Field and Laboratory Evaluation of the CS655 Soil Water Content Sensor

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Soil moisture sensors infer volumetric soil water content (SWC) from other properties of the bulk porous media. The CS655 water content reflectometer is a relatively new, low-frequency electromagnetic sensor that determines relative permittivity ($K_a$) using the two-way travel period and voltage attenuation of the applied signal along two 12-cm rods. This measured attenuation is quadratically related to bulk electrical conductivity (EC). Along with an onboard thermistor, the CS655 allows a more robust correction of propagation time and $K_a$, which its predecessors, the CS615 and CS616, lacked. However, with new sensors it is necessary to quantify their practical accuracy in the field. Here, we present an overview of the CS655 sensor and an evaluation under both laboratory and field conditions, using five surface soils (0–10-cm depth) in the laboratory and gravimetric samples collected in the field. Overall, a site-specific calibration using a two-term linearization of the SWC–$K_a$ function reduced the root mean square error (RMSE) of the factory-derived SWC of 0.073 and 0.043 m$^3$ m$^{-3}$ during batch and infiltration experiments, respectively, to 0.025 and 0.028 m$^3$ m$^{-3}$. Results further indicate that a soil-specific calibration additionally reduced the RMSE to <0.02 m$^3$ m$^{-3}$. Field evaluation across the Texas Soil Observation Network found that calibration reduced the variance across the network but did not affect the arithmetic mean or the RMSE against gravimetric sampling, which remained $\sim$0.05 m$^3$ m$^{-3}$ regardless of the SWC–$K_a$–EC function applied. At the regional scale, a global calibration is sufficient.

Soil moisture is a key state variable in hydrology and climate systems, coupling the water and energy cycles (Vereecken et al., 2008; Seneviratne et al., 2010). Much like soil formation itself (Jenny, 1941), climate, topography, vegetation, and soil physical properties each manifest themselves at decreasing scale to produce a heterogeneous soil moisture field. Interpreting soil moisture measurements are inherently challenging because of this variability in both time and space and the discrepancy of scales between measurement volumes and data requirements (Robinson et al., 2008; Ochsner et al., 2013).

Soil moisture is quantitatively measured as volumetric soil water content (SWC). All soil moisture sensors infer SWC from some change in either thermal properties (Bristow et al., 1993; Mori et al., 2003) or electrical properties of the soil; the latter tends to be more popular due to the wider availability of commercial sensors and perceived simplicity of measurement. Most electrical sensors used to measure SWC are based on the propagation of an electromagnetic wave in a porous medium and fall into many different classes including time domain reflectometry (TDR), time domain transmissometry, transmission line oscillators, capacitance sensors, and impedance sensors (Vaz et al., 2013). The apparent relative permittivity ($K_a$) of the soil measured by electromagnetic sensors is a combination of the real (in-phase) permittivity associated with the SWC in the substrate and the imaginary (out-of-phase) component related to dielectric loss and relaxation (Topp et al., 2000). The latter (e.g., bound water related to high specific surface areas and organic and solute contents) affect the imaginary component of permittivity and the travel time of...
Many electromagnetic SWC sensors report \( K_d \) directly, facilitating the use of well-established empirical relationships based on the “universal” three-term Topp et al. (1980) or a similar two-term linearization (Ledieu et al., 1986). Both equations have standardized (noted as STD here) coefficients for TDR that fit a wide range of mineral soils. More recently, Evett et al. (2005) added bulk electrical conductivity (EC) and effective frequency as independent variables to the Topp calibration function. Today, many sensor manufacturers provide factory calibrations (e.g., Kizito et al., 2008) or allow the user to pick among different soil textures (Seyfried and Murdock, 2004), but these STD factory calibrations perform less accurately than user-defined calibration functions (Vaz et al., 2013). Thus, the validity for lower frequency SWC sensors of empirical relationships of SWC–\( K_d \) derived using TDR needs to be addressed. In most cases, the experienced user finds that a site- or soil-specific calibration is still required to optimize the coefficients in many of these models.

The sensor used in this research is a transmission line oscillator sensor (Model CS655, Campbell Scientific). The CS65x water content reflectometers are relatively new (developed ~2011) and operate at a higher frequency (175 kHz). The original Campbell Scientific CS615 water content reflectometer was introduced in 1995 based on a time-transmission line oscillator described by Campbell and Anderson (1998). It was later replaced by the CS616 and several other variants. The CS65x sensor is available with waveguides of either 30 cm (CS650) or 12 cm (CS655) in length. Unlike its predecessors, the CS65x has not yet undergone rigorous evaluation. This sensor potentially makes significant advances, with onboard processing to estimate \( K_d \) and determine SWC, along with EC and temperature. The objectives of this study were to: (i) evaluate the CS655 performance under controlled laboratory conditions; (ii) evaluate the field performance of the sensor; and (iii) compare SWC based on the factory standardized calibration under both field and laboratory conditions based on soil- and site-specific calibration.

We have used this sensor exclusively in the Texas Soil Observation Network (TxSON) for calibration and validation of the NASA Soil Moisture Active Passive (SMAP) satellite mission (Chan et al., 2016). The TxSON serves as a core validation site (Colliander et al., 2017). The factory STD calibration SWC was used in early evaluations of SMAP and related root-zone modeling (Reichele et al., 2017). In all such cases, SMAP products met the mission objectives of an unbiased root-mean square error (RMSE) of <0.04 m³ m⁻³ at TxSON. In this study, we assessed the performance of the STD coefficients at a subset of locations and derived a site-specific CAL for the network.

The **CS65x Water Content Reflectometer Sensor**

The CS65x (e.g., CS650 and CS655) sensor is a transmission line oscillator (TLO) smart sensor that uses two parallel rods, each 3.2 mm in diameter separated by 32 mm, to form an open-ended transmission line or a waveguide. The CS650 is equipped with 30-cm waveguides, while the CS655 has 12-cm waveguides, the only difference being rod length. Inserting the longer waveguides into field soils can be challenging and given that voltage attenuation is proportional to waveguide length, we chose to focus on the shorter CS655 sensor for this work. Both CS65x sensors are based on CS616 technology, with improvements made to the oscillator circuitry, voltage attenuator, sensor firmware, and SDI-12 communication protocols (see the Supplemental Material for more detail).

A bistable multivibrator embedded in the sensor head generates a square wave with an amplitude of ±2.5 V at ~175 MHz. The oscillator’s state is triggered by the return of the reflected pulse down the waveguides. The measured oscillation frequency or two-way travel time is multiplied by 128 to obtain the period average (PA, \( \mu s \)) which is inversely related to the apparent dielectric permittivity (\( K_d \)). However, the travel time for TLO is also affected by EC, which can delay the arrival time, increasing the PA (Kelleners et al., 2005).

New to the CS65x, the signal attenuation of the non-polarizing waveform is also measured at 100 kHz. The ratio of excitation to return voltage is reported as the voltage ratio (VR), which is quadratically proportional to the bulk EC through an empirical relationship derived using dielectric liquids. The PA is corrected for EC effects and converted to \( K_d \) and ultimately SWC using STD coefficients. A thermistor in contact with one stainless steel waveguide is housed within the epoxy head, necessitating that the sensor be placed horizontally in the field if accurate \( \pm 0.5^\circ C \) soil temperatures are needed. The thermistor has a range of ~10 to 70°C and a precision of ~0.02°C. Note that soil temperature is not used for any corrective function in the CS65x firmware (v2) at this time. Lastly, sensor-to-sensor variability is minimized by normalizing at the factory for each probe to readings in air and ethylene glycol (Seyfried and Murdock, 2001; Kelleners et al., 2005) and using that to program a probe-specific multiplier and offset into the firmware.

