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Performance Assessment of Electromagnetic Soil Water Sensors in Different Soil Textural, Temperature, and Salinity Conditions

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PERFORMANCE ASSESSMENT OF ELECTROMAGNETIC SOIL WATER SENSORS IN DIFFERENT SOIL TEXTURAL, TEMPERATURE, AND SALINITY CONDITIONS

by

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PERFORMANCE ASSESSMENT OF ELECTROMAGNETIC SOIL WATER SENSORS IN DIFFERENT SOIL TEXTURAL, TEMPERATURE, AND SALINITY CONDITIONS

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Determination of accurate and continuous measurements of volumetric water content (θ_v) is extremely valuable for irrigation management and other agronomic decisions. Lately, electromagnetic (EM) sensors are being widely used to monitor θ_v continuously which also offer the benefits of ease of installation, fewer regulatory and safety concerns, and cost effectiveness. However, the accuracy of parameters [soil temperature, electrical conductivity (EC_a), dielectric permittivity (ε_{ra}), and θ_v] reported by EM sensors need to be evaluated for them to be utilized for agricultural water management. In the current study, the accuracy of a wide range of EM sensors was evaluated over field and laboratory conditions. The performance of eight EM sensors (TDR315, CS655, HydraProbe2, 5TE, EC5, CS616, Field Connect, AquaCheck), was analyzed through a field study in a loam soil. In addition, performance assessment of two improved and recently developed EM sensors (TDR315 and CS655) was done in a laboratory over different soil type, temperature, and salinity conditions. For the field study, the reported temperature and EC_a difference among the sensors were within 1°C and 1 dS m^{-1}, respectively. Among the single-sensor probes, the range of depth-combined (0.15 and 0.76 m) RMSD for factory calibration varied from 0.039 m^3 m^{-3} (5TE) to 0.157

$m^3 m^{-3}$ (CS616). Regression calibrations improved θ_v accuracy substantially beyond factory calibrations and the betterment in θ_v accuracy gained by using offset calibrations was smaller and less consistent than the improvements gained by using regression calibrations. For the laboratory study, the models for estimation of θ_v at hot (35°C) and cold (23.9°C) temperature were not significantly different from each other (two-tail p-value within 0.1387 and 0.7231) for TDR315 and CS655 sensors. The models for no salinity and added salinity were significantly different from each other (two-tail p-value within 2.2×10^{-16} and 0.005). It was found that CS655 and TDR315 calibration varied with soil type and the relationship of the calculated coefficients (quadratic, linear, and intercept) for CS655 and TDR315 sensors across each soil type were investigated with respect to their clay content. Based on external validation of the relationships of TDR315 and CS655 sensors with the clay content, it was found that soil type has a noteworthy effect on the performance of CS655, but not TDR315 sensors. Future work aiming to test the developed universal calibration would strengthen the claims of this study and may signal new opportunities.

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CHAPTER I

INTRODUCTION

Accurate and continuous determination of soil water quantity and quality is vital in many soil-water and hydrologic studies as it can better inform the timing and depth of irrigation applications and reduce the likelihood of excessively or insufficiently irrigating. Excessive irrigation increases fertilizer and irrigation pumping costs as well as generates additional nitrate leaching and greenhouse gas emissions. On the opposite extreme, inadequate soil water, as a result of insufficient irrigation, limits transpiration and photosynthesis and, in turn, can hinder crop growth and yield potential. Measurements of soil water quantity is arguably the most necessary geophysical estimate for implementing deficit irrigation, in which crop water status is carefully managed to maximize grain yield with a limited water supply (Geerts and Raes, 2009).

The direct method to measure volumetric water content (θ_v) is by the thermogravimetric method which involves removing a known volume of soil, drying at 105°C until it reaches a constant weight, and then determining the volume of water loss (Walker et al., 2004). Unfortunately, this method is destructive, non-continuous, tedious, and time-consuming, and therefore, not a suitable option for most applications, including irrigation scheduling. Alternatively, neutron attenuation via a neutron moisture meter (NMM) is a reliable and accurate non-destructive (after installation) indirect measure of θ_v. Although the NMM improves the stability in monitoring of θ_v as compared to the thermogravimetric method by allowing for repeated measures in a single location, it too is limited in applications due to a radioactive source, which requires proper training, licensing, and safety measures when handling, storing, and transporting the instrument (Rudnick et al., 2015). However, a calibrated NMM can be used to compare other soil water monitoring devices (Leib et al., 2003).

Since electromagnetic (EM) properties of soil vary with θ_v, various EM sensors have been developed, tested, and adopted over the last several decades. Some of these EM sensors also measure apparent electrical conductivity (EC_a) and temperature. These extra capabilities undoubtedly broaden the applicability of EM sensors in both research and production scenarios. For example, measurement of EC_a can be used to monitor soil salinity (Rhoades et al., 1976) if calibrated using saturation extract electrical conductivity (EC_e), and to monitor nitrate-nitrogen (NO_3-N) concentrations in soil and water (Payero et al., 2006). Temperature is a key environmental variable for plants during the vegetative period as it affects time of emergence (Schneider and Gupta, 1985).

The ability of EM sensors to provide continuous measurements of θ_v, EC_a, and temperature has broadened their applicability in research and production scenarios. However, merely deploying EM sensors and amassing a large dataset does not guarantee improvements in research and management. Predictive models, revealing findings, and better informed decisions require more accurate soil water quantity and quality data. Despite commonalities among EM sensors, the distinctions in measurement technology, design, installation method, internal adjustments, and factory calibration culminate in substantial disparities in measurement accuracy across sensors. Furthermore, dielectric properties of soil are influenced by other factors like temperature, salinity, soil texture, and bulk density (ρ_b), so a deliberate investigation of these factors is vital for accurate determination of EM sensor estimated θ_v (Paige and Keefer, 2008). Therefore, it is imperative that disparities among sensors are recognized to identify appropriate sensors across regions and applications as well as to develop improved calibrations.

A field study was conducted to analyze the performance of eight EM sensors—TDR315, CS655, HydraProbe2, 5TE, EC5, CS616, Field Connect, and AquaCheck—in a loam soil of west central Nebraska. This field study was designed to generate new peer-reviewed information on EM sensors whose performance, to our knowledge, have scarcely been reported in the literature (e.g., CS655, TDR315, AquaCheck, and Field Connect) as well as supplement the body of knowledge on the accuracy of EM sensors that have been widely studied in the literature (e.g., HydraProbe2, 5TE, EC5, and CS616) across diverse settings.

Alongside, a laboratory study was conducted to analyze the performance of two recently developed electromagnetic (EM) sensors – TDR315 and CS655 in five different textured soils collected across the state of Nebraska. This lab study was designed to evaluate statistical and practical significance on sensor performance at different temperatures, salinity levels, and clay content (soil type) settings.

- The specific objectives for the field experiment were -
    - Evaluate factory calibrations of the EM sensors for temperature, EC_a, ε_{ra}, and θ_v.
    - Compare the factory calibrations for θ_v against two custom calibration approaches, the first a conventional approach based on regression and the second an offset approach based on one known data point.

- The specific objectives for the laboratory experiment were -
  - Evaluate sensor (TDR315 and CS655) performance across five soil types that range in clay content.
  - Assess the effects of increased salinity and temperature differences on sensor (factory calibration) reported θ_v across soil types.
  - Develop a general calibration equation for both sensors by accounting for the effects of clay content on the calibration coefficients between sensor reported and reference θ_v.

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CHAPTER-II

PERFORMANCE ASSESSMENT OF FACTORY AND FIELD CALIBRATIONS FOR ELECTROMAGNETIC SENSORS IN A LOAM SOIL

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2.1 INTRODUCTION

Accurate determination of soil water quantity and quality can better inform the timing and depth of irrigation applications and reduce the likelihood of excessively or insufficiently irrigating. Excessive irrigation increases fertilizer and irrigation pumping costs as well as generates additional nitrate leaching and greenhouse gas emissions. Furthermore, by subjecting soil and plant canopies to frequent and prolonged wet conditions, excessive irrigation can decrease harvestable yield due to greater occurrence and severity of disease, anaerobic soil conditions, nutrient deficiencies, and inability to operate farm machinery. On the opposite extreme, inadequate soil water, as a result of insufficient irrigation, limits transpiration and photosynthesis and, in turn, hinders crop growth and yield potential (Doorenbos and Kassam, 1979). Measurements of soil water quantity is arguably the most necessary geophysical estimate for implementing deficit irrigation, in which crop water status is carefully managed to maximize grain yield with a limited water supply (Geerts and Raes, 2009).

Although most attention in irrigation scheduling is focused on soil water quantity, soil water quality likewise deserves consideration. Measurements of soil salinity can guide the use of irrigation to leach salts out of the crop root zone to maintain soil salinity levels within a crop's tolerable range (U.S. Salinity Laboratory Staff, 1954). Limited irrigation can be applied if rescue fertilizer applications are undesired or infeasible, based on the detection of nutrient stressed crops. . Rudnick and Irmak (2014b) observed a reduction in corn evapotranspiration (ET) when the crops were subjected to nitrogen stress. Irrigation exceeding a crop's ET rate can cause further reduction in nutrient availability through leaching, and consequently affect grain yield and the environment.

Repeated nondestructive measurement of soil water status is ideal because temporal trends can be determined without the potentially confounding influence of soil spatial variability. Neutron moisture meter (NMM) is the current standard to measure accurate, repeated, and non-destructive field volumetric water content (θ_v) (Chanasyk and Naeth, 1996) and, if calibrated with respect to thermogravimetric method, it can be used to compare other soil water monitoring devices (Leib et al., 2003). However, the NMM is not typically an option for on farm management or collecting high spatiotemporal dense data due to the radioactive source, which requires proper training, licensing, and safety measures when handling, storing, and transporting the instrument (Rudnick et al., 2015).

Since electromagnetic (EM) properties of soil vary with θ_v, various EM sensors that can be installed into the soil to provide continuous measurement of soil water quantity have been developed, tested, and adopted over the last several decades. Some of these EM sensors also measure apparent electrical conductivity (EC_a) and temperature (T). These extra capabilities undoubtedly broaden the applicability of EM sensors in both research and production scenarios. For example, measurement of EC_a can be used to monitor soil salinity (Rhoades et al., 1976) if calibrated using saturation extract electrical conductivity (EC_e), and to monitor nitrate-nitrogen (NO_3-N) concentrations in soil and water (Payero et al., 2006). Temperature is a key environmental variable for plants during the vegetative period as it affects time of emergence (Schneider and Gupta, 1985) and grain yield (Bollero et al., 1996).

However, merely deploying EM sensors and amassing a large dataset does not guarantee improvements in research and management. Predictive models, revealing findings, and better informed decisions require accuracy in soil water quantity and quality data. Despite commonalities among EM sensors, some studies have shown that the distinctions in measurement technology, design, installation method, internal adjustments, and factory calibration could culminate in substantial disparities in θ_v measurement accuracy across sensors (Varble and Chavez, 2011; Chavez and Evett, 2012; Mittelbach, 2012; Vaz et al., 2013). It is imperative that these disparities among sensors are recognized to identify appropriate sensors across regions and applications, and develop improved calibrations.

A field study was conducted to analyze the performance of eight EM sensors—TDR315, CS655, HydraProbe2, 5TE, EC5, CS616, Field Connect, and AquaCheck—in a loam soil of west central Nebraska. This field study was designed to generate new peer-reviewed information on EM sensors whose performance, to our knowledge, have scarcely been reported in the literature, e.g., CS655, TDR315, AquaCheck, and Field Connect(Kisekka et al., 2014; Rudnick, 2015; Zeelie, 2015; Schwartz et al., 2016) as well as supplement the body of knowledge on the performance of EM sensors that have been widely studied in the literature, e.g., HydraProbe2, 5TE, EC5, and CS616 (Ojo et al., 2014; Ojo et al., 2015; Rüdiger et al., 2010; Udawatta et al., 2011; Varble and Chávez, 2011; Mittelbach et al., 2012) across diverse settings. Results of this field study may be somewhat directly transferable to similar environments, useful for meta-analyses in understanding sensor performance between divergent environments, and laying a foundation for future research.

The specific objectives of the research were to 1) evaluate factory calibrations of the EM sensors for T, EC_a, apparent dielectrical permittivity (ε_{ra}), and θ_v and 2) compare the factory calibration for θ_v against two custom calibration approaches, the first a conventional approach based on regression and the second an offset approach based on one known data point.

2.2 Material and Methods

2.2.1 Site, Soil, and Experimental Descriptions

A field experiment was conducted at the University of Nebraska-Lincoln West Central Research and Extension Center (WCREC) in North Platte, NE (41.1° N, 100.8° W, and 861 m above sea level) during the 2016 growing season. The research site is located in a semi-arid climate zone with average annual precipitation and standardized alfalfa reference ET (EWRI, 2005) of 514 and 1,530 mm, respectively (HPRCC, 2016; NCDC, 2015). The research was performed with soybean at 0.76 m spacing planted on

May 26, 2016. During the study period, which was 28 July to 5 September, 2016, three significant rain events occurred: 31 mm on 28 July, 17 mm on 11 August, and 9 mm on 26 August. Textural composition, organic matter content (OMC), and bulk density (ρ_b) were determined at soil depth intervals of 0.15 m from 0.08 to 0.84 m (Table 2.1).

Table 2.1. Textural composition, organic matter content (OMC), and bulk density (ρb) of the soil at the study site as determined from four soil cores; mean ± standard deviation were reported for each property.

Depth (m)	Sand (%)	Silt (%)	Clay (%)	OM (%)	ρ_b (g cm^{-3})
0.08-0.23	46 ± 5	36 ± 8	18 ± 3	2.3 ± 0.2	1.40 ± 0.03
0.23-0.38	38 ± 7	41 ± 6	22 ± 2	1.9 ± 0.0	1.34 ± 0.06
0.38-0.53	33 ± 5	43 ± 6	25 ± 1	2.1 ± 0.2	1.16 ± 0.06
0.53-0.69	32 ± 3	45 ± 4	24 ± 1	2.0 ± 0.2	1.16 ± 0.02
0.69-0.84	41 ± 4	42 ± 9	17 ± 5	2.0 ± 0.2	1.10 ± 0.04

A pit was dug between two rows of soybeans. Single-sensor probes were inserted into one of the pit walls so that the prongs were oriented horizontally and located directly underneath a single row of soybeans. Two replicates of the following sensors—5TE, EC5, HydraProbe2, CS616, CS655, and TDR315—were installed at a depth of 0.15 m, and two replicates of the same sensors were installed at a depth of 0.76 m. At each depth, the arrangement of the sensors along the soybean row was randomized, and the sensors were 0.08 m apart from each other. This spacing was chosen so that every sensor was outside the measurement volumes of the other sensors. The sensor outputs were recorded every hour. In addition, two replicates of the Field Connect and AquaCheck probes and four replicates of NMM aluminum access tubes were installed in the crop row neighboring the aforementioned sensors. All sensors were installed following manufacturer recommendations and allowed to equilibrate with the surrounding soil prior to the start of the study.

2.2.2 Description of Sensors

2.2.2.1 TDR315

The Acclima TDR315 (Acclima, Inc., Meridian, ID) is a time domain reflectometer with three parallel rods serving as the waveguide. The sensor head has all necessary electronics and firmware to generate an EM pulse and construct a waveform to determine the propagation time of the EM wave, which is used to estimate ε_{ra}. The sensor is equipped with a thermistor to measure soil T. TDR315 measures EC_a based on Giese and Tiemann method (Giese and Tiemann, 1975) like conventional TDR equipment. A proprietary dielectric mixing model is used to estimate θ_v from ε_{ra}. However, Topp equation (Equation 1; Topp et al., 1980) was considered for determination of θ_v from ε_{ra} reported by TDR315 as well.

$$\theta_v = 4.3 \times 10^{-6} (\varepsilon_{ra}^3) - 5.5 \times 10^{-4} (\varepsilon_{ra}^2) + 2.92 \times 10^{-2} (\varepsilon_{ra}) - 5.3 \times 10^{-2} \quad (1)$$

2.2.2.2 CS616 and CS655

The Campbell Scientific CS616 and CS655 (Campbell Scientific, Inc., Logan, UT) are water content reflectometers with two parallel rods forming an open-ended transmission line. The sensors measure the two-way travel time of an EM pulse to determine a period average. The CS616 uses a quadratic equation relating period average to calculate θ_v; whereas, the CS655 uses a factory calibrated empirical model involving voltage ratio and period average to determine ε_{ra} and then estimates θ_v from ε_{ra} using the Topp equation (Eqn. 1). The CS655 sensor also measures soil T using a thermistor and EC_a by determining the ratio between the excitation voltage and the measured voltage.

The manufacturer's T adjustment was also considered for CS616 by using T measurements by CS655.

2.2.2.3 HydraProbe 2

The Stevens HydraProbe2 (Stevens Water Monitoring Systems, Inc., Portland, OR) is an impedance sensor with three tines surrounding one center tine. It measures real (ε_r') and imaginary (ε_r'') relative permittivity separately from the response of a reflected standing EM wave at a radio frequency of 50 MHz. The ε_r' is used to estimate θ_v using a square root mixing model; whereas, ε_r'' is used to estimate EC_a. In addition, Topp equation (Eqn. 1) was considered for determination of θ_v from ε_r' reported by HydraProbe2 as well. This sensor also measures soil T using a thermistor. The default θ_v calibration, which is the "loam calibration", is stated to be suitable for most medium textured soils, and therefore, was used in this study.

2.2.2.4 5TE and EC5

The Decagon Devices 5TE and EC5 (Decagon Devices, Inc., Pullman, WA) are a three and two pronged capacitance sensor, respectively, and are designed to use an oscillator running at 70 MHz frequency to measure ε_{ra}. The 5TE sensor estimates θ_v from ε_{ra} using the Topp equation (Eqn. 1); whereas, the EC5 sensor uses a linear calibration equation to determine θ_v from output voltage. However, Topp equation (Eqn. 1) was considered for determination of θ_v from ε_{ra} reported by EC5 as well. The 5TE sensor also measures soil T using a thermistor that is in thermal contact with the sensor prongs as well as EC_a using screws on the surface of the sensor to form a two-sensor electrical array.

