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Propagation of soil moisture sensing uncertainty into estimation of total soil water, evapotranspiration and irrigation decision-making

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ABSTRACT

Soil moisture sensors are subject to uncertainty (inaccuracy) in measuring soil water status, that hinders various applications. User groups (researchers and growers/advisers) rely on these sensors for estimating critical agricultural water management decisions and information such as total soil water in the crop root zone (TSW), crop evapotranspiration (ET_c) and predicting irrigation triggers (IT), i.e., when TSW is equal to or lower than readily available water. There is a lack of translation of errors in sensor-reported soil moisture (θ_v) into TSW, ETc, and IT, which is critical to farm-level decision-making as well as research assessments. Nine soil moisture sensors (based on principles of time-domain reflectometry, capacitance and electrical resistance) were investigated in field conditions for silt loam and loamy sand soils under two installation orientations (vertical and horizontal) during two growing seasons (2017 and 2018). Accurate representation of TSW, ET_c, and IT was found to be a function of sensor-type, soil-type as well as calibration-type [factory calibration (F.C.) vs. site-specific calibration (S.S.C.)]. Sensor installation orientation did not affect sensor accuracy. Uncertainties in estimation of TSW, ET_c and IT were quantified under each condition of use, and sensors were comparatively ranked for effective selection. It was found that all sensors underestimated ET_c in silt loam soil. The deviation of sensor-measured ET_c from true ET_c ranged from −14 to −31 %, which implies that the choice of sensor under a given soil type impacts the quantification of consumptive use of the soil-vegetation system being monitored. Sensors showed both overestimation and underestimation of ET_c in loamy sand soil with deviations of sensor-estimated ET_c from true ET_c ranging from 14 to −61 %. The S.S.C. resulted in 45 and 17 % improvement in TSW and ET_c in silt loam soil, respectively, and 42, 80 and 86 % improvement observed in TSW, IT and ET_c in loamy sand soil, respectively. The research findings showed that suitability of soil moisture sensors can differ when different target metrics are used as criteria. These findings emphasize the need for evaluating soil moisture sensors based on practical and application-oriented criteria, in addition to reliance on θ_v accuracy. To the best of authors' knowledge, this research is the first to translate traditional θ_v accuracy assessments into practical and application-oriented criteria and use them to evaluate sensors for these specific applications. Sensor rankings and uncertainty associated with their use presented here will allow diverse users to effectively identify sensors for targeted applications in water management decision-making and research.

1. Introduction

Numerous sensing methods exist for estimation of soil moisture and since they function based on diverse principles, they are subject to errors and uncertainties. These methods extend from manual gravimetric sampling to technology-based tools including neutron scattering, time domain reflectometry (TDR), capacitance-based sensing, and electric resistance-based sensing (ER). Extensive research has been conducted to evaluate their accuracy across global conditions of use, spanning dozens of commercial sensors and all soil textural classes [Evett et al. (2002); Leib et al. (2003); Baumhardt et al. (2000); Varble and Chávez (2011); Jabro et al. (2018); Zhu et al. (2019); Chow et al. (2009)]. Primarily, the objectives of these research studies were to investigate the accuracy of sensor(s) to represent soil moisture (expressed by volumetric water content or θ_v), as well as develop appropriate correction strategies to improve θ_v estimation. As a result, useful mathematical/empirical functions have been developed and proposed under various conditions of sensor use (e.g., soil texture, salinity, structure, etc.) to aid in accurate estimation of θ_v.

The research conducted in this direction (Evett and Steiner, 1995;

