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Temporal transferability of soil moisture calibration equations

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ABSTRACT

Several large-scale field campaigns have been conducted over the last 20 years that require accurate measurements of soil moisture conditions. These measurements are manually conducted using soil moisture probes which require calibration. The calibration process involves the collection of hundreds of soil moisture cores, which is extremely labor intensive. In 2012, a field campaign was conducted in southern Manitoba in which 55 fields were sampled and calibration equations were derived for each field. The Soil Moisture Active Passive Experiment 2016 (SMAPVEX16) was conducted in this same region, and 21 of the same fields were resampled. This study examines the temporal transferability of calibration equations between these two field campaigns. It was found that the larger range in soil moisture over which samples were collected in 2012 (average range 0.11–0.41 $m^3\ m^{-3}$) generally resulted in lower errors when used in 2016 (average range 0.24–0.44 $m^3\ m^{-3}$) than the equations derived in 2016 when used with data collected in 2012. Combining the data collected in 2012 and 2016 did not improve the errors, overall. These results suggest that the transfer of calibration equations from one year to the next is not recommended.

1. Introduction

Knowledge of soil moisture variability, both spatially and temporally, at different scales is important for the validation of applications such as land surface models and remote sensing products (Crow et al., 2012; Famiglietti et al., 2008; Western et al., 2002). Although gravimetric sampling provides the most accurate estimation of soil moisture, it is labor intensive and time consuming. Electromagnetic sensors have been investigated extensively as an alternative for measuring soil moisture. Numerous studies have been conducted which investigate calibration strategies for soil moisture sensors that relate the measured soil dielectric permittivity to soil water content through (e.g. Bogena et al., 2017; Ojo et al., 2015; Rosenbaum et al., 2010; Rowlandson et al., 2013; Seyfried et al., 2005). Studies have also examined the variability between different commercially available soil moisture sensors. A study by Walker et al. (2004) found that sensors requiring soil disturbance for installation presented the highest errors in soil moistures retrieval despite calibration efforts. Cosh et al. (2016), using data from a soil moisture sensor testbed, found that electromagnetic sensors installed at a depth of 5 cm, when scaled to the field, had similar root mean square errors, all of which were <0.04 $m^3\ m^{-3}$. More specifically, studies have noted that lower frequency sensors exhibit sensitivity in the measurements of the soil dielectric permittivity resulting from the soil electrical conductivity (Seyfried et al., 2005; Seyfried and Murdock, 2004) and changes in soil temperature (Merlin et al., 2007; Wraith and Or, 1999). Inter-sensor variability is an issue that has been noted in several studies (e.g. (Bogena et al., 2017; Cosh et al., 2016; Rosenbaum et al., 2010; Seyfried and Murdock, 2004)); however, it has been noted that sensor-specific calibrations, which prior deriving a relationship between the soil water content and the soil dielectric permittivity, measurements are first made in media of known dielectric permittivity to determine inter-sensor variability (Rosenbaum et al., 2010).

Large-scale field campaigns (~$50^2\ km^2$) have been held where surface soil moisture measurements have been collected across a defined domain in an effort to capture the intra and inter-field soil moisture variability, particularly as it relates to remote sensing applications. Some of these field campaigns include: the Southern

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Great Plains 1997 (SGP97) Hydrology Experiment (Mohanty et al., 2002), the Soil Moisture Experiments (SMEX) in 2002 (Bindlish et al., 2006), 2003 (Bosch et al., 2006; Cosh et al., 2005), 2004 (Bindlish et al., 2008), and 2005 (Cosh et al., 2005); National Airborne Field Experiment 2006 (NAFE'06, Australia) (Merlin et al., 2008); Australian Airborne Cal/Val Experiments for SMOS (AACES) (Peischl et al., 2012); Canadian Experiment for Soil Moisture in 2010 (CanEX-SM10) (Magagi et al., 2013), Soil Moisture Active Passive (SMAP) Validation Experiment in 2012 (SMAPVEX12) (McNairn et al., 2015); and most recently, the SMAPVEX16 field experiment, which was conducted in the same general region as the SMAPVEX12 campaign.

In each of the aforementioned field campaigns, transects or grids of soil moisture were manually sampled at varying spatial scales. For each field campaign, large quantities of soil cores were collected to derive calibration equations (Cosh et al. 2005; Rowlandson et al. 2013). In SMAPVEX12 for example, over 700 cores were collected over the duration of the six week field campaign (Rowlandson et al., 2013). These cores provide the volumetric water content estimates upon which calibration equations are developed for dielectric soil moisture probes. Efficiency and accuracy are critical, because the SMAP mission requirement is to estimate surface soil moisture with an unbiased root mean square error (RMSE) of 0.04 $m^3\ m^{-3}$ relative to ground measurements (Chan et al., 2016). Dielectric probes are an efficient method for estimating soil moisture in the field. However, careful calibration of the ground sampled soil moisture is essential to ensure that the error in ground sampling measurements is less than this threshold.

The purpose of the large field campaigns described above is in the estimation of large-scale soil moisture estimates for the purpose of remote sensing calibration and validation. Therefore, the basis of the design is to collect statistically accurate soil moisture values for contributing land surfaces within the domain of the study in question. Efficient sampling is a key factor in this type of sampling, as time is of the essence in conducting the sampling over large spatial scales. Many of these campaigns are held within the same domain, separated by several years or months (e.g. SMAPVEX12 and SMAPVEX16 in Manitoba, SMAPEx-1 through SMAPEx-3 (Panciera et al., 2014), July 2010, December 2010, September 2011, respectively in Australia's Murrumbidgee catchment). Understanding if it is possible for transferring calibration equations over the same domain from one year to the next would enable future experimental design to be improved.