On-board processing and firmware (see the Supplemental Material for a full description) handle all necessary calculations and logical steps to infer \( K_d \) and SWC from the raw measurements of PA and VR (Campbell Scientific, 2017). The SDI-12 output is a digital array including measurements of PA, VR, and temperature and derived values of \( K_d \), EC, and SWC. The Topp equation has been posed as “universal” for TDR instruments but also subject to much debate in the literature. For our purposes, we use the derived \( K_d \) and EC to evaluate CS655 estimates of SWC using the STD and optimized coefficients (noted here as CAL) with other parametric equations discussed below.

**Materials and Methods**

**Study Area**

The TxSON is located in central Texas (30.31° lat., ~98.78° long.; 510 m asl), along the Pedernales River and within the middle
reaches of the Colorado River. The study areas lies in the transition zone between the Edwards Plateau and the Gulf Coastal Plain called the Hill Country. The Hill Country is stepped terrain resulting from streams incising into the Edwards and Glen Rose formations. These formations are primarily limestones with interbedded shales (often called marls) that gently dip toward the Gulf of Mexico. The strata are offset by linear faults of the Balcones Fault Zone trending northeast and resulting in a stepped landscape of “risers” and “treads” (Maclay and Small, 1983; Woodruff and Wilding, 2008). According to the US Soil Taxonomy, the soils on the flat to gently sloping treads are Lithic Haplusterts, Lithic Calciusterts, Lithic Calciustolls, and Lithic Petrocalcic Calciustolls (Wilcox et al., 2007). The gently sloping risers can have significantly deeper soils. The valley bottoms have incised into the Hensel formation, which forms the rich, deep soils along the Pedernales River.

Vegetation includes a mix of oaks (Quercus sp.), tall woody shrubs (cedar [Juniperus ashei J. Buchholz], honey mesquite [Prosopis glandulosa Torr.]), grasses (grama [Bouteloua sp.], curly-mesquite [Hilaria belangeri (Steed.) Nash], bluestem [Schizachyrium scoparium (Michx.) Nash], switchgrass [Panicum virgatum L.]), and forbs that are well-suited for grazing. The soils are not appropriate for agriculture due to high erosion rates and low water retention capacity (Woodruff and Wilding, 2008). Mean annual precipitation across the Edwards Plateau decreases from 887 mm in the east to 442 mm in the west (decreasing by about 10 cm every 100 km), while the mean annual temperature is relatively constant, averaging 19.2°C annually—a meso-thermal semiarid climate.

**Site Selection**

Our goal with the following analysis was to determine if statistical metrics of TxSON are actual soil moisture heterogeneity or simply an artifact of using STD calibrations on soils of varying texture and salinity. The TxSON is a dense soil moisture monitoring network of 40 stations covering an area of 1300 km². The network currently consists of 34 soil moisture and six meteorological stations. At each site, we used a power auger to excavate a 30-cm-diameter hole to 60 cm or bedrock, whichever was reached first. Each sensor was installed horizontally at 5-, 10-, 20-, and 50-cm depths into the undisturbed soil and the hole carefully backfilled. All soil moisture sensors make measurements every 5 min and the data are averaged hourly. The network exclusively uses the CS655, with 150 sensors in operation since 1 Jan. 2015. The TxSON was selected as one of 13 core validation sites (Colliander et al., 2017) required for the data science calibration and validation of the satellite retrievals of soil moisture from NASA’s SMAP mission (Jackson et al., 2012). Initial results using the factory STD calibration show a strong correlation (R = 0.94) between site-mean TxSON SWC at the 5-cm depth and SMAP retrievals (Chen et al., 2016). To date, we have used the STD SWC–Kᵢ of Topp et al. (1980) for all comparisons.

The 40 TxSON sites were selected to represent the dominant soil types within the 36- by 36-km (1300-km²) SMAP passive radiometer footprint. The corresponding area was extracted from the gridded SSURGO database (Soil Survey Staff, 2014), summed, and sorted by areal coverage of each major soil map unit. The top 10 dominant soil classes, which represent 70% of the total area, were replicated with three sites per soil on participating landowners’ ranches. Because of the large number of TxSON sites and the inherent heterogeneity of SWC at this scale, we chose a subset of sites, using temporal stability (Vachaud et al., 1985; Cosh et al., 2004) to verify the SWC–Kᵢ. Temporal stability allowed us to identify sites that are consistently wetter or drier than the network mean. Our goal was to determine whether such sites are truly extremes or simply biased from sensor calibration.

We first derived the mean relative difference (MRD) across all monitoring sites using STD SWC for calendar year 2015, with MRD defined as

\[
\text{MRD}_i = \frac{1}{t} \sum_{j=1}^{t} \frac{\text{SWC}_{i,j} - \text{SWC}_{i}}{\text{SWC}_{j}}
\]

where SWC is the daily mean SWC at the jth time at the ith location, and SWC is the daily mean SWC of all locations at the jth time. The MRD (m³ m⁻³) quantifies the bias of an individual location to be drier than (−), wetter than (+), or comparable to (±0) the network arithmetic mean, while its variance (σ) is

\[
\sigma[(\text{SWC})]^2 = \frac{1}{1-t} \sum_{j=1}^{t} \left( \frac{\text{SWC}_{i,j} - \text{SWC}_{i}}{\text{SWC}_{j}} - \text{SWC}_{j} \right)^2
\]

which represents the accuracy of the individual station (i) to reproduce the network mean SWC (Jacobs et al., 2004; Joshi et al., 2011) during a given time period (t). Combining these two measures, we obtained the root mean square error of the relative difference (RMSE-RD) at each location:

\[
\text{RMSE-RD} = \sqrt{\text{MRD}_i^2 + \sigma[(\text{SWC})]^2}
\]

We then ranked ordered the network by MRD (Fig. 1a) and selected five locations, two sites with lower bias (2-1 and 2-5), two sites with higher bias (2-24 and 2-4), and another with an extremely high RMSE-RD (2-29).

Not only do these five sites display a range of MRD and RMSE-RD, they also cover a range of soil textures and parent materials. The Bastrop loamy fine sand (BaC) at Site 2-1 consists of a very deep, well-drained, moderately permeable soil formed in loamy alluvium derived from Quaternary age sandstone and shale. The Hensley loam (HnD) at Site 2-5 is a well-drained, non-calcareous soil that is generally shallow, forming on indurated limestone of Lower Cretaceous and Pennsylvanian age. Both of these sites were biased dry. The Purves clay (PuC) at Site 2-29, with an extremely large RMSE-RD, consists of a shallow, well-drained, moderately permeable soil that formed from interbedded...
limestone and marl. The Oakalla silty clay loam (Fr) at Site 2-16 is a very deep, well-drained soil formed in loamy alluvium derived from limestone of Cretaceous age. The Luckenbach clay loam (LuB) at Site 2-4 is a deep, well-drained, moderately low permeability soil formed in ancient loamy or clayey alluvium.

