Journal of Hydrology 498 (2013) 335–344

Contents lists available at SciVerse ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Evaluation of several calibration procedures for a portable soil moisture sensor

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ARTICLE INFO

Article history:
Received 12 March 2013
Received in revised form 7 May 2013
Accepted 9 May 2013
Available online 27 May 2013
This manuscript was handled by Corrado Corradini, Editor-in-Chief

Keywords:
Soil moisture
Calibration
Impedance probes

SUMMARY

The calibration and validation of remotely sensed soil moisture products relies upon an accurate source of ground truth data. The primary method of providing this ground truth is to conduct intensive field campaigns with manual surface soil moisture sampling measurements, which utilize gravimetric sampling, soil moisture probes, or both, to estimate the volumetric soil water content. Soil moisture probes eliminate the need for labor-intensive gravimetric sampling. To ensure the accuracy of these probes, several studies have determined these probes need various degrees of localized calibration. This study examines six possible calibration techniques using data collected during a field campaign conducted in 2012, with soil moisture samples being collected over 55 fields in southern Manitoba, as part of the Soil Moisture Active Passive Validation Experiment 2012 (SMAPVEX12). The use of a general equation, applied to all collected data, resulted in the largest error regardless of whether a linear or third order polynomial relationship was established for the calibration of the soil moisture probes. Calibration equations based on soil texture or vegetation land cover reduced the error; however, the individual calibration equations established for each field in the study had the lowest error of all the calibration techniques. Although average bias was low for all of the calibration techniques, the use of the general equation to calibrate individual fields resulted in high biases for some fields.

1. Introduction

The Soil Moisture Active Passive (SMAP) mission was developed by the National Aeronautics and Space Administration (NASA) in response to the report, *Earth Science and Applications from Space: National Imperatives for the Next Decade and Beyond*, produced by the National Research Council (National Academies Press, 2007). This report highlighted the need for large scale environmental observations, including soil moisture (Entekhabi et al., 2010). One of the SMAP mission prerogatives is to estimate land surface fluxes of water and energy (Entekhabi et al., 2010). Soil moisture is a large reservoir for the storage of water and has high evaporative potential. Understanding of these processes at large scales will enable better weather and hydrological forecasting (Koster et al., 2011; Drewitt et al., 2012).

The SMAP mission has a requirement to be within ±0.04 $m^3\ m^{-3}$ accuracy of the volumetric soil moisture within the first five centimeters of the soil when the vegetation water content is $\leqslant$5 kg m^{-2} (Entekhabi et al., 2010). The SMAP satellite has an anticipated launch date of October, 2014, but prior to the launch, several field calibration and validation campaigns were conducted to ensure that this accuracy is possible. These campaigns, using similar instrumentation aboard aircraft, aim to develop and improve the soil moisture retrieval algorithms. One of the primary validation campaigns for SMAP was the SMAP Validation Experiment 2012 (SMAPVEX12), held in Winnipeg, Manitoba, Canada during June and July, 2012. Prior to SMAPVEX12, several field campaigns were conducted for the calibration and validation of other remote sensing instrumentation and missions, such as the AMSR-E instrument aboard the Aqua satellite and the Soil Moisture and Ocean Salinity (SMOS) mission, developed by the European Space Agency. SMOS, launched in 2009, also has a mission objective of ±0.04 $m^3\ m^{-3}$ accuracy of the volumetric soil moisture within the first five centimeters of the soil (Kerr et al., 2010). Other field campaigns include, but are not limited to: (Soil Moisture Experiment in 2002) SMEX02, SMEX03, SMEX04, SMEX05, National Airborne Field Experiment of

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0022-1694/$ - see front matter
http://dx.doi.org/10.1016/j.jhydrol.2013.05.021

2006 (NAFE'06) and (the Canadian Experiment for Soil Moisture in 2010) CanEX-SM10. Like SMAPVEX12, these campaigns consisted of intensive soil moisture sampling regimes, where surface soil moisture (0–6 cm) measurements were made manually, typically along established transects within multiple agricultural fields across the study regions. Although the most accurate soil moisture estimates would result from gravimetric sampling (Gardner, 1986), this is extremely labor intensive and impractical, as well as introduces its own variability because of the skill needed to sample volumetric soil moisture. Therefore, in each of the calibration and validation field campaigns listed above, surface soil moisture is measured using electronic-based soil moisture measurement methods.

Impedance type soil moisture probes have distinct advantages over gravimetric sampling in field-based soil measurement campaigns, particularly when a large number of observations are necessary. Studies suggest that impedance probes are precise with little inter-sensor variability (Seyfried and Murdock, 2004); however, several authors suggest that individual soil type calibrations be used for greater accuracies than those calibration equations provided by the manufacturer (e.g. Huang et al., 2004; Seyfried and Murdock, 2004).

A study by Cosh et al. (2005) examined the calibration of the soil moisture probes used in the SMEX02 (conducted in Iowa) and SMEX03 (using data from the Oklahoma sites) field campaigns. In this study, four different calibration techniques were compared to gravimetrically based volumetric water content samples, collected with co-located soil moisture probe measurements, specifically the Theta probe (Delta-T, Cambridge, UK). The calibration approaches included: a general calibration equation established for each region in the campaign and then applied to all fields individually within that region; a calibration equation based on three soil textural classes, clay loam, silt loam/loam, and sandy-loam/sand; a calibration equation based on land-cover type; and finally, calibration equations were established for individual fields. In this study, the root mean square error (RMSE) values for the application of a general equation to all fields were the highest, and the bias over some fields was also high. There was some improvement (reduction) in RMSE when using soil texture based calibration equations; however, values were still >0.04 $m^3\,m^{-3}$. The calibration based on land-cover yielded similar results. Calibration of the soil moisture probes using field-specific equations resulted in RMSE $\leqslant$ 0.04 m^3m^{-3} for four of the five regions. The use of individual field calibration equations also resulted in little to no bias.