This study evaluates the temporal transferability of calibration equations, in an effort to minimize the labor intensity associated with core collection during these types of large field campaigns while retaining low calibration RMSEs. The manufacturer of the

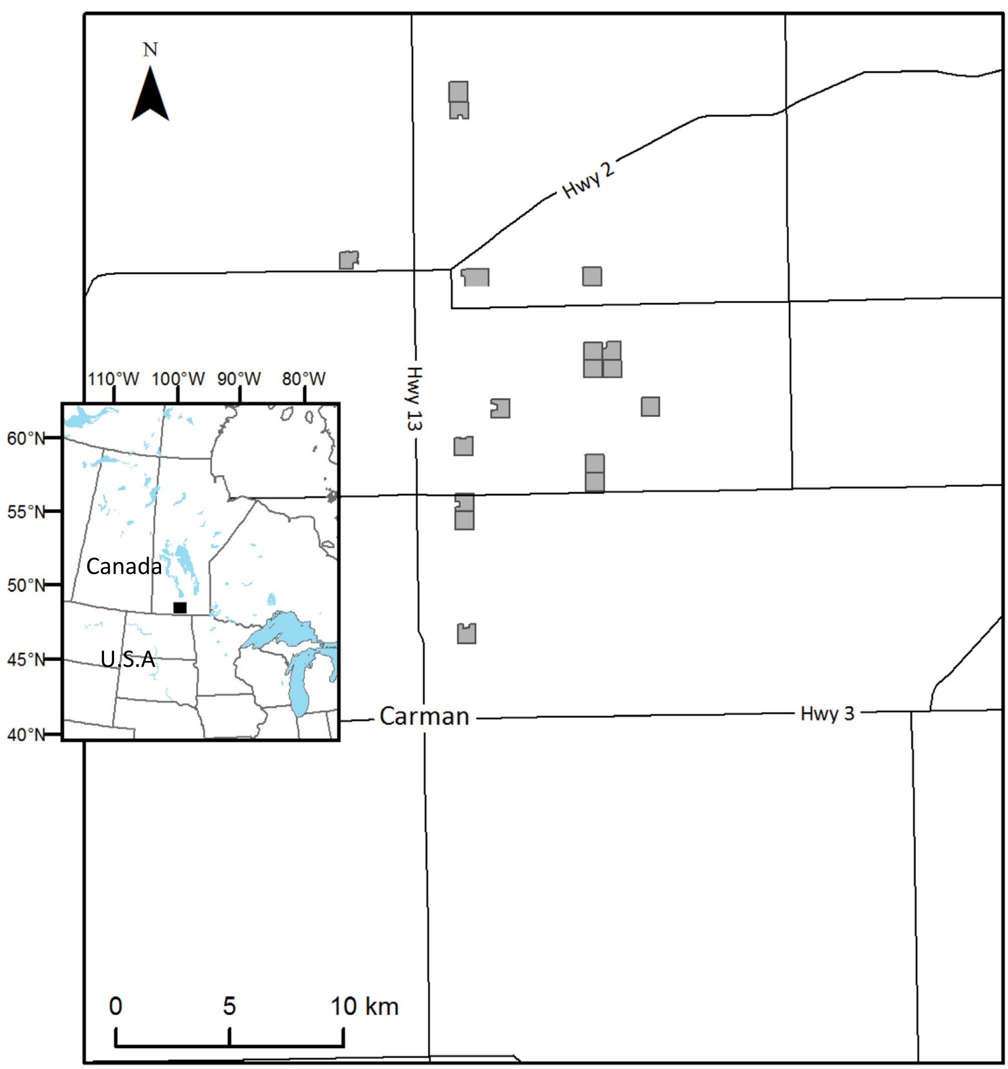

Fig. 1. Map of the SMAPVEX16 Manitoba study region. The fields that are light gray are fields that were sampled in both 2012 and 2016 (17 fields used in this study). Note the location of the study region in the insert.

Hydra probe has indicated that the sensor should not require recalibration due to a lack of temporal drift in sensor measurements due to probe calculations being based on the ratio of the incident and reflected signals (K. Bellingham, pers. communication). However, the transferability of the calibration equations needs to be assessed; otherwise errors could be needlessly propagated. Also, factors that could impact the temporal transferability of calibration equations from year to year are investigated.

2. Materials and methods

The SMAPVEX-16 (Soil Moisture Active Passive Validation Experiment 2016) field campaign was held southwest of Winnipeg, MB, in the same general region as the SMAPVEX-12 (2012) pre-launch field campaign (McNairn et al., 2015). This region is dominated by annual row crops, including corn, soybeans, oats, wheat, and canola. In total 50 fields were sampled for soil and vegetation characteristics, of which 21 had previously been sampled in 2012 (Fig. 1). The field sizes within the SMAPVEX-16 domain included in this study range from 55 ha to 88 ha. In 2016 the soil moisture sampling transects were relocated in four of the 21 fields, and particle size analysis indicated that there was a significant difference in the soil textures that were sampled suggesting that the sampled regions were conducted over different portions of the field. For this reason in the following analysis, these fields are removed from consideration and the study is limited to 17 fields. Readers are encouraged to refer to McNairn et al. (2015) and Rowlandson et al. (2013) for a detailed description of the study area.

Unlike the six weeks of continuous measurements in 2012 (June 6-July 17), the SMAPVEX-16 field campaign was conducted during two windows, the first from June 8–20 and the second, July 14–22. In total, soil moisture was sampled on 13 days (7 in the first window and 6 in the second). On each sampling date, soil moisture was collected along two transects, consisting of eight sampling points per transect in each field (refer to Fig. 2, Rowlandson et al., 2013). Each transect was 490 m long (8 points per transect, each 70 m apart) positioned in the same direction as crop seeding. The transects were located 100 m from the edges of the fields to ensure that sampling did not occur in regions subjected to compaction from equipment.

Soil moisture was sampled at each point along the transects using a Stevens Hydra probe (POGO) portable sensor (Stevens Water Monitoring Systems, Inc. Portland, OR), herein referred to as Hydra probe, a frequency domain reflectometry sensor operating at a 50 MHz frequency (Stevens Water Monitoring Systems, Inc., 2007). The Hydra probe measures the real and imaginary components of the soil permittivity. A voltage is applied to the probe and the reflected voltages are measured. The change in impedance between the emitted signal and reflected signal is related to the dielectric permittivity of the material in which the probe is embedded. The sensor provides an estimate of the complex soil relative permittivity, integrated from 0 to 5.7 cm The real component of the soil permittivity can be related to volumetric soil water content using an appropriate calibration function (e.g. Topp et al., 1980; Seyfried et al., 2005; Rowlandson et al., 2013). As mentioned previously, the measurements of the soil dielectric permittivity can be sensitive to temperature (Merlin et al., 2007; Wraith and Or, 1999) and soil electrical conductivity (Seyfried et al., 2005; Seyfried and Murdock, 2004).