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Irmak and Haman, 2001; Heng et al., 2002; Quinones et al., 2003; Irmak and Irmak, 2005; Jabro et al., 2005; Brocca et al., 2007; Irmak et al., 2010; Mittelbach et al., 2012; Su et al., 2014; Datta et al., 2018; Irmak, 2019a; Zhu et al., 2019) emphasizes the importance of accurate θ_v estimation to address the suitability of a sensor for a given application. Ideally, a sensor is regarded acceptable if it produces accurate θ_v information either under factory-calibration (F.C.) or a combination of the F.C. sensor output and a site-specific calibration (S.S.C.). It is crucial to reconsider and reevaluate this notion of using θ_v as the target metric, when evaluating soil moisture sensing technology, because of its limited direct use in farm-level decision-making or scientific research. Other metrics hold greater relevance for real-world applications like commercial operations (such as irrigation decisions) and scientific research (such as soil water storage and crop evapotranspiration). For instance, investment on a soil moisture sensor in a commercial operation (non-research settings) is expected to add significant value to irrigation decisions, rather than merely reporting an accurate θ_v. Similarly, its use by a researcher in a multi-plot experiment is expected to aid in acceptable estimation of total soil water (TSW) in the plant root zone profile and crop evapotranspiration (ET_c), so as to discern the impacts of any imposed treatments on soil-water balance. A sensor that does not report an accurate θ_v might still be valuable to make an effective irrigation decision or convey ET_c. This is due to the fact that soil water balance calculations rely on change in the θ_v value or its trends, rather than the absolute value itself. Thus, it is practically logical that emphasis is laid on accurate representation of these "decision-making" or "end-user targeted" variables (TSW, ET_c, and irrigation management), in addition to θ_v. Therefore, it would be ideal if the errors and uncertainties associated with these sensors are reported in terms of these variables rather than only θ_v, so that sensor evaluation and selection can be based on metrics that will actually be used in real world applications. For instance, Evett et al. (2012) stated that errors of the magnitude 0.05 $m^3\ m^{-3}$ in θ_v translated into errors of up to 50 mm day^{-1} in soil-water flux (change in soil water storage over time) estimation, making them unsuitable for use in water balance, ET and water use efficiency (WUE). It is critical that the methodologies used to estimate these "end-user targeted" variables are held constant, so that the performance is a function of only θ_v obtained from the sensors investigated, and not any differences in assumptions or methods adopted.

To the best of our knowledge, extremely limited body of research has evaluated and compared several soil moisture sensors for success in representing some measure of these practical metrics (to both commercial and research audiences). Mittelbach et al. (2012) evaluated four soil moisture sensors in clay loam soil in Switzerland using sensor-estimated change in soil moisture storage in comparison with lysimeter-measured ET_c. Walker et al. (2004) used three soil moisture sensors in loam soil in Australia to quantify change in soil moisture storage and compare it against a bucket water balance model. Paige and Keefer (2008) compared three TDR and capacitance-based sensors in a sandy gravelly loam site in Arizona by assessing change in soil moisture storage against the same computed using a soil-water balance model, where ET_c was measured using a Bowen Ratio System, and runoff was measured using an H flume. By using different approaches, these studies addressed the success (or failure) of soil moisture sensors to accurately represent the soil-water balance. In research-oriented and commercial production-oriented use, soil moisture sensors are often expected to reflect seasonal dynamics of TSW and seasonal total ET_c, and their ability to call irrigation triggers (IT) (Irmak, 2015a, b; Djaman and Irmak, 2012; Irmak et al., 2014; Kukal and Irmak, 2019), and any sensor technology has not been evaluated for these important applications.

This research aims to address these knowledge gaps in the literature by evaluating soil moisture sensors in silt loam and loamy sand soils for two complete growing seasons. Nine commercial sensors [TrueTDR-315 L (*Acclima, Inc., Meridian, ID*), CS616 and CS 655 (*Campbell Scientific, Inc., Logan, UT*), 5 TE, 10HS, EC-5 and MPS-6 (*Meter Group, Pullman, WA*), SM150 (*Delta-T Devices Ltd., Cambridge, UK*) and John Deere Field Connect (*John Deere Water, San Marcos, Cal.*)] were included in an investigation of how errors in θ_v sensing by using various sensor technologies can propagate into: (a) assessments of TSW and ET_c by the scientific research community and (b) irrigation decision-making in commercial agricultural operations (producer-oriented). The specific objectives were to: (i) evaluate performance of sensors to accurately determine TSW, ET_c, and IT in row crop and pasture grass agricultural systems; (ii) assess any improvement of TSW, ET_c, and IT estimates when site-specific calibrations (S.S.C.) were used relative to factory calibrations (F.C.); and (iv) rank all the sensors for their success in estimating TSW, ET_c, and IT for both the soil types so as to facilitate sensor selection aimed at these applications. It is emphasized that in order to estimate TSW, ET_c, and IT, the process of conversion from θ_v was the same across sensors, and thus the uncertainties observed in these variables are translated from uncertainties in θ_v only. Also, the information presented in this manuscript should only be deemed true for silt loam and loamy sand soils, as the experiments were limited to these soil textures only.

