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A pragmatic, automated approach for retroactive calibration of soil moisture sensors using a two-step, soil-specific correction

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A B S T R A C T

Soil moisture sensors are increasingly deployed in sensor networks for both agronomic research and precision agriculture. Soil-specific calibration improves the accuracy of soil water content sensors, but laboratory calibration of individual sensors is not practical for networks installed across heterogeneous settings. Using daily water content readings collected from a sensor network (42 locations × 5 depths = 210 sensors) installed at the Cook Agronomy Farm (CAF) near Pullman, Washington, we developed an automated calibration approach that can be applied to individual sensors after installation. As a first step, we converted sensor-based estimates of apparent dielectric permittivity to volumetric water content using three different calibration equations (Topp equation, CAF laboratory calibration, and the complex refractive index model, or CRIM). In a second, "re-calibration" step, we used two pedotransfer functions based upon particle size fractions and/or bulk density to estimate water content at wilting point, field capacity, and saturation at each sensor insertion point. Using an automated routine, we extracted the same three reference points, when present, from each sensor's record, and then bias-corrected and re-scaled the sensor data to match the estimated reference points. Based on validation with field-collected cores, the Topp equation provided the most accurate calibration with an *RMSE* of 0.074 $m^3\,m^{-3}$, but automated re-calibration with a local pedotransfer function outperformed any of the calibrations alone, yielding a network-wide *RMSE* of 0.055 $m^3\,m^{-3}$. The initial calibration equation used in the first step was irrelevant when the re-calibration was applied. After correcting for the reference core measurement error of 0.026 $m^3\,m^{-3}$ used for calibration and validation, the error of the sensors alone ($RMSE_{adj}$) was computed as 0.049 $m^3\,m^{-3}$. Sixty-five percent of individual sensors exhibited re-calibration errors less than or equal to the network $RMSE_{adj}$. The incorporation of soil physical information at sensor installation sites, applied retroactively via an automated routine to *in situ* soil water content sensors, substantially improved network sensor accuracy.

1. Introduction

There is growing interest in the use of sensor networks to address the "right time" dimension of precision agricultural management (Camilli et al., 2007; López Riquelme et al., 2009; Ojha et al., 2015), both through commercial applications and research on improved water-use-management (Mueller et al., 2012). Sensors that record temporally dense soil, crop or atmospheric measurements can be combined with spatial data to develop spatio-temporal models (Camilli et al., 2007; Gooley et al., 2014; Gasch et al., 2015). For agricultural sensor networks, the most commonly measured parameter is soil water content (López Riquelme et al., 2009; Greenwood et al., 2010; Coates et al., 2013; Lorite et al., 2013; Gooley et al., 2014; Goumopoulos et al., 2014).

Soil water content sensor networks can improve our understanding of vadose zone hydrologic processes at the catchment- or field-scale. Two- and three-dimensional dynamic soil water data can be used for incorporation into and validation of hydrologic and biophysical models (Frankenberger et al., 1999; Johnson et al., 2003; Stöckle et al., 2003; Mehta et al., 2004; Brooks et al.,

Abbreviations: CAF, Cook Agronomy Farm; CRIM, complex refractive index model; *RMSE*, Root Mean Squared Error; $RMSE_{adj}$, Adjusted Root Mean Squared Error; *SEL*, standard error of laboratory measurements.

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2007), and they can directly aid in our understanding of how soil water relates to environmental properties across space and time, such as terrain (Western et al., 1999; Brocca et al., 2007), soils and tillage (Hébrard et al., 2006; Al-Mulla et al., 2009; Ibrahim and Huggins, 2011), vegetation (Korres et al., 2015), and climate (Cantón et al., 2004). Sensor networks can also facilitate soil water monitoring and inform management decisions in irrigated landscapes (O'Connell and Snyder, 2004; Salinari et al., 2014). There is great interest in developing wireless and reactive devices to ease the use of inexpensive *in situ* soil water sensors for diverse research and irrigation management applications (Cardell-Oliver et al., 2004, 2005; Akyildiz and Stuntebeck, 2006; Bogena et al., 2007; Pierce and Elliott, 2008; Ritsema et al., 2009; Korres et al., 2015), and in developing software tools for storing, screening, and delivering the vast amounts of data produced by the sensor networks (Collins et al., 2006; Illston et al., 2008; Ritsema et al., 2009; Dorigo et al., 2011).

A major challenge in obtaining network data is ensuring the sensor accuracy and precision across heterogeneous soils needed for research and management purposes (Vereecken et al., 2008). Many commercially available soil water sensors assess the relative permittivity (dielectric constant) of the bulk soil (see review by Bogena et al., 2007; Robinson et al., 2008), which is then converted to volumetric water content with a "calibration" equation—typically a quadratic function such as the Topp equation (Topp et al., 1980). Sensors may also be factory calibrated using a variety of soils and/or non-soil media (Bogena et al., 2007; Kizito et al., 2008; Decagon Devices, Inc., 2014), such that the sensors produce accurate readings in a wide range of soil types and physicochemical conditions. Using factory calibrations, manufacturers report water content accuracies of 0.01–0.03 $m^3\ m^{-3}$ in a variety of mineral and organic soils under laboratory conditions (Kizito et al., 2008; Vaz et al., 2013; Decagon Devices, Inc., 2014). However, specific characteristics of the soil at installation sites may influence the accuracy of sensor readings (Rosenbaum et al., 2010; Spelman et al., 2013; Vaz et al., 2013; Ojo et al., 2015a, 2015b), requiring sensor calibrations that account for specific soil conditions at sensor insertion sites.