Two soil cores (average core volume was 85 cm^3 in both 2012 and 2016) were collected on each of the sampling days for each field. On each day a core was extracted at the first point of the transect and an additional core was sampled at one of the remaining 15 sampling locations, where the location of the core changed on each sampling date, until cores had been collected across the entire field. With each core sampled, three Hydra probe measurements were taken around the core, within 10 cm of the core edge.

The cores were taken to a lab, weighed (M_t), dried at 105 °C for 24 h and re-weighed (M_s). The bulk density (ρ_b) of each core was

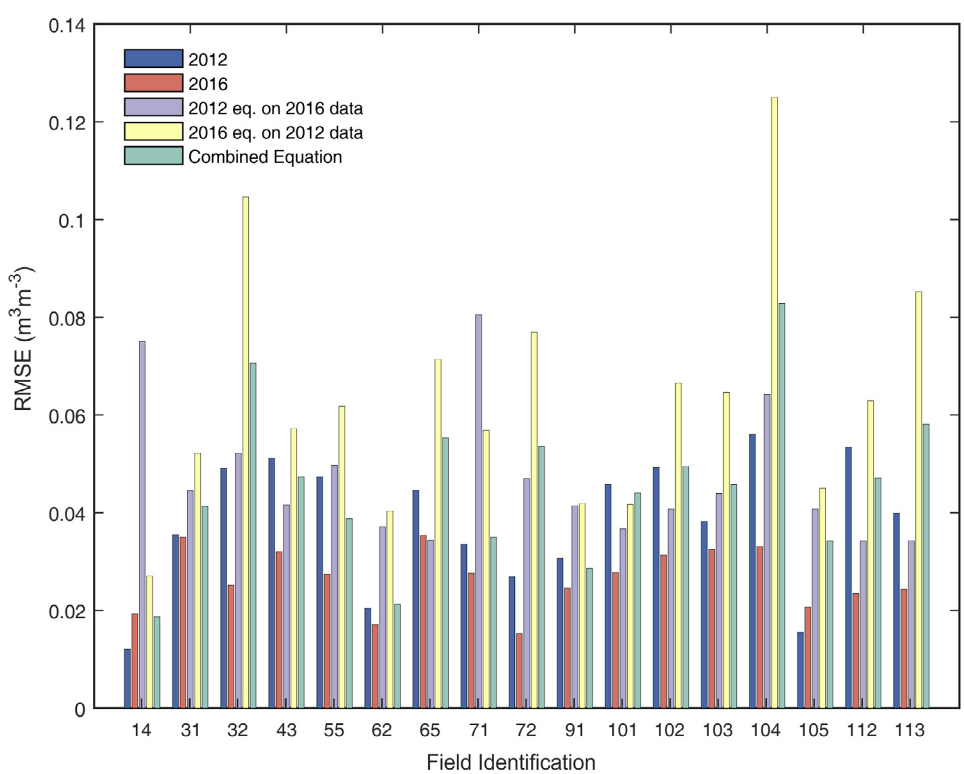

Fig. 2. RMSE values for 2012 and 2016 calibrations, the calibration equations derived in 2012 and applied to Hydra probe data collected in 2016, the calibration equations derived in 2016 and applied to Hydra probe data collected in 2012 and the average RMSE from the 10,000 Monte Carlo simulations using data from 2012 and 2016. Note that the sample size is the same for all scenarios with the exception of the combined equation, where the sample size is Nx2.

determined from (1) (V_t is the total volume of the core) and the volumetric water content (θ) was calculated from the product of the θ_g and ρ_b (2). The field average ρ_b was used in the calculation of the volumetric water content to correspond with the methodology used in 2012 (Rowlandson et al., 2013). The sampled cores were the basis for the calibration of the Hydra probe measurements.

$$\rho_b = M_s/V_t \quad (1)$$

$$\theta_{core} = (M_t - M_s)/M_s * \rho_b \quad (2)$$

For the 17 fields, the number of cores extracted ranged from 21 to 27 samples, which is nearly twice the number of cores collected per field in 2012. Volumetric water content of cores that were outside of two times the standard deviation of all cores were considered outliers and removed from the analysis, as recommended in Rowlandson et al. (2013). Due to the disparity in sample sizes, a Monte Carlo simulation was conducted which randomly selected the same number of N samples from the 2016 dataset (10,000 times) as were available from the 2012 dataset for each field. This random selection of 2016 measurements is used throughout the analysis and is referred to as the 2016 dataset. Many studies have published relationships between the square root of the Hydra probe measured relative permittivity and soil volumetric water content (e.g. Seyfried et al., 2005; Rowlandson et al., 2013; Burns

Table 1
Minimum (Min) and range of the core volumetric water content (VWC) for each field as measured in 2012 and 2016, the average (Avg) and standard deviation (Std) of the soil bulk density (BD) for each field for 2012 and 2016, the average (Avg) and standard deviation (Std) core gravimetric water content (GMC) for each field in 2012 and 2016, and soil texture (S = sand, Si = silt, L = loam, C = clay, HC = heavy clay).