2. Materials and methods

2.1. Description of soils, vegetative characteristics and management at the experimental sites

The field experiments were conducted during 2017 and 2018 growing seasons at two sites (Fig. 1), which were selected so that the two ecosystems and agriculturally- predominant soil types are represented in this research. Site 1 and Site 2 are referred to as by their soil types, i.e., silt loam and loamy sand, respectively, hereon. The growing seasons for maize and soybean, as well as the active photosynthetic period in the pasture grass was monitored, as these periods coincide with the predominant conditions of use (soil temperatures and wetting patterns primarily) of soil moisture sensors. The sensors were installed in 2017 growing season and remained in the soil until the end of experiment to minimize any effects arising from insufficient contact and disturbance due to repeated installation and removal.

Silt loam (site 1): The first experimental site (Site 1) was at the University of Nebraska-Lincoln South Central Agricultural Laboratory (SCAL) (40° 43′ N and 98°8′ W at an elevation of 552 m above mean sea level), near Clay Center, Nebraska. The long-term average annual precipitation in this area is 730 mm and the long-term average growing season (May 1st – September 30th) precipitation is 437 mm, although both variables vary substantially and inter-annually. A wide range of soil temperatures (measured with the CS655 sensor at 60 cm depth) were encountered throughout 2017 and 2018 growing seasons: 11 °C to 26 °C,. This site has well-drained Hastings silt loam soil (Crete fine, smectitic, mesic Pachic Argiustolls) with field capacity and permanent wilting point of 0.34 $m^3\ m^{-3}$ and 0.14 $m^3\ m^{-3}$, respectively (measured at site; Table 1). Irrigated row crops were grown during the experimental period. Field maize (*Zea mays* L.) and soybean (*Glycine max*) were grown in 2017 and 2018, respectively. Typical effective rooting depth of field maize and soybean at the experimental site is 1.50 m and 1.20 m, respectively (measured across > 15 years of experiments at the site). Total available water holding capacity of the top 1.50-m soil profile is approximately 300 mm. The experimental field (16.5 ha) was irrigated using a four-span hydraulic and continuous-move center-pivot irrigation system (T-L Irrigation, Co., Hastings, Nebraska). Irrigation management was conducted to maintain crops at optimum growth conditions and maintain root zone (0 − 120 cm) soil-water near 40–45 % of maximum allowable depletion (Irmak, 2015a). Following this criterion of management, total irrigation water depth of 159 mm in 2017 and 64 mm in 2018 were applied.

Loamy sand (Site 2): The second experimental site (Site 2) was at Central City, (41°16′ N 97°56′ W at an elevation of 549 m above mean sea level) approximately 10 km north of the Platte River, Nebraska.