2.2.2.5 Multi-Sensor Capacitance Probes

The multi-sensor capacitance probes used in this study were the John Deere Field Connect (Deere & Company, Moline, IL) and AquaCheck Classic Probe (AquaCheck Ltd, Durbanville, South Africa). Each sensor along the probe shaft emits an EM field into the soil. The reported count, which is proportional to the sensor circuit (resonant) frequency, is used to calculate a scaled frequency. The scaled frequency is then converted to θ_v. Field Connect performs this conversion using a proprietary calibration procedure, and each probe has sensors located at depths of 0.1, 0.2, 0.3, 0.5, and 1.0 m. For AquaCheck, the conversion was not built-in, but the manufacturer provided six equations, five soil specific and one generic. The five texture-specific equations were each generated from field calibrations in South Africa, whereas the "generic" equation used the pooled data from three soil types (sand, silt loam, and clay [Zeelie, 2015]). According to the textural classification of the soil, loam calibration was selected for conversion of scaled frequency to θ_v, and generic calibration was selected as well. One version of AquaCheck probes was included in this study with sensors located at depths of 0.10, 0.20, 0.30, 0.41, 0.61, and 0.81 m.

2.2.2.6 Neutron Moisture Meter

The neutron moisture meter (NMM) used in this study was a CPN 503DR Hydroprobe Moisture Neutron Depth Gauge (Campbell Pacific Nuclear International Inc., Concord, CA). A NMM is comprised of a nuclear source and detector. The nuclear source is lowered into an access tube at a desired depth (0.15, 0.30, 0.46, 0.76, and 0.91 m), where high energy neutrons are emitted into the soil and thermalized (slowed down) by colliding with hydrogen atoms. The thermalized, low energy neutrons are counted by a helium-3 detector and are compared against a standard count to estimate θ_v from a linear calibration equation with slope ‘a’ and intercept ‘b’:

$$\boldsymbol{\theta_v = a \times \left[\frac{Neutron\ Count}{Standard\ Count}\right] + b} \quad \textbf{(2)}$$

The standard count is used to monitor the performance and verify that the NMM is operating without faults. A NMM is not typically sensitive to changes in T and salinity (Evett et al., 2006); however, it can be influenced by OMC, clay content, soil texture, and chemical elements (Hauser, 1984), and therefore, a site-specific calibration of a NMM is recommended.

A site-specific calibration of the CPN 503DR NMM was performed at the depths 0.15, 0.30, 0.46, 0.76, and 0.91 m, respectively for this study. Ordinary least squares regression was used to fit a linear calibration equation between observed neutron count ratios and thermo-gravimetrically determined θ_v of 30 intact soil samples ranging between 0.104 and 0.302 $m^3\ m^{-3}$. The soil samples used for the calibration were collected within 2 m of the investigated sensors. The resulting calibration root mean squared difference (RMSD), evaluated with the calibration dataset, was 0.007 $m^3\ m^{-3}$ and the coefficient of determination (R^2) was 0.99.

2.2.3 Analysis

In this study, temperature (T), apparent electrical conductivity (EC_a), apparent dielectric permittivity (ε_{ra}) and volumetric water content (θ_v) were analyzed, with emphasis on θ_v determined from all the single-sensor and multiple-sensor probes. Among the sensors under evaluation, TDR315, CS655, HydraProbe2, and 5TE reported ε_{ra} as well as T and EC_a. Apart from θ_v, ε_{ra} was also reported by EC5. T, EC_a, and ε_{ra} reported by each sensor were compared with the average reported values for these parameters among all sensors at depths of 0.15 and 0.76 m to investigate the comparability of these parameters amongst different sensors. The purpose of such analyses was to determine how closely these parameters (T, EC_a, and ε_{ra}) were reported by different sensors rather than an accuracy assessment. Because EC_a reported by 5TE have been automatically normalized to 25°C (Decagon Devices, 2016), EC_a reported by TDR315, CS655, and HydraProbe2 were manually normalized to 25°C for consistency using equation 3 (Campbell Scientific, 2016).

$$\boldsymbol{EC_{a,25} = \frac{EC_a}{1+0.02\times(T-25)}} \quad (3)$$

where, $EC_{a,25}$ (dS m^{-1}) is the apparent electrical conductivity after normalization to 25°C, EC_a (dS m^{-1}) is the apparent electrical conductivity before normalization to 25°C, and T is the soil temperature at time and space of apparent electrical conductivity measurement (°C).

Average mean deviation (AMD; Eqn.4) of the sensor-reported values of T, EC_a, and ε_{ra} from the corresponding overall average of all EM sensors was computed from the data pairs considered in the analysis. Each data pair consisted of an average sensor-reported parameter (T, EC_a, or ε_{ra}) and overall average among all sensors at a certain time. AMD was calculated as:

$$\boldsymbol{AMD = \frac{\sum_i^n(s_i - m_i)}{n}} \quad (4)$$

where, i is the index of the data pairs, n is the number of data pairs, s_i is the sensor reported value of the i^{th} data pair, and m_i is the mean of all sensors of the i^{th} data pair.

The field calibrated NMM was used as the reference for θ_v following Bell et al. (1987), Leib et al. (2003), and Rudnick et al. (2015). On each of 14 dates during the study period, a 16-second NMM reading was collected at each of five depths (0.15, 0.30, 0.51, 0.61, and 0.76 m) in each of four access tubes. The reference value of θ_v at a given depth on a given date was obtained by averaging the four readings (one from each tube) at that depth on that date. Besides the default factory calibrations for the EM sensors, alternate calibrations were explored for some of the sensors. The Topp equation (eqn. 1) was considered for TDR315, HydraProbe2, and EC5. .

Sensor-reported and reference θ_v values for each sensor were compared at two depths (0.15 and 0.76 m for single-sensor probes; 0.30 and 0.51 m for Field Connect; 0.30 and 0.61 m for AquaCheck) separately and combined. The sensor-reported θ_v recorded at the time closest to each NMM reading (always within one hour) was considered, and the pair of sensor-reported θ_v and reference θ_v formed a set of comparison for the analysis. Several statistics were calculated to summarize each set of comparisons. The mean difference (MD; Eqn. 5) and standard deviation of difference (SDD; Eqn. 6) of the sensor-reported values from corresponding reference values were calculated. The equations for calculating MD (Eqn. 5) and AMD (Eqn. 4) are similar. However, MD compares sensor reported θ_v against the reference (NMM average) θ_v, whereas AMD compares sensor-reported parameter (T, EC_a, or ε_{ra}) against the overall average parameter (T, EC_a, or ε_{ra}) among all sensors. The root mean squared difference (RMSD), on the other hand, was the commonly computed indicator of the absolute magnitude of the differences between sensor-reported and reference values while penalizing larger differences (Eqn. 7).

$$\boldsymbol{MD = \frac{\sum_i^n (s_i - r_i)}{n}} \tag{5}$$

$$\boldsymbol{SDD = \sqrt{\frac{\sum_i^n [(s_i - r_i) - MD]^2}{n-1}}} \tag{6}$$

$$\boldsymbol{RMSD = \sqrt{\frac{\sum_i^n (s_i - r_i)^2}{n}}} \tag{7}$$

where, i is the index of the data pairs, n is the number of data pairs, s_i is the sensor reported value of the i^{th} data pair, and r_i is the reference value of the i^{th} data pair.

For θ_v, two types of custom calibrations were developed to compare with the factory calibration. The first type was regression calibration of sensor-reported values to reference values. A linear model and a quadratic model were considered in every case. To obtain a more conservative RMSD value for comparison with the factory calibration, the RMSD of each model was calculated using the leave-one-out cross validation (LOOCV) approach. Instead of comparing each reference value against the model fitted using all data pairs, in LOOCV RMSD calculations each reference value was compared against the model fitted using all data pairs except the pair to which the particular reference value belonged. The model with the smaller LOOCV RMSD was selected. LOOCV RMSD was reported with the best-fit coefficient estimates of the selected model according to ordinary least squares with all data pairs included. Calculations were conducted in statistical computing language R (R version 3.3.2, R Foundation for Statistical Computing, Wein, Austria).

The second type of custom calibration for θ_v was offset calibration based on one known data pair. This type of calibration would be performed by making one highly accurate (e.g., thermo-gravimetric or NMM) θ_v measurement to determine a constant offset with which to shift all other sensor-reported θ_v values. As a simulation, an offset was calculated as the difference of the sensor-reported value from the corresponding reference value of one data pair, and that offset was subtracted from the sensor-reported values of all other data pairs. The RMSD between the shifted sensor-reported values and the reference values of those data pairs was calculated, and the process was repeated until every data pair had been used to calculate the offset exactly once. With the number of RMSD values equal to the number of data pairs, a 95% confidence interval of the mean RMSD based on the Student's t distribution was computed using the t-test function in statistical computing language R.

2.3 Results and Discussion

2.3.1 Temperature

Weather and time-of-day caused daily soil T fluctuations with large amplitudes at the shallower depth (0.15 m) but were dampened and integrated into roughly weekly fluctuations with small amplitudes at the deeper soil depth (0.76 m; fig. 2.1). Each EM sensor-average was compared against the average of all EM sensors.

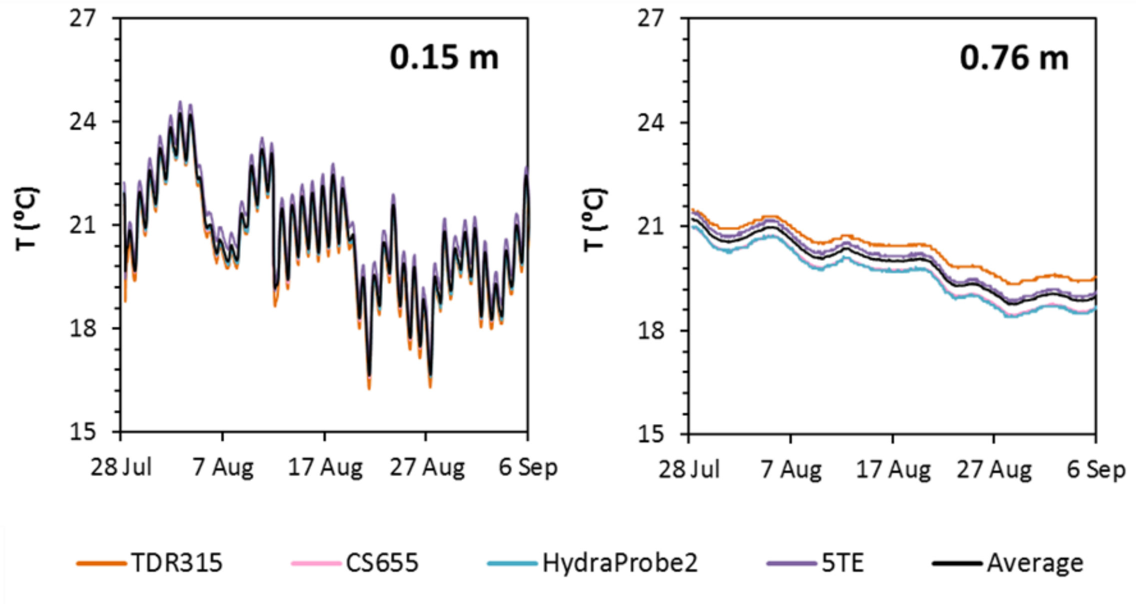


Figure 2.1. Temporal trend in sensor-average temperature (T, °C) for TDR315, CS655, HydraProbe2, 5TE, and overall average of EM sensors at depths of 0.15 and 0.76 m during the study period.

The comparisons above would suggest that two of the same or different EM sensors could be expected to report T values generally within 1°C of each other when subjected to the same environmental conditions. Therefore, the investigated sensors would be able to differentiate, for example, soil T between coulter planting and conventional planting, which has been reported to have a mean difference as low as 2.2°C (Griffith et al., 1973). Such comparability among sensors provides confidence that the sensors can be used for crop modeling and planting decisions.

Table 2.2. Average Mean Deviation (AMD) of TDR315, CS655, HydraProbe2, and 5TE sensors using factory calibration from the overall average sensors for temperature at 0.15 m, 0.76 m, and combined depths.

Sensor Temperature (°C)	Average Mean Deviation (AMD) 0.15 m	0.76 m	Combined
TDR315	**-0.20**	**0.45**	**0.12**
CS655	**-0.04**	**-0.27**	**-0.16**
HydraProbe2	**0.12**	**-0.31**	**-0.21**
5TE	**0.34**	**0.14**	**0.24**

2.3.2 APPARENT ELECTRICAL CONDUCTIVITY (EC_A)

In general, all sensors had a decreasing trend in EC_a overtime and appeared to follow the wetting and drying cycle of the soil. It was observed that following a wetting event (precipitation) of 17 mm on 11 August, there was an increase in EC_a (fig. 2.2; Rhoades et al., 1976). The 0.15 m soil depth responded more to wetting events as compared to the 0.76 m soil depth. A comparison for each EM sensor-average EC_a against the average EC_a of all EM sensors was made. The range for reported EC_a among all sensors at both depths was within 1 dS m^{-1}.

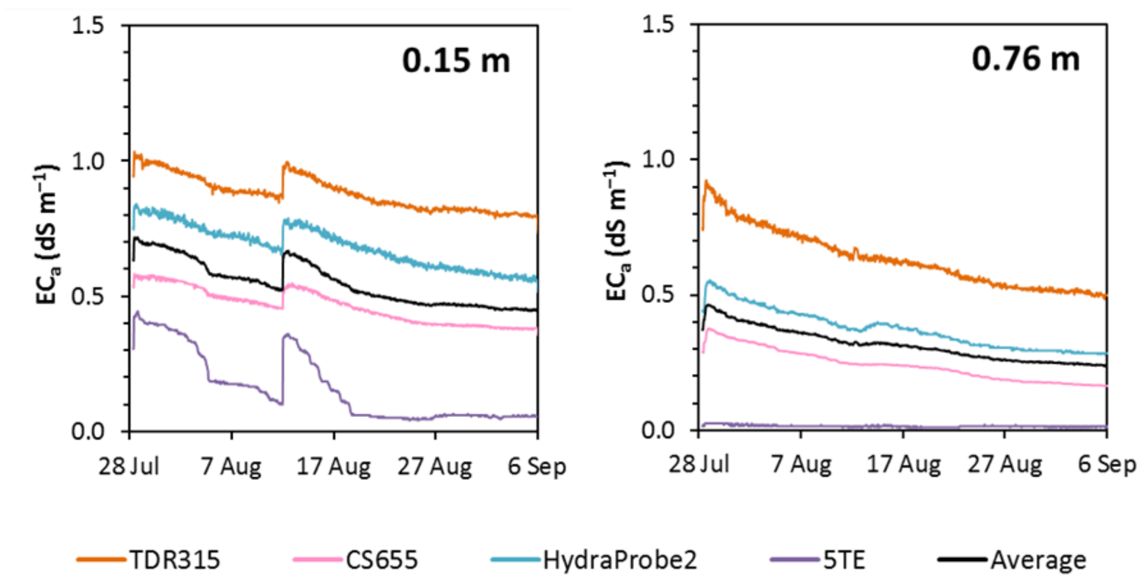


Figure 2.2. Temporal trend in sensor-average apparent electrical conductivity (ECa, dS m-1) for TDR315, CS655, HydraProbe2, 5TE, and overall average of EM sensors at depths of 0.15 and 0.76 m during the study period.

Within the observed range of EC_a for the EM sensors, HydraProbe2 and CS655 reported EC_a were comparable to the overall average at both depths. Seyfried and Murdock (2004) compared EC_a measurements by HydraProbe and by a conductivity electrode calibrated with standard solutions. They found that the two sensors reported EC_a values in KCl solutions were similar up to a range (0-1.5 dS m^{-1}) and there was an accuracy deterioration with increasing solution EC_a and concentration. Logsdon et al. (2010) reported that measured EC_a by HydraProbe was very similar to theoretical EC for fluids, and suggested that an adjustment was needed in the HydraProbe reported EC to account for dielectric relaxation in soils.

At 0.76 m depth, where the EC_a reported by other sensors was within the range 0.16 to 0.92 dS m^{-1}, the two 5TE replicates were essentially nonresponsive and only reported EC_a between 0.00 and 0.03 dS m^{-1}. The contrasting performance of 5TE sensors at both depths relative to other sensors was unlikely due to defective sensors because the differences were consistent across replicates and depths. Chávez and Evett (2012) reported an underestimation of EC_a for 5TE sensor by about 35% in comparison to conventional TDR. However, Schwartz et al. (2013) witnessed that EC_a reported by 5TE sensor was very similar to EC_a reported by conventional TDR.

Table 2.3. Average Mean Deviation (AMD) of TDR315, CS655, HydraProbe2, and 5TE sensors using factory calibration from the overall average sensors for apparent electrical conductivity at 0.15 m, 0.76 m, and combined depths.

Sensor Apparent Electrical Conductivity (EC_a)	Average Mean Deviation (AMD)		
	0.15 m	0.76 m	Combined
TDR315	0.33	0.32	0.33
CS655	-0.08	-0.07	-0.08
HydraProbe2	0.14	0.06	0.10
5TE	-0.39	-0.30	-0.34

2.3.3 Apparent Dielectric Permittivity (ε_{ra})

Similar to the temporal trends in EC_a, all sensors had a decreasing trend in ε_{ra} overtime and followed the wetting and drying cycle of the soil, where ε_{ra} increased following a wetting event (fig. 2.3). As expected, the 0.15 m soil depth responded more to wetting events as compared to the 0.76 m soil depth, since the near surface soil is subjected to more transient water dynamics as compared with lower soil depths according to Rudnick and Irmak (2014a). Cross comparison amongst ε_{ra} reported by different EM sensors was made with the average ε_{ra} of all EM sensors. The AMD within reported ε_{ra} spanned across a wide range at shallower depth (2.12-14.05) and a narrow range at deeper depth (0.31-9.52) comparatively, with the observed range of ε_{ra} within 10.50 to 40.99 at 0.15 m, and 6.56 to 28.55 at 0.76 m depth (table 2.4).