Soils, Preparation, and Characterization

At each location, we collected ~4 kg of soil from the top 10 cm of the profile. Samples were air dried and gently crushed to pass through a 2-mm sieve. A subsample (~50g) was removed and oven dried at 105°C for 24 h and used for physical and chemical soil characterization. Sample preparation for particle size analysis involved mixing 0.5 g of soil with 5 mL of H₂O₂ (30%) to reduce organic matter aggregates. After bubbling ceased (generally within 30 min), 25 mL of sodium hexametaphosphate solution (5% v/v) was added and mechanically shaken for 24 h. The dispersed soil was analyzed by laser diffraction (Mastersizer 3000, Malvern Instruments) to obtain a particle size distribution from 0.1 to 2000 μm in diameter (Loizeau et al., 1994) and binned into sand, silt, and clay fractions (Makó et al., 2017).
A conductivity meter (Model HI991300, Hanna Instruments) was used to measure saturated soil EC and pH following Thomas (1996). Sample preparation included mixing 5 g of oven-dry soil with 25 mL of deionized water (1:5 soil/water) in a 50-mL centrifuge tube, mechanically shaking it for 30 min, and then allowing the solids to settle for 30 min before measuring the supernatant. Sample preparation for measuring the pH included mixing 5 g of soil with 10 mL of a 0.01 M calcium chloride dihydrate solution (1:2 soil/solution ratio) in a 50-mL centrifuge tube, shaking for 30 min, and measuring the supernatant (Thomas, 1996).

**Laboratory Evaluation of CS655**

The algorithm and logical statements in the CS65x firmware are far more complex than other soil moisture sensors (see the Supplemental Material). To evaluate the sensitivity of the algorithm, we developed a response surface for derivatives $K_s$, SWC, and EC given a range of PA and VR values. Constraints for each input were derived using the logical statements in the firmware to $1 < VR < 9$ and $1 < PA < 2.5$. The response surface was generated by randomly sampling at a large parameter space (100,000 iterations) of VR and PA and then interpolating the results onto a 1/200 contour surface.

Next, we ran a series of sensor calibrations in both soil and liquids to assess the CS655. Three methods of water addition to soil columns were tested including (i) batch mixing, (ii) downward infiltration, and (iii) upward infiltration. Each experiment was conducted using 12-cm-diameter, 30-cm-tall polycarbonate columns. For all three calibration methods, the soil columns were packed to a target dry bulk density (BD) found in the field (Table 1) in 5-cm increments, carefully weighing each lift and gently tamping to reach the desired height (15 cm). All tests were performed using one of two CS655 sensors, with measurements taken every 30 s and averaged every 5 min using a CR1000 datalogger (Campbell Scientific). All laboratory evaluations were conducted at an ambient laboratory temperature of 25°C.

### Table 1. Soil physical and chemical properties at the five sites selected for laboratory evaluations in rank-order (dry to wet bias) by mean relative difference across the Texas Soil Observation Network (TxSON).

<table>
<thead>
<tr>
<th>Site</th>
<th>Soil</th>
<th>BD†</th>
<th>d†</th>
<th>Sand</th>
<th>Silt</th>
<th>Clay</th>
<th>1:5</th>
<th>1:1 estimated</th>
<th>pH</th>
<th>dS m⁻¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-1</td>
<td>BaC</td>
<td>1.33 (0.15)</td>
<td>0.50</td>
<td>79.0</td>
<td>16.2</td>
<td>4.8</td>
<td>0.13</td>
<td>1.26</td>
<td>6.97</td>
<td></td>
</tr>
<tr>
<td>2-5</td>
<td>HnD</td>
<td>1.24 (0.12)</td>
<td>0.53</td>
<td>74.5</td>
<td>19.7</td>
<td>5.9</td>
<td>0.17</td>
<td>1.46</td>
<td>6.81</td>
<td></td>
</tr>
<tr>
<td>2-29</td>
<td>PuC</td>
<td>0.98 (0.05)</td>
<td>0.63</td>
<td>28.9</td>
<td>50.0</td>
<td>21.2</td>
<td>0.18</td>
<td>1.54</td>
<td>7.58</td>
<td></td>
</tr>
<tr>
<td>2-16</td>
<td>Fr</td>
<td>1.23 (0.12)</td>
<td>0.54</td>
<td>29.4</td>
<td>50.1</td>
<td>20.5</td>
<td>0.19</td>
<td>1.59</td>
<td>7.50</td>
<td></td>
</tr>
<tr>
<td>2-4</td>
<td>LuB</td>
<td>1.23 (0.16)</td>
<td>0.54</td>
<td>41.3</td>
<td>40.9</td>
<td>17.8</td>
<td>0.20</td>
<td>1.62</td>
<td>6.90</td>
<td></td>
</tr>
</tbody>
</table>

† Dry soil bulk density was determined for the 0–6-cm depth in the field using replicated soil cores. One standard deviation is presented in parentheses.

§ Porosity = 1 – (BD/particle density), assuming particle density = 2.65 g cm⁻³.

Table 6. Soil electrical conductivity measured at a 1:5 soil/water ratio and also estimated for a saturated paste (Khorsandi and Yazdi, 2011).

The batch calibration method is perhaps the most common method and achieves a uniform SWC throughout the test column; however, it is time consuming and difficult to repack the soils to a consistent dry BD with each increase in SWC (Topp et al., 1980; Dirksen and Dasberg, 1993; Evett et al., 2005; Western and Seyfried, 2005; Kelleners et al., 2009). A volume of water was added, mixed thoroughly with the <2-mm soil, and stored overnight in an airtight plastic bag to equilibrate. Soil was packed to a uniform BD until the length of the sensor rods was exceeded (e.g., 15 cm). A CS655 sensor was inserted vertically, and measurements were initiated for 3 min. The sensor was exchanged for the other CS655 and measurements were repeated. No difference between sensors was found (paired t-test, $p < 0.01$), so we averaged the output from both sensors, resulting in a single measurement. The mean CS655 response (for all output variables) was determined and paired against the observed SWC in the column. This process was repeated for each soil type at increasing SWC in ~0.10 m³ m⁻³ increments. The cycle ended when each soil was at or near saturation based on an estimate of porosity from the soil BD. At the end of each experiment, all soil was removed from the column and placed in a drying oven for at least 24 h at 105°C to verify the final SWC.

For the downward infiltration calibration (Seyfried et al., 2005; Rüdiger et al., 2010; Burns et al., 2014), air-dry soil was packed to the same target dry BD in a similar manner as for the batch experiment. The test column was placed on a scale, a CS655 was inserted vertically, and readings were initiated. Water (~80 mL) was then slowly added to the top of the column using a volumetric burette, increasing the SWC by 0.04 m³ m⁻³ for each step. After the CS655 readings (e.g., PA) stabilized, additional water was added incrementally until saturation was achieved. The core was sealed with Parafilm between water additions to minimize evaporation. The final water contents were monitored with the scale, then verified at the end of each test gravimetrically. Generally, we waited 6 to 8 h between steps for the first four or five water additions, as they required much longer times to stabilize. We used the mean CS655 response of the 30 min prior to each water addition in our sensor calibration value.