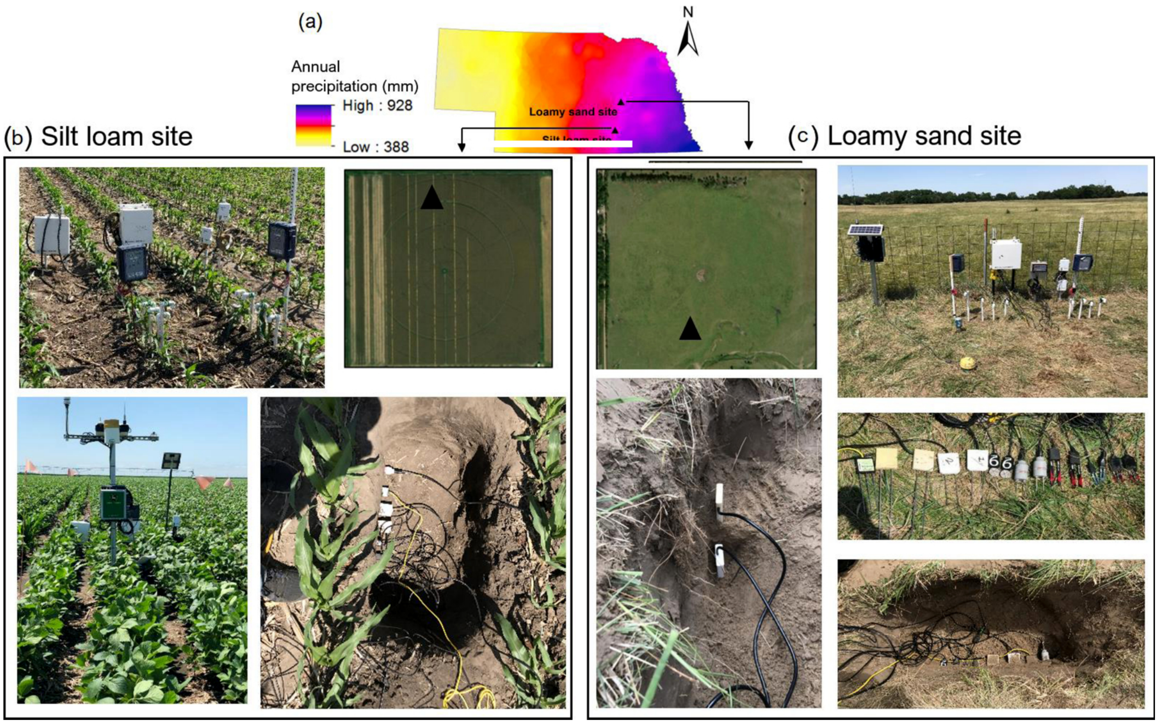

Fig. 1. (a) Geographic location of the two experimental sites in the Irmak Research Laboratory research facilities, as shown on a map of Nebraska. The map shows the gradient of long-term mean annual precipitation; (b) visual depiction of the experimental site via photographs taken during the experimental period at the silt loam soil; and (c) visual depiction of the experimental site via photographs taken during the experimental period at the loamy sand soil.

Here, the long-term average annual and growing season precipitation is 732 mm and 464 mm, respectively. The soil temperature ranged from 14 °C to 25 °C. This site has deep, moderately drained, and moderately permeable loamy sand (Ipage mixed, mesic, Oxyaquic Ustipsamments) with a field capacity and permanent wilting point of 0.19 m^3 m^{-3} and 0.05 m^3 m^{-3}, respectively (measured at site; Table 1). This site was a rainfed native grassland approximately 70 ha in size and contains primarily buffalograss [Bouteloua dactyloides (Nutt.)] (~90 %) and tall fescue (Festuca arundinacea). Total available water holding capacity of the top 1.50-m soil profile is approximately 210 mm. This grassland was established in 1980 and still maintains its natural establishment conditions. Due to rainfed conditions, the vegetation experiences water stress, especially during July and August. It is grazed throughout most of the growing season, and the grass height varies between approximately 5 and 13 cm throughout the season (Irmak, 2010). The small area where this experiment was located within the pasture grass field was fenced and no cattle was allowed to keep the setup undisturbed, uncompacted, and maintain pristine infiltration characteristics that are inherent to a representative pasture grass-vegetated loamy sand site.

Nebraska has approximately 19.6 million ha of land that comprises approximately 12 million ha of grassland (rangeland), 1.9 million ha of irrigated maize and 0.8 million ha of irrigated soybean (Irmak, 2010). Thus, the vegetative surfaces in these experiments are well representative of Nebraska (and other Midwestern states), and hence hold significance for the state and other states with similar soil texture and soil water holding characteristics and cropping systems. Table 1 presents some of the measured basic soil characteristics at both sites. These data serve as metadata for the conditions in which this research was conducted, with the intention of improving transferability of the findings and information gained from this research. These data were measured using soil samples collected at the experimental sites and analyzed using standard physical and chemical properties laboratory techniques. The inclusion of these two soil types in these experiments provides an opportunity to evaluate the sensors for use in conditions that are representative of a major proportion of the state's irrigated and rainfed agricultural production.