Field ID	Min Core VWC 2012 (m^3 m^{-3})	Range VWC 2012 (m^3 m^{-3})	Min Core VWC 2016 (m^3 m^{-3})	Range VWC 2016 (m^3 m^{-3})	BD Avg 2012	BD Std 2012	BD Avg 2016	BD Std 2016	GMC Avg 2012	GMC Std 2012	GMC Avg 2016	GMC Std 2016	Soil Texture
14	0.08	0.09	0.07	0.33	1.26	0.09	1.21	0.13	0.09	0.07	0.15	0.06	S
31	0.16	0.33	0.28	0.24	0.97	0.11	0.87	0.09	0.38	0.09	0.45	0.08	SiCL
32	0.05	0.48	0.29	0.2	1.04	0.14	0.95	0.13	0.34	0.14	0.42	0.08	C
43	0.15	0.36	0.24	0.23	0.87	0.14	0.84	0.08	0.34	0.10	0.43	0.06	HC
55	0.17	0.29	0.33	0.21	0.84	0.11	0.92	0.1	0.36	0.11	0.49	0.07	HC
62	0.03	0.25	0.11	0.19	1.20	0.09	1.20	0.11	0.11	0.05	0.17	0.04	S
65	0.12	0.29	0.25	0.23	1.10	0.08	1.13	0.12	0.24	0.09	0.29	0.06	C
71	0.02	0.16	0.15	0.16	1.32	0.08	1.37	0.22	0.08	0.03	0.16	0.04	S
72	0.02	0.33	0.09	0.18	1.29	0.14	1.25	0.09	0.12	0.11	0.14	0.03	S
91	0.03	0.29	0.11	0.16	1.14	0.13	1.04	0.14	0.15	0.05	0.19	0.05	LS
101	0.14	0.27	0.27	0.16	0.90	0.12	0.79	0.07	0.29	0.11	0.44	0.06	HC
102	0.14	0.56	0.34	0.15	0.94	0.08	0.8	0.08	0.36	0.18	0.51	0.05	HC
103	0.18	0.46	0.30	0.20	0.91	0.10	0.83	0.1	0.39	0.14	0.47	0.07	HC
104	0.16	0.38	0.35	0.17	0.86	0.13	0.83	0.07	0.30	0.11	0.51	0.07	HC
105	0.16	0.24	0.32	0.21	0.82	0.08	0.89	0.11	0.35	0.09	0.49	0.07	HC
112	0.20	0.32	0.32	0.21	1.00	0.10	0.85	0.11	0.34	0.09	0.44	0.08	HC
113	0.12	0.45	0.24	0.16	0.97	0.11	0.84	0.12	0.31	0.14	0.47	0.07	HC

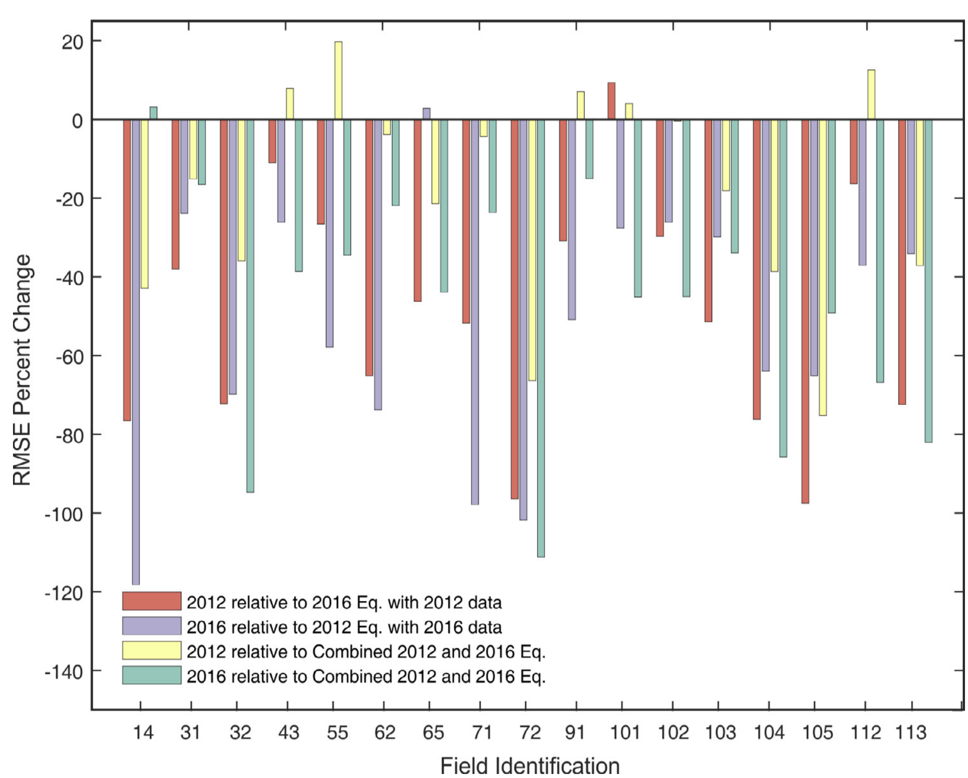

Fig. 3. The percent change in RMSE as calculated by, for example, [RMSE 2012 – RMSE 2016 Eq. with 2012 data]/[(RMSE 2012 + RMSE 2016 Eq. with 2012 data)/2], where the RMSE 2016 Eq. with 2012 data is the calibration equations derived in 2012 and applied to the Hydra probe and core volumetric water content collected in 2012.

et al., 2014; Ojo et al., 2015) and such relationships were used as the basis for the Hydra probe calibrations for this study. Individual calibration equations were developed for each agricultural field, as per the Rowlandson et al. (2013) recommendations, based on Eq. (3), where $\mathcal{E}'$ is the Hydra probe measured relative permittivity (or real component of the complex relative dielectric permittivity) and m and b are the derived slope and intercept of the regression equation with the core measured volumetric water content. For the cores collected in both 2012 and 2016, a leave-one-out approach was conducted to determine the robustness of the calibration equations.

$$\theta_{probe} = m\sqrt{\varepsilon'} + b \tag{3}$$

To test the transferability of the soil calibration equations, the field calibration equations (m and b, Eq. (4)) derived in 2012 for 17 of the same fields that were measured in 2016 were applied to the Hydra probe $\mathcal{E}'$ data collected in 2016. Similarly, the equations derived from cores and $\mathcal{E}'$ values obtained in 2016 were applied to the 2012 $\mathcal{E}'$ data. Errors were assessed using RMSE (4) and bias (5) and were calculated for each field.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\theta_{core} - \theta_{probe})^2}{n}} \tag{4}$$

$$Bias = \frac{\sum_{i=1}^{n}(\theta_{core} - \theta_{probe})}{n} \tag{5}$$

The core data collected in 2012 and 2016 were merged to create a single dataset for the development of calibration equations. For comparison, this combined dataset was also confined to the numbers of samples collected in 2012. A Monte Carlo simulation was conducted to randomly select cores from data collected in both 2012 and 2016 that equaled the number of cores extracted in 2012. This random selection was repeated 10,000 times for each field. With each random selection, for each field, the RMSE was calculated with (4).