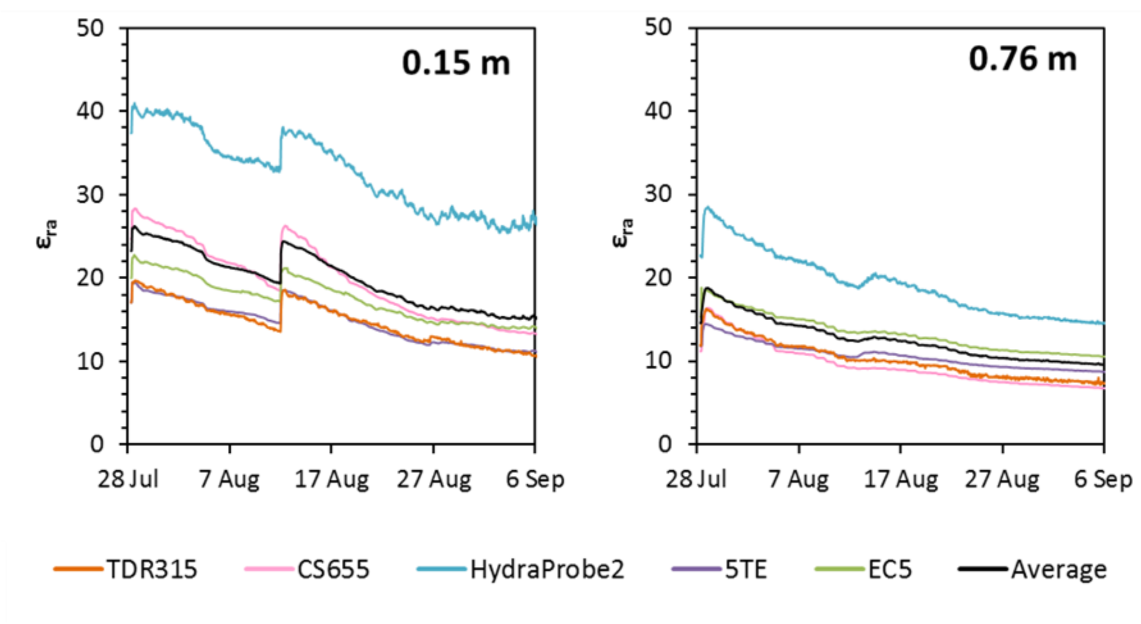


Figure 2.3. Temporal trends in sensor-average apparent relative permittivity (εra) for TDR315, CS655, HydraProbe2, 5TE, EC5, and overall average of EM sensors at depths of 0.15 and 0.76 m during the study period.

The HydraProbe2 sensor recorded the largest average ε_{ra} difference with respect to the overall average.. The difference was consistent for both the replications in comparison to the overall average at two depths. This remarkable difference in ε_{ra} was possibly due to differences in operating measurement frequency amongst sensors. Seyfried and Murdock (2004) synthesized the findings of multiple researchers on the differences between soil permittivity measured at around 1 GHz (standard) by TDR and at 50 MHz (standard) by HydraProbe2. They claimed that the real (ε_r') and imaginary (ε_r'') relative permittivity, and consequently ε_{ra}, of soils except sands were often larger at 50 MHz than at around 1 GHz. If this interpretation holds true, it would not be appropriate to directly compare ε_{ra} reported by different sensors due to the differences in measurement frequency in our context.

Table 2.4. Average Mean Deviation (AMD) of TDR315, CS655, HydraProbe2, 5TE, and EC5 sensors using factory calibration from the overall average sensors for apparent dielectric permittivity at 0.15 m, 0.76 m, and combined depths.

Sensor Apparent Dieletric Permittivty (ε_{ra})	Average Mean Deviation (AMD) 0.15 m	0.76 m	Combined
TDR315	-6.01	-2.42	-3.79
CS655	-0.12	-3.08	-1.60
HydraProbe2	12.84	6.72	9.78
5TE	-5.14	-1.97	-3.56
EC5	-2.42	0.76	-0.83

2.3.4 VOLUMETRIC WATER CONTENT (θ_V)

2.3.4.1 TEMPORAL TRENDS

The study period could be characterized as a drying cycle that began with a 31 mm rain on 28 July and was interrupted by a 17 mm rain on 11 August and a 9 mm rain on 26 August. Reference θ_v, which was the average NMM θ_v from four access tubes, ranged from 0.180-0.332 m^3 m^{-3} at 0.15 m, 0.173-0.260 m^3 m^{-3} at 0.30 m, 0.139-0.189 m^3 m^{-3} at 0.51 m, 0.130-0.192 m^3 m^{-3} at 0.61 m, and 0.131-0.214 m^3 m^{-3} at 0.76 m. With increasing depth, the range of reference θ_v narrowed because deeper depths received less of infiltrated rainfall and contributed less to ET as compared to shallower depths.

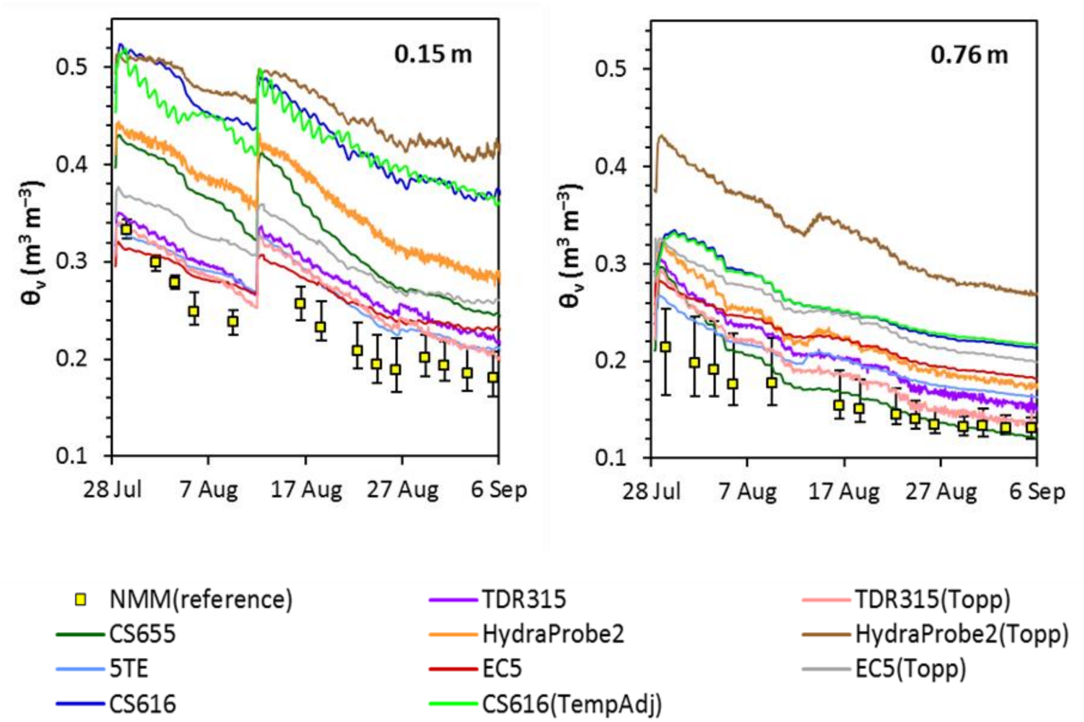
The differences between sensor-reported and reference θ_v varied among sensors and over time (fig.2. 4). However, for all evaluated sensors, the factory calibrations and the considered alternate calibrations followed the general trend of reference θ_v. All evaluated sensors, nonetheless, commonly overestimated θ_v relative to the reference.

Using the Topp equation (eq. 1) instead of the factory calibration improved the performance of TDR315 but not HydraProbe2 or the EC5. By switching to Topp equation, combined RMSD for TDR315 decreased by 0.013 m^3 m^{-3} whereas combined

RMSD for HydraProbe and EC5 increased by 0.029, and 0.100 m^3 m^{-3}, respectively. The Topp equation was developed using TDR (Topp et al., 1980) and has been demonstrated to be applicable in many soils (Dane and Topp, 2002). Thus, the suitability of the Topp equation for TDR315 was not surprising. The overestimation of ε_{ra} by HydraProbe2 is discussed in the previous subsection. Therefore, applying the Topp equation to ε_{ra} based on HydraProbe2 measurements would tend to inflate the calculated θ_v, matching the observations in the present study. In fact, overestimation of θ_v also occurred when Vaz et al. (2013) applied the Topp equation to ε_r' as measured by HydraProbe2.

The influence of ambient T on CS616 has been described in the literature (Udawatta et al., 2011; Varble and Chávez, 2011; Mittelbach et al., 2012). In the present study, CS616-reported θ_v at 0.15 m using the factory calibration exhibited diurnal fluctuations in which θ_v appeared to decrease with decreasing soil T and increase with increasing soil T. Or and Wraith (1999) attributed these diurnal fluctuations not to actual changes in θ_v but to both the volume fraction of bound water and the T effects on the permittivity of bulk water. Besides altering the EM properties of the surrounding media, T could also affect sensor electronics (Seyfried and Grant, 2007). The manufacturer's T adjustment, however, arguably did not improve the accuracy of CS616-reported θ_v in the present study. When this adjustment was applied to the CS616 data at 0.15 m, the diurnal fluctuations was simultaneously reversed and amplified. Such an outcome may indicate overcompensation by the manufacturer's T adjustment, which Rüdiger et al. (2010) noticed.

Single-Sensor Probes



Multi-Sensor Probes

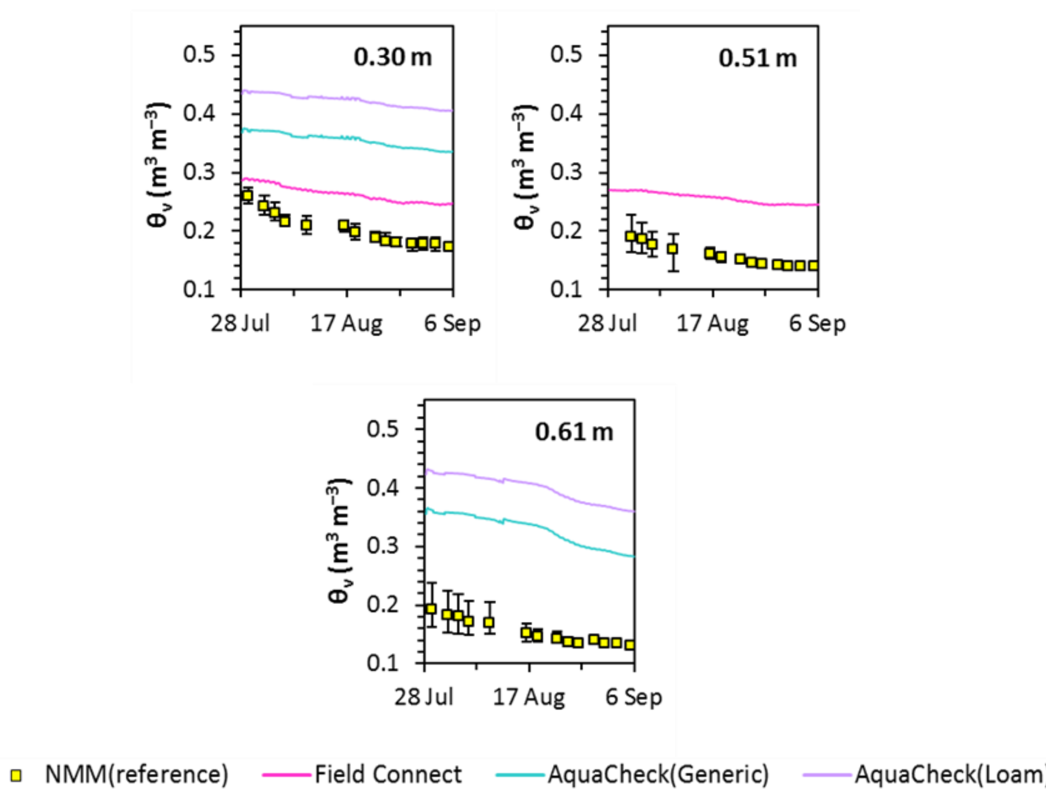


Figure 2.4. Temporal trends in volumetric water content (θv) at various depths reported by the evaluated sensors using default factory calibrations (and/or alternate calibrations noted in parentheses) as compared with the field-calibrated neutron moisture meter (NMM). The average of two replications per depth was shown for each sensor, and the average and range of four replications per depth were shown for the NMM.

While the soil at the field site was a loam, AquaCheck-reported θ_v was further from reference θ_v when using the "loam" calibration than when using the "generic" calibration. Loam was intermediate among the five soil textural classes for which a specific calibration was provided by the manufacturer. Yet, the loam calibration was most unlike the other calibrations because the former computed a much higher θ_v when the same scaled frequency was measured. As compared to the sites where the other calibrations were developed, the site where the loam calibration was developed might have differed in one or more non-textural soil properties that heavily impacted AquaCheck response.

2.3.4.2 Factory Calibrations

Commonalities in performance statistics were found among the evaluated sensors (table 2.5). MD was positive for all evaluated sensors at all depths, a result in agreement with the earlier finding that sensor-reported θ_v was predominantly higher than reference θ_v. Except in the cases of CS655 and EC5, SDD never exceeded half of MD at any depth or for combined data, signifying that the deviations of sensor-reported θ_v from reference θ_v for each of the other six sensors were rather consistent in direction and magnitude. Consequently, RMSD mostly followed the patterns of MD.

Table 2.5. Mean difference (MD) statistics comparing volumetric water content (θ_v) reported by the evaluated sensors using factory calibrations against reference θ_v from average of four neutron moisture meter (NMM) access tubes.

θ_v (m^3 m^{-3}) Sensor	0.15 m	0.76 m	Combined

TDR315 CS655 HydraProbe2 5TE EC5 CS616	**0.046 0.093 0.125 0.032 0.034 0.197**	**0.047 0.018 0.065 0.041 0.062 0.100**	**0.047 0.056 0.095 0.036 0.048 0.149**
	0.30 m	**0.51 m**	**Combined**
Field Connect	**0.061**	**0.098**	**0.079**
	0.30 m	**0.61 m**	**Combined**
AquaCheck[a]	**0.152**	**0.172**	**0.162**

[a] While two replicates of other evaluated sensors were included, only one replicate of AquaCheck using the generic calibration was included.

The performance statistics varied among depths. MD was smaller at the shallower depth and larger at the deeper depth for five sensors (TDR315, 5TE, EC5, Field Connect, and AquaCheck), while the opposite was true for three sensors (CS655, HydraProbe2, and CS616). Except in the cases of TDR315 and EC5, SDD was similar at individual depths but larger for the combined data.

Table 2.6. Standard Deviation of Difference (SDD) statistics comparing volumetric water content (θ_v) reported by the evaluated sensors using factory calibrations against reference θ_v from average of four neutron moisture meter (NMM) access tubes.

θ_v (m^3 m^{-3}) Sensor	**0.15 m**	**0.76 m**	**Combined**
TDR315 CS655 HydraProbe2 5TE EC5 CS616	**0.016 0.049 0.018 0.015 0.029 0.013**	**0.022 0.026 0.022 0.014 0.011 0.017**	**0.019 0.055 0.036 0.015 0.026 0.051**
	0.30 m	**0.51 m**	**Combined**
Field Connect	**0.021**	**0.018**	**0.027**
	0.30 m	**0.61 m**	**Combined**
AquaCheck[a]	**0.016**	**0.012**	**0.017**

[a] While two replicates of other evaluated sensors were included, only one replicate of AquaCheck using the generic calibration was included.

With RMSD ranging between 0.032 and 0.197 m^3 m^{-3} at individual depths and between 0.039 and 0.163 m^3 m^{-3} for combined data, the evaluated sensors ranged between fair (0.05 m^3 m^{-3} > RMSD ≥ 0.01 m^3 m^{-3}) and very poor (RMSD ≥ 0.1 m^3 m^{-3}) on the accuracy scale of Fares et al. (2011). On the same scale, the performance of Field Connect was poor (0.1 m^3 m^{-3} > RMSD ≥ 0.05 m^3 m^{-3}), and AquaCheck was very poor

(RMSD ≥ 0.1 $m^3\ m^{-3}$) for combined data, with the RMSD values of Field Connect and AquaCheck as 0.083 and 0.163 $m^3\ m^{-3}$, respectively. Among the single-sensor probes, RMSD of 5TE was smallest both at 0.15 m and for combined data with values of 0.035 and 0.039 $m^3\ m^{-3}$, respectively, whereas RMSD of CS655 was the smallest at 0.76 m with a value of 0.032 $m^3\ m^{-3}$. RMSD of CS616 was the largest among the single-sensor probes at both depths and combined.

Table 2.7. Root Mean Square Difference (RMSD) statistics comparing volumetric water content (θ_v) reported by the evaluated sensors using factory calibrations against reference θ_v from average of four neutron moisture meter (NMM) access tubes.

θ_v ($m^3\ m^{-3}$) Sensor	0.15 m	0.76 m	Combined
TDR315	0.049	0.052	0.050
CS655	0.105	0.032	0.078
HydraProbe2	0.126	0.069	0.102
5TE	0.035	0.043	0.039
EC5	0.044	0.063	0.054
CS616	0.197	0.102	0.157
	0.30 m	0.51 m	Combined
Field Connect	0.064	0.100	0.083
	0.30 m	0.61 m	Combined
AquaCheck[a]	0.153	0.172	0.163

[a] While two replicates of other evaluated sensors were included, only one replicate of AquaCheck using the generic calibration was included.