Upward infiltration experiments (Ledieu et al., 1986; Hudson et al., 1996; Young et al., 1997; Burns et al., 2014) were conducted using the same soil column and packing procedure described above. After the column was packed to a 15-cm height with oven-dry soil, it was placed on a balance, a CS655 was inserted vertically, and measurements were started. Rather than measuring the change in mass of the water reservoir, as done by Young et al. (1997), we installed a differential pressure transducer (PX170, Omega Engineering) in a Mariotte bottle and connected it to the...
We reversed its orientation and reran the tests; the pressure head at the top of the column was increased to allow the core to saturate. Pressure head data were collected every 2 min and converted to change in water volume using the inside diameter of the Mariotte bottle. As the experiment progressed, the wetting front migrated upward from the probe tips to the sensor head until saturation was reached. The SWC throughout the experiment was determined by subtracting the water mass added to the column from the final mass of the column after the experiment was completed. All data were binned into equal increments of 0.02 m³ m⁻³ SWC to achieve uniform distributions prior to fitting the representative calibration equations to the data. In essence, both downward and upward tests are transient, unsteady infiltration processes compared with the batch test.

Lastly, we tested the CS655 in deionized water and 1 mmol NaCl (~1 dS m⁻¹) at ambient temperatures to determine the effective averaging regime along the sensor. A CS655 sensor was placed in an empty container with the sensor pointed down and then pointed up. First, deionized water was added in 1-cm increments until the sensor was completely covered with water. We reversed its orientation and reran the tests; the process was repeated again using 1 dS m⁻¹ water. Assuming a simple two-layer model of water ($K_{a,w} = 80$) and air ($K_{a,a} = 1$), we fit the refractive index method derived using TDR, based on the summation of each layer’s contribution to the total $K_a$ (Whalley, 1993; Schaap et al., 2003) as

$$K_a = \frac{l_w}{l} K_{a,w} + \frac{l_a}{l} K_{a,a} \tag{4}$$

where $l$ is the total length of the probe (12 cm), $l_w$ is the length in water, and $l_a$ is the length in air. Equation (4) implies that the sensor measurement is the arithmetic average along the probe. Chan and Knight (2001) modified this model to show that the propagation velocity was not a summation but a geometrical mean of the two dielectrics using TDR:

$$K_a = \left( \frac{l_w}{l} \sqrt{K_{a,w}} + \frac{l_a}{l} \sqrt{K_{a,a}} \right)^2 \tag{5}$$

Schaap et al. (2003) concluded that TDR tends to follow the reflective model (Eq. [5]) but that at lower frequencies (<500 MHz), the arithmetic average is more likely.

**Field Evaluation of the CS655**

Triplicate samples were collected throughout Calendar Year 2016 using a soil core sampler to obtain the SWC (0–6 cm) and dry BD. For each field visit, soil samples were collected in three randomized cardinal directions 5 m away from the data acquisition system, essentially encompassing (but not sampling directly) soils proximal to the CS655 sensors. Our field gravimetric sampling plan will obtain a range of SWC conditions and eventually evaluate 40 individual soil-specific calibrations for each station in TxSON. In this study, we were working to develop a single, site-specific CAL based on a subset of the five diverse sites and apply it globally across TxSON.

The soil sampler (Model 0200, Soil Moisture Equipment Corp.) has an inner diameter of 5.4 cm and contains two, 3-cm-tall brass rings and two, 1-cm-tall guard rings on top and bottom. The sampler was driven into the soil with a slide hammer until flush with the surface and removed. The center rings were pushed out of the corer and trimmed flush with a knife, removing uneven material within the upper and lower guard rings. The soil within the two interior rings (0–3 and 3–6 cm) was transferred to pint-size freezer bags and returned to the laboratory. Gravimetric SWC was determined after oven drying for 24 h at 105°C. Bulk density was obtained by dividing the dry mass by the sampler volume (137 cm³).

In the field, we noted a qualitative BD index of 3 (excellent), 2 (good), or 1 (poor). Collecting and extracting a perfectly intact soil core is challenging, and occasionally rocks and/or human error yielded incomplete volumes in the sampling rings. We designated a 1 to omit the sample from site BD calculation (i.e., no confidence), 2 for difficult insertion or extraction (moderate confidence), and 3 for full confidence. For each core ranked 2 or 3, the gravimetric SWC was multiplied by the actual BD to obtain the volumetric SWC. For a core ranked 1, the gravimetric SWC was determined but multiplied by the site-specific mean BD. For each location and date, the mean SWC and its standard deviation were determined from the triplicate cores. The coincident raw output (6-h mean prior to sampling time) from the 5-cm-depth CS655 sensor at the field location was extracted and paired with the mean SWC from these cores.

**Soil Water Content–Permittivity–Electrical Conductivity Relationships**

The dependence of $K_a$ on SWC is generally derived by a third-order empirical equation by Topp et al. (1980) as

$$\text{SWC} = C_0 + C_1 K_a + C_2 K_a^2 + C_3 K_a^3 \tag{6}$$

where the coefficients $C_0$, $C_1$, $C_2$, and $C_3$ were determined to be $-5.3 \times 10^{-3}$, $2.92 \times 10^{-2}$, $-5.5 \times 10^{-4}$, and $4.3 \times 10^{-6}$, respectively. The relationship was later simplified using a physical additive model of the constituents to $K_a$ and TDR two-way travel time (Ledieu et al., 1986) as

$$\text{SWC} = C_0 + C_1 \sqrt{K_a} \tag{7}$$

which is essentially a linearization of Eq. (6) but requiring just two coefficients. The equivalent formulation of Eq. (6) using Topp coefficients becomes $C_0$ and $C_1$ of ~0.173 and 0.115, respectively (Topp and Reynolds, 1998). Considering that TDR travel time also increases with the root of EC, Evett et al. (2005) added it to Eq. (7), resulting in...
For both the laboratory and field evaluations, we fit coefficients for Eq. [6], [7], and [8] using aggregated measurements from the CS655 sensor paired to observed SWC data. All coefficients were obtained using linear and nonlinear least-squares optimization in MATLAB (The Mathworks, Version 2016b) using the default bi-square weights to minimize the weighted sum of squares difference between the observed and predicted SWC. The resulting calibrated coefficients are noted as CAL. We further assessed CAL skill using the coefficient of determination ($R^2$), the RMSE, and mean bias error (MBE) for each SWC–$K_a$–EC function for each of the five soils and then combining all into one data set. Last, we assessed the performance of the factory STD calibration using the Topp coefficients in Eq. [6].

### Results and Discussion

#### Soil Properties at Selected Sites

Laboratory analyses are presented in their rank-order MRD (dry to wet) at the five selected field sites (Table 1). The gravel fraction (>2 mm) was low (<1.3% w/w) for all soils except the PuC soil at Site 2-29, which was particularly rocky at 23%. Bulk density at this field site was also the lowest, at 0.98 ± 0.04 g cm$^{-3}$. Gravel was removed prior to all remaining laboratory analyses, and we assumed that the rock fragments would have minimal influence on the derived $K_a$. The mean BD values determined from field cores also represented the targeted packing BD for laboratory experiments. The estimated porosity ($\phi$) was used to determine endpoints for the experiments (although several reached saturation well below these values). The fine-earth fractions (<2 mm) were binned into soil textural classes according to Makó et al. (2017), who found that clay (<6.6 μm) and silt (6.6–60.3 μm) boundaries from laser diffraction were more comparable to size classes from traditional methods. The rank order of MRD illustrates that bias correlates to the sand fraction, with lower values leading to higher MRD. Sands with lower water holding capacity and higher infiltration rates should, on average, have lower SWC than a finer textured soil under similar environmental drivers. Electrical conductivity, measured at 1:5 (soil/water) also increased with MRD from 0.13 to 0.20 dS m$^{-1}$. Using the method of Khorsandi and Yazdi (2011), we estimates the 1:1 EC, which indicates all of these samples are non-saline (<2 dS m$^{-1}$). However, the combined influence of clay mineralogy and EC on the $K_a$–SWC relationship is well established, particularly at lower frequency (Campbell, 1990; Jones and Or, 2004; Evett et al., 2005; Seyfried et al., 2005). For our purpose in this study, this subset represents a texturally diverse sampling of TxSON.