Over the aforementioned field campaigns there is significant variation in the calibration efforts of the impedance-based soil moisture measurement probes. For the NAFE'06 (Merlin et al., 2008), SMEX02 (Bindlish et al., 2006) and SMEX03 field campaigns, all soil moisture measurements for the Georgia (Bosch et al., 2006) and Oklahoma (Cosh et al., 2005) regions were calibrated using field-specific calibration equations, whereas the fields measured in the Alabama region were calibrated using the general Theta probe calibration equation as provided by the manufacturer (Jackson et al., 2005). The SMEX04 data from the Arizona region was calibrated using a site-specific calibration (Bindlish et al., 2008), whereas the measurements in the Sonora region were calibrated using the manufacturer suggested calibration equation because of a lack of infrastructure to process soil samples. Finally, the soil moisture data collected during SMEX05, conducted in Iowa, was calibrated using a site-specific calibration, using the same methodology as Cosh et al., 2005. During the CanEX-SM10 field campaign a general calibration equation was established from co-located gravimetric soil moisture samples and probe readings, and applied that equation to all manual soil moisture measurements taken over 60 fields during the experiment (Magagi et al., 2013).

The SMAPVEX12 field campaign was one of the longest satellite calibration campaigns conducted, with soil moisture measurements occurring over a 6-week period. Measurements were taken over a large range of soil textures, vegetation growth stages and soil moisture conditions. This study examines calibration techniques used in previous campaigns (Cosh et al., 2005; Famiglietti et al., 2008; Magagi et al., 2013), in addition to alternatives, in an attempt to obtain RMSE values that reflect of the accuracy goals of the SMOS and SMAP missions.

In this study, we investigate six different impedance probe calibration approaches using data from the SMAPVEX12 field campaign. The calibration approaches are divided into four categories, one technique which investigates the development of a general equation, two techniques which take into account soil texture, one which considers the vegetation land cover, and finally, the development of unique calibration equations for individual fields. The calibration techniques are described in detail in Section 3.2. During this campaign, over 700 core samples were taken from 55 fields, upon which calibration of the field data was based. These samples had a range of soil textures, from high sand content to clay, including some samples from fields with high organic matter content.

2. SMAPVEX12 field campaign

The SMAPVEX12 campaign was conducted approximately 70 km southwest of Winnipeg, Manitoba, in the Red River watershed as part of a pre-launch validation campaign for the NASA SMAP mission (Fig. 1). The experimental region was approximately 15 × 70 km in size and had minimal changes in topography. Intensive soil moisture measurements were taken on 55 fields within the experimental region, where field size ranged from approximately 20–60 ha. The land-use in this region is dominated by annual crops with some grassland and pasture. Of the fields used in the campaign, 16 fields were cereals (wheat, winter wheat, oats),

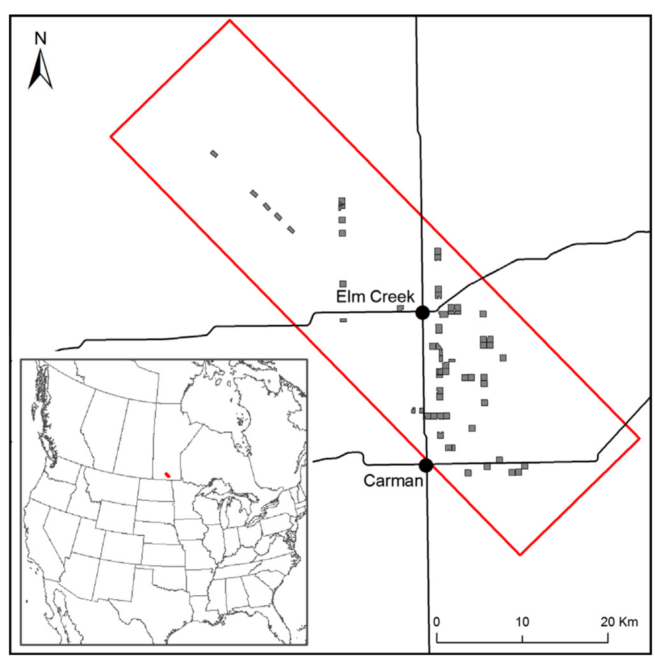

Fig. 1. Map of the SMAPVEX12 field campaign. The red box defines the campaign limits, with the study fields indicated by the gray boxes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

19 planted as soybean or edible beans, eight planted as corn, six as canola, four fields were classified as pasture, and one as forage. One field was also planted in half corn and half canola.

The campaign was conducted from June 6th to July 17th, 2012, with measurements taken on 17 days over 55 fields. Samples could not always be collected for each of the 55 fields during the experiment due to issues with field access or inclement weather conditions. During the campaign, the Passive/Active L-Band (PALS) instrumentation flew aboard a Twin Otter aircraft. In addition to this instrumentation, the Uninhabited Aerial Vehicle Synthetic Aperture RADAR (UAVSAR) was flown aboard a Gulfstream III, with both planes flying over the study region simultaneous to soil moisture measurements. Soil moisture was measured by 12 teams of two people, with each team assigned to sample four or five fields. Sampling was conducted from approximately 8 am to 1 pm, synchronized with the flight times of the PALS and UAVSAR instrumentation.

3. Calibration methods

3.1. Soil moisture sampling procedure

Soil moisture was measured in each of the 55 fields at 16 locations, along two transects, each containing eight sampling points (illustrated in Fig. 2). The first transect was placed 100 m from the field edge, and the transect points were all 75 m apart. The two transects were separated by 200 m, and were oriented so that sampling occurred along the rows. At each transect point, three soil moisture samples were taken using a Hydra probe (Stevens Water Monitoring Systems, Inc., Portland, OR). The Hydra probe is a frequency domain reflectometry sensor, operating at a frequency of 50 MHz, with a manufacturer reported sensor accuracy of ±0.03 $m^3\ m^{-3}$ (Stevens Water Monitoring Systems, 2007). With this sensor, a voltage is applied and the reflected voltage, related to the real dielectric constant (ε_r) of the soil, is measured. The sensor operates using the principle that the dielectric constant for water is close to 80, 1 for air, and for dry soil, in the range of 2–5. The relationship between ε_r and soil water content is well documented (e.g. Topp et al., 1980; Campbell, 1990; Seyfried et al., 2005).