The calibration of soil water content instruments can be separated into two steps: (1) the conversion of sensor electromagnetic output to apparent dielectric permittivity, and (2) the conversion of apparent dielectric permittivity to volumetric water content (Robinson, 2001). In practice, our interest in calibration accuracy primarily lies in the second step, since it is the source of most *in situ* calibration error. The conversion of apparent dielectric permittivity to volumetric water content may be customized for the specific soil of interest, or published equations can be assessed for their use and accuracy in a given soil.

The laboratory calibration approach is to measure the dielectric constant of a soil of known bulk density at different gravimetric water contents (Gardner, 1986; Young et al., 1997). Burns et al. (2014) reported a root mean squared error (*RMSE*) between 0.01 and 0.04 $m^3\ m^{-3}$ using this approach to calibrate a Stevens Hydra Probe (Stevens Water Monitoring Systems, Portland, OR) in a variety of soil textures. Spelman et al. (2013) reported errors of 0.01–0.06 $m^3\ m^{-3}$ for Decagon 10HS probes calibrated in four sandy soils using this method. Sensors can also be calibrated in the field, wherein the gravimetric water content and bulk density of field soils are used to obtain volumetric water content and regressed with sensor output. Ojo et al. (2015b) and (2015a) reported improved sensor accuracies across multiple soils using *in situ* calibration, compared with the sensor default calibrations, laboratory calibrations, and other published calibrations.

While defining soil specific calibration equations based on empirical relationships is reported to improve sensor accuracy, individual lab calibration of many sensors prior to installation is unrealistic, particularly for large sensor networks distributed across heterogeneous soils. Furthermore, if field conditions are not known or are not properly replicated in the lab, sensor performance during lab calibration may not represent performance in the field (Ojo et al., 2015b). Retroactive calibration of sensors *in situ* using the thermogravimetric method requires repeated destructive sampling, which negates the minimal disturbance benefits of using *in situ* sensors, and manipulation of soil water content in the field for sensor calibration can be difficult (Robinson, 2001). Ideally, we would like to apply a calibration method to a large number of installed sensors that accounts for site-specific soil characteristics across a heterogeneous setting.

The objective of this study was to develop an appropriate method for retroactive, sensor-specific calibration of a large number of soil water content sensors based on static, easily measured, soil physical properties (e.g. texture and bulk density). We examined variations of a two-step calibration process: (1) conversion of apparent dielectric permittivity to volumetric water content using three calibration equations, and (2) re-calibration of volumetric water content based on estimates of soil saturation, field capacity, and wilting point derived from two different pedotransfer functions.

2. Materials and methods

2.1. Site description & data collection

The R.J. Cook Agronomy Farm (CAF) is a Long-Term Agroecosystem Research site operated by Washington State University, located near Pullman, Washington, USA (Fig. 1). The farm is 37 ha in size, receives an average annual precipitation of 550 mm, primarily as winter snow and rain (Western Regional Climate Center, 2013), and is representative of dryland annual cropping systems (direct-seeded cereal grains and legume crops) of the Inland Pacific Northwest. Deep silt loam soils (Palouse, Naff, and Thatuna soil series) formed on loess hills are found at CAF, with argillic silty clay loam horizons often occurring within 1.5 m of the surface (Natural Resource Conservation Service, 2013). Long term water and tillage erosion from the steep slopes of the region have resulted in drastic redistribution of topsoil horizons and the exposure of clay rich subsoil layers, especially at soil crest positions (USDA, 1978; Kok et al., 2009; Brooks et al., 2012). The complex topography and soils of the Palouse region (including CAF) lead to variable soil profile moisture regimes influenced by watershed hydrology, microclimate, soil horizonation, cropping system, and their interactions.

To capture soil moisture variability, soil moisture sensors were installed throughout CAF from 2007 to 2009 and continue to operate today. In April 2007, we selected twelve geo-referenced locations from an existing non-aligned grid and installed ECH_2O-TE sensors (Decagon Devices, Inc., Pullman, WA) at five depths (0.3, 0.6, 0.9, 1.2, and 1.5 m) at each location. In June 2009, we installed 5TE sensors (an updated version of the ECH_2O-TE; Decagon Devices, Pullman, WA) at an additional 30 locations. At each location, we excavated a small pit to insert the 0.3 m sensor horizontally into undisturbed soil by hand; for the deeper sensors, we used an auger to create a vertical hole of appropriate depth, then inserted the sensor vertically into the undisturbed base of the hole using a hollow steel pipe modified for positioning and inserting the sensor. After placement, holes were re-filled and packed with soil. The 42 instrumented locations (a total of 210 sensors) are distributed across the research farm to represent the variety of landscape and soil conditions (see Fig. 1). Since installation, sensors have recorded volumetric water content (θ_{sensor}, $m^3\ m^{-3}$), soil temperature (°C), and bulk electrical conductivity (dS m^{-1}) hourly