#### Laboratory Evaluation of the CS655 Sensor

First, the numerical response surface of CS65x derivatives ($K_a$, SWC, and EC), derived using a random sampling of the feasible measurement range of PA and VR, is presented in Fig. 2. The white regions resulted from a not-a-number error. A steeper gradient in the response surface implies a decreased precision of the output given small errors in either measurement. At lower VR (<3), both $K_a$ (Fig. 2a) and SWC (Fig. 2b) have lower gradients (e.g., PA has the widest range). As VR (and thus EC) increases, the response of both $K_a$ and SWC becomes highly nonlinear and the surface gradient steepens. The response of EC is highly linear with VR (Fig. 2c), and we can infer that the sensor’s peak performance would be for VR < 3, which equates to EC < 1 dS m$^{-1}$. The sensitivity to PA is diminished above a VR of 4, where minor changes in PA result in large changes in $K_a$ and SWC. In our non-saline range of EC, the CS65x response appears to be the optimal range of measurements. Note that the manufacturer-reported accuracy for $K_a$ is ±2% + 0.6 for EC < 3 dS m$^{-1}$, which equates to ±0.03 m$^3$ m$^{-3}$ increasing to ±3% + 0.8 for EC < 8 dS m$^{-1}$ (Campbell Scientific, 2017).
Our batch mixing laboratory results showed that calibrations deviated from both the STD Ledieu (Fig. 3a) and STD Topp model (Fig. 3b). Both underpredicted SWC at \( K_a \) less than \( \sim 15 \) and overpredicted SWC above. Experiments with the repacked columns generally maintained consistent BDs at each SWC increment (Fig. 3c), except for BaC, where the wettest SWC was more compact (1.8 g cm\(^{-3}\)) than the others (\( \sim 1.5 \) g cm\(^{-3}\)).

However, this point is still close to the CAL model prediction and is not considered erroneous, but it does point to the difficulties in this method. The STD Topp (which is also the derived SWC in the CS655 firmware) resulted in a minimum RMSE of 0.044 m\(^3\) m\(^{-3}\) for BaC (a sandy soil) and a maximum RMSE of 0.097 m\(^3\) m\(^{-3}\) on PuC, the most clay-rich soil (Table 2). Considering the rank order of these soils, the RMSE using the STD Topp appears to increase with MRD, indicating that the bias may be inherent in the derivation of the \( K_a \)-SWC function. Individually, each soil is well above the manufacturer-specified accuracy of 0.03 m\(^3\) m\(^{-3}\); however, the MBE is near zero because the dry- and wet-end biases essentially cancel the total. The BaC soil is the only sizeable MBE at \( -0.039 \) m\(^3\) m\(^{-3}\) using the STD coefficients. The soil-specific, optimized batch CAL to Ledieu reduces the RMSE to \( \leq 0.03 \) m\(^3\) m\(^{-3}\) while virtually eliminating any bias (MBE \( \sim 10^{-17} \) m\(^3\) m\(^{-3}\)). Combining all five soils into a network-specific data set yields a RMSE and MBE for the STD coefficients of 0.073 and \(-0.011\) m\(^3\) m\(^{-3}\), respectively. Fortunately, optimizing this relationship reduces the RMSE and MBE to 0.025 and \(-2 \times 10^{-17}\) m\(^3\) m\(^{-3}\), which is well under the 0.04 m\(^3\) m\(^{-3}\) requirement for the SMAP mission but also implies that a network-specific CAL is warranted.

Downward infiltration tests allow a consistent BD and more step increments of water, increasing the number of observed SWC values; however, the water distribution within the soil is not necessarily uniform throughout the sensing volume (\( \sim 3600 \) cm\(^3\)) of the sensor. The factory STD performed better under downward tests than batch tests, with a minimum RMSE of 0.020 m\(^3\) m\(^{-3}\) for HnD and a maximum of 0.064 m\(^3\) m\(^{-3}\) for LuB (Table 3) while calibrating the Topp equation reduced the RMSE to \(<0.02\) m\(^3\) m\(^{-3}\) for all soils individually. Combined, the STD RMSE was 0.043 m\(^3\) m\(^{-3}\) and much closer to the reported accuracy, but the MBE was \(-0.016\) m\(^3\) m\(^{-3}\). Optimizing the Topp SWC–\( K_a \) coefficients. The soil-specific, optimized batch CAL to Ledieu reduces the RMSE to \( \leq 0.03 \) m\(^3\) m\(^{-3}\) while virtually eliminating any bias (MBE \( \sim 10^{-17} \) m\(^3\) m\(^{-3}\)). Combining all five soils into a network-specific data set yields a RMSE and MBE for the STD coefficients of 0.073 and \(-0.011\) m\(^3\) m\(^{-3}\), respectively. Fortunately, optimizing this relationship reduces the RMSE and MBE to 0.025 and \(-2 \times 10^{-17}\) m\(^3\) m\(^{-3}\), which is well under the 0.04 m\(^3\) m\(^{-3}\) requirement for the SMAP mission but also implies that a network-specific CAL is warranted.

<table>
<thead>
<tr>
<th>Site</th>
<th>Soil</th>
<th>STD RMSE</th>
<th>STD MBE</th>
<th>CAL RMSE</th>
<th>CAL MBE</th>
<th>( R^2 )</th>
<th>( P )</th>
<th>( C_0 )</th>
<th>( C_1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-1</td>
<td>BaC</td>
<td>0.044</td>
<td>-0.039</td>
<td>0.014</td>
<td>-6 \times 10^{-17}</td>
<td>0.861</td>
<td>0.048</td>
<td>-0.0705</td>
<td>0.0903</td>
</tr>
<tr>
<td>2-5</td>
<td>HnD</td>
<td>0.064</td>
<td>0.008</td>
<td>0.024</td>
<td>3 \times 10^{-17}</td>
<td>0.917</td>
<td>0.028</td>
<td>-0.0235</td>
<td>0.0721</td>
</tr>
<tr>
<td>2-29</td>
<td>PuC</td>
<td>0.097</td>
<td>-0.006</td>
<td>0.011</td>
<td>7 \times 10^{-18}</td>
<td>0.978</td>
<td>0.007</td>
<td>0.0451</td>
<td>0.0563</td>
</tr>
<tr>
<td>2-16</td>
<td>Fr</td>
<td>0.076</td>
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<td>0.030</td>
<td>3 \times 10^{-17}</td>
<td>0.861</td>
<td>0.048</td>
<td>0.0028</td>
<td>0.0656</td>
</tr>
<tr>
<td>2-4</td>
<td>LuB</td>
<td>0.073</td>
<td>-0.017</td>
<td>0.024</td>
<td>5 \times 10^{-17}</td>
<td>0.909</td>
<td>0.031</td>
<td>0.0081</td>
<td>0.0671</td>
</tr>
<tr>
<td></td>
<td>Combined</td>
<td>0.073</td>
<td>-0.011</td>
<td>0.025</td>
<td>-2 \times 10^{-17}</td>
<td>0.928</td>
<td>6 \times 10^{-12}</td>
<td>0.0035</td>
<td>0.0660</td>
</tr>
</tbody>
</table>