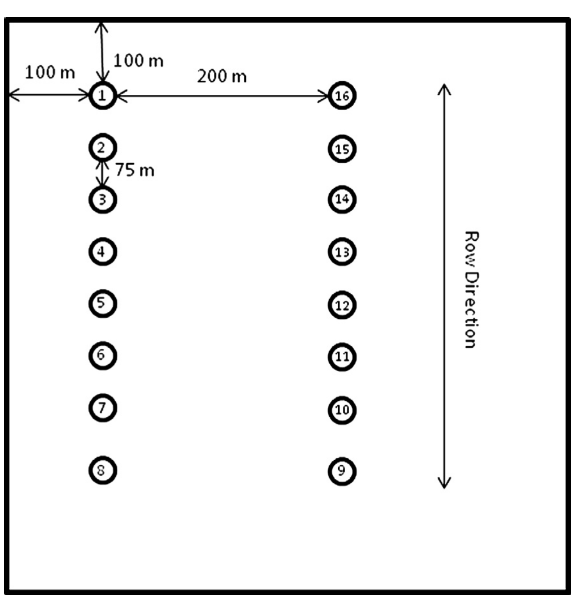

Fig. 2. Diagram of the manual soil moisture sampling transects. Sampling would begin at point 1 and progress in numerical order until point 16. The diagram is not drawn to scale.

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

$$\theta = \frac{M_w/M_s}{\rho_{b_{avg}}/\rho_w} \quad (2)$$

On each sampling date, a gravimetric sample was taken at a single point in each of the 55 sampling fields. The gravimetric sample was taken by inserting a core of known volume into the soil until the top edge of the core was flush with the soil surface. The cores were extracted and placed in a metal tin, which was subsequently sealed in a plastic zip-topped bag. The bulk density (ρ_b) was determined from (1), and along with the determined mass of water in each sample, the volumetric water content (θ) was calculated from (2), assuming a density of water (ρ_w) of 1 g cm^{-3}. Due to the temporal frequency of sampling and the number of fields being sampled on each sampling date, 130 different cores were used. Each core was identified with a number, and the internal volumetric dimensions of each core were known (V_t). The cores were returned to the lab, weighed and oven dried at 105 °C for 24 h, and reweighed to determine the mass of water (M_w) and mass of the soil solids (M_s). On the first sampling date, the gravimetric sample was taken at the first transect point, and each sampling day thereafter, the transect point advanced by one until a gravimetric sample was obtained at all 16 points. For each gravimetric sample, three soil moisture measurements were taken around the core using the Hydra probes, set to the loam texture setting regardless of soil type (as recommended by Seyfried et al. (2005)). The gravimetric samples and the average of these three soil moisture measurements were the basis for the calibration of the Hydra probes. Samples were collected over a range of soil moisture over the study time period. Volumetric soil water content of the gravimetric samples ranged from <0.05 $m^3\ m^{-3}$ (for fine sandy loam and loam soils) to 0.64 $m^3\ m^{-3}$ (measured on a clay soil). In total, over all 55 fields, 702 core samples were obtained, with some samples lost to laboratory or sampling errors. Soil moisture sampling in the field, with the Hydra probes was rapid, not allowing for the equilibration of the sensor to soil temperature. As such, all calibration techniques used the measured real dielectric constant, and not the temperature corrected value.

The average bulk density $\left(\rho_{b_{avg}}\right)$ of each field was determined by taking the average of all the bulk densities determined from the core samples using (1). The average field bulk density was used in the determination of the volumetric water content (2) for each core sample. The calibration results showed improvement when using the average field bulk density in the calculation of the volumetric soil water content as opposed to the individual core bulk density values.

3.2. Calibration techniques

Six different calibration techniques were examined using the data set collected during the SMAPVEX12 campaign. In previous soil moisture measurement campaigns, the calibration of measurements have either used a general equation (e.g. Magagi et al., 2013; Famiglietti et al., 2008) or developed individual calibration equations for each field (e.g. Cosh et al., 2005). In this paper, different calibration techniques are investigated to determine if an alternative to traditional approaches results in lower RMSE values. The calibration techniques are presented, and range from developing a general calibration equation, using all available data, to calibration equations for each of the individual fields. Overall, the goal of this experiment is to identify appropriate techniques for reducing the RMSE when calibrating impedance sensors. With respect to the SMAPVEX12 campaign, the goal is to reduce the RMSE of impedance soil moisture sensors below RMSE 0.04 $m^3\ m^{-3}$ with minimal bias (±0.01 $m^3\ m^3$) as compared to the in situ soil core samples; this goal corresponds to the overall SMAP/SMOS mission accuracy requirement of ±0.04 $m^3 m^{-3}$ of volumetric soil moisture (Entekhabi et al., 2010; Kerr et al., 2010).

$$RMSE = \sqrt{\frac{(\theta_{core} - \theta_{probe})^2}{n}} \quad (3)$$

$$Bias = \frac{\Sigma(\theta_{core} - \theta_{probe})}{n} \quad (4)$$

For this study, RMSE was calculated using (3), where θ_{core} is the volumetric water content determined from the gravimetric core samples. The volumetric water content from the probes (θ_{probe}) will differ based on the calibration technique used, but is the calculated value using the measured probe ε_r. In (3), n is the number of samples. Information regarding bias is also presented for each calibration technique, calculated using (4). The calibration techniques investigated are:

1. Development of a general calibration equation.
2. General equation with sample outliers removed from the data set.
3. Calibration based on soil texture threshold for clay content.
4. Calibration based on soil texture categories.
5. Calibration based on vegetation land cover.
6. Development of individual calibration equations for each field.

The first calibration method was to establish a general equation, developed from using the gravimetric core samples and the corresponding Hydra probe measurements, which was applied to the data obtained from all fields during the campaign. With this approach, both a linear and a third-order relationship were investigated. The second approach was similar, however outliers in the calibration data were determined and removed from the data set, and once again, a general equation was developed.

Two calibration techniques took into account soil texture. The first was a threshold technique, where two calibration equations were established. One equation was developed for samples which were classified as having a coarse soil texture, with clay content <40%, and another for fine textured samples, with clay content >40%. The 40% threshold was chosen based on the Canadian System of Soil Classification, which uses 40% clay content as the lower limit for a soil to be classified as clay (Agriculture and Agri-Food Canada, 1998). The second of the soil texture approaches uses data from a soil map of the region to classify each field into a soil texture category, where a calibration equation was determined for each textural category. The dominant soil texture was available for each transect point in each field from the Agriculture and Agri-Food Canada (AAFC) Soil Landscapes of Canada. This database can be accessed through the Canadian Soil Information Service (http://sis.agr.gc.ca/cansis/nsdb/slc/index.html). Using this information, the sand and clay content of the soil at each measurement point was estimated. The percent sand and clay was determined from a soil texture triangle. When using a soil texture triangle, the percent sand and clay were estimated from the triangle by using the central values for the specific soil texture. The soil textures and the estimated percentage of sand and clay are shown in Table 1.

