. *Soil Sci. Soc. Amer. J.*, **59**, 961–968, doi:10.2136/sssaj1995.03615995005900040001x.

Hanson, B. R., and D. Peters, 2000: Soil type affects accuracy of dielectric soil moisture sensors. *Calif. Agric.*, **54**, 43–47, doi:10.3733/ca.v054n03p43.

Hubbard, K. G., J. You, V. Sridhar, E. Hunt, S. Korner, and G. Roebke, 2009: Near-surface soil-water monitoring for water resources management on a wide-area basis in the Great Plains. *Great Plains Res.*, **19**, 45–54.

Illston, B. G., J. Basara, D. K. Fischer, R. L. Elliott, C. Fiebrich, K. C. Crawford, K. S. Humes, and E. Hunt, 2008: Mesoscale monitoring of soil moisture across a statewide network. *J. Atmos. Oceanic Technol.*, **25**, 167–182, doi:10.1175/2007JTECHA993.1.

Joetzjer, E., H. Douville, C. Delire, and P. Ciais, 2013: Present-day and future Amazonian precipitation in global climate models: CMIP5 versus CMIP3. *Climate Dyn.*, **41**, 2921–2936, doi:10.1007/s00382-012-1644-1.

Kristensen, K. J., 1973: Depth intervals and topsoil moisture measurement with the neutron depth probe. *Hydrol. Res.*, **4**, 77–85.

Pan, F., 2012: Estimating daily surface soil moisture using a daily diagnostic soil moisture equation. *J. Irrig. Drain. Eng.*, **138**, 625–631, doi:10.1061/(ASCE)IR.1943-4774.0000450.

——, C. D. Peters-Lidard, and M. J. Sale, 2003: An analytical method for predicting surface soil moisture from rainfall observations. *Water Resour. Res.*, **39**, 1314, doi:10.1029/2003WR002142.

Pan, W., R. P. Boyles, J. G. White, and J. L. Heitman, 2012: Characterizing soil physical properties for soil moisture monitoring with the North Carolina Environment and Climate Observing Network. *J. Atmos. Oceanic Technol.*, **29**, 933–943, doi:10.1175/JTECH-D-11-00104.1.

Schaefer, G. L., M. H. Cosh, and T. J. Jackson, 2007: The USDA Natural Resources Conservation Service Soil Climate Analysis Network (SCAN). *J. Atmos. Oceanic Technol.*, **24**, 2073–2077, doi:10.1175/2007JTECHA930.1.

Schmugge, T. J., T. J. Jackson, and H. L. McKim, 1980: Survey of methods for soil moisture determination. *Water Resour. Res.*, **16**, 961–979, doi:10.1029/WR016i006p00961.

Sheffield, J., G. Goteti, F. Wen, and E. F. Wood, 2004: A simulated soil moisture based drought analysis for the United States. *J. Geophys. Res.*, **109**, D24108, doi:10.1029/2004JD005182.

Stillman, S., J. Ninneman, X. Zeng, T. Franz, R. L. Scott, W. J. Shuttleworth, and K. Cummins, 2014: Summer soil moisture spatiotemporal variability in southeastern Arizona. *J. Hydrometeor.*, **15**, 1473–1485, doi:10.1175/JHM-D-13-0173.1.

WARM, 2014: Illinois Climate Network. Prairie Research Institute Illinois State Water Survey, accessed 23 April 2015, doi:10.13012/J8MW2F2Q.

Ye, S., M. Yaeger, E. Coopersmith, L. Cheng, and M. Sivapalan, 2012: Exploring the physical controls of regional patterns of flow duration curves—Part 2: Role of seasonality, the regime curve, and associated process controls. *Hydrol. Earth Syst. Sci.*, **16**, 4447–4465, doi:10.5194/hess-16-4447-2012.

Zreda, M., D. Desilets, T. P. A. Ferre, and R. L. Scott, 2008: Measuring soil moisture content non-invasively at intermediate spatial scale using cosmic-ray neutrons. *Geophys. Res. Lett.*, **35**, L21402, doi:10.1029/2008GL035655.