Table 2. Batch laboratory calibration (CAL) results using four prescribed soil water contents at \( \sim 0.10 \) m\(^3\) m\(^{-3}\) increments and optimizing (\( C_0 \) and \( C_1 \)) the Ledieu Eq. [7] for each of five soils and combined for all data. The results are also compared with the factory standardized (STD) Topp coefficients (Eq. [6]) in terms of the coefficient of determination (\( R^2 \)), root mean square error (RMSE), and mean bias error (MBE).
reduced the RMSE to 0.027 with essentially no bias. Given the more easily controlled water additions, we conclude that the downw ard infiltration tests are preferred over batch mixing.

We further present the downward infiltration results in Fig. 4. As in the batch experiments, the STD calibration (Eq. [6]) underestimated SWC at lower $K_a$ while overestimating SWC at higher $K_a$ with a crossover point again near 15, resulting in a low MBE ($-0.016 \text{ m}^3 \text{m}^{-3}$). The CAL Ledieu (Eq. [7]) with its two coefficients resulted in a RMSE and MBE of 0.028 and $-4 \times 10^{-18} \text{ m}^3 \text{m}^{-3}$, respectively (Table 4). The three-term CAL Topp equation (Eq. [6]) in Fig. 4b, and the Evett equation (Eq. [8]) in Fig. 4c led to reduced RMSE while maintaining a negligible MBE. Including the bulk EC in Eq. [8] seems to produce an excellent and parsimonious site-wide CAL with a RMSE of 0.027 $\text{m}^3 \text{m}^{-3}$, MBE of $-1 \times 10^{-11} \text{ m}^3 \text{m}^{-3}$, and strong correlation with an $R^2$ of 0.95 (Table 4). The Ledieu CAL (Eq. [7]) performed well and could theoretically be constrained by a two-point calibration (Kelleners et al., 2005; Campbell Scientific, 2017); however, the addition of EC (Evett et al., 2005) allows a more generalized calibration although not explicitly accounting for relaxation losses.

The empirical coefficients of the STD equation using the linearization of Ledieu for $C_1$ (slope) and $C_0$ (intercept) are 0.115 and $-0.176$ using TDR (Topp and Reynolds, 1998). The slopes from the batch calibration using the CS655 were lower, ranging from 0.05 to 0.09, while the intercepts were greater (Table 2). The downward infiltration tests (Table 4) were more comparable with the combined data set, producing a $C_1$ of $0.093$ and $C_0$ of $-0.081$.

For Evett et al. (2005), $C_1$ is comparable but EC in the $C_2$ term is $0.031$ indicates some influence on the optimized RMSE at the site level. We presume the lower operating frequency of the CS655 reduces the sensitivity of $K_a$ to SWC over 1 GHz TDR. Similar results were obtained for the CS615 and CS625 sensors (Kelleners et al., 2009). Kelleners et al. (2009) attributed pulse attenuation of EC and relaxation losses to delaying the triggering of subsequent pulses in water content reflectometers, noting that soil-specific calibration will overcome this effect.

The upward infiltration test, however, produced different results entirely (Fig. 5). Here, soils started at air-dry condition, with the wetting front initiated at the probe tips. Only the two coarser soils have a Topp-like concavity in the SWC–$K_a$ function;

<table>
<thead>
<tr>
<th>Site</th>
<th>Soil</th>
<th>STD RMSE</th>
<th>STD MBE</th>
<th>CAL RMSE</th>
<th>CAL MBE</th>
<th>$R^2$</th>
<th>$P$</th>
<th>$C_0$</th>
<th>$C_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
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<tbody>
<tr>
<td>2-1</td>
<td>BaC</td>
<td>0.023</td>
<td>-0.006</td>
<td>0.005</td>
<td>$2 \times 10^{-13}$</td>
<td>0.996</td>
<td>0.055</td>
<td>-2.32 $\times 10^{-2}$</td>
<td>2.39 $\times 10^{-2}$</td>
<td>-1.74 $\times 10^{-3}$</td>
<td>5.13 $\times 10^{-5}$</td>
</tr>
<tr>
<td>2-5</td>
<td>HnD</td>
<td>0.020</td>
<td>-0.004</td>
<td>0.014</td>
<td>$-8 \times 10^{-13}$</td>
<td>0.988</td>
<td>0.097</td>
<td>1.91 $\times 10^{-2}$</td>
<td>1.59 $\times 10^{-2}$</td>
<td>1.12 $\times 10^{-4}$</td>
<td>-5.64 $\times 10^{-6}$</td>
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<tr>
<td>2-29</td>
<td>PuC</td>
<td>0.052</td>
<td>0.008</td>
<td>0.006</td>
<td>$1 \times 10^{-13}$</td>
<td>0.997</td>
<td>0.001</td>
<td>3.06 $\times 10^{-2}$</td>
<td>2.38 $\times 10^{-2}$</td>
<td>-7.88 $\times 10^{-4}$</td>
<td>1.29 $\times 10^{-5}$</td>
</tr>
<tr>
<td>2-16</td>
<td>Fr</td>
<td>0.042</td>
<td>-0.035</td>
<td>0.013</td>
<td>$-5 \times 10^{-14}$</td>
<td>0.991</td>
<td>0.001</td>
<td>-2.35 $\times 10^{-2}$</td>
<td>3.94 $\times 10^{-2}$</td>
<td>-1.75 $\times 10^{-3}$</td>
<td>3.48 $\times 10^{-5}$</td>
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<tr>
<td>2-4</td>
<td>LuB</td>
<td>0.064</td>
<td>-0.039</td>
<td>0.009</td>
<td>$4 \times 10^{-15}$</td>
<td>0.990</td>
<td>0.019</td>
<td>3.69 $\times 10^{-2}$</td>
<td>3.19 $\times 10^{-2}$</td>
<td>-1.51 $\times 10^{-3}$</td>
<td>3.18 $\times 10^{-5}$</td>
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<tr>
<td>Combined</td>
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<td>0.043</td>
<td>-0.016</td>
<td>0.027</td>
<td>$-2 \times 10^{-14}$</td>
<td>0.948</td>
<td>0.003</td>
<td>3.83 $\times 10^{-2}$</td>
<td>1.75 $\times 10^{-2}$</td>
<td>-1.15 $\times 10^{-4}$</td>
<td>-1.04 $\times 10^{-6}$</td>
</tr>
</tbody>
</table>

Fig. 4. Downward infiltration results using standardized (STD) and calibrated (CAL) soil water content (SWC)–apparent permittivity ($K_a$)–electrical conductivity (EC) formulations of the (a) first-order Ledieu (Eq. [7]), (b) third-order Topp (Eq. [6]), and (c) first-order Evett (Eq. [8]) using the combined five test soils.
Table 4. Downward infiltration calibration (CAL) results optimizing the linearized Ledieu Eq. [7] and dual-parameter apparent permittivity ($K_a$) and electrical conductivity (EC) Evett Eq. [8] for each of the five soils individually and combined. The statistical metrics are presented for root mean square error (RMSE), mean bias error (MBE), coefficient of determination ($R^2$), and $P$ value, along with the optimized coefficients ($C_0$–$C_2$) for both Eq. [7] and [8].