Table 1
Average estimated sand and clay content based on soil texture classifications.

Soil texture	% Sand	% Clay
Clay	30	50
Loamy fine sand	80	8
Fine sandy loam	65	15
Loamy very fine sand	75	12
Loam	45	15
Clay loam	30	50
Silty clay loam	65	15
Silt loam	20	15

The fifth calibration approach produced a calibration equation for fields with similar land cover. Information regarding the vegetation cover for each field was collected during SMAPVEX12. The calibration vegetation classes were: wheat (included both spring and winter wheat, and one field of oats), corn, canola, beans (included both soybeans and edible beans), and pasture (included pasture and forage). There were 16 fields classified as wheat, 8 as corn, 6 as canola, 19 as beans, and 5 as pasture/forage. There was one field in the study where one of the soil moisture transects was in corn and the second transect in canola. Data from this field was divided into the corn and canola categories depending on the location from which the gravimetric sample was obtained.

The final calibration techniques looked at calibrating fields individually. A calibration for each field was determined through a linear regression using data from only that field. This technique sought to reduce the RMSE and the bias. High bias can occur when using a general equation for calibration, but studies have shown that the bias can be reduced when fields are calibrated individually (Cosh et al., 2005).

4. Calibration results and discussion

4.1. Establishment of a general equation

$$\theta = A\sqrt{\varepsilon_r} + B \quad (5)$$

$$\theta = 0.0838\sqrt{\varepsilon_r} - 0.0846 \quad (6)$$

A study conducted by Seyfried et al. (2005) examined the relationship between volumetric water content and the real dielectric constant of the soil measured by Hydra probes. They conducted their experiment over a range of soil textures, and investigated the use of a linear relationship between volumetric water content (θ) and the square root of the real dielectric ($\sqrt{\varepsilon_r}$), as shown in (5). Following the Seyfried et al. (2005) approach, a linear regression was determined between the volumetric water content measured by the core samples, and the square root of the real dielectric measured from the probes for the SMAPVEX12 data. Eq. (6) resulted from this linear regression, using all 702 data points. Fig. 3 shows the relationship between the calculated volumetric soil water content using (6) and the volumetric soil water content determined from the gravimetric core samples. This approach resulted in a RMSE of 0.0623 $m^3 m^{-3}$ with a bias <0.001 $m^3 m^{-3}$.

$$\theta = A\varepsilon_r^3 + B\varepsilon_r^2 + C\varepsilon_r + D \quad (7)$$

Stevens Water Monitoring, Inc., the developer of the Hydra probe, suggest that a calibration equation can be developed which uses a third order polynomial relationship with the real dielectric constant (ε_r), as shown in (7) (Stevens Water Monitoring Systems, 2007; Topp et al., 1980). This relationship was tested using all 702 measurements to determine if this provided a calibration with a RMSE value that was lower than the value provided by (6). As reported in Table 2, there was no statistically significant difference in the r^2 and RMSE values between the linear and third order polynomial calibration using all of the 702 measurements.

Fig. 3 suggests that some data points could be classified as outliers. Outliers were classified as points which fell outside of two times the standard deviation of the residuals, for both the linear regression and the cubic regression. This procedure indicated that there were 30 outliers in the data set (the outliers were the same for both regressions). Outliers in the soil moisture samples could

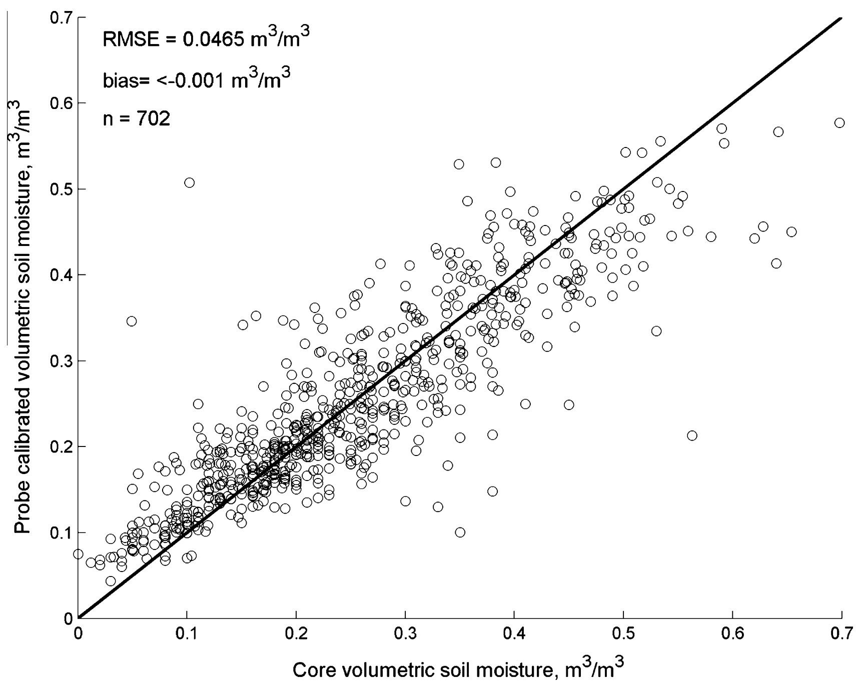

Fig. 3. Comparison of volumetric soil water content measured from the gravimetric core samples and the calculated volumetric water content using (6). The number of samples used in the establishment of (6) was 702. The solid line is the 1:1 line.

Table 2
Results of the calibration techniques. The general equations were applied to all data, and the texture based equations were applied to the all field data that was classified as that texture.