Finally, field variables that could influence the difference in calibration equations between 2012 and 2016 were examined. The coefficient of variation (CV) (6) was calculated for the core measured bulk density and soil gravimetric water content, where $\sigma_{pb,\theta g}$ is the standard deviation and $\mu_{pb,\ \theta g}$ is the mean for either the bulk density (pb) or soil gravimetric soil moisture content (θg) measured values.

$$CV = \frac{\sigma_{\rho_{b,\theta g}}}{\mu_{\rho_{b,\theta g}}} \tag{6}$$

3. Results and discussion

3.1. Calibration comparison between 2012 and 2016

The calibration for 2016 (using the random selection of the same N as 2012) indicated that all fields had a calibration mean RMSE between the core measured volumetric water content (θ_v) and the calibrated Hydra probe θ_v that was <0.04 $m^3\ m^{-3}$ (Fig. 2). In all cases, the linear regression relationship between the calibrated Hydra probe θ_v and the core θ_v were significant at the 99% level (in 2012, the calibration equation for field 122 was not significant). For the majority of the fields sampled, the mean RMSE in 2016 was lower than those obtained in 2012 (15 out of 17 fields).

A leave-one-out approach was examined to test the robustness of the calibration equations derived for both 2012 and 2016. The leave-one-out approached indicated that the calibration equations were robust for all fields both in 2012 and 2016. The leave-one-out approach for 2012 indicated higher RMSE values for the calibrations for all fields, likely due to the decrease in the number of samples used for the analysis. However, a Wilcoxon rank sum test indicated that there was no significant difference between the calculated volumetric water content from the Hydra probes using all the samples or using the leave-one-out for any of the fields ($p > .1$). For the 2016 data set, a random selection was conducted to match the smaller sample size associated with the 2012 leave-one out

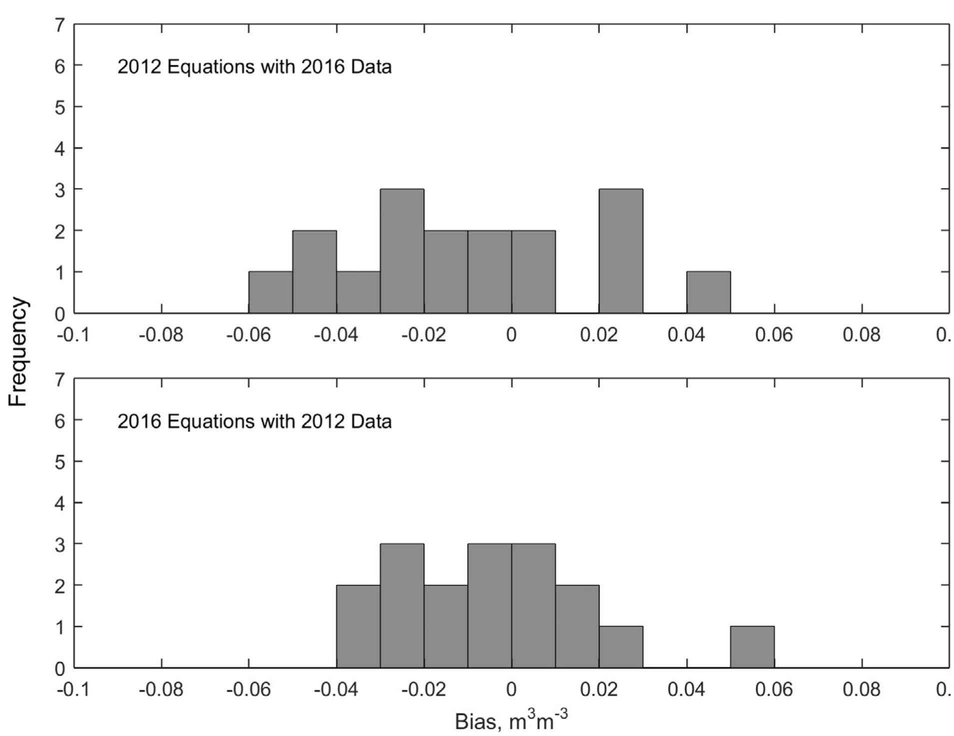

Fig. 4. Top: Bias associated with using the equations derived from the 2012 field campaign to the Hydra probe data collected in 2016 (and relative to the core volumetric water content from 2016); bottom: the bias from using the equations derived in 2016 on the data collected in 2012.

approach (2012 N-1 for each iteration). The resulting RMSE values were very similar to the 2016 dataset, with differences in the mean RMSE <0.002 for all fields. Similarly to the 2012 leave-one-out results, there was no significant difference in the calculated volumetric water content from the Hydra probes.

Table 1, which provides a summary statistics for the sampled fields, indicates the minimum soil moisture content measured via the core samples for 2012 and 2016, showing that for the majority of the fields, the minimum soil moisture was lower in 2012 than that observed in 2016. The maximum soil moisture content measured was similar between the two years. Fig. 2 (third bar for each field), shows the use of the calibration equations derived in 2012 on the data collected in 2016 resulted in degraded RMSEs relative to the equations derived in 2016 for all fields with the exception of Field 65, which experienced a small decrease in RMSE when the 2012 equation was used with the Hydra probe data collected in 2016. Overall, using the 2016 equations resulted in 12 of 2017 having RMSE >0.04 $m^3 m^{-3}$; two fields had RMSE >0.06 $m^3 m^{-3}$. When applying the equations developed in 2016 to the data collected in 2012, even further degradation in RMSE was observed (Fig. 2). The RMSE values utilizing the 2016 equations with 2012 data resulted in higher RMSEs for all fields relative to the 2012 equations, with the exception of Field 101. In this instance, 16 of the 17 fields had RMSE values >0.04 $m^3 m^{-3}$ (8 of which had RMSE >0.06 $m^3 m^{-3}$) and a degradation in the RMSE for all fields relative to their field-specific 2012 calibration equation (Fig. 3). The bias resulting from using calibration equations developed in the alternative year are presented in Fig. 4. The biases for using the 2012 equations with 2016 data, and vice versa, are similar in that the majority of the fields experienced biases within ±0.04 $m^3 m^{-3}$. Overall, 11 of the 17 fields using the 2012 equations on 2016 data resulted in negative biases, where this was the case for 10 of the 17 fields using the 2016 equations on 2012 data, indicating that in both years, the calculated volumetric water content using the calibration equations and Hydra probe data overestimated the volumetric water content relative to the sample cores.