<table>
<thead>
<tr>
<th>Site</th>
<th>Soil</th>
<th>RMSE</th>
<th>MBE</th>
<th>$R^2$</th>
<th>$P$</th>
<th>$C_0$</th>
<th>$C_1$</th>
<th>$C_2$</th>
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<tbody>
<tr>
<td>CAL Ledieu et al. (1986)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-1</td>
<td>BaC</td>
<td>0.007</td>
<td>$5 \times 10^{-17}$</td>
<td>0.992</td>
<td>$2 \times 10^{-6}$</td>
<td>$-0.100$</td>
<td>0.092</td>
<td></td>
</tr>
<tr>
<td>2-5</td>
<td>HnD</td>
<td>0.015</td>
<td>$-6 \times 10^{-17}$</td>
<td>0.986</td>
<td>$1 \times 10^{-9}$</td>
<td>$-0.132$</td>
<td>0.104</td>
<td></td>
</tr>
<tr>
<td>2-29</td>
<td>PuC</td>
<td>0.008</td>
<td>$3 \times 10^{-17}$</td>
<td>0.994</td>
<td>$6 \times 10^{-9}$</td>
<td>$-0.042$</td>
<td>0.077</td>
<td></td>
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<td>2-16</td>
<td>Fr</td>
<td>0.019</td>
<td>$-4 \times 10^{-17}$</td>
<td>0.981</td>
<td>$6 \times 10^{-10}$</td>
<td>$-0.105$</td>
<td>0.105</td>
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<tr>
<td>2-4</td>
<td>LuB</td>
<td>0.010</td>
<td>$-8 \times 10^{-17}$</td>
<td>0.989</td>
<td>$4 \times 10^{-7}$</td>
<td>$-0.012$</td>
<td>0.077</td>
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</tr>
<tr>
<td>Combined</td>
<td></td>
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<td>$-4 \times 10^{-18}$</td>
<td>0.946</td>
<td>$4 \times 10^{-30}$</td>
<td>$-0.081$</td>
<td>0.093</td>
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<tr>
<td>CAL Evett et al. (2005)</td>
<td></td>
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<tr>
<td>2-1</td>
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<td>$-1 \times 10^{-12}$</td>
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<td>$1 \times 10^{-6}$</td>
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<td>0.112</td>
<td>$-0.040$</td>
</tr>
<tr>
<td>2-29</td>
<td>PuC</td>
<td>0.008</td>
<td>$4 \times 10^{-14}$</td>
<td>0.994</td>
<td>$1 \times 10^{-4}$</td>
<td>$-0.043$</td>
<td>0.077</td>
<td>$0.002$</td>
</tr>
<tr>
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<td>0.985</td>
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<td>$-0.101$</td>
<td>0.088</td>
<td>$0.064$</td>
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<td>2-4</td>
<td>LuB</td>
<td>0.009</td>
<td>$4 \times 10^{-13}$</td>
<td>0.990</td>
<td>$1 \times 10^{3}$</td>
<td>$-0.027$</td>
<td>0.069</td>
<td>$0.039$</td>
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<tr>
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<td>$2 \times 10^{-30}$</td>
<td>$-0.081$</td>
<td>0.085</td>
<td>$0.031$</td>
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</table>

Fig. 5. The CS655 output of (a) apparent dielectric permittivity ($K_a$) with the calibrated (CAL) Ledieu and factory (STD) function, (b) electrical conductivity (EC), (c) period average (PA), and (d) voltage ratio (VR) vs. the observed volumetric soil water content (SWC) from batch, downward infiltration, and upward infiltration tests in the laboratory for all five soils.
results from the other soils indicated a more linear relationship to $K_a > 30$ (Fig. 5a). Similarly, the derived EC values were higher at lower water contents but never reached similar EC levels of the other tests as the experiment progressed (Fig. 5b). Raw measurements of both PA (Fig. 5c) and VR (Fig. 5d) started higher but ended lower, having steeper slopes than either batch or downward infiltration tests. A higher PA leading to a higher $K_a$ can result from a longer delay in the triggering of the next pulse by the oscillator. Thus, when the sensor head is in dry soil and the end of the waveguides are in wet soil, with a sharp water content gradient separating the two, the CS655 does not appear to be reporting an arithmetic average of SWC along the entire probe length. Similarly, VR, which is linearly proportional to EC, is influenced by a heterogeneous SWC where the pulse moves from dry to wet soil (Fig. 5d), possibly triggering a premature reflection back to the TLO. Results from the batch and downward tests are more comparable and we cannot recommend downward CAL tests; however, we can learn something about the sensor’s functionality in heterogeneous SWC along the waveguides.

To evaluate CS655 signal propagation in layered media, we tested the sensor at two orientations, vertically with its waveguides pointed down (\(\bar{z}\)) and up (\(\bar{y}\)), then we filled a polycarbonate container in 1-cm steps with deionized and 1 mmol NaCl water (Fig. 6). We have a two-layered medium: air ($K_a = 1$) and water ($K_a = 80$) with the pulse originating in high [up (\(\bar{y}\))] and low [down (\(\bar{z}\))] $K_a$ media. The CS655 in up (\(\bar{y}\)) position follows the refractive model (Eq. [5]) in both deionized and \(\sim1\) dS m\(^{-1}\) water (Fig. 6a). However, in the down (\(\bar{z}\)) position, both $K_a$ and PA (Fig. 6c) are higher than the arithmetic average model (Eq. [4]) until >50% of the 12-cm-long probe is in water. Similar results were also observed in the upward infiltration tests. However, VR (and by derivation, EC) followed the arithmetic averaging in both directions using 1 mmol NaCl (Fig. 6d). Similarly, the derived volumetric water content (VWC) was linear for up (\(\bar{y}\)) orientation tests, regardless of the solution EC (Fig. 6b). Thus, the PA depends on orientation while VR does not.

These results show that the CS655 is sensitive to the type of variations in SWC along its waveguides. We began our efforts with the CS655 sensor assuming that upward tests would be the most time efficient and robust, but results indicate that PA values are affected by the geometry of wet and dry material. Heterogeneous SWC along the waveguides was shown to enhance the electric field in wet zones vs. dry and resulted in higher $K_a$ estimates for the CS616 (Logsdon, 2009). Here, we found that this effect is also dependent on the position of the heterogeneity in reference to the sensor’s oscillator. Calibration using downward infiltration appears to be robust and batch mixing to a lesser extent. Evaporation or dry-down calibrations, which are preferred for the Hydra Probe (Burns et al., 2014), could likely produce poor results similar to our upward infiltration tests because the sensor head would be in the drier soil.