1.3.4.3 Regression Calibrations

Out of the 24 regression calibration equations, five were linear and 19 were quadratic (fig. 2.5). Here, polynomial order was selected by minimization of LOOCV RMSD and not by statistical significance tests with $\alpha = 0.05$. If the latter method was applied, the regression calibration equations for CS616 at 0.76 m and for Field Connect at 0.30 m would be linear because the p-value for the true quadratic coefficient being zero was 0.10 and 0.14, respectively, for these two datasets. Interestingly, the estimate of the intercept was greater than zero for all regression calibration equations. In all linear calibration equations (reference $\theta_v = m \times$ sensor $\theta_v + c$), the estimate of the linear coefficient '*m'* was positive but less than 1. Hence, the sensors to which these linear calibration equations were fitted were more sensitive than the reference. The quadratic calibration equations, on the other hand, implied that sensitivity generally increased with θ_v within the observed θ_v range. Some of the regression calibration equations for θ_v were negatively sensitive under dry conditions and/or highly sensitive under wet conditions. At the minimum sensor value observed, eight regression calibrations specify that increases in sensor-reported θ_v would signify decreases in reference θ_v. These calibrations are those for CS655, HydraProbe2, 5TE, and EC5 at 0.15 m; Field Connect at 0.30 m and for combined data; and AquaCheck at 0.51 m and for combined data. At the maximum sensor value observed, six regression calibrations specify that one unit of increase in sensor-reported θ_v would signify more than two units of increase in reference θ_v. These calibrations are those for TDR315, 5TE, and EC5 at 0.15 m; Field Connect for combined data; and AquaCheck at 0.30 m and for combined data.

Table 2.8. Leave-one-out cross validation RMSD calibration of regression calibration for comparing volumetric water content (θ_v) reported by the evaluated sensors using factory calibrations against reference θ_v from average of four neutron moisture meter (NMM) access tubes.

θ_v (m^3 m^{-3}) Sensor	0.15 m	0.76 m	Combined
TDR315	0.014	0.010	0.016
CS655	0.024	0.005	0.022
HydraProbe2	0.011	0.009	0.013
5TE	0.010	0.011	0.013
EC5	0.028	0.008	0.025
CS616	0.011	0.007	0.016
	0.30 m	0.51 m	Combined
Field Connect	0.021	0.016	0.026
	0.30 m	0.61 m	Combined
AquaCheck[a]	0.009	0.005	0.013

[a] While two replicates of other evaluated sensors were included, only one replicate of AquaCheck using the generic calibration was included.

Regression calibrations led to substantial improvement in θ_v accuracy beyond factory calibration (table 2.8). For example, RMSD of CS616 exceeded by 0.10 m^3 m^{-3} at both depths when using factory calibration, yet when using regression calibration, RMSD of CS616 dropped below 0.02 m^3 m^{-3} for depth-specific and combined data. In general, RMSD of the evaluated sensors were below 0.015 m^3 m^{-3} using depth-specific regression calibrations and below 0.020 m^3 m^{-3} using combined regression calibrations. The exceptions were CS655 at 0.15 m, EC5 at 0.15 m, and Field Connect at all depths. Among all considered regression calibrations, the combined regression calibration of Field Connect resulted in the largest RMSD of 0.026 m^3 m^{-3}.

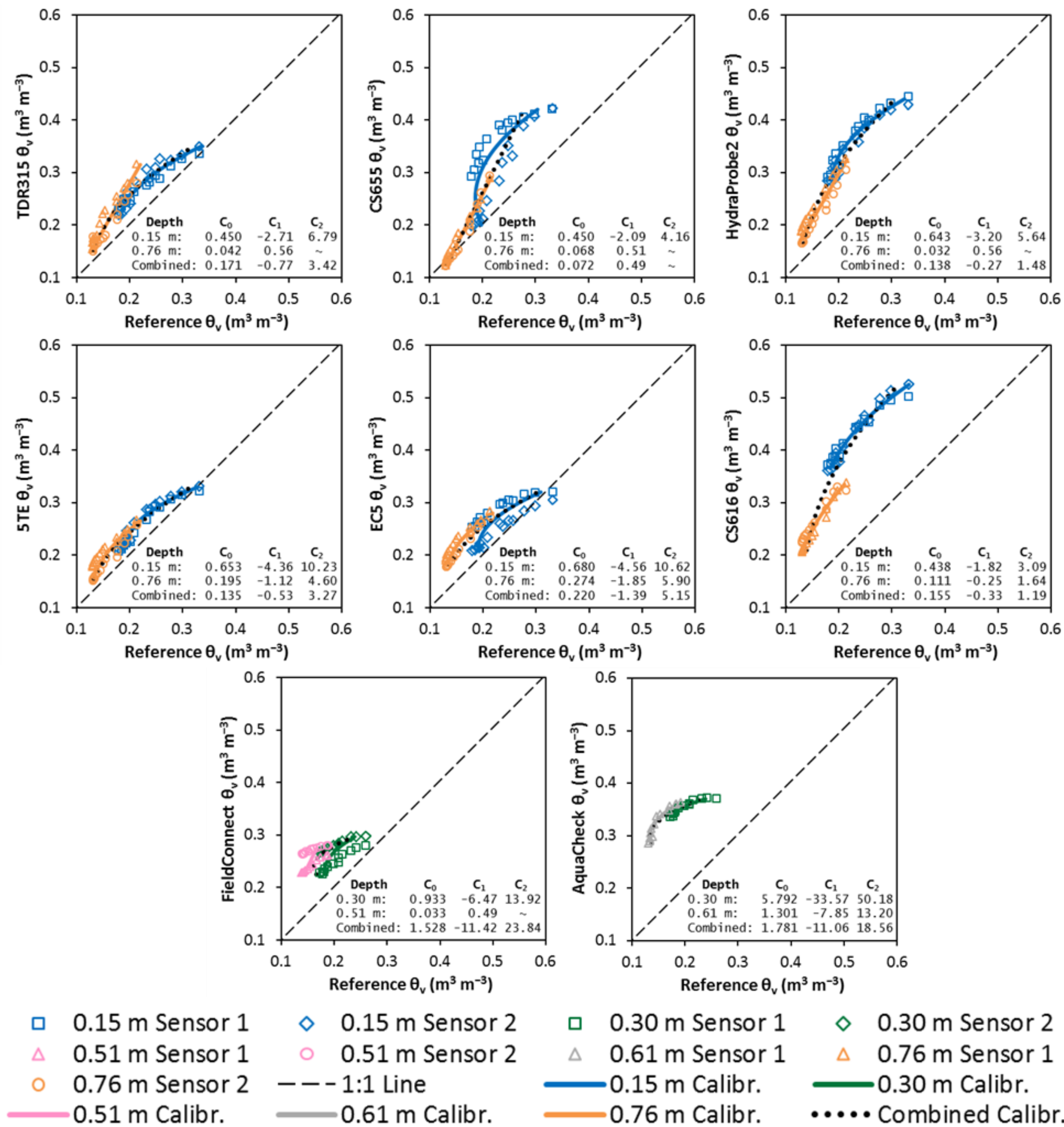


Figure 2.5. Scatterplots with 1:1 line comparing volumetric water content (θv) reported by the evaluated sensors using factory calibrations against reference θv from average of four NMM access tubes. Regression calibration curves were displayed with the estimates of the coefficients in the corresponding equation (Reference θ_v) = $C_0 + C_1 \times$ (Sensor θ_v) + $C_2 \times$ (Sensor $\theta_v)^2$.

2.3.4.3 Offset Calibrations

Though the improvements in θ_v accuracy gained by using offset calibrations were smaller and less consistent than the improvements gained by using regression calibrations, offset calibrations were nonetheless valuable for several sensors under evaluation (table 2.9). For example, RMSD of HydraProbe2 exceeded 0.10 $m^3 m^{-3}$ at 0.15 m and for combined data when using factory calibration. Using offset calibrations, the upper bound of the confidence interval for mean RMSD of HydraProbe2 was below 0.03 $m^3 m^{-3}$ at 0.15 m and below 0.06 $m^3 m^{-3}$ for combined data. The lower and upper bounds of the confidence interval for mean RMSD of most sensors were below 0.02 and 0.04 $m^3 m^{-3}$, respectively, when using depth-specific offset calibrations. For CS655, HydraProbe2, CS616, and Field Connect using combined offset calibrations tended to result in higher RMSD than using depth-specific offset calibrations. The highest confidence interval for mean RMSD among all offset calibrations was 0.072-0.082 $m^3 m^{-3}$ for CS655 with combined data.

Table 2.9. 95% confidence interval of mean RMSD of offset calibration for comparing volumetric water content (θ_v) reported by the evaluated sensors using factory calibrations against reference θ_v from average of four neutron moisture meter (NMM) access tubes.

θ_v ($m^3 m^{-3}$) Sensor	0.15 m	0.76 m	Combined
TDR315	0.019-0.026	0.028-0.035	0.025-0.030
CS655	0.063-0.076	0.032-0.042	0.072-0.082
HydraProbe2	0.023-0.027	0.027-0.035	0.048-0.054
5TE	0.017-0.025	0.019-0.021	0.019-0.024
EC5	0.036-0.045	0.014-0.017	0.032-0.040
CS616	0.016-0.021	0.022-0.026	0.070-0.075
	0.30 m	0.51 m	Combined
Field Connect	0.027-0.033	0.023-0.027	0.035-0.041
	0.30 m	0.61 m	Combined
AquaCheck[a]	0.015-0.028	0.014-0.019	0.019-0.028

[a] While two replicates of other evaluated sensors were included, only one replicate of AquaCheck using the generic calibration was included.

An offset calibration determined the difference between sensor-reported θv and reference θv for one data point and then shifted all other data points by that difference. Offset calibrations were therefore most beneficial if data points fitted tightly around one line whose slope was around 1. For example, the distribution of all 5TE data points generally matched one line with a slope of 1, so RMSD of both depth-specific and combined offset calibrations were relatively low. As for CS616, the distribution of 0.15 m data points generally matched one line with a slope of 1, and the distribution of 0.76 m data points generally matched a different line with slope of 1. The ultimate result was low RMSD for depth-specific offset calibrations but high RMSD for combined offset calibrations. Offset calibrations could also be worse than factory calibrations if the differences from reference θv values were extremely variable among sensor-reported θv values. One instance was CS655 data points at 0.76 m, for which factory calibration RMSD was lower than the lower bound of the confidence interval for mean RMSD when using depth-specific offset calibrations. These data points were located near the 1:1 line at the dry end of reference θv but increased in sensor-reported θv following a slope exceeding 1 as reference θv increased. Since it might not be possible to know beforehand the uniformity in the differences between sensor-reported and reference θv, the risk of worsening sensor accuracy is unavoidable when applying an offset calibration based on one known data point. Therefore, unless the user has confidence that changes in sensor-reported θv are almost identical to changes in true θv, the use of an offset calibration cannot yet be recommended. Further research can investigate optimal sampling timing for offset calibrations and further explore other simplified calibration procedures such as Sakaki et al. (2011).

2.4 Discussion

Overestimation of θ_v has been reported in the literature for most of the evaluated sensors: CS655 (Kisekka et al., 2014; Michel et al., 2015), HydraProbe2 (Ojo et al., 2014; Ojo et al., 2015), 5TE (Varble and Chávez, 2011), EC5 (Ojo et al., 2014), CS616

(Rüdiger et al., 2010; Udawatta et al., 2011; Varble and Chávez, 2011; Mittelbach et al., 2012), and Field Connect (Rudnick et al., 2015). Some of these studies commented that the occurrence and/or magnitude of overestimation was dependent on θ_v (Udawatta et al., 2011; Mittelbach et al., 2012; Ojo et al., 2014; Kisekka et al., 2014; Rudnick et al., 2015). In the present study, such dependence on θ_v could be argued particularly at the 0.76 m depth. Whereas, others remarked that overestimation increased with clay content (Rüdiger et al., 2010; Varble and Chávez, 2011). The average clay content of the present study site ranged from 17 to 25% (table 2.1).

The differences in results across depths have tended to be associated with soil textural differences in the literature. Mittelbach et al. (2012) showed that CS616 underestimated θ_v in a clay loam topsoil at the depth of 0.05 m but overestimated θ_v in the underlying loam subsoil at depths of 0.25, 0.35, 0.55, and 0.80 m. Rudnick et al. (2015) noted that overestimation of θ_v by Field Connect was greater at 1.00 m than at 0.30 m and attributed this phenomenon to the higher clay content at the deeper depth. In the present study site, however, soil texture at 0.15 and 0.76 m depths was alike (table 2.1). RMSD values of comparable magnitudes for factory calibrations have been published for the evaluated sensors. For TDR315, RMSD was 0.0324 $m^3\ m^{-3}$ in a clay loam repacked in the lab (Schwartz et al., 2016). For HydraProbe2, RMSD was 0.048 $m^3\ m^{-3}$ in five soils repacked in the lab (Vaz et al., 2013), 0.131 $m^3\ m^{-3}$ in a clay in the field (Ojo et al., 2014), 0.018 $m^3\ m^{-3}$ in a coarse-textured soil in the field, and 0.052 $m^3\ m^{-3}$ in a medium-textured soil in the field (Ojo et al., 2015). For 5TE, RMSD was 0.028-0.037 $m^3\ m^{-3}$ in a sandy clay loam in the field (Varble and Chávez, 2011). For EC5, RMSD was 0.058 $m^3\ m^{-3}$ in clay in the field (Ojo et al., 2014). For CS616, RMSD was 0.144 $m^3\ m^{-3}$

in five silty soils in the field (Rüdiger et al., 2010), 0.15 $m^3 m^{-3}$ in three soils repacked in the lab (Udawatta et al., 2011), 0.034-0.289 $m^3 m^{-3}$ in three soils repacked in the lab (Varble and Chávez, 2011), 0.192-0.337 $m^3 m^{-3}$ in a sandy clay loam in the field (Varble and Chávez, 2011), and 0.01-0.14 $m^3 m^{-3}$ across seven depths in a medium-fine textured soil in the field (Mittelbach et al., 2012). For Field Connect, RMSD was 0.066-0.069 $m^3 m^{-3}$ across two depths in a medium-fine textured soil in the field (Rudnick et al., 2015).

The abundance of previous evaluations on θ_v measurement accuracy of HydraProbe2 and CS616 generally agree on two points. First, obtaining RMSD values in excess of 0.05 and 0.10 $m^3 m^{-3}$ for these two sensors, respectively, as did the present study, would be ordinary when using factory calibrations (Rüdiger et al., 2010; Udawatta et al., 2011; Varble and Chávez, 2011; Mittelbach et al., 2012; Ojo et al., 2014; Ojo et al., 2015). Second, the accuracy of HydraProbe2 and CS616 factory calibrations often deteriorates with increasing clay content, as shown by Varble and Chávez (2011), Vaz et al. (2013), and Ojo et al. (2015), but not by Udawatta et al. (2011). The ε_r' measurements at 50 MHz by HydraProbe2 and period measurements around 175 MHz by CS616 are both affected by dielectric dispersion (Seyfried and Murdock, 2004; Kelleners et al., 2005). The latter is affected additionally by EC (Kelleners et al., 2005). Because both dielectric dispersion and EC are related to clay content and clay mineralogy (Seyfried and Murdock, 2004), the relationship between measured ε_r' and true θ_v for HydraProbe2 and the relationship between measured period and true θ_v for CS616 may vary among soils.

In support of the results of our study, some field studies have noted that RMSD in θ_v was smaller when using site-specific regression calibrations developed in undisturbed field soil than when using factory calibrations (Varble and Chávez, 2011;

Nolz, 2012; Ojo et al., 2014; Ojo et al., 2015; Rudnick et al., 2015). Just as the accuracy of factory calibrations has been evaluated with independent data, the accuracy of new regression calibrations should be evaluated (by cross-validation or external validation) with sufficiently diverse data to include the full spectrum of conditions under which these new regression calibrations would be applied. Factors that may differ between calibration conditions and validation conditions would include the observed range of θ_v, the strength of confounding/interfering variables (e.g., T and EM properties), and the magnitude of inter-replicate variability in electronics and installation. By splitting a time series of AquaCheck data into an earlier portion for regression calibration and a later portion for validation, RMSD across six depths was 0.005-0.019 $m^3 m^{-3}$ during calibration, but roughly doubled to 0.009-0.037 $m^3 m^{-3}$ (Nolz, 2012). By using a regression calibration based on 12 Field Connect replicates in the same field during the previous growing season, RMSD in θ_v reported by 18 Field Connect replicates was reduced to 0.038 $m^3 m^{-3}$ from 0.067 $m^3 m^{-3}$ as obtained by using the factory calibration. If a new regression calibration performed worse than the factory calibration in such evaluations, then the benefit of the former would be in question.

It may be possible to manage irrigation by monitoring changes in sensor-reported θ_v instead of exact values of sensor-reported θ_v. This approach is very similar to the offset calibration because it is based on the same assumption that sensor θ_v and reference θ_v have equal sensitivity, i.e. with 1 unit increase in reference θ_v, there is 1 unit increase in sensor θ_v. But on the basis of assessing the scatterplots with 1:1 line comparing sensor θ_v with reference θ_v (fig. 2.5), we observe that slope of the relationship between sensor θ_v and reference θ_v is not consistently one. Instead, many of these relationships are curvilinear indicating that the sensitivity of sensor θ_v varies with the reference θ_v. Therefore, we cannot recommend at this that the offset calibration/monitoring changes in θ_v will always be appropriate for irrigation management. We did note that some of the EM sensors had slopes closer to one at certain depths. Further research could be conducted to analyze if the appropriateness of offset calibrations or tracking changes is a property of each EM sensor or is merely site-specific.

2.4.1 Implications

While the differences between reference and sensor-reported θ_v were sometimes large when using factory calibrations in this study, regression calibrations of θ_v resulted in excellent fit nonetheless for all sensors at individual depths or for combined data. This finding would suggest that much of the uncertainty in sensor-reported θ_v for the sensors under evaluation was systematic and could be modeled. The dominance of systematic error reported by the investigated sensors highlights that the development of more accurate calibrations is a principal key to improving sensor-reported θ_v. Increasing the number of sensor replicates would only reduce variance due to random errors such as inter-replicate variability, inter-cycle variability, and fluctuations.

For a calibration to be transferable the sensor must either be highly resistant to potentially confounding factors (e.g., T, EC_a, clay mineralogy and content) or the calibration must account for these factors internally. If the major factors can be identified and quantified and the effects of these factors can be well-modeled, perhaps sensor calibrations similar to pedo-transfer functions for estimating the soil water characteristics curve can be developed. An alternative to devising a universal calibration is performing site-specific calibrations. Although, conducting comprehensive regression calibrations at each field site might be impractical if a sensor is widely applied. However, the relative success of offset calibrations for certain sensors in this field study was encouraging and may signal new opportunities. How regression and offset calibrations can be conducted practically and accurately for the purpose of irrigation management is yet to be investigated.