A Monte Carlo simulation was conducted to determine if combining data from both field campaigns could result in improved calibration equation. In the simulation, a random selection of the same number of cores from the 2016 dataset as collected in 2012 (to account for differences in the number of samples between years) was repeated 10,000 times. The results from the combined calibration equation indicated that the average RMSE from the 10,000 iterations showed an improvement over the 2016 calibration results for only 1 of the 17 fields (Fig. 2), Field 14 (the overall percent change in the RMSE relative to 2012 and 2016 is shown in Fig. 3). There was an improvement in the RMSE for 4 fields relative to the 2012 calibration. The standard deviation of the calculated RMSEs from the Monte Carlo was <0.004 $m^3 m^{-3}$ for all fields. The resulting equations from the Monte Carlo simulation were not significantly different from the equation derived by combining all data from 2012 and 2016, not taking into consideration the difference in sample sizes.

3.2. Factors influencing calibrations

Changes in the soil electrical conductivity or temperature during measurements between the two sampling years could also have an impact on the derived calibration equations. (Seyfried and Murdock, 2004) noted the sensitivity of the Hydra probe to soil electrical conductivity particularly when values exceed 0.142 S m^{-1}. In both 2012 and 2016, the measured average soil electrical conductivity did not exceed 0.10 S m^{-1}. There was also no significant difference between the soil electrical conductivity between the two field campaigns (p = .153). It is anticipated, based on these measurements, that the changes in the soil electrical conductivity had a minimal impact on calibrations. Studies have also indicated that there is an impact of temperature on the measurement of the soil dielectric permittivity (e.g. Rosenbaum et al., 2011; Seyfried and Murdock, 2004; Wraith and Or, 1999). The majority of the measurements made in both 2012 and 2016 were obtained between 15 and 25 °C. Based on the results of Wraith and Or (1999), which indicate that there is a minimal change in the measured soil dielectric permittivity when measured between 15 and 25 °C across a range of soil moisture contents. Issues in the measurement of soil dielectric permittivity become more apparent at low (5 °C; Rosenbaum et al., 2011) higher temperatures (≥40 °C; Rosenbaum et al., 2011; Wraith and Or, 1999). Similar to the soil electrical conductivity, it likely that differences in soil temperature between the two campaigns is not a major source of error in the calibrations.

Inter-sensor variability is a potential source of error in regards to the temporal transferability of calibration equations. Coopersmith et al. (2016) found that using a triple co-location method, using data collected at 114 sites across the continental United States, the inter-sensor variability for the Hydra probe was approximately 0.01 $m^3 m^{-3}$. Seyfried et al. (2005), using ethanol as a proxy for a typical range in dielectric permittivity observed in soil, found that the inter-sensor variability to be similar to that of Coopersmith et al. (2016). This inter-sensor variability does not account for the large difference in RMSE values derived with the temporal transferability of calibration equations, particularly when the 2016 equations are applied to the 2012 data. If inter-sensor variability were a major source of error between the two field campaigns, it is anticipated that the RMSE values would be similar when the 2012 equations were applied to the 2016 data, relative to the 2016 calibrations as they would be for the 2016 calibration equations applied to the 2012 data. However, for 14 of the 17 fields sampled, when based on the calibration equations derived in 2016 on the data collected in 2012, relative to using the calibration equations derived in 2012, the difference in the RMSE values exceeds the inter-sensor variability. This was not the case when the 2012 equations were applied to the 2016 data, RMSE (and relative to the 2016 calibration equations). In this scenario, only 9 of the 17 fields exhibited differences in RMSE values that were larger than the inter-sensor variability. To eliminate variation in soil properties between the two study years, only fields with the same soil textural definition throughout the sample cores were used (indicating minimal inter-field variability in soil texture) and reducing the possibility sample location had an impact on the calibration equations. The CV in the bulk densities of the cores were examined for both years. A Wilcoxon ranks sum test indicated that there was no significant difference in the CV of the bulk densities between 2012 and 2016. This minimizes the effect of inter-field variability of soil properties. However, another possible difference between the 2012 and 2016 calibrations is the inter-field variability of soil moisture of the sample cores. Given that the field average bulk density was used in both years for the calculation of the volumetric water content (in an attempt to derive a field-scale calibration equation), the gravimetric water content was examined. It was found that there was a significant difference in the CV of the sampled gravimetric water content between 2012 and 2016 ($p < .001$, 99% confidence interval – Wilcoxon Rank Sum test), with much larger CV observed in 2012, as would be expected with a decrease in mean (e.g. Famiglietti et al. 2008).

4. Conclusions

The SMAPVEX-16 field campaign was held in the same general region as the SMAPVEX-12. There were 17 fields sampled in the 2012 campaign that were re-sampled in 2016, allowing an investigation into the temporal transferability of the calibration equations developed in 2012 to the data collected in 2016, and vice versa. The results indicated that the field RMSE values were lower in 2016 relative to 2012, likely due to the decreased range in soil moisture over which the calibration equations were developed in 2016.