Our results show a decreased sensitivity of the CS655 sensor to SWC–$K_a$ in the TDR-derived Topp relationship. Plauborg et al. (2005) also found a reduced slope for the CS616 vs. a conventional TDR, while the Hydra capacitance probe had a response similar to the CS655 (Fig. 4); however, their optimized CAL intersected the Topp STD at $K_a \sim 25$ (Seyfried et al., 2005). We found this intersection to be closer to \(\sim15\). Many studies have also shown that the factory STD can be improved with a CAL of the sensor output. In a study using the capacitance-based Hydra probe (Stevens Water Monitoring Systems), Bosch (2004) reduced the RMSE using a STD to CAL to <0.05 m\(^3\) m\(^{-3}\) for $K_a < 20$ with an increased slope ($C_1$, Eq. [6]) in the CAL Topp relationship ranging from 0.04 to 0.07 vs. the 0.03 $C_1$ term in the STD. Thus, the sensitivity of $K_a$ reported from non-TDR sensors requires more signal gain. These results concur
with an increased effect of Maxwell–Wagner polarizations on complex permittivity relationships at low frequencies (Chen and Or, 2006). Using CS615 and CS616 sensors, Rüdiger et al. (2010) binned 26 different Australian soils into three distinct groups based on particle size and EC from saturated pastes. The combined measurement of both EC along with $K_a$ by the CS655 makes the CAL (Eq. [8]) SWC–$K_a$–EC model (Evett et al., 2005) very attractive for more generalized calibration functions, which we found to have a global RMSE of 0.027 m$^3$ m$^{-3}$ with essentially zero bias.

### Field Evaluation of the CS655 Sensor

We present findings from in situ daily mean data from sensors at the 5-cm depth for the five sites of TxSON for Calendar Year 2015. The SWC data were derived from the STD, CAL batch, and CAL downward coefficients in the simplest Ledieu optimized Eq. [7], noting again that they are presented in rank order of MRD (Fig. 7). All in situ sensors responded to precipitation events in both late May and November, with a long dry-down period between. The batch CAL (blue) leads to the highest SWC during dry-down and the lowest SWC when wet.

![Fig. 7](image.png)

Fig. 7. Time series of (a) cumulative precipitation (PPT) for the 2015 calendar year and derived in situ soil water content (SWC) at 5 cm using the standardized equation (STD) and laboratory batch and downward infiltration Ledieu calibrations for (b) the BaC soil at Site 2-1, (c) the HnD soil at Site 2-5, (d) the PuC soil at Site 2-29, (e) the Fr soil at Site 2-16, and (f) the LuB soil at Site 2-4.
while the STD (dashed black) results in the lowest SWC during the dry-down. Thus, the CAL compensates for the dry–wet bias observed in laboratory CAL above and below the crossover point at $15\ K_a$.

The RMSE-RD from Site 2-29 (PuC soil) was the highest of the sites tested (Fig. 1a), which is evident in the time series (Fig. 7d) where SWC went to zero in the spring, then exceeded 0.4 m$^3$ m$^{-3}$ during early spring rains. Using site-specific downward CAL, the range of MRD, its variance, and the RMSE-RD are greatly reduced when applied across all 40 sites (Fig. 1b). The rank order of each station remains relatively stable with CAL. Several stations do shift one position up or down (e.g., 2-19/2-7, 2-18/2-2, 2-5/2-3, etc.), but generally there is a reduction in MRD range and RMSE-RD. This is also apparent in the subset of five locations where the CAL reduced the MRD $\sigma$ by 50% and the RMSE-RD from 0.553 to 0.381 (Table 5), implying that half of the network $\sigma$ can be attributed to sensor calibration while the remainder is actual soil moisture heterogeneity at the 36-km scale.

Figure 8 compares global CAL of the CS655 extracted from the in situ data against field gravimetric SWC cores. In general, the RMSE ($\sim 0.053$ m$^3$ m$^{-3}$) and $R^2$ ($\sim 0.6$) are comparable using either the STD or any of the CAL functions. While the $\sigma$ is reduced, the network average is unaffected by CAL across TxSON, which explains the excellent correspondence to SMAP regardless of the upscaling routine (Collander et al., 2017). Given the large variance in gravimetric SWC (Fig. 8) at the field scale ($\sim 10$ m) around each respective in situ sensor, the observed heterogeneity in SWC seems to significantly outweigh any error related to individual sensor calibrations. Nevertheless, the CAL data suggest that the STD Topp calibration can be improved on with CAL and results in no detriment to TxSON’s prior performance to SMAP.

A recent study (Singh et al., 2018) compared the CS655, among other sensors, to field calibrated neutron moisture meter measurements and found a RMSE of 0.11 m$^3$ m$^{-3}$ at the 15-cm depth and 0.032 m$^3$ m$^{-3}$ at the 76-cm depth; they found that a simple linear regression could reduce this error to <0.02 m$^3$ m$^{-3}$. Field calibration is often preferred over laboratory calibration (Chandler et al., 2004; Logsdon, 2009; Ojo et al., 2015), and more generalized methodologies have been proposed for the

### Conclusions

The CS65x sensor is an improvement over their CS615 and CS616 water content reflectometers that lack both EC and temperature measurements. We summarize here that $K_a$ and by surrogate SWC is the result of a complex interaction between both PA and VR, with better sensitivity at lower EC. The factory SWC–$K_a$ Topp relationship was derived using TDR at higher resonant frequency ($\sim 900$ MHz), while the CS65x operates variably around 175 MHz (Campbell Scientific, 2017). Through laboratory and field verification, we found this relationship to have a crossing point at $K_a \sim 15$; SWC was biased low below this point and high above it with minimal bias overall. Both batch and downward infiltration experiments using five soils of varying properties produced RMSE values using the STD Topp model of 0.073 and 0.043 m$^3$ m$^{-3}$, respectively. The RMSE values were reduced to 0.025 and 0.028 m$^3$ m$^{-3}$ by optimizing coefficients in the linearized (Ledieu et al., 1986) SWC–$K_a$ model, while using the SWC–$K_a$–EC model (Evett et al., 2005) in downward calibration resulted in a RMSE value of 0.027 m$^3$ m$^{-3}$. Upward infiltration experiments produced unsatisfactory results, indicating some influence of the wetting front position and soil wetness relative to the oscillator circuitry (i.e., the sensor head). Further laboratory tests in air–water mixtures found that PA was strongly influenced by the propagation direction while the

<table>
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<th>$\sigma$</th>
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Table 5. Temporal stability rank (dry to wet), mean relative difference (MRD), variance ($\sigma$), and root mean square error of the relative difference (RMSE-RD) for five out of 40 Texas Soil Observation Network sites using the factory standardized (STD) Topp equation and the globally optimized calibration (CAL) of Ledieu (Eq. [7]).
VR was not. Thus, our results suggest that this sensor does not arithmetically average SWC equally along the probes, and vertical installation should be avoided. Implementation of the CAL coefficients reduced the SWC variance at each site; however, it did not affect the RMSE against gravimetric samples, which was generally $\sim 0.05 \text{ m}^3 \text{ m}^{-3}$ regardless. A soil-specific CAL may be more appropriate at smaller scale, but for large-scale SWC, a global CAL results in a robust SWC–$K_a$–EC model that is easy to implement across a network such as the TxSON. Future work will evaluate the use of a global CAL vs. a site-specific function at all 40 sites. The CS655 sensor, although the SWC–$K_a$ relationship is less sensitive than TDR, provides a robust SWC across a wide range of central Texas soils.

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