Qualitative information about soil water status can be determined from the EM sensors installed at different depths, since the factory calibrations and the alternate calibrations followed the general trend of reference θ_v. However, scheduling irrigation by considering EM sensor-reported θ_v as the true θ_v might be misleading and can result in unintended consequences such as over- or under-irrigating. For irrigation management, alternate paradigms of sensor use, possibly analyzing trends and relative values at one or more depths rather than relying on conversions from raw output to water content for decision-making, might also deserve scientific attention. All these issues can be further explored in future research.

2.5 CONCLUSIONS

A field study was conducted at the University of Nebraska-Lincoln West Central Research and Extension Center in North Platte, NE, to evaluate the performance of eight electromagnetic (EM) soil water sensors, TDR315, CS655, HydraProbe2, 5TE, EC5, CS616, Field Connect, and AquaCheck, in a loam soil at two depths. Factory calibrations of the EM sensors were evaluated against the overall average of EM sensors for temperature (T), apparent electrical conductivity (EC_a), and apparent dielectric permittivity (ε_{ra}), and volumetric water content (θ_v) was compared with a field calibrated CPN 503DR Hydroprobe Moisture Neutron Depth Gauge (NMM) following Bell et al. (1987), Leib et al. (2003), and Rudnick et al. (2015).

All T measuring sensors followed the temporal trends in T generally within 1^{0}C of each other. The average mean deviation (AMD) ranged from -0.20°C for TDR315 to 0.34°C for 5TE at depth of 0.15 m and from -0.31°C for HydraProbe2 to 0.45°C for TDR315 at depth of 0.76 m. The range for reported EC_a among all sensors at both depths was within 1 dS m^{-1}. Such comparability among sensors provides confidence that the sensors can be used for crop modeling and planting decisions.

Sensor performance assessment of 5TE, EC5, HydraProbe2, CS616, CS655, TDR315, Field Connect, and AquaCheck with default factory, regression, and offset calibrations against the field calibrated NMM was carried out. The Topp equation for TDR315, HydraProbe2, and EC5; manufacturer's T adjustment for CS616 using T measurements by CS655; and both "generic" and the "loam" calibrations for AquaCheck were considered in addition to the factory calibrations. Among the single-sensor probes, the range of RMSD using factory calibration varied from 0.039 m^3 m^{-3} for 5TE to 0.157 m^3 m^{-3} for CS616. In comparison with the single-sensor probes, RMSD of Field Connect was moderate (0.083 m^3 m^{-3}) and RMSD of AquaCheck was high (0.163 m^3 m^{-3}). Using regression calibrations improved θ_v accuracy beyond factory calibration. In general, RMSD of the evaluated sensors were below 0.025 m^3 m^{-3} using regression calibrations with exceptions of 5TE and Field Connect. The betterment in θ_v accuracy gained by using offset calibrations was smaller and less consistent than the improvements gained by using regression calibrations. The relative success of offset calibrations for certain sensors in this field study is encouraging and may signal new opportunities. In addition, alternate models of sensor use, possibly analyzing trends and relative values at one or more depths rather than relying on conversions from raw output to water content for decision-making for irrigation management can be further explored in future research.

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CHAPTER III

EVALUATION OF THE EFFECTS OF CLAY CONTENT, TEMPERATURE, AND SALINITY ON THE PERFORMANCE OF REFLECTOMETERS

3.1 INTRODUCTION

Determination of accurate and continuous soil water content is vital in many soil-water and hydrologic studies as well as assisting producers in making optimal irrigation management decisions. Monitoring of soil water status can be used to schedule irrigations by triggering water application when soil water is depleted to a defined threshold based on crop and soil type. Direct measurement of soil volumetric water content (θ_v) can be done by the thermo-gravimetric method which involves removing a known volume of soil, drying at 105°C until it reaches a constant weight, and then determining the volume of water loss (Walker et al., 2004). Unfortunately, this method is destructive, non-continuous, tedious, and time-consuming, and therefore, not a suitable option for most applications, including irrigation scheduling. Alternatively, neutron attenuation via a neutron moisture meter (NMM) is a reliable and accurate non-destructive (after installation) indirect measure of θ_v. Although the NMM improves stability in monitoring of θ_v as compared to the thermo-gravimetric method by allowing for repeated measures in a single location, it is also limited in applications due to a radioactive source, which requires proper training, licensing, and safety measures when handling, storing, and transporting the instrument (Rudnick et al., 2015). Consequently, electromagnetic (EM) sensors are widely used to monitor θ_v due to ease of installation, fewer regulatory and safety concerns, cost effectiveness, continuous measurement, and data can be stored on-site and transmitted to a remote computer. In addition, some EM sensors have the capability to measure additional soil properties such as temperature, apparent electrical conductivity (EC_a), and dielectric permittivity (ε_{ra}).

Electromagnetic soil water sensors estimate θ_v by determining dielectric permittivity. The dielectric permittivity of water is high in comparison to other soil constituents. However, the dielectric properties of soil can be influenced by other factors such as temperature, salinity, textural composition (sand, silt, and clay), organic matter content (OMC), and bulk density (ρ_b), and therefore, a deliberate investigation of these factors is vital for accurate determination of θ_v (Paige and Keefer, 2008). Several studies have investigated the reliability and accuracy of EM sensors under various soil conditions.

Some studies have reported low sensitivity of soil temperature on ε_{ra} measured by Time domain reflectometry (TDR) (Pepin et al., 1995; Blonquist et al., 2005). Conversely, some researchers found that the ε_{ra} measured by TDR can possibly increase with the increase in temperature due to release of bound water (Wraith and Or, 1999; Gong et al., 2003). Variations in temperature were found to introduce slight errors in θ_v estimated by TDR315 sensors as well (Adayemi et al., 2016). On the other hand, fluctuations in soil temperature have shown to effect the performance of water content reflectometers (WCR) (CS616) as well in the literature (Seyfried and Murdock, 2001; Western and Seyfried, 2005; Lodgson, 2009; Mittelbach et al., 2012).

The influence of variations in salinity (EC_a) has shown to effect θ_v measurements by TDR (Dalton, 1992; Wyesure et al., 1997; Topp et al., 1980; Nadler et al., 1991). An overestimation of TDR reported θ_v measurements at higher EC_a was witnessed by Dalton (1992). In addition, Wyesure et al. (1997) observed that EC_a influenced the overestimation of θ_v by TDR, however, the overestimation stayed within reasonable limits if EC_a was kept under 2 dS m^{-1}. In contrast, some studies have suggested that θ_v and EC_a calculations are independent of each other (Topp et al., 1980; Nadler et al., 1991).

The effects of soil type on the performance of EM sensors have been considered in the past as well. According to the findings of Jacobsen and Schjønning (1993), a correlation of ρ_b, clay content, and OMC with TDR reported θ_v measurement yielded an improved (in comparison to a third-order polynomial relationship between θ_v and the ε_{ra}), and statistically significant calibration.

Several studies have been conducted in the last few decades with EM sensors and many have concluded that a soil specific calibration would improve the accuracy of these sensors. These calibrations have been extensively developed for different soils, either in the field (Evett and Steiner, 1995; Chandler et al., 2004; Varble and Chavez, 2011; Mittelbach et al., 2012; Rudnick et al., 2015; Singh et al., 2017) or laboratory (Seyfried and Murdock, 2001; Western and Seyfreid, 2005; Udawatta et al., 2011; Varble and Chavez, 2011; Adayemi et al., 2016). However, minimal research has been conducted to develop universal calibrations (i.e., calibration that can work across various conditions). The models for these calibrations could be applied to different soil and environmental conditions. Researchers have modeled for the compensating effects of temperature and salinity on the accuracy of conventional TDR in the literature (Evett et al. 2005; Schwartz et al., 2009). However, there is still a need of universal calibrations for recently developed EM sensors.

A laboratory study was conducted to evaluate the performance of two recently developed EM sensors – TDR315 and CS655 in five different textured soils collected across different topographic regions of Nebraska. This lab study was designed to evaluate practical significance on sensor performance at different temperatures, salinity, and clay content conditions. Specific objectives of the research were to 1) evaluate the effects of temperature difference, increased salinity, and clay content (soil type) on sensor (factory calibration) reported θ_v, and 2) develop a general non-soil type specific calibration equation for the TDR315 and CS655 sensors based on the investigated relationship between clay content and the calibration coefficients relating sensor and reference θ_v.

3.2 Material and Methods

3.2.1 Site and Soil Descriptions

Soil samples of varying textural composition, organic matter content (OMC), and bulk density (ρ_b) were collected across Nebraska (fig. 3.1). The soils were Valent sand (mixed, mesic Ustic Torripsamments), Cozad silt loam (coarse-silty, mixed, superactive, mesic Typic Haplustolls), Kuma silt loam (fine-silty,mixed, superactive, mesic Pachic Argiustolls) Hastings silt loam (fine, smectitic, mesic Udic Argiustolls), and Wymore silty clay loam (fine, smectitic, mesic Aquertic Argiudolls). The description for soil depth, location, and horizon associated with each soil type are presented in Table 3.1, and soil properties are presented in Table 3.2. The soils ranged from 5 ± 1% clay content for the Valent sand to 49 ± 4% for the Wymore silty clay loam soil. The corresponding soil associations for each site in Nebraska are presented in fig. 3.1.

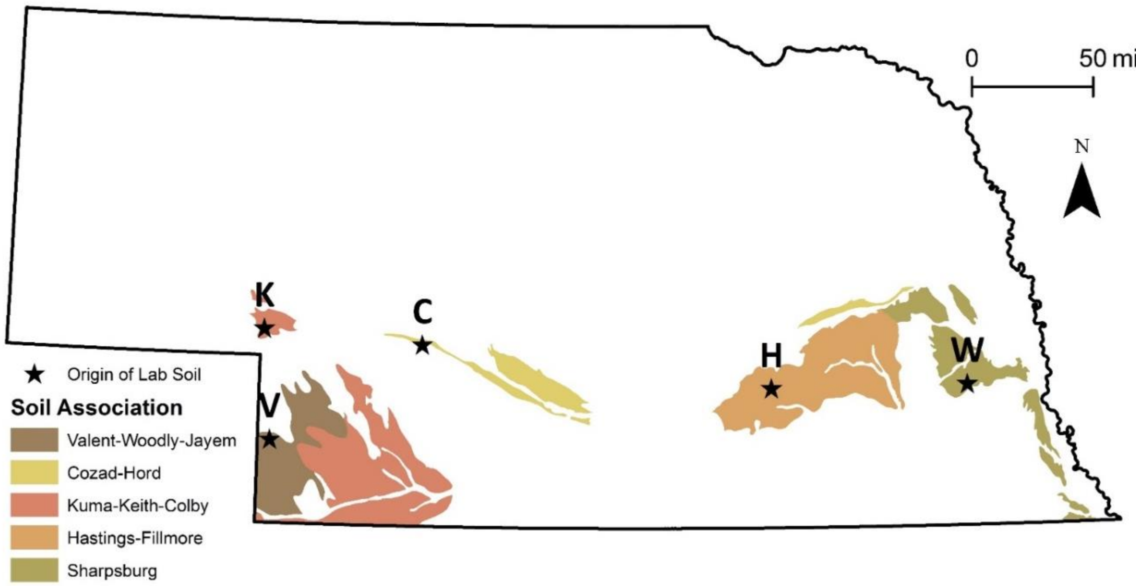

Figure 3.1. Site locations where soil samples were collected for the experiment, along with their soil associations in Nebraska.

Table 3.10. Site description for various locations of soil collection across Nebraska including soil type, depth (m), location, and horizon, respectively.

Soil type	Depth (m)	Location	Horizon
Valent	**(0.46-0.91)**	**Lamar, Nebraska**	**C**
Cozad	**(0.08-0.23)**	**North Platte, Nebraska**	**Ap**
Kuma	**(0.08-0.23)**	**Big Springs, Nebraska**	**A**
Hastings	**(0.30-0.46)**	**Aurora, Nebraska**	**Bt**
Wymore	**(0.30-0.46)**	**Lincoln, Nebraska**	**Bt**

Table 3.2.Textural composition and organic matter content (OMC) as determined from three soil samples; mean ± standard deviation were reported for each property, and ground bulk density (oven-dried and passed through 2 mm sieve) (ρ_b) of all soil types.

Soil type	Sand (%)	Silt (%)	Clay (%)	OMC (%)	ρ_b (g cm^{-3})
Valent	88 ± 1.0	7 ± 1	5 ± 1	0.2 ± 0	1.62
Cozad	55 ± 3.5	23 ± 3	22 ± 0	2.1 ± 0	1.20
Kuma	35 ± 2.0	35 ± 3	30 ± 2	2.6 ± 0	1.15
Hastings	14 ± 3.0	40 ± 5	46 ± 2	2.4 ± 0	1.38
Wymore	8 ± 4.0	42 ± 1	49 ± 4	2.5 ± 0	1.23

3.2.2 Description of Sensors

Campbell Scientific CS655 and Acclima TDR315/315-L were the investigated sensors in the study. A short description of each sensor is provided below.

3.2.2.1 Acclima TDR315/315-L

The Acclima TDR315/315-L (Acclima, Inc., Meridian, ID) are time domain reflectometers (TDR) with three parallel rods (15 cm long by 3.2 mm diameter) serving as the waveguide. The sensor head for TDR315 has all necessary electronics and firmware to generate an EM pulse and construct a waveform to determine the propagation time of the EM wave, which is used to estimate apparent dielectric permittivity (ε_{ra}). The TDR315-L has similar electronics and firmware as the TDR315, but it is not capable of exporting the waveform spectrum. The power consumption for TDR315-L is lower in comparison to TDR315. Temperature effects on ε_{ra} for TDR315 and TDR315-L are minimal and similar (Scott, 2017). Soil volumetric water content (θ_v) is calculated from ε_{ra} using a proprietary dielectric mixing model. Schwartz et al. (2016) observed that the fitted θ_v calibrations of the Pullman clay loam soil for TDR315 sensors were nearly indistinguishable from conventional TDR calibrations with similar root mean square errors (RMSE) of 0.017 to 0.020 $m^3\ m^{-3}$.

3.2.2.2 Campbell Scientific CS655

Campbell Scientific CS655 (Campbell Scientific, Inc., Logan, Utah) sensor is configured as a water content reflectometer with two 12 cm parallel rods forming an open-ended transmission line. It measures temperature by a thermistor, apparent electrical conductivity (EC_a) by determining the ratio between the excitation voltage and measured voltage, and period average from two way travel time of an electromagnetic pulse. The ε_{ra} is calculated from a factory calibrated empirical model involving voltage ratio and period average, and then ε_{ra} is used to determine θ_v using Topp et al. (1980) equation (Eqn. 1).

$$\theta_v = 4.3 \times 10^{-6} (\varepsilon_{ra}^3) - 5.5 \times 10^{-4} (\varepsilon_{ra}^2) + 2.92 \times 10^{-2} (\varepsilon_{ra}) - 5.3 \times 10^{-2} \qquad (1)$$

Chavez and Evett (2012) reported that the factory calibration of CS655 for θ_v compared well with locally calibrated conventional TDR sensors (Chavez and Evett, 2012). However, proper installation has been observed to be a key to optimum performance of CS655 sensors (Aguilar et al., 2015).

3.2.3 Experiment Description

A laboratory experiment was conducted in a temperature controlled walk-in room. Three replicates of each soil type were packed at respective bulk density (ρ_b) as mentioned in Table 3.2. The soils were packed in PVC pipe sections of 0.254 m nominal diameter and 0.223 m length after oven-drying and passing the soil through 2 mm sieve. A metallic plate was fabricated slightly smaller than the internal diameter of the PVC pipe. It was used to pack the soil using a hydraulic press at the desired ρ_b for each soil type. Then, one TDR315-L (or TDR315 for three Cozad columns and one Kuma column) sensor and one CS655 sensor were inserted downward into each soil column until the bottom of the sensor head was flush with the top of the soil column. The dimensions of the soil columns and the placement of the two sensors were carefully designed so that the sensing volume of each sensor extended almost the full height of the column, remained entirely within the column, and did not include the hardware of the other sensor in the column. At the same time, the sensor probes were inserted at a distance > 0.08 m from the column section so that the sensed volume was not restrained by the PVC pipe. From here forward, the TDR315 and TDR315-L sensors will be referred to as TDR315. The sensors were aligned perpendicular to the diameter of the soil column. Each pipe section was secured by layers of landscape mesh and window screen at the bottom so that the packed soil in these columns could be saturated from the bottom up. The soil columns were saturated in large clean containers and following saturation, these soil columns were drained briefly and sealed with a plastic wrap at the bottom.

The columns were suspended to be weighed by a strain gauge load cell. The weights of these soil columns were used as reference θ_v against which the sensor-reported θ_v were compared. The soil columns were saturated three times to evaluate for the effects of temperature, clay content, and added salinity on sensor performance of CS655 and TDR315 in terms of θ_v. The water used for saturation was heated to the ambient air temperature prior to and throughout the wetting cycles to minimize potential temperature effects on sensor performance. The drying cycles were carried out under the following conditions, 1) at constant temperature (35^{o}C) and no added salinity, 2) at two different temperature levels (23.9 and 35^{o}C) with no added salinity, and 3) with constant temperature (35^{o}C) and added salinity, respectively. For all drying cycles, temperature of the walk-in room was maintained at 35°C except for the drying cycle where the effect of temperature was analyzed. For that drying cycle, two temperature levels, 35 and 23.9°C rotating weekly, were maintained for the walk-in room. The lower and higher extreme temperatures were selected to cover the range of observed temperature throughout the growing season field conditions at the location where the experiment was carried out. For the salinity evaluation saturation was accompanied with 0.3094% (w/w) $CaCl_2$ solution. At the end of the entire experiment, soil from each column was extracted and oven-dried separately.