This study shows that the temporal transferability of soil calibration equations results in increased error in the estimate of soil moisture due changes in the temporal variability of soil moisture. It was shown that the CV in the gravimetric water content significantly differs between the two sampling years, indicating that the variability in soil moisture is the main limitation on the transferability of equations. This is also evident in the errors associated with the transferability of the calibration equations. Using the equations developed in 2016 (over a smaller and wetter range of soil moisture) on the data collected in 2012, the RMSE was >0.04 $m^3 m^{-3}$ for the majority of the fields (16 of 17 fields). However, when the calibration equations derived in 2012 were applied to the 2016 data, the instances where the RMSE values were >0.04 $m^3 m^{-3}$ was reduced to 12 of the 17 fields, suggesting that the transferability is improved when a larger range of soil moisture is incorporated into their development.

A lack of knowledge, *a priori*, on how the variability of soil moisture has changed from one year to another may indicate that calibration of surface soil moisture measurements should be conducted each year, if the need to keep ground measurement error below an RMSE threshold of 0.04 $m^3 m^{-3}$ is required. It has been well documented that errors in soil moisture estimates using probes can be reduced if a sensor-specific calibration equation is utilized (Bogena et al., 2017; Rosenbaum et al., 2010; Seyfried et al., 2005) and that soil-specific calibrations are an improvement to factory-derived calibrations (Huang et al., 2004; Seyfried and Murdock, 2004). In this study, given that the same sensor was used in each field, a sensor- and soil-specific calibration was conducted. It has been shown in this study that the there was no significant difference in the soil electrical conductivity between the two sampling years and values fell below values of concern for calibrations of Hydra probes (Seyfried et al., 2005). The range in soil temperature, over which the experiments were conducted would indicate a potential change in the measured ε' of <0.5. The estimated inter-sensor variability of the Hydra probe is approximately 1% volumetric soil moisture, does not account for the large RMSE differences in RMSE observed particularly when applying the equations derived in 2016 to the data collected in 2012. However, there was a significant difference in the range of soil moisture over which the calibration equations were derived in 2012 and 2016. This suggests that soil moisture calibration equations may not successfully transfer spatially or temporally when the desire is to keep the measurement error below 0.04 $m^3 m^{-3}$.

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Appendix A

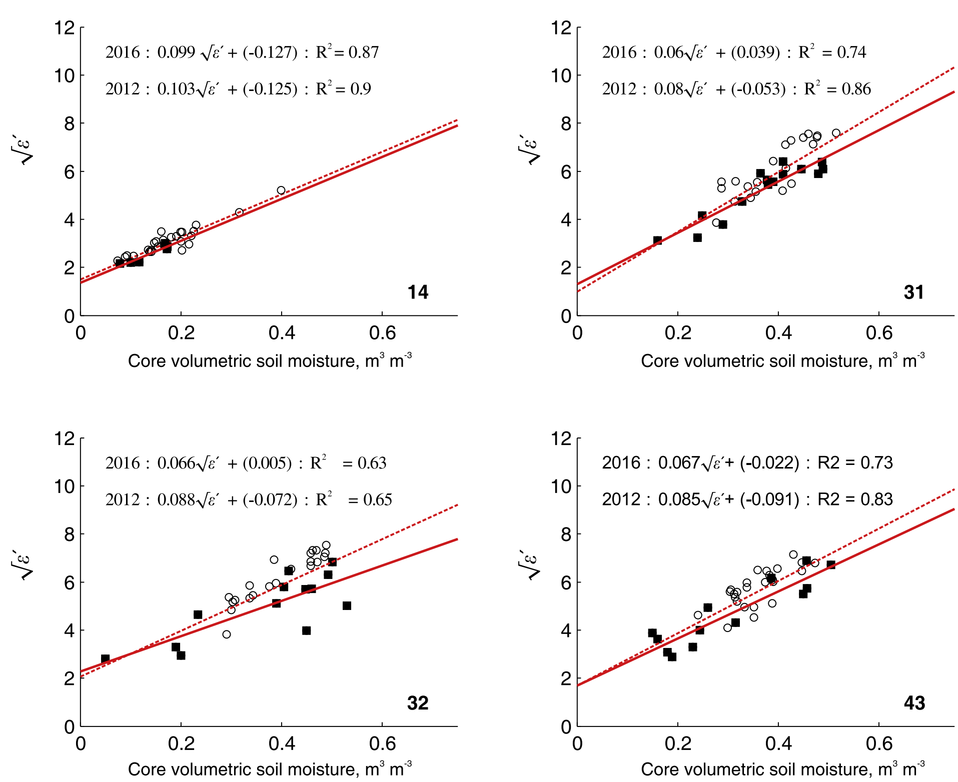

Fig. A1. The core measured volumetric water content (x-axis) measured in both 2012 (squares) and 2016 (circles) versus the real component of the soil dielectric permittivity measured by the Hydra probes for each field. The regression lines are shown in red for 2012 (solid line) and 2016 (dashed line). Fields are identified numerically in the bottom right corner of each panel.