Calibration technique	r^2	RMSE ($m^3\ m^{-3}$)	Bias ($m^3\ m^{-3}$)	Calibration equation
General equation, linear	0.7663	0.0623	<0.001	$\theta = 0.0838\sqrt{\varepsilon_r} - 0.0846$
General equation, 3rd order polynomial	0.7663	0.0623	<0.001	$\theta = 3.548 \times 10^{-6}\varepsilon_{r3} - 4.187x10^{-4}\varepsilon_{r2} + 0.022\varepsilon_r - 0.0024$
General equation, Linear with outliers removed	0.8523	0.0475	<0.001	$\theta = 0.0862\sqrt{\varepsilon_r} - 0.0962$
General equation, 3rd order polynomial with outliers removed	0.8532	0.0473	<0.001	$\theta = 3.985 \times 10^{-6}\varepsilon_{r3} - 4.555 \times 10^{-4}\varepsilon_{r2} + 0.023\varepsilon_r - 0.014$
Texture, coarse (<40% clay)	0.8512	0.0424	<−0.001	$\theta = 0.0971\sqrt{\varepsilon_r} - 0.1326$
Texture, fine (>40% clay)	0.8104	0.0505	<−0.001	$\theta = 0.0787\sqrt{\varepsilon_r} - 0.0626$

occur due to operator error during the collection, transportation, oven weighing and recording of data. Removal of outliers was considered a separate calibration technique to highlight the impact erroneous samples can have on the error estimation of a calibration technique. A brief evaluation of the data described as outliers did not suggest systematic bias. The outliers occurred for measurements in 23 different fields, which suggested that the identified outliers do not represent a systematic bias that would occur if a single sampling team was improperly sampling the soil cores. Information on the dominant soil texture for each field indicates that 11 of the outliers occurred in fields where the soil texture was coarser, whereas the remaining occurred in fields with higher clay content. For 17 of the outliers, the volumetric soil water content of the core was higher than the soil moisture estimated from the probes.

$$\theta = 0.0862\sqrt{\varepsilon_r} - 0.0962 \tag{8}$$

The linear regression between the gravimetric core sample and the square root of the real dielectric constant was repeated with the outliers removed from the data set. As shown in Table 2, this improves the r^2 from 0.7663 to 0.8532 and reduced the RMSE from 0.0623 $m^3\ m^{-3}$ to 0.0475 $m^3\ m^{-3}$, and the regression equation becomes (8). Improvement was also seen in the cubic regression, with the RMSE reduced to 0.0473 $m^3\ m^{-3}$. Although the application of a general equation resulted in low bias on average, the bias for individual field was as large as 0.0520 $m^3\ m^{-3}$. Fig. 4 shows the histogram of the bias for each field using (8) for calibration. The histogram indicates that the majority of the fields experienced a positive bias, where the probe estimated soil moisture content was larger than indicated by the core samples. Large biases for individual fields were also found by Cosh et al. (2005) when using a general calibration equation. For both of these techniques, the calibrated soil moisture resulted in a RMSE value that is still above the aforementioned goal of having a RMSE less than 0.04 $m^3\ m^{-3}$ for the regional soil moisture estimate from the impedance probes (Entekhabi et al., 2010).

The robustness of the general equation was examined through a leave-one-out approach. A calibration equation was established for each field based on the data collected from all other fields in the campaign. The only field omitted from the regression analysis was the field for which the calibration equation was being established. This approach indicated that the general Eq. (8) was robust, as the average of the slope and intercept for all of the calibration equations produced the same slope and intercept as (8).

From this point onward, the dataset used for each calibration technique had the 30 identified outliers removed.

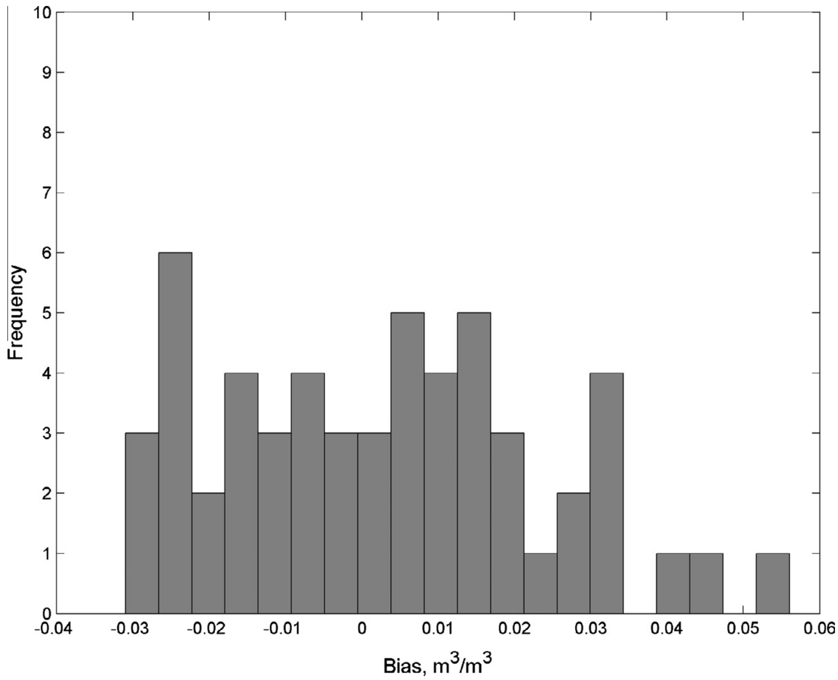

Fig. 4. Histogram of the bias values for each field using the general Eq. (8) for the calibration.

4.2. Calibration based on soil texture

4.2.1. Including soil texture in calibration equation

A multiple linear regression analysis was evaluated to determine if including the percent sand or clay (or both) improved the general equation calibration. It was found that including soil texture as an independent variable in a multiple regression did not result in a statistically significant change in the r^2 or RMSE values when just percent sand was considered (Table 2), when just percent clay was considered, or when both percent sand and clay were considered. A study conducted by Jacobsen and Schjønning, 1993, examining the calibration of time domain reflectometry (TDR) probes, found that inclusion of sand content in the calibration equation did not significantly improve the calibration, however inclusion of the clay and organic matter content, and the bulk density did, although the overall improvement on the retrieved soil moisture was minimal. The inclusion of bulk density in a calibration equation for TDR probes has shown to improve the soil moisture estimates. For the SMAPVEX12 study, a multiple linear regression which included the field average bulk density reduced the RMSE by <0.005 $m^3\ m^{-3}$ and improved the r^2 to 0.8563, compared to the linear general equation, with bulk densities ranging from 0.82 to 1.32 g cm^{-3}. Malicki et al. (1996) found that by including bulk density (bulk densities ranged from 0.22 to 1.29 g cm^{-3}), the RMSE could be reduced to ±0.03 $m^3\ m^{-3}$ and a change in the bulk density of 0.1 g cm^{-3} resulted in a change in the absolute error of the soil moisture estimated by the probes of 0.004–0.018 $m^3\ m^{-3}$. These results are contrasted by Ledieu et al. (1986), who found that an error in the estimate of the soil bulk density of 0.1 g cm^{-3} (bulk densities ranged from 1.38 to 1.78 g cm in the study) resulted in a change in soil moisture of 0.0034 $m^3\ m^{-3}$.