3.2.4 Analysis

In this study, effects of temperature, salinity, and textural composition (clay content) of different soil types on sensor-reported θ_v for TDR315 and CS655 in comparison to a standard (reference) θ_v were analyzed. For each replication, reference θ_v was determined using the following formula:

$$\theta_v = \frac{(W_{total} - W_{soil} - W_{setup})}{\rho_w V_{soil}} \qquad (2)$$

where, W_{total} is the total weight of the soil column, W_{soil} is the weight of the dry soil in the column, W_{setup} is the weight of the empty soil column setup, ρ_w is the density of water, and V_{soil} is the volume of the soil in the column.

The sensor-reported θ_v recorded at the time closest to each reference reading (always within 3 minutes) was considered for the analysis. Sensor-reported and reference

θ_v were compared separately for TDR315 and CS655. The average of three replicates of TDR315 and CS655 for each soil type and the average of three replicates of reference θ_v for that particular soil type formed a set of comparison for the analysis. The sets of comparisons to analyze for the effects of temperature, salinity, and textural composition were 8, 40, and 33, respectively. For the drying cycle at two different temperatures with no added salinity, the walk-in room temperature alternated weekly between 35 and 23.9°C for eight times to evaluate for the effects of temperature. The drying cycle which was started following salinization was compared to the drying cycle carried out at constant temperature and no added salinity to determine the effects of salinity. For the drying cycle with constant temperature and no added salinity, it was investigated if different soil types (table 3.1) had an effect on sensor-performance.

For each sensor in each soil at each weighing time, the standard deviation of difference (SDD) was calculated to evaluate inter-replicate variability in sensor θv accuracy among the three replicate soil columns (eqn. 3).

$$SDD = \sqrt{\frac{\sum_i^m \left[(s_{i,t} - r_{i,t}) - \frac{1}{m}\sum_i^m (s_{i,t} - r_{i,t})\right]^2}{m-1}} \tag{3}$$

where, i is the index of the soil column, m is the number of soil columns per soil type, t is the index of the weighing time, $s_{i,t}$ is the sensor θ_v of the i^{th} soil column at the t^{th} weighing time, and $r_{i,t}$ is the reference θ_v of the i^{th} soil column at the t^{th} weighing time.

In the remainder of the analyses, for each sensor in each soil at each weighing time, average sensor θ_v among the replicate columns was compared against average reference θ_v among the replicate columns. Root mean square difference (RMSD; eqn. 4) was calculated for each sensor in each soil over each drying cycle to indicate the absolute magnitude of differences between sensor θ_v and reference θ_v while penalizing larger differences.

$$RMSD = \sqrt{\frac{\sum_i^n \left[\frac{1}{m}\left(\sum_i^m s_{i,t}\right) - \frac{1}{m}\left(\sum_i^m r_{i,t}\right)\right]^2}{n}} \tag{4}$$

where, n is the number of weighing times during the drying cycle.

The effects of temperature, salinity, and textural composition were analyzed both statistically and practically. For each variable (temperature, salinity, and soil type) a regression model with a set of coefficients ignoring the level of each variable (e.g., 23.9 vs 35°C) and one regression model with separate coefficients for each level were constructed. Statistical significance of the effect of this factor can be quantified by comparing the two regression models in an analysis of variance (ANOVA). Practical significance of the effect of this factor can be quantified by comparing the RMSD of the two regression models and by comparing the various sets of coefficient values in the second regression model.

A general clay content correction was proposed for θ_v measurements by TDR315 and CS655, individually. The basis of each correction was the five soil-specific regression calibration equations relating sensor to reference θ_v during the drying cycle with constant temperature and no added salinity. Then, a set of regression interpolation equations were developed to estimate the value of each calibration coefficient as a function of clay content. The polynomial order of each interpolation equation was chosen using leave-one-out cross-validation.

The general clay content corrections would be theoretically applicable to any soil whose clay content is within the range spanned by the five soils in this experiment. However, the magnitude of improvement from applying the corrections would be best assessed by external validation in soils that were not part of this experiment. A comprehensive validation effort was prevented by the limited number of published studies that presented graphs or equations relating sensor θ_v of TDR315 (Schwartz et al., 2016; Singh et al., 2018) or CS655 (Chávez and Evett, 2012; Singh et al., 2018) to reference θ_v. Nonetheless, validation with these available studies generated preliminary information about the effectiveness of the general clay content corrections.

3.3 Results and Discussion

3.3.1 Temporal Trends

The study period was characterized as drying cycles of soil columns at 1) constant temperature with no added salinity, 2) at two temperature levels with no added salinity, and 3) constant temperature with added salinity. The cycle length for these drying cycles ranged within 40 to 56 days. Each drying cycle was started after all the soil columns were completely saturated, briefly drained, and covered with plastic from the bottom. Reference θ_v, which was determined from the average weight of three soil columns, ranged within 0.001 to 0.291 $m^3\ m^{-3}$ for Valent soil type, 0.078 to 0.477 $m^3\ m^{-3}$ for Cozad soil type, 0.111 to 0.446 $m^3\ m^{-3}$ for Kuma soil type, 0.199 to 0.472 $m^3\ m^{-3}$ for Hastings soil type, and 0.213 to 0.488 $m^3\ m^{-3}$ for Wymore soil type across all drying cycles.

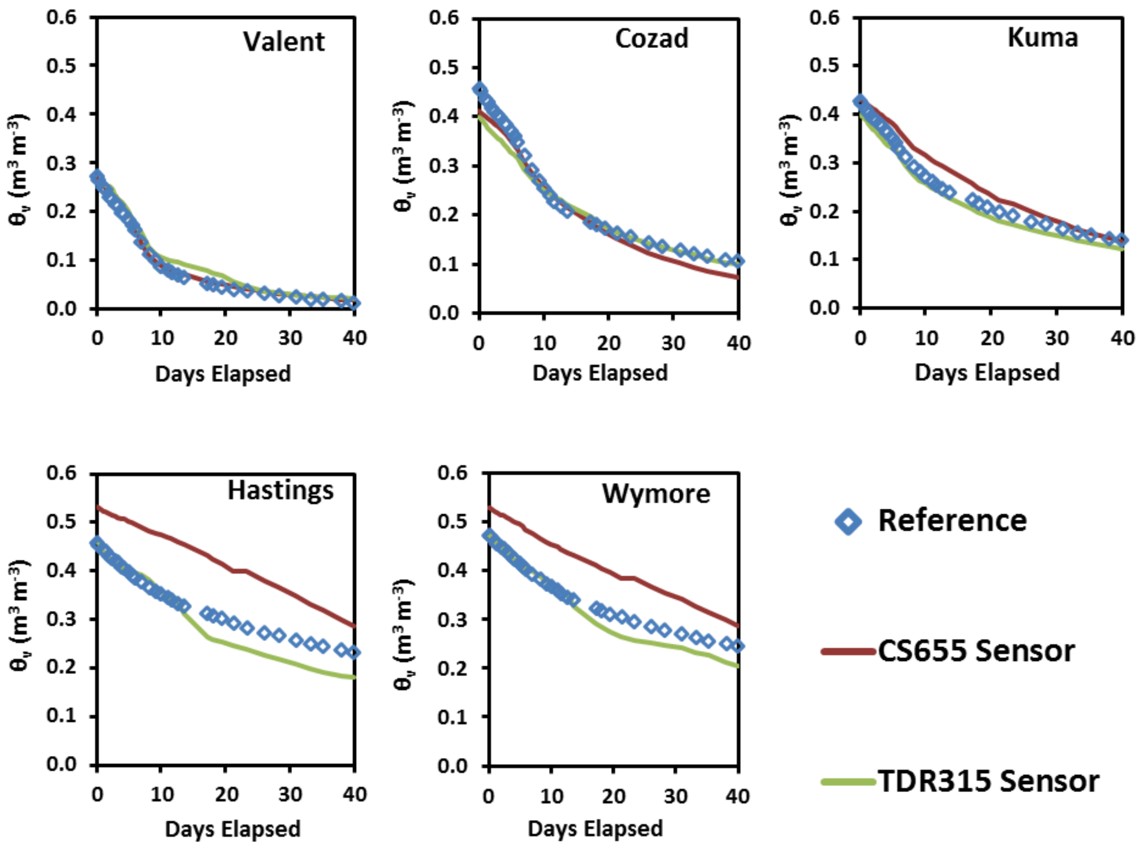

Figure 3.2. Temporal trends in volumetric water content (θ_v) for various soil classes at the drying cycle of soil columns at constant temperature with no added salinity by evaluated sensors compared with θ_v determined from the weight of soil column. The average of three replications per soil class was shown for each sensor, and the reference.

Though the differences between sensor and reference θ_v varied among sensor type and over time (fig. 3.2), both TDR315 and CS655 followed the general trends of reference θ_v across all soil types. The CS655 θ_v for Cozad soil type was similar to the reference θ_v with slight underestimation near the drier end (< 0.20 m^3 m^{-3}) for all drying cycles. Underestimation by CS655 near the drier end was also witnessed by Singh et al. (2018) in a case study of sensor-comparison on a Cozad soil. On the other hand, CS655 overestimated θ_v in comparison to the reference for Kuma, Hastings, and Wymore soil types. Overestimation by CS655 has also been reported by Kisseka et al., 2014, Michel et al., 2015, and Singh et al., 2018. Some studies have stated that the magnitude and/or occurrence of overestimation of θ_v by EM sensors was dependent on θ_v at different θ_v ranges (Udawatta et al., 2011; Mittelbach et al., 2012; Kisekka et al., 2014; Rudnick et al., 2015). In the current study, such dependence of θ_v could be argued for CS655 sensor in the Kuma soil type, since the temporal trends during three drying cycles indicated that CS655 sensor tended to overestimate more in the mid-range of θ_v under non-saline conditions. Also, Hastings and Wymore soil types witnessed less overestimation by CS655 from the mid-range θ_v till the end of drying cycle under saline conditions.

The TDR315 for Hastings and Wymore soil classes was close to the reference θ_v in the beginning of all drying cycles, but underestimated for the latter part of the drying cycles with no and with added salinity with constant temperature; whereas, slight overestimation in mid-range θ_v for the Valent soil type across all drying cycles was observed for TDR315. For the Cozad soil type, underestimation by TDR315 was witnessed in the beginning of the drying cycles with both no and added salinity at constant temperature.

During the drying cycle at two temperatures and no salinity added, evident fluctuations in the overestimation by CS655 and TDR315 were observed for Hastings and Wymore soil types. The temporal trends suggest that the degree of overestimation by CS655 was slightly more at the lower temperature (23.9°C) and slightly less at the higher temperature (35°C) for Hastings and Wymore soil types. However, the temperature effect on CS655 sensor-reported θ_v for Valent, Cozad, and Kuma soil types was not observed. TDR315 sensor-reported θ_v witnessed more overestimation at lower temperature and less overestimation at higher temperature for Hastings and Wymore soil types and not for Valent, Cozad, and Kuma soil types.

3.3.2 Effects of soil type on sensor performance

The soil types with higher clay content (Hastings and Wymore) displayed higher water retention capacity in comparison to the other soils throughout the drying cycles. The response of CS655 in comparison to reference θ_v varied among soil types across the three drying cycles. However, the response of TDR315 in comparison to reference θ_v was similar for Valent, Cozad, and Kuma soil types across all three drying cycles.

Performances in terms of RMSDs for CS655 and TDR315 across all drying cycles were determined and are presented in Table 3.3. The RMSD values for CS655 sensor was 0.090 and 0.062 $m^3\ m^{-3}$ for Hastings and Wymore during the drying cycle when temperature was kept constant and no salinity was added. However, during the same round TDR315 sensor had RMSD values of 0.039 and 0.032 $m^3\ m^{-3}$ for Hastings and Wymore soil types, respectively. For Valent, Cozad, and Kuma soil types, the TDR315 and CS655 performed similarly with RMSD values ranging from 0.012 to 0.045 $m^3\ m^{-3}$ for TDR315, and 0.009 to 0.044 $m^3\ m^{-3}$ for CS655. The performance of CS655 for Valent, Cozad, and Kuma soil types (with RMSD ranging between 0.012 and 0.045 $m^3\ m^{-3}$) was found to better than Hastings and Wymore soil types (with RMSD ranging between 0.048 and 0.129 $m^3\ m^{-3}$) due to consistently lower RMSD values across all the drying cycles. Whereas, TDR315 performed better for Valent and Kuma soil types in comparison to Cozad, Hastings, and Wymore soil types consistently across all drying cycles.

The inter-replicate differences for each sensor type varied across the five soil types (table 3.3). The θ_v standard deviation of difference (SDD) was within 0.000 and

0.030 $m^3 m^{-3}$ for three replicates of CS655, and 0.001-0.050 $m^3 m^{-3}$ for three replicates of TDR315 across all soil types and all drying cycles. The SDD range of inter-replicate differences for CS655 was smaller than TDR315 for all soil types except Cozad. On the other hand, RMSD for TDR315 was lower than CS655 for Valent, Hastings, and Wymore soil types (table 3.4). The SDD range of CS655 for Cozad soil type (0.001-0.007 $m^3 m^{-3}$) was considerably lower than TDR315 (0.002-0.029 $m^3 m^{-3}$); whereas, their RMSD values were similar (Table 3.3). The performance of TDR315 and CS655 for Valent and Kuma soil types was similar with comparable RMSD (Table 3.4) and ranges in SDD (standard deviation) (Table 3.3).

Table 3.3. Range of standard deviation of difference (SDD) statistics comparing volumetric water content (θ_v) reported by three TDR315 and CS655 sensors using factory calibrations against reference θ_v from three weights for three drying cycles.

Sensor θ_v ($m^3 m^{-3}$)	Range of Standard Deviation in between replicates				
	Valent	Cozad	Kuma	Hastings	Wymore
TDR315	0.001-0.018	0.002-0.029	0.002-0.027	0.002-0.040	0.007-0.050
CS655	0.000-0.027	0.001-0.007	0.005-0.026	0.004-0.017	0.001-0.030

Table 3.4. Root mean square difference (RMSD) comparing volumetric water content (θ_v) reported by average of three TDR315 and CS655 sensors using factory calibrations against reference θ_v from average of three weights for three drying cycles.

Drying cycle at constant temperature and no salinity added					
Sensor θ_v ($m^3 m^{-3}$)	Root Mean Square Difference (RMSD)				
	Valent	Cozad	Kuma	Hastings	Wymore
TDR315	0.010	0.044	0.036	0.039	0.032
CS655	0.014	0.038	0.016	0.090	0.062
Drying cycle at two temperature levels and no salinity added					
	Valent	Cozad	Kuma	Hastings	Wymore
TDR315	0.018	0.014	0.009	0.022	0.020
CS655	0.012	0.018	0.036	0.129	0.099
Drying cycle at constant temperature and added salinity					
	Valent	Cozad	Kuma	Hastings	Wymore
TDR315	0.009	0.044	0.013	0.032	0.027
CS655	0.036	0.045	0.015	0.081	0.048

The observed range for reference θ_v was within 0.03 and 0.029 $m^3\ m^{-3}$ for Valent, 0.12 and 0.48 $m^3\ m^{-3}$ for Cozad, 0.16 and 0.45 $m^3\ m^{-3}$ for Kuma, 0.25 and 0.47 $m^3\ m^{-3}$ for Hastings, and 0.26 and 0.49 $m^3\ m^{-3}$ for Wymore soil type. Nine out of ten regressions between sensor-reported and reference θ_v were quadratic (fig. 3.3). The polynomial order for regression calibration of each soil type for CS655 and TDR315 versus reference θ_v was selected based on statistical significance tests with $\alpha = 0.05$ (observed p-values ranged from 2×10^{-16} to 0.004). When the regression calibrations were determined, it was revealed that CS655 and TDR315 calibration varied with soil type (Table 3.5). The regression calibration for CS655 in Valent soil type was linear because the fitted quadratic coefficient was not significantly different from zero (two-tail p value = 0.676), but quadratic coefficients were reported for comparison with other soil types. The quadratic equation coefficients relating sensor and reference θ_v for each soil type is presented in Table 3.5. Chandler et al. (2004) found that water content reflectometers (WCR) calibration varied with soil type, which corroborates our finding. Seyfried and Murdock (2001) concluded that separate calibrations were required to accurately predict θ_v in different soils during a laboratory test involving six CS615 sensors. Kelleners et al. (2005) found that there was a notable overestimation of ε_{ra} by CS615 and CS616 in comparison with TDR in sandy loam and silt loam soils due to dielectric dispersion and ionic conductivity. However, in our study CS655 sensor did not remarkably underestimate or overestimate θ_v, most likely due to an improved factory calibration in comparison to CS616 and CS615. Quantitative and qualitative knowledge about soil water status can be established from the sensors installed in different soils based on the developed clay content – sensor θ_v calibration equations (fig. 3.3 and Table 3.5), since the general trend of factory calibration for the sensors and reference θ_v were similar.

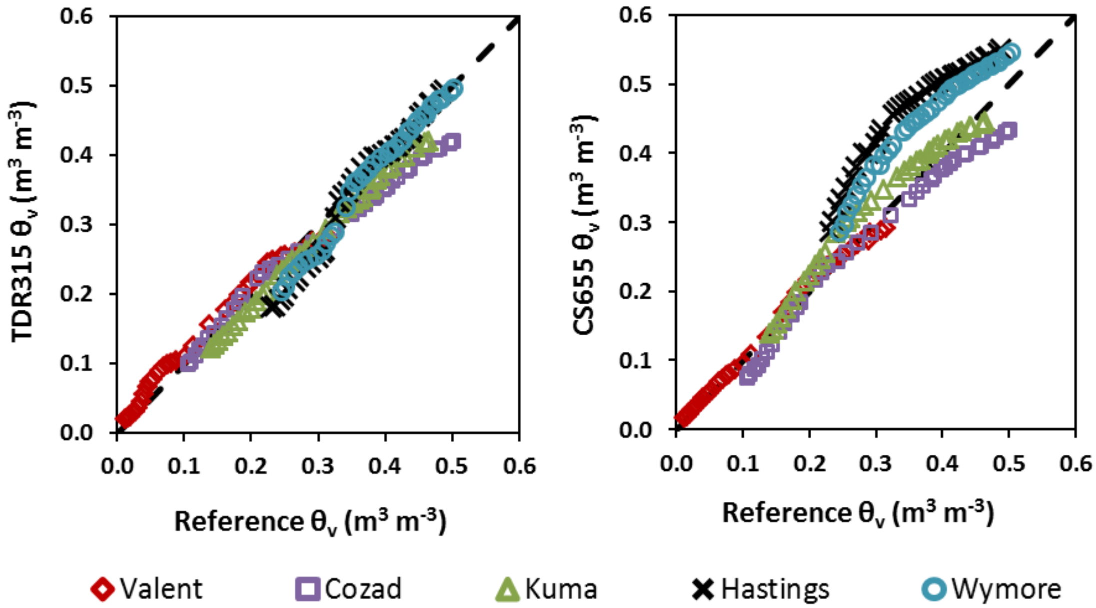

Figure 3.3. Scatterplots with 1:1 line comparing volumetric water content (θ_v) reported by CSS655 and TDR315 (for Valent, Cozad, Kuma, Hastings, and Wymore) against reference θ_v from average of three replicates of weight of soil columns.