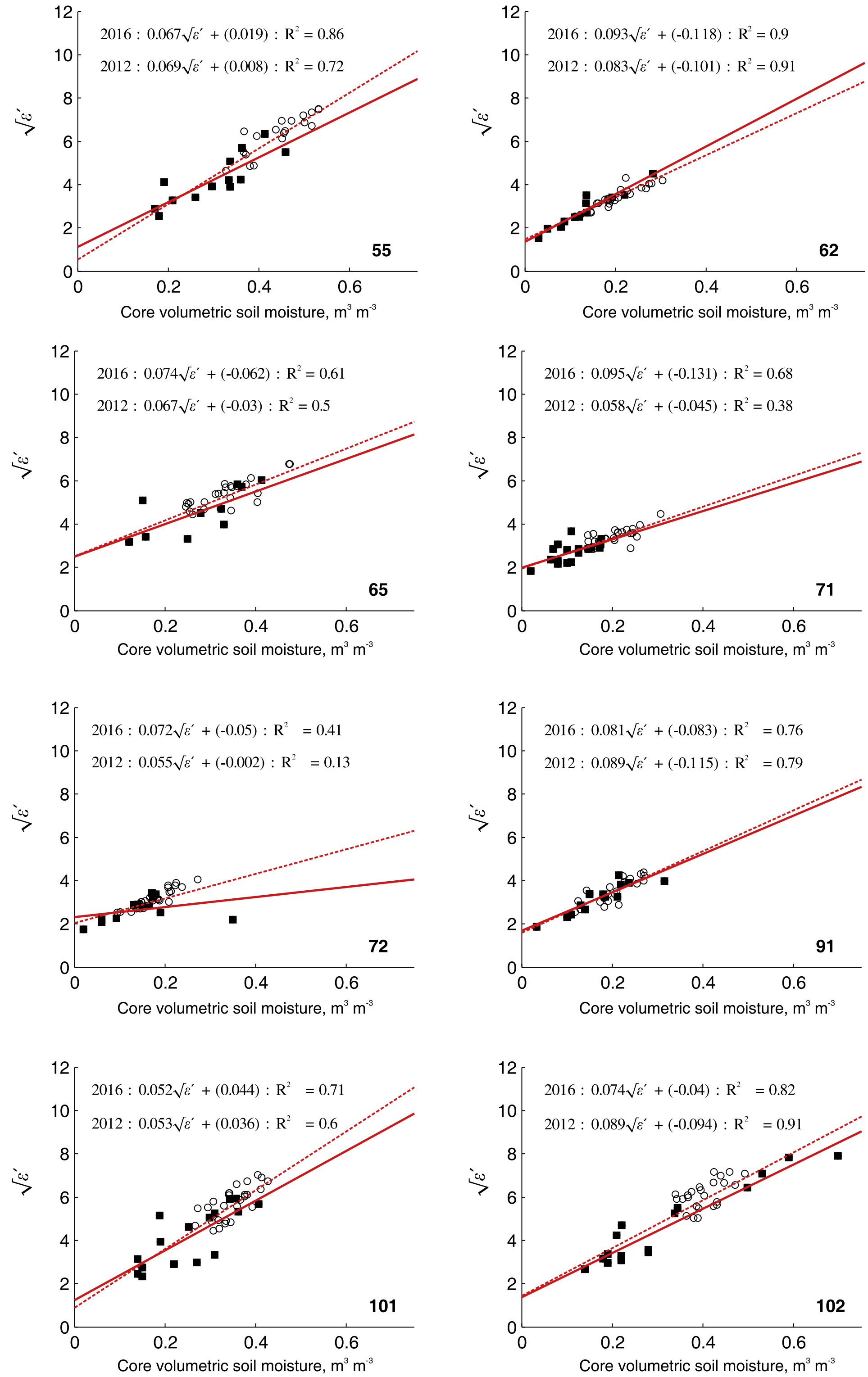

Fig. A1 (*continued*)

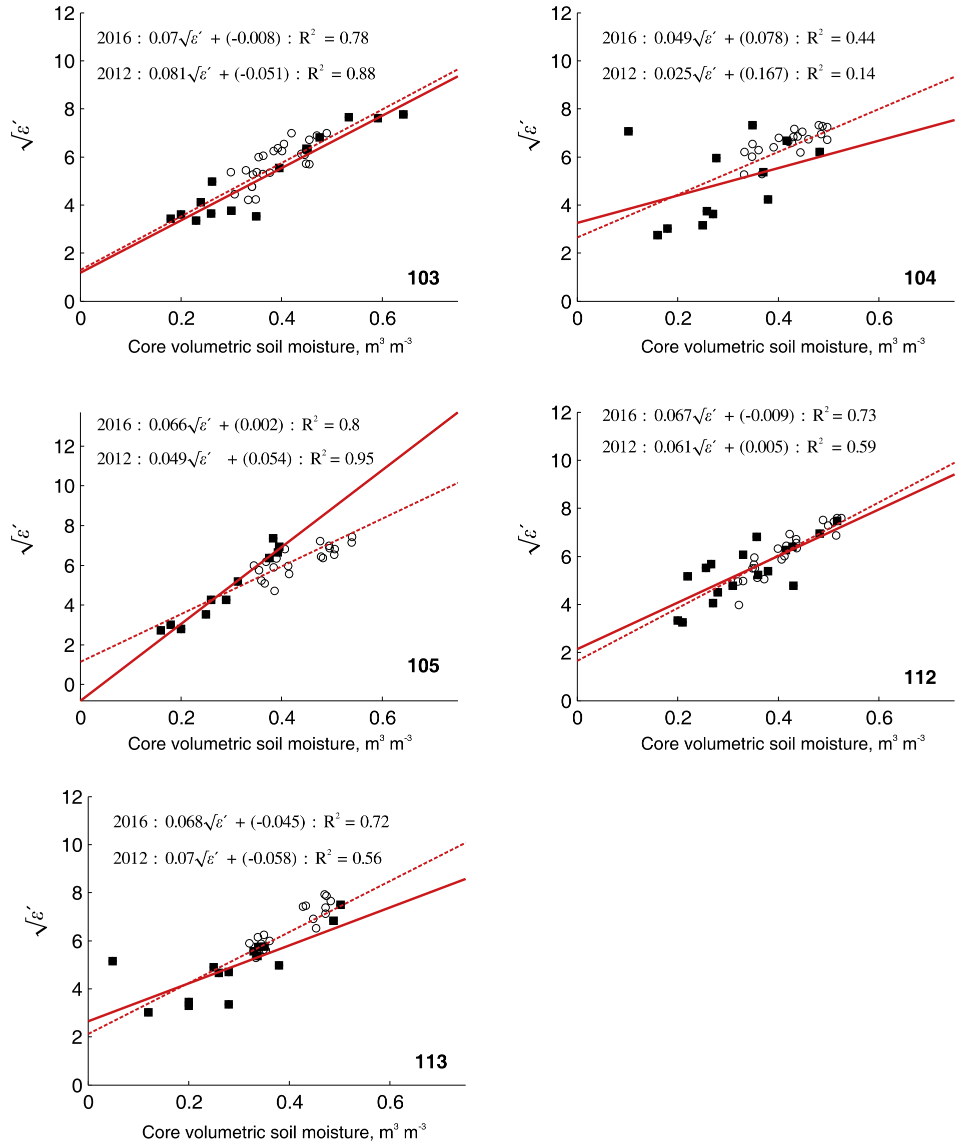

Fig. A1 (*continued*)

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