4.2.2. Calibration based on soil texture threshold

$$\theta = 0.0971\sqrt{\varepsilon_r} - 0.1326 \tag{9}$$

$$\theta = 0.0787\sqrt{\varepsilon_r} - 0.0626 \tag{10}$$

Across the SMAPVEX12 study region, the soil texture of the fields ranged from very fine sand to clay. The AAFC Soil Landscapes of Canada database was used to provide an estimate of the clay content for each field. Separate calibration equations were developed for the group of fields with heavier soils where clay content was >40% and coarser textured fields with clay content <40%. A linear regression was conducted using the volumetric soil water calculated from the core samples (θ) and the square root of the real dielectric constant ($\sqrt{\varepsilon_r}$) from 30 fields (with approximately 16 observations on each field) classified as having coarser soil texture. The resulting Eq. (9), was used for the calibration of all measurements from the coarse textured fields. A linear regression was also created for the remaining 25 fine textured fields. Eq. (10) was applied to the field data with clay content >40%. Fig. 5 shows the relationship between the core volumetric soil water content and the calibrated volumetric soil water content. The statistics which characterized this relationship (r^2 and RMSE) are provided in Table 2. The RMSE value for the coarse textured fields was reduced from the other calibration techniques; however, there is no improvement in the RMSE value for fields with higher clay content. When combining all fields, and applying the appropriate texture-based calibration equation, the overall RMSE for this texture-based approach is 0.0465 $m^3\ m^{-3}$.

4.2.3. Calibration using soil map

As mentioned, each point along the sampling transects had information regarding the dominant soil texture from the AAFC Soil Landscapes of Canada database. This was used to classify each field to specific soil type. If a field contained more than one soil texture, the field was classified as a single soil texture based on the dominant soil texture for that field. Fields were classified into one of eight soil textures: clay, clay loam, loam, fine sandy loam, loamy fine sand, loamy very fine sand, silty clay loam, and silt loam. A linear regression was conducted between the volumetric water content determined from the core samples (θ) and the square root of the real dielectric constant ($\sqrt{\varepsilon_r}$) from the Hydra probes for each soil texture. The percent sand or clay was not used in the regression analysis. The resulting calibration equations were

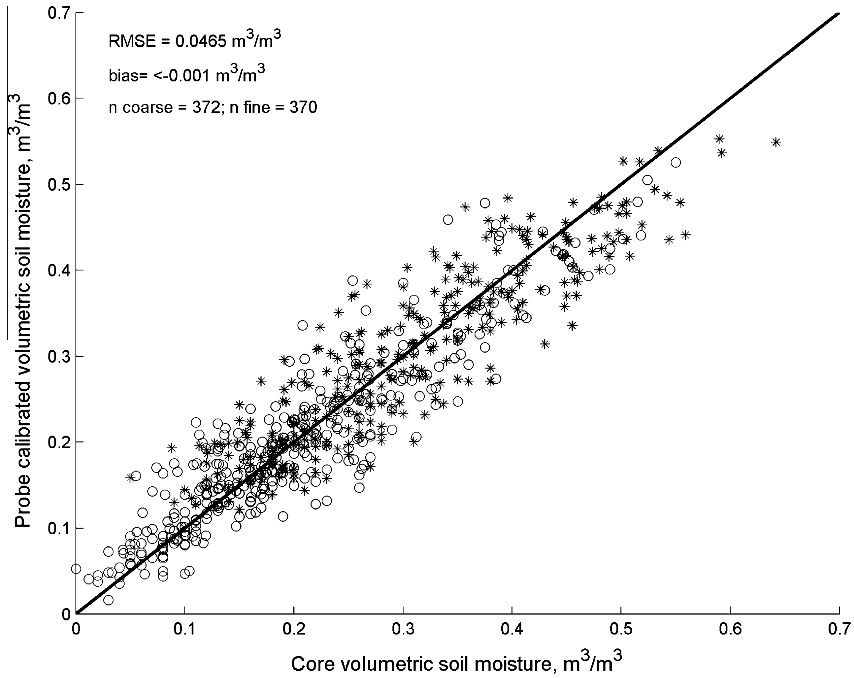

Fig. 5. Comparisons of volumetric soil water content measured from the gravimetric core samples and the calculated volumetric soil water content using (9) and (10). The circles represent the coarse textured soils, and the stars those with clay content >40%. The number of points used in establishing the model for the coarse and fine textured soils were 371 and 370, respectively. The solid line is the 1:1 line.

Table 3
Results of the calibration equations developed for each soil texture category, and the number of fields classified as each soil texture.

Soil texture	Number of fields	r^2	RMSE ($m^3\,m^{-3}$)	Bias ($m^3\,m^{-3}$)
Clay	25	0.8061	0.0546	<0.001
Loamy fine sand	6	0.9515	0.0326	<0.001
Fine sandy loam	7	0.8582	0.0341	<0.001
Loamy very fine sand	6	0.6180	0.0521	<0.001
Loam	7	0.7905	0.0450	<0.001
Clay loam	2	0.6445	0.0520	<0.001
Silty clay loam	1	0.8367	0.0389	<0.001
Silt loam	1	0.5627	0.0423	<0.001

applied to the data only within that soil texture category. The results for this calibration method are shown in Table 3. This calibration technique resulted in a bias <0.001 $m^3\,m^{-3}$ and an overall RMSE value of 0.0440 $m^3\,m^{-3}$. This calibration approach was most successful for the loamy fine sand, the fine sandy loam and the silty clay loam, where the RMSE values were all under 0.04 $m^3\,m^{-3}$. The worst RMSE values (over 0.05 $m^3\,m^{-3}$) occurred for clay and clay loam soil textures. Note that for the silty clay loam and the silt loam, where there was only one field of each in the study region, the results are the same as those generated for individual field calibration. These results are similar to the findings of Cosh et al. (2005), where only three texture categories were used in comparison to the eight categories used in the present study. The overall RMSE in this study was slightly lower than for Cosh et al. (2005). Both in this study, and in Cosh et al. (2005), the application of this approach resulted in an overall RMSE value that is >0.04 $m^3\,m^{-3}$.