Table 3.5. The values for estimated calibration coefficients quadratic (c_2), linear (c_1), and intercept (c_0) for CS655 and TDR315 sensors in different soils for the corresponding equation: (Reference θ_v) = $C_0 + C_1 \times$ (Sensor θ_v) + $C_2 \times$ (Sensor θ_v)^2.

Soil type class	Sensor	c_2	c_1	c_0	Multiple R^2
Valent	TDR315	1.229638	0.6622	0.000	0.995
	CS655	0.912627	0.9529	-0.002	0.996
Cozad	TDR315	1.458782	0.4931	0.041	0.997
	CS655	1.440271	0.3184	0.079	0.999
Kuma	TDR315	0.386172	0.8289	0.034	0.999
	CS655	1.883720	-0.1293	0.128	0.999
Hastings	TDR315	0.962550	0.1456	0.185	0.982
	CS655	3.862300	-2.3110	0.585	0.992
Wymore	TDR315	0.750000	0.3026	0.158	0.990
	CS655	2.707150	-1.2899	0.395	0.999

3.3.3 Temperature and salinity effects on sensor performance across soil types

Sensor-reported θ_v in comparison to reference θ_v were determined at two temperature levels (23.9 and 35^{o}C) as well as two salinity levels across all soil types. It was found that the polynomial order for six out of ten relationships between TDR315 and reference θ_v as well as between CS655 and reference at two temperature levels across five soil types were linear and four were quadratic (fig. 3.4) using statistical significance tests with $\alpha = 0.05$. However, all relationships between TDR315 and reference and between CS655 and reference at two salinity levels across five soil types were found to be quadratic (fig. 3.5) using statistical significance tests with $\alpha = 0.05$.

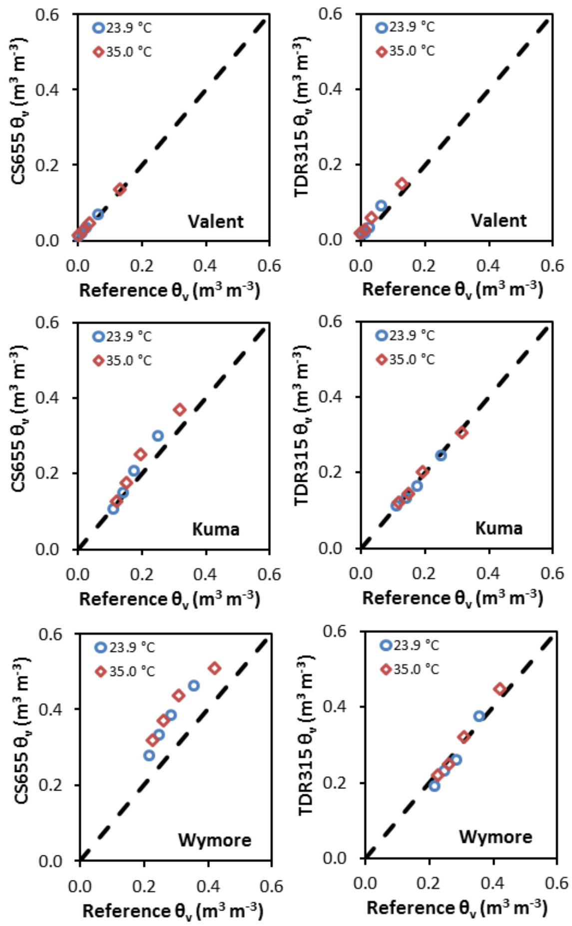

Figure 3.4. Scatterplots with 1:1 line comparing volumetric water content (θ_v) reported by evaluated sensors in the drying cycle of soil columns at two temperature levels (23.9 ^{0}C, and 35 ^{0}C) with no added salinity by evaluated sensors compared with θv determined from the weight of soil columns. The average of three replications per soil class was shown for each sensor, and the reference.

The regression model for estimating θ_v at combined (23.9 and 35^{0}C) temperatures was not statistically different from the regression model for estimating θ_v at temperatures separately as the range of two-tail p-value was within 0.1387 and 0.7231. The regression models for both TDR315 and CS655 at two temperature levels witnessed low range of residual sum of squares using ANOVA (0.0004 to 0.0023 m^3 m^{-3} for TDR315 and 0.0003 to 0.0055 m^3 m^{-3} for CS655), which is beyond the accuracy range reported by the manufacturers. Therefore, it can be claimed with confidence that the performance of TDR315 and CS655 sensors was not practically different across two investigated temperatures. However, 9 out of 10 regression models (comprising models for both TDR315 and CS655) for no salinity versus added salinity were statistically different from each other with two-tail p-value within the range of 2.2×10^{-16} and 0.005. The response of TDR315 in Valent soil was not statistically different at two salinity levels (p-value = 0.322). On the other hand, the residual sum of squares using ANOVA for TDR315 was within 0.0002 and 0.0026 $m^3 m^{-3}$ and was within 0.0026 and 0.0137 $m^3 m^{-3}$ for CS655, which is of low practical significance and within the range of the manufacturer's reported accuracies.

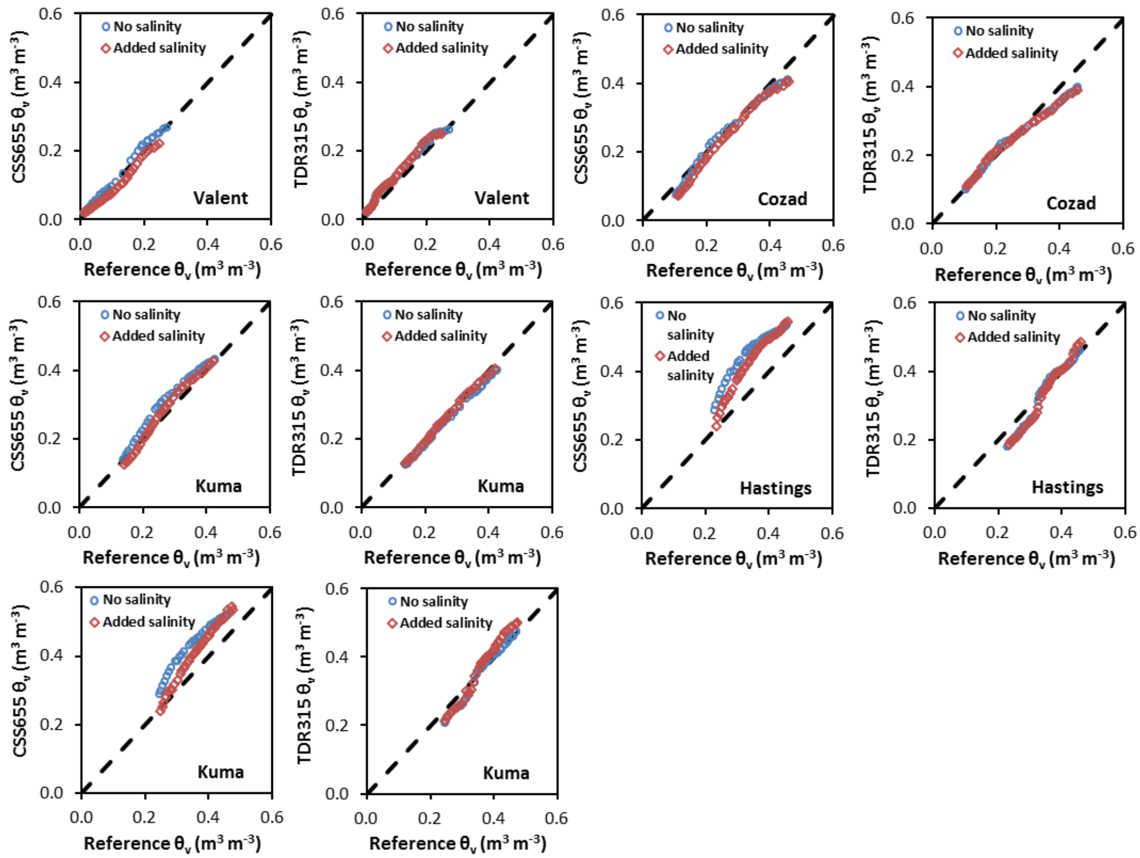

Figure 3.5. Scatterplots with 1:1 line comparing volumetric water content (θ_v) reported by evaluated sensors in the drying cycles of soil columns at constant temperature with no salinity and added salinity by evaluated sensors compared with θ_v determined from the weight of soil columns. The average of three replications per soil class was shown for each sensor, and the reference.

Laboratory experiments have also reported low sensitivity of temperature variability on θ_v measurement. Blonquist et al. (2005) suggested that the TDR measured EM signal property is sensitive in some degree to temperature leading to potential errors in θ_v prediction, which was also witnessed in our study for TDR315 although the error in θ_v prediction was quite low (0.0003 to 0.0023 m^3 m^{-3}) using ANOVA across five soil types. Furthermore, Pepin et al. (1995) claimed that θ_v determined from TDR has low sensitivity to soil temperature taking in account of practical changes in temperature in field conditions, which is supported by the results of this study as TDR315 was not statistically different at two temperature levels (23.9 and 35^{0}C) with the range of two-tail p-value between 0.1387 and 0.7231. However, Wraith and Or (1999) witnessed a substantial influence of temperature on measured θ_v based on ε_{ra} for TDR under certain soil and wetness conditions, which they attributed to the competing effects of temperature on ε_{ra} of bulk and hindered soil water. The ε_{ra} of bulk soil water decreases with increased temperature, while that of bound water is presumed to increase with temperature, which is supported by the findings of Gong et al. (2003) who observed that temperature affected θ_v measurement of TDR. Substantial temperature effect on θ_v estimation was not witnessed in our study for TDR315 possibly due to the smaller temperature range of 23.9 and 35^{0}C considered in our study as compared to a range of 5 to 65^{0}C by Wraith and Or (1999) and 5 to 45^{0}C by Gong et al. (2003).

The effect of temperature on WCR sensors has been reported in the literature. A significant effect of temperature variations (5 to 45^{0}C) on reported θ_v by WCR sensors was witnessed in an experiment conducted by Seyfried and Murdock (2001). However, field studies investigating CS655 were carried out by Western and Seyfried (2005) and Mittelbach et al. (2012), and they found no significant effect of temperature on CS655 reported θ_v. Their findings are supported by the results of our study as CS655 sensor-reported θ_v was not statistically different at two temperature levels (23.9 and 35^{0}C). The possible difference in reported effects of temperature on WCRs is most likely due to the incorporation of an embedded temperature adjustment for CS655, which was not included in its predecessors (CS616 and CS615). Sensor performance at 23.9 and 35^{0}C was evaluated with four dataset points. Increasing the number of observations for comparison would increase the confidence in the findings.

Conflicting findings on the effect of salinity on ε_{ra} and θ_v have been reported for TDR. Dalton (1992) demonstrated that an overestimation of θ_v by TDR occurs when the pore water EC is approximately equal to or greater than 8 dS m^{-1} due to known effects of ion concentration on the dielectric constant. However, the salinity across five soil types for our study was less than 5 dS m^{-1} (according to EC_a reported by TDR315 sensor) even after adding salinity and we did not witness overestimation of θ_v across five soil types after adding salinity. In fact, the TDR315 residual sum of squares using ANOVA were within the range of 0.0002 and 0.0026 m^3 m^{-3} for the drying cycles with no salinity and added salinity. In addition, Wyseure et al. (1997) suggested that measure of salinity of a soil influences the measurement of θ_v by TDR and if the salinity is kept less than 2 dS m^{-1}, the overestimation stays within reasonable limits and can be disregarded. For our study, salinity was around 3 dS m^{-1} for Cozad, Kuma, Hastings, and Wymore soil types and less than 2 dS m^{-1} for Valent soil type and the error in CS655 sensor-reported θ_v was less than 0.0137 m^3 m^{-3} with no added salinity and added salinity as determined from residual sum of squares using ANOVA. On the other hand, Topp et al. (1980) claimed that the relationship between θ_v and ε_{ra} measured by TDR is independent of soil salinity, type, density, and temperature. This was further supported by Nadler et al. (1991) who evaluated TDR in layered soil columns and found that θ_v and salinity calculations were independent of each other. In our study both TDR315 and CS655 had significant differences in estimated θ_v when evaluated between the two salinity levels with two-tail p-value within the range of 2.2×10^{-16} and 0.005 for TDR315, and within 2.2×10^{-16} and 1.7×10^{-6} for CS655. The only exception was the response of TDR315 for Valent soil type when evaluated at two salinity levels (two-tail p-value = 0.322), implying that the increase in salinity did not statically affect the performance of TDR315 in the Valent soil, which has a clay content of 5 ± 1%. However, the calculated residual sum of squares using ANOVA for TDR315 and CS655 was less than 0.0026 and 0.0137 m^3 m^{-3}, respectively. This may be attributed to a large number of data points for comparison, which were 33 points for the round with lower salinity and 40 points for the round with higher salinity. The development of calibration equations for the differences between sensor-reported θ_v (using factory calibrations) and reference θ_v in the study with no salinity, fitted well for all the sensors and soil types with the drying cycle of added salinity. This observation suggested that the uncertainty in the sensor-reported θ_v was systematic and could be modeled through development of a calibration equation determining reference θ_v from sensor-reported θ_v.

3.3.4 Universal Calibration

In the current study, the relationship of the calculated coefficients (quadratic, linear, and intercept) between sensor (CS655 and TDR315) and reference (Table 3.5) across each soil type was investigated with respect to the clay-content of each soil type. It was found that the estimated quadratic (c_2), linear (c_1), and intercept (c_0) coefficients for CS655 had a statistically significant linear relationship (with two-tail p-values ranging within 0.021 and 0.045) with clay content percentage (fig. 3.6). The LOOCV RMSD for c_2, c_1, and c_0 of CS655 sensor was 0.7936, 0.8127, and 0.1771, respectively. However, the estimated c_2 and c_1 coefficients for TDR315 had a linear relationship and c_0 had a quadratic relationship with the clay content percentage. The reported LOOCV RMSD for c_2, c_1, and c_0 of TDR315 was 0.4227, 0.2652, and 0.0496, respectively.

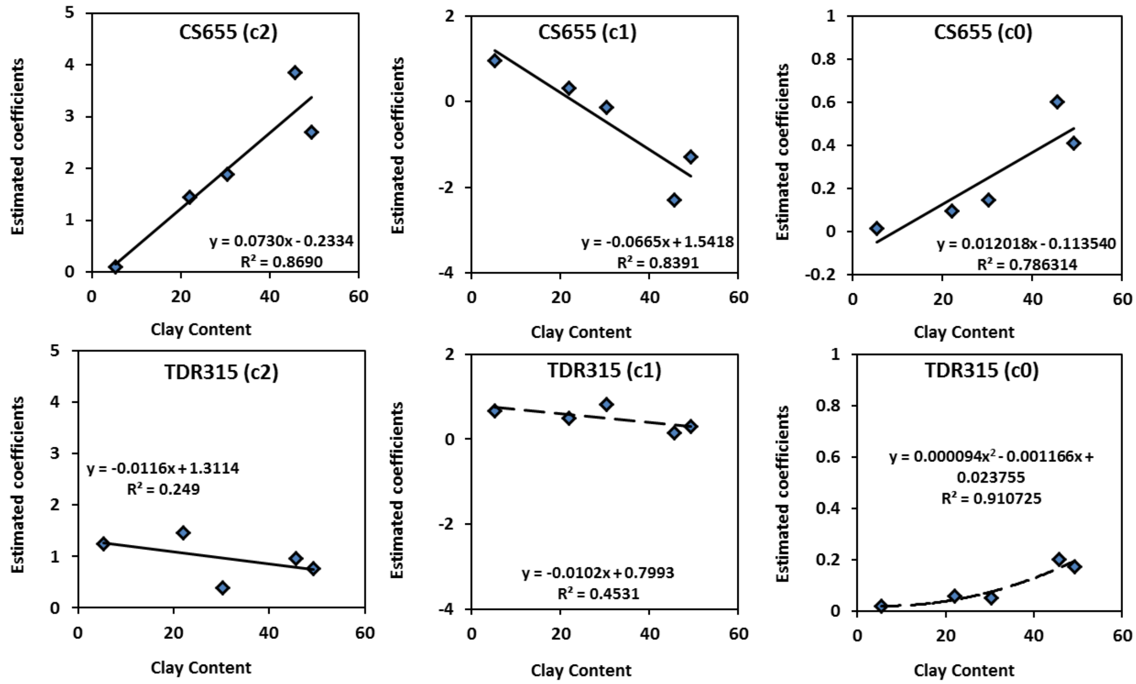

Figure 3.6. Scatterplots showcasing the relationship of estimated quadratic (c_2), linear (c_1), and intercept (c_0) coefficients for CS655 and TDR315 with the clay content of soil class types. The coefficients (c_2, c_1, and c_0) for TDR315 and CS655 sensors came from their relationship with different soil types (table 5). The solid lines represent that the relationship of coefficient (c_2, c_1, or c_0) with the clay content is significant and the dashed lines represent that the relationship is not significant.