2.2. Soil moisture sensors investigated

Nine different commercial soil moisture sensors that fall into three main categories when classified by operational principles were investigated. At each site, two sets of each sensor were evaluated, one of

Table 1
Measured physical and hydraulic properties of the soils at the two experimental sites.

Soil Type/Site	Soil Layer (cm)	Particle Size Distribution			ρ_b[1]	OMC[2]	Field capacity	Permanent wilting point	Saturation	Slope	Compaction	EC[3]
		(%) Sand	%) Silt	(%) Clay	(g cm^{-3})	(%)	(m^3 m^{-3})	(m^3 m^{-3})	(m^3 m^{-3})	(%)	kPa	dS/m
Silt loam (Site 1)	0 – 30	18.7	55.6	25.6	1.35	2.81	0.34	0.17	0.50	1.0	0.90	0.35
	30 – 60	16.2	45.3	38.5	1.13	2	0.38	0.23	0.50			
	60 – 90	15.8	51	33.2	1.18	1.3	0.36	0.20	0.47			
	90 – 120	15.8	56.1	28.1	1.24	1.07	0.35	0.17	0.46			
Loamy sand (Site 2)	0 – 120	77	16	7	1.54	1.1	0.19	0.05	0.42	1.0	0.96	0.13

[1] ρ_b: bulk density.
[2] OMC: organic matter content.
[3] EC: electrical conductivity.

which was installed in horizontal (parallel to the ground surface) orientation and the other in vertical (perpendicular to the ground surface) orientation. The only exceptions were JD probe, which can only be installed vertically, being a multi-sensor probe, and TDR315 L (Acclima), which was only evaluated in horizontal orientation. The lack of replication of different sensors at each site and orientation was due to (1) already extensive financial investment, and (2) the need for careful consideration of minimizing the spatial moisture variability from soil, crop, and management factors, and thus evaluating sensors in a confined (small) volume to further minimize probability of spatial heterogeneity. Moreover, given a specific financial investment, the goal was to include more type of commercial sensors to investigate, as stakeholders have a wide range of sensor options, and research should cater to that need by evaluating a wide panel of sensors in the same framework. Following are all the sensors included in this research under their corresponding principles of operation.

- Time-Domain Reflectometry (TDR)-based Sensors
o TrueTDR-315 L Acclima (Acclima, Inc., Meridian, ID)
o CS616 (Campbell Scientific, Inc., Logan, UT)
o CS655 (Campbell Scientific, Inc., Logan, UT)
- Capacitance-based Sensors
o 5TE (Meter Group, Pullman, WA)
o 10HS (Meter Group, Pullman, WA)
o EC-5 (Meter Group, Pullman, WA)
o SM150 (Delta-T Devices, Cambridge, U.K.)
o John Deere (JD) Field Connect (John Deere Water, San Marcos, Cal.)
- Electrical Resistance-based Sensor

TEROS 21 (MPS-6) (Meter Group, Pullman, WA)

All the sensors are indirect methods of soil moisture determination, i.e., they use an intermediate soil property to indirectly estimate volumetric water content (θ_v). For example, TrueTDR-315 L uses apparent dielectric permittivity, CS616 and CS655 use oscillation frequency and consequently apparent dielectric permittivity, 5TE, 10HS, EC-5 and SM150 use dielectric constant, JD Field Connect uses a count proportional to the sensor resonant frequency, and TEROS 21 uses soil matrix potential. These intermediate variables are related to θ_v via previously developed relationships such as the Topp's equation (Topp et al., 1980). All the sensors report soil moisture status as volumetric water content (θ_v), except TEROS 21 (MPS-6), which reports soil matric potential (Ψ_m) (kPa). All Ψ_m measurement were converted to θ_v using a soil-specific soil-water characteristic curve developed by Irmak (2019b). It is useful to mention here that the accuracy assessments in this manuscript are based on the final sensor θ_v output (and Ψ_m in TEROS 21), and not the intermediate soil properties that the sensing components measure. The final θ_v or Ψ_m output from the sensor is a function of estimation characteristics of intermediate soil property as well as effectiveness of the conversion approach used (e.g., Topp's equation). Since all sensors use different intermediate soil properties as well as different conversion approaches, it would be challenging to systematically compare accuracy individually at intermediate and final sensor output levels. Moreover, the approach used in this research seems the most apt in the light of the fact that most of the practical applications also rely on the final sensor output, and not intermediate variables.