4.3. Calibration based on vegetation land cover

Fields had one of five crop covers – wheat, corn, canola, beans, or pasture/forage. In this analysis, fields were categorized

Table 4
Results of the calibration equations developed for each vegetation land cover, and the number of fields classified as each land cover.

Land cover	Number of fields	r^2	RMSE ($m^3\,m^{-3}$)	Bias ($m^3\,m^{-3}$)
Beans	19	0.8309	0.0477	<0.001
Canola	6.5	0.7729	0.0491	<0.001
Corn	8.5	0.8481	0.0325	<0.001
Pasture	5	0.9510	0.0338	<0.001
Wheat	16	0.8525	0.0460	<0.001

according to these crop types. Linear regression models were created between the square root of the real dielectric constant ($\sqrt{\varepsilon_r}$) and the core sampled volumetric water content (θ) for each of the vegetation classes. The results for this calibration technique are shown in Table 4. The bias for all five calibration classes was <0.001 $m^3\,m^{-3}$. The RMSE value was highest for the canola class at 0.0491 $m^3\,m^{-3}$, followed by the bean (RMSE = 0.0477 $m^3\,m^{-3}$) and wheat (RMSE = 0.0460 $m^3\,m^{-3}$) land covers. The error was the lowest for corn and pasture, with RMSE values of 0.0325 and 0.0338 $m^3\,m^{-3}$, respectively. The soils in the pasture/forage category were organic within the first 5 cm for most sampling points in all five fields. The general calibration Eq. (8), was determined from data sampled predominantly from mineral soils, and when applied to the pasture/forage fields large errors resulted and RMSE values were >0.05 $m^3\,m^{-3}$. Overall, the calibration based on vegetation land cover resulted in a RMSE of 0.0418 $m^3\,m^{-3}$. Cosh et al. (2005) found no improvement in using land cover type for calibration compared to their soil texture calibration. This study reports a small improvement of 0.002 $m^3\,m^{-3}$; however, for wheat, beans and canola, the RMSE values are greater than the SMAP/SMOS error requirements (Entekhabi et al., 2010; Kerr et al., 2010).

4.4. Calibration of fields individually

$$\mathrm{RMAE} = \frac{\sum_{i=1}^{N}|\theta_{probe} - \theta_{core}|}{\sum_{i=1}^{N}\theta_{core}} \tag{11}$$

Although the application of a general equation to individual fields resulted in RMSE values for several fields lower than $0.04\ m^3\ m^{-3}$, the overall RMSE was still higher than desired. Thus, development of calibration equations for each individual field was investigated. In this approach, 55 linear regression equations were generated, one for each of the SMAPVEX12 fields, using measurements from each individual field to create the model for that field. The RMSE values for this approach ranged from 0.0121 to $0.0572\ m^3\ m^{-3}$, with a mean RMSE value of $0.0374\ m^3\ m^{-3}$ and a bias of $0.0015\ m^3\ m^{-3}$. The plot of the volumetric soil water content and the square root of the real dielectric using individual field equations for calibration are shown in Fig. 6. Table 5 provides examples of the *A* and *B* parameters, as shown in Eq. (5), determined through the linear regression. Values are presented for each soil type and vegetation land cover. The fields with the highest RMSE using this calibration approach were fields with higher clay content. These fields also had higher mean volumetric soil water content as measured by the sampled cores. At volumetric soil water content $>0.5\ m^3\ m^{-3}$, the probe estimated volumetric water content underestimates compared to the core samples. These instances occurred predominantly in clay soils. With clays, which can have a higher specific surface area, the dielectric constant can be underestimated (Roth et al., 1990). This would result in an underestimation of the soil water content.

These results illustrate the error is higher for finer texture soils, a result supported by several studies (Topp et al., 1980; Yu et al., 1997; Bosch, 2004; Cosh et al., 2005). The relative mean absolute error (RMAE) was calculated using (11) for both the fine and coarse textured soils, using the 40% clay content as the division between the two classes. A Welch's *t*-test was conducted to determine if the means of the RMAE for the two classes were similar. The resulting *p*-value was 0.05, indicating that, at the 95% confidence level, there is not a significant difference in the RMAE between the two textural categories.

A third order polynomial was investigated for calibrating fields with high clay content (Stevens Water Monitoring Systems, 2007; Topp et al., 1980). This approach was applied to fields where the RMSE value using the third order polynomial calibration was less than by using the linear calibration approach. There was an improvement in the RMSE values for eight fields. When the use of the third order calibration equation was examined by comparing the calibrated and uncalibrated soil moisture outputs of the Hydra probes, it was noted that during dry periods, this model artificially increased the soil moisture. For some fields, the difference between the calibrated and uncalibrated soil moisture values was greater than $0.1\ m^3\ m^{-3}$. Additionally, during periods of high soil moisture, the use of a third order model for calibration has the potential to underestimate the soil moisture.