For CS655, the quadratic (c_2) and intercept (c_0) coefficients had a positive relationship with the clay content with R^2 values of 0.869 and 0.786, respectively, and the linear coefficient (c_1) decreased with increasing clay content (R^2 of 0.839). Whereas for TDR315, the quadratic (c_2) and linear (c_1) coefficients had a negative relationship with clay content with R^2 values of 0.249 and 0.453, respectively, and the intercept (c_0) coefficient increased with the increasing clay content (R^2 of 0.911). The stronger relationship (larger R^2) of the coefficients (c_2, c_1, or c_0) with the clay content for CS655 sensor suggest that more confidence can be entrusted in the developed relationships for these coefficients.

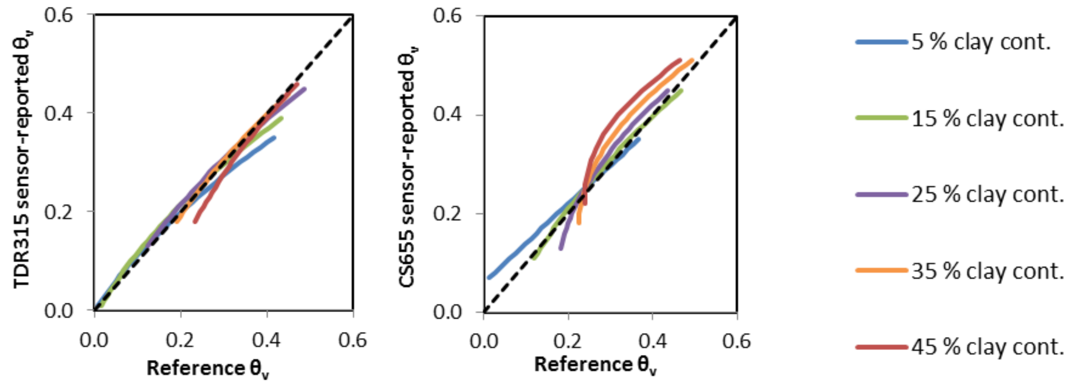

Figure 3.7. Interpretation of coefficients (c_2, c_1, and c_0) for TDR315 and CS655 sensor-reported θ_v at clay content range from 5% to 45% with an interval of 10% within each level.

A visual illustration of the universal calibration for both TDR315 and CS655 for clay content ranging from 5 to 45% with an interval of 10% is presented in fig. 3.7. For CS655, it was observed that for soils with clay content 25% and higher, there was overestimation of θ_v near the saturated end, and underestimation of θ_v near the drier end. However, for the soils with 15% clay content and below, slight underestimation of θ_v was witnessed near the wet end. On the other hand, while interpreting the coefficients for TDR315, underestimation of θ_v was witnessed at the wet end for the entire range of clay content (5–45 %). The degree of underestimation increased at a clay content of 45% near the drier end, whereas it decreased for the other range of soil types (15-35 %) at the drier end.

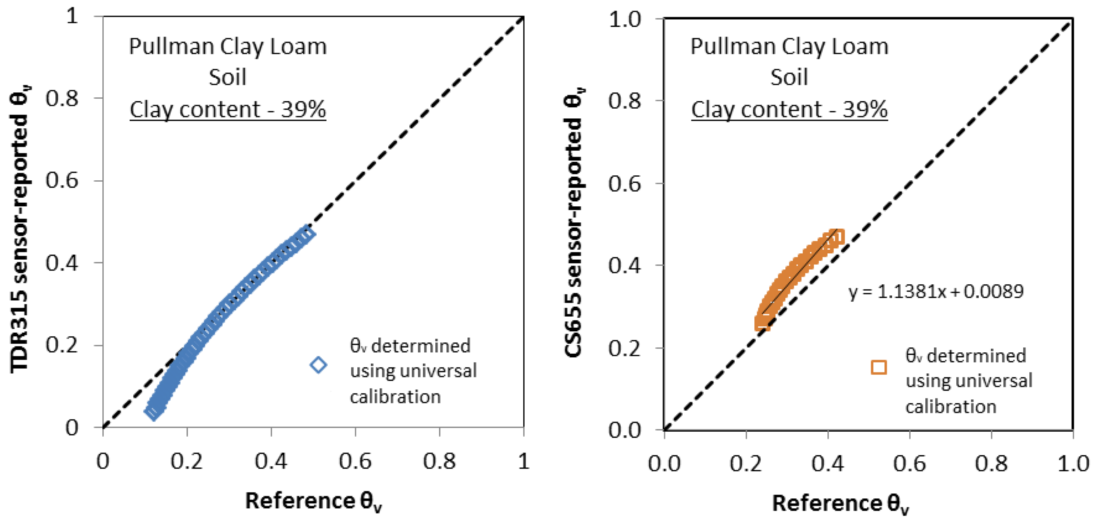

Figure 3.8. Comparison of TDR315 sensor-reported θ_v for Pullman Clay Loam soil (clay content = 39%) over the evaluated range of θ_v (0.04 to 0.47 m^3 m^{-3}) reported by Schwartz et al. (2016) and using the universal calibration.

The performance of the universal calibration, which adjusts the factory calibrations of TDR315 and CS655 based on percent clay content, were evaluated for some findings in the literature. The calibration equation coefficients (c_2, c_1, and c_0) for each sensor were adjusted according to the clay content setting of the study it was being compared with. In a laboratory experiment with ten TDR315 sensors in a Pullman clay loam soil (clay content – 39%), Schwartz et al. (2016) observed that the factory calibration consistently underestimated over the evaluated range of θ_v (0.04 to 0.47 m^3 m^{-3}), and the magnitude of underestimation decreased with decreasing θ_v. Underestimation by TDR315 within the same range (0.04 to 0.47 m^3 m^{-3}) was also witnessed using the universal calibration for the Pullman clay loam (fig. 3.8). Furthermore, the model underestimated θ_v throughout the drying cycle, and the magnitude of underestimation decreased with θ_v between 0.35 m^3 m^{-3} and near saturation (0.47 m^3 m^{-3}).

In a field experiment with Pullman clay loam soil, Chavez and Evett (2012) observed overestimation by CS655 sensors. Fitting a line with sensor θ_v as the function of reference θ_v, they obtained a slope slightly larger than unity with a small positive intercept. Our calibration was tested and it worked well for a θ_v range of 0.26 $m^3\ m^{-3}$ to near saturation (0.42 $m^3\ m^{-3}$), the results were similar with a slope slightly larger than unity and a small positive intercept. A comprehensive evaluation of the developed universal calibrations for TDR315 and CS655 based on clay content is difficult due to limited availability of published data on these two sensors. The universal calibration was validated for TDR315 and CS655 sensors placed at 0.15 and 0.76 m depths according to the dataset of Singh et al. (2018). It was observed that the RMSD for CS655 reduced by 0.008 $m^3\ m^{-3}$ at 0.15 m and 0.005 $m^3\ m^{-3}$ at 0.76 m depth using the universal calibration. However, using universal calibration for TDR315 the RMSD increased in comparison to the factory calibration.

Based on our results, it can be inferred that soil type had a noteworthy effect on the performance of CS655, but not TDR315 sensors. However, qualitative information about TDR315 sensor-reported θ_v (underestimation or overestimation) can be extracted from the universal calibrations. For the study, there was a wide spread in the range of clay content for the soils selected, as it was considered the treatment effect. For the soils selected in the experiment, there was a variable range in ρ_b (1.15 to 1.62 g cm^{-3}) and OMC (2.1 to 2.6% for four soil types and 0.2% for Valent soil). In addition to clay content, relationship of ρ_b and OMC were also analyzed for comparison with the coefficients of sensor-reported θ_v. However, there was a variation and no specific trend for ρ_b and OMC with the estimated coefficients based on visual inspection of the graphs (not presented). Some studies have witnessed the effect of ρ_b and OMC on the determination of θ_v in the literature (Adeyemi et al., 2016; Jacobsen and Schjønning, 1993). The performance of TDR315 was investigated in an air-dried, sieved, and compacted sandy loam soil at ρ_b of 1.37 and 1.42 g cm^{-3} by Adeyemi et al. (2016). It was observed that there was a general underestimation of θ_v for both compaction levels, but the magnitude of θ_v underestimation increased with increasing soil ρ_b. While evaluating a conventional TDR after air-drying, sieving, and packing a range of five different textured soils, Jacobsen and Schjønning (1993) observed that a third-order polynomial relationship between θ_v and ε_{ra} was found suitable for calibration. However, a correlation of ρ_b, clay content, and OMC with θ_v yielded statistically significant improvement in calibration.

While transferring the calibration for external validation, potentially confounding factors (ρ_b, OMC, temperature, and salinity) should be accounted for. If the effects of these factors could be well-modeled, it would lead to a better calibration equation.

3.4 Conclusions

A laboratory experiment was conducted in a walk-in oven room setup at West Central Research and Extension Center, North Platte, Nebraska to analyze the performance of two recently developed electromagnetic (EM) sensors – TDR315, and CS655 in five different textured soils (Valent, Cozad, Kuma, Hastings, Wymore) collected across the state of Nebraska. Factory calibrations of EM sensors reported θ_v were evaluated at different levels of temperature, salinity (EC_a), and clay content (soil type). Three columns for each soil type were packed at a bulk density (ρ_b) close to the natural ρ_b of the soil types considered for the experiment. After packing the soil, a TDR315 and a CS655 sensor were installed in each one of the soil columns. Reference θ_v was calculated based on the average weight of three replicates of soil columns, calculated by a load cell. Statistical significance for the differences in θ_v at different levels of temperature, EC_a, and clay content were tested. In addition, the polynomial order (quadratic or linear) of relationship for both TDR315 and CS655 sensors with each soil type was selected and then the relationship of coefficients of the polynomial order of sensor-reported θ_v for TDR315 and CS655 with clay content was determined. The performance of the universal calibration, which adjusts the factory calibrations of TDR315 and CS655 based on percent clay content, were evaluated for some findings in the literature.

The regression models for both estimating θ_v at combined (23.9 and 35 °C) temperatures was not statistically different from the regression model for estimating θ_v at temperatures separately (two-tail p-value was within 0.1387 and 0.7231). In addition, the regression models for TDR315 and CS655 at two temperature levels witnessed low range of residual sum of squares using ANOVA (0.0004 to 0.0023 $m^3\ m^{-3}$ for TDR315 and 0.0003 to 0.0055 $m^3\ m^{-3}$ for CS655), On the other hand, the regression models for TDR315 and CS655 sensors in different soil types were statistically different from each other at two salinity levels (two-tail p-value within the range of 2.2×10^{-16} and 0.005). The only exception was the response of TDR315 sensor in Valent soil which was not statistically different at two salinity levels (p-value = 0.322). Furthermore, the residual sum of squares using ANOVA for TDR315 was within 0.0002 and 0.0026 $m^3\ m^{-3}$ and was within 0.0026 and 0.0137 $m^3\ m^{-3}$ for CS655. The results of the study reveal that the calibration of CS655 and TDR315 sensors varied with soil type. The regression calibrations for TDR315 and CS655 sensors among different soil types were determined. It was found that nine out of ten regressions between sensor-reported and reference θ_v were quadratic (observed p-values ranged from 2×10^{-16} to 0.004), and the regression calibration for CS655 in Valent soil type was linear (two-tail p value for quadratic relationship order = 0.676), but quadratic coefficients were reported for comparison with the coefficients of other soil types.

It was found that the estimated coefficients (quadratic, linear, and intercept) for CS655 sensor-reported θ_v among different soil types had statistically significant linear relationships with the clay content of the corresponding soil types (the LOOCV RMSD for c_2, c_1, and c_0 were 0.7936, 0.8127, and 0.1771). However for TDR315, significantly linear relationships of the coefficients (c_2, and c_1) with clay content were found (LOOCV RMSD for c_2, and c_1 was 0.4227, and 0.2652, respectively), but a quadratic calibration equation fitted well for the estimation of c_0 (LOOCV RMSD for c_0 was 0.0496). The developed calibration was also subjected to external validation with some studies done in the literature (Chavez and Evett, 2012; Schwartz et al., 2015; Singh et al., 2018). Fitting the developed calibration to Chavez and Evett (2012) it was observed that the calibration worked well for CS655 sensor-reported θ_v range of 0.26 m^3 m^{-3} to near saturation (0.42 m^3 m^{-3}) and the results were similar with a slope slightly larger than unity and a small positive intercept. However, on applying the regression calibration to the observed θ_v range of Schwartz et al. (2016) for TDR315 sensor, underestimation by TDR315 within the range 0.04 to 0.47 m^3 m^{-3} was witnessed with underestimation of θ_v throughout the drying cycle, and the magnitude of underestimation decreased with θ_v between 0.35 m^3

m^{-3} and near saturation (0.47 m^3 m^{-3}). The findings of Schwartz et al. (2016) were also similar. At last, the universal calibration was validated for TDR315 and CS655 sensors placed at 0.15 and 0.76 m depths according to the dataset of Singh et al. (2018) and it was observed that the RMSD for CS655 reduced by 0.008 m^3 m^{-3} at 0.15 m depth and 0.005 m^3 m^{-3} at 0.76 m depth using the universal calibration. However, using universal calibration for TDR315 the RMSD increased in comparison to the factory calibration. Therefore, it can be inferred that soil type had a noteworthy effect on the performance of CS655, but not TDR315 sensors. Potentially confounding factors (bulk density, organic matter, temperature, and salinity) should be accounted while transferring the calibration for external validation. However, limited availability of literature for evaluating accuracy of TDR315 and CS655 sensors comprehensively by external validation is a challenge. The performance of sensor-reported θ_v might be able to be improved with more accurate calibrations with the inclusion of more parameters like ρ_b and OMC. The relative success of fitting of results from general calibration with external validation is very encouraging and may signal new opportunities and can be explored in future research.

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CHAPTER IV

CONCLUSIONS

A field study was conducted at the University of Nebraska-Lincoln West Central Research and Extension Center in North Platte, NE, to evaluate the performance of eight electromagnetic (EM) soil water sensors, TDR315, CS655, HydraProbe2, 5TE, EC5, CS616, Field Connect, and AquaCheck, in a loam soil at two depths. All temperature (T) measuring sensors followed the temporal trends in T generally within 1^0C of each other at both depths. Similarly, the reported EC_a among all sensors at both depths was within 1 dS m^{-1} of each other. Such comparability among sensors provides confidence that the sensors can be used for crop modeling and planting decisions. Sensor performance assessment of 5TE, EC5, HydraProbe2, CS616, CS655, TDR315, Field Connect, and AquaCheck for θ_v determination with default factory, regression, and offset calibrations against the field calibrated neutron moisture meter (NMM) was carried out. The Topp equation (Topp et al., 1980) for TDR315, HydraProbe2, and EC5; manufacturer's T adjustment for CS616 using T measurements by CS655; and both "generic" and the "loam" calibrations for AquaCheck were considered in addition to the factory calibrations. Among the single-sensor probes, the range of depth-combined (0.15, and 0.76 m) RMSD for factory calibration varied from 0.039 m^3 m^{-3} (5TE) to 0.157 m^3 m^{-3} (CS616). In comparison to single-sensor probes, RMSD of Field Connect at combined depths (0.30, and 0.51 m) was moderate (0.083 m^3 m^{-3}), and RMSD of AquaCheck at combined depths (0.30, and 0.61 m) was high (0.163 m^3 m^{-3}). Using regression calibrations improved θ_v accuracy beyond factory calibration. In general, RMSD of the evaluated sensors were below 0.025 m^3 m^{-3} using regression calibrations with exceptions of 5TE and Field Connect. The betterment in θ_v accuracy gained by using offset calibrations was smaller and less consistent than the improvements gained by using regression calibrations. The relative success of offset calibrations for certain sensors in this field study is encouraging and may signal new opportunities. In addition, alternate models of sensor use, possibly analyzing trends and relative values at one or more depths rather than relying on conversions from raw output to water content for decision-making for irrigation management can be further explored in future research.

A laboratory experiment was conducted in a walk-in oven room setup at West Central Research and Extension Center, North Platte, Nebraska conducted to analyze the performance of two recently developed electromagnetic (EM) sensors – TDR315, and CS655 in five different textured soils (Valent, Cozad, Kuma, Hastings, Wymore) collected across the state of Nebraska. Factory calibrations of EM sensors reported θ_v were evaluated at different temperatures (T), salinity (EC_a) levels, and clay content (soil type) settings. Based on the investigated relationship of sensor θ_v and clay content, a general calibration equation for estimation of sensor-reported θ_v by both sensors for different soil types based on clay content was developed, and tested for statistical significance. The models for estimation of θ_v at hot (35°C) and cold (23.9°C) temperature were not significantly different from each other both statistically and practically for both the sensors, which was supported by the fact that the calculated RMSD was less than 0.01 m^3 m^{-3} for the developed models. The models for no salinity and added salinity were significantly different from each other (possibly due to high number of dataset points). But there is no practical significance of the difference as the range of RMSD for TDR315 sensor-reported θ_v varied across 0.0003 - 0.0023 $m^3\ m^{-3}$, and the calculated RMSD ranged from 0.0023 – 0.0125 $m^3\ m^{-3}$ for CS655 sensor-reported θ_v with the increase in salinity. The study revealed that CS655 (water content reflectometer) and TDR315 calibrations varied with the soil type. CS655 sensor has a significant linear relationship for the estimated coefficients (quadratic, linear, and intercept) with clay content of the investigated soil types. For TDR315 sensor, a linear calibration equation for coefficient estimation from clay content was reported for quadratic and linear coefficients, and a quadratic calibration equation fitted well for the estimation of intercept. An underestimation of sensor-reported θ_v was witnessed at the wet end for the entire range of clay content with the difference in behavior at the drier end while interpreting the coefficients for TDR315 sensor. The developed calibration was also subjected to external validation with some studies done in the literature (Adeyemi et al., 2016; Chavez and Evett, 2012; Schwartz et al., 2015) and fitted well to the findings of those studies to a good extent. This validation was performed at different clay contents within the similar θ_v range for the developed calibration for both sensors. Potentially confounding factors (bulk density, organic matter, temperature, and salinity) should be accounted while transferring the calibration for external validation. However, limited availability of literature for evaluating accuracy of TDR315 and CS655 sensors comprehensively by external validation is a challenge. However, the relative success of fitting of results from general calibration with external validation in our study was encouraging and may signal new opportunities and can be explored in future research.

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