2.3. Reference moisture measurement

A new Troxler Model 4302 neutron probe (NP) soil moisture gauge (*Troxler Electronic Laboratories, Inc., Research Triangle Park, N.C.*) represented reference θ_v (θ_{vref}) information in the research. All other sensors investigated have been compared, assessed, and calibrated against NP measurements. In order to collect data for NP calibration, the NP was used to estimate volumetric soil water content at the soil depths of 0 − 0.30, 0.30 − 0.60, 0.60 − 0.90 and 0.90 − 1.20 m to be able to capture a wide range of soil water content during the calibrations at both sites. Aluminum access tubes were installed in the center of each plot that were established specifically for calibration process. Gravimetric soil samples were taken in the same vertical distance as the soil layers in which NP reading were taken such that soil core samples were taken from the entire 0.30 m soil layer increments (0 − 0.30, 0.30 − 0.60, 0.60 − 0.90 and 0.90 − 1.20 m) in each site to be able to represent the same soil area in the vertical domain as the NP's sphere of influence (which is approximately 0.30 m in diameter). Additional undisturbed soil core samples were taken in each research site at each soil layer at approximately 1 m distance from the NP access tubes to quantify the soil bulk density. Once the soil bulk density and gravimetric soil water content (on a percent weight basis) were determined, the volumetric soil water content was determined by multiplying the soil bulk density values with the associated weight-basis water content for each soil layer. The neutron probe was calibrated by correlating probe readings with volumetric water content of soil core samples (100 cm^3) taken at each depth. During the soil sampling procedure for calibration and bulk density, a minimum to negligible amount of organic matter (e.g., plant root) was observed and visible macropores or biopores (vertical infiltration channels) or cracks were not present. This process (collecting NP and gravimetric samples) was carried out continuously following one major rain event and took approximately two weeks to complete. The soil moisture and bulk density measurements for calibration were conducted at different periods/date. Thus, starting from near field capacity (foe silt loam soil) or saturation (for loamy sand) after a heavy rain event, different range of soil water content was measured as the soil moisture was depleted by plants and/or decreased due to evaporation losses, which resulted in covering almost the entire range from field capacity to near permanent wilting point for the silt loam soil (i.e., 14–35 % vol) and from near-saturation to permanent wilting point for the loamy sand soil (5–35 % vol). This process also ensured that the NP was calibrated for different soil layers and

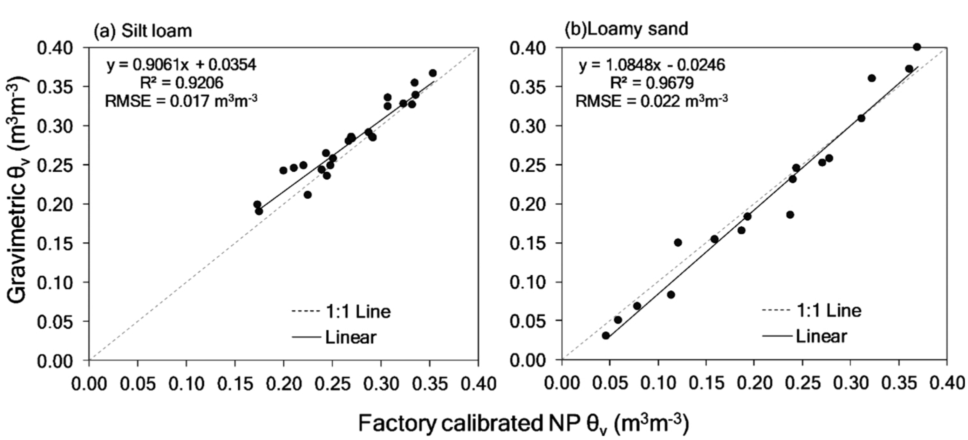

Fig. 2. Regression among the model Troxler 4302 neutron gauge (NP) factory-calibrated volumetric soil-water content and the