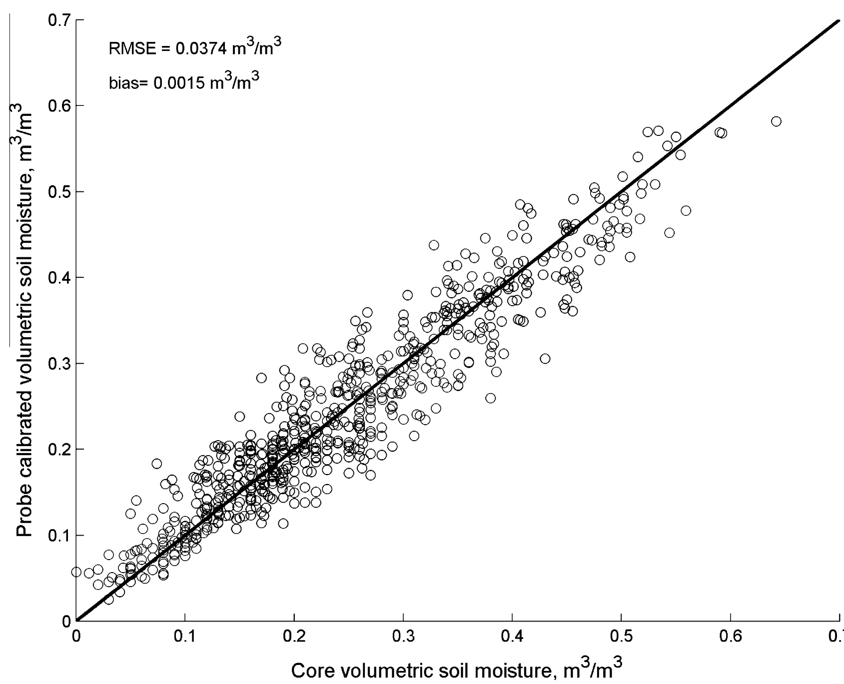

Fig. 6. Comparison of volumetric soil water content measured from the gravimetric core samples and the calculated volumetric soil water content, with individual field equations applied to data from the appropriate field. The solid line is the 1:1 line.

Table 5
Sample *A* and *B* parameters for the individual field equations using the relationship, $\theta = A\sqrt{\varepsilon_r} + B$, for each soil texture and vegetation land cover. The number of samples (*n*) used in the development of the model for each fields is indicated.

Soil texture	Land cover	*A*	*B*	r^2	RMSE ($m^3\ m^{-3}$)	Bias ($m^3\ m^{-3}$)	*n*
Loamy fine sand	Pasture	0.1054	−0.1505	0.9657	0.0121	0.0012	10
Clay	Wheat	0.0975	−0.1489	0.8821	0.0491	0.0024	11
Loam	Soybeans	0.0967	−0.1518	0.7304	0.0391	0.0015	17
Loamy very fine sand	Canola	0.0762	−0.0829	0.8370	0.0241	<0.001	13
Silty loam	Soybeans	0.0898	−0.0952	0.5627	0.0398	0.0016	16
Silty clay loam	Wheat	0.0770	−0.0390	0.8367	0.0356	0.0013	12
Fine sandy loam	Corn	0.1153	−0.1905	0.8339	0.0337	0.0011	13
Clay loam	Canola	0.0936	−0.1073	0.8031	0.04	0.0016	11

The *F*-statistic was examined to determine if the linear regression model developed for each field was statistically significant. The model was not significant for five fields. The regression for three of these five fields was not significant due to too few degrees of freedom, as only 4 core samples were taken in these fields in conjunction with Hydra probe measurements. The other two fields had the second and third lowest r^2 values out of the 55 regressions. For these five fields, instead of using the individual calibration equation developed, Eq. (8) was used for calibration.

5. Conclusions

The SMAPVEX12 field campaign was held as a validation campaign for the SMAP mission. Soil moisture measurements were collected over 55 fields of varying soil texture and vegetation land cover using Hydra probes. In conjunction with the probe measurements, core samples were collected in order to calibrate the probes used in the campaign. Six calibration techniques were investigated: development of a general calibration equation; general equation with sample outliers removed from the data set; calibration based on soil texture threshold for clay content; calibration based on soil texture categories; calibration based on vegetation land cover type; development of individual calibration equations for each field.

The various calibration techniques resulted in RMSE values that ranged from 0.0374 $m^3 m^{-3}$, for the calibration of individual fields, to 0.0623 $m^3 m^{-3}$, using a general equation without data outliers removed. Regardless of the calibration technique, the average bias was low for all. However, the application of the general Eq. (8) to individual fields resulted in biases that were >0.04 $m^3 m^{-3}$. The lowest RMSE resulted from calibrating the Hydra probes using individual equations for each field of the study. These site specific models were based on the linear relationship between the core sampled volumetric soil water content (θ) and the square root of the real dielectric ($\sqrt{\varepsilon_r}$), as measured by the Hydra probes. Although a third-order polynomial relationship between the Hydra probe measured real dielectric constant (ε_r) and the volumetric soil water content may be more appropriate (Topp et al., 1980; Campbell, 1990), particularly for fine textured soils, it was found that during periods of low soil moisture, the use of a third-order polynomial overestimated the soil moisture, in some cases, by more than 0.1 $m^3 m^{-3}$.

There were five out of 55 fields where the linear relationship was not significant when calibrating the field individually. This was due either to too few core measurements taken on these fields, resulting in too few degrees of freedom for the linear regression, or low correlation between the square root of the real dielectric constant and the volumetric soil water content values from the core samples. This finding highlights the importance of ensuring that sufficient numbers of core samples are collected. For these five fields, the general equation developed using all the sample data gathered during the campaign with data outliers removed (8) was used. For this campaign, the development of individual calibration equations for each field was possible due to the large number of core samples taken through the study period. For situations where this is not the case, this study found that taking soil texture into consideration, by developing individual calibration equations based on soil texture categories, or developing calibration equations based on vegetation land cover, yielded the lowest RMSE values.

The study conducted by Cosh et al. (2005) examined soil moisture data from 180 fields in Iowa and Oklahoma during SMEX02 and SMEX03 using different type of impedance based sensor to those used in SMAPVEX12. During SMEX02, the vegetation was predominantly corn and soybeans, whereas in SMEX03, sampling was conducted in fields that were harvested winter wheat or rangeland. Additionally, based on their soil texture analysis, soils ranged from sand to clay loam, with a maximum clay content of 40%. The present study was conducted over a wider range of vegetation land cover, soils that ranged from very fine sand to clay contents above 40% and used an alternate soil moisture sampling probe. Yet even with these differences, the results from both studies were similar. The results from this SMAPVEX12 study indicated that calibration of the soil moisture probes can result in a RMSE of surface soil moisture measures that are within the ±0.04 $m^3 m^{-3}$ accuracy requirements of SMAP and SMOS.

Acknowledgments

The authors would like to thank all participants in SMAPVEX12. Their assistance in the collection of the data set was vital and is much appreciated. We would also like to thank the anonymous reviewers for their suggestions for improving the paper. The authors would also like to thank the Canadian Space Agency, Environment Canada, Agriculture and Agri-Food Canada, US Department of Agriculture and the National Aeronautics and Space Administration for their support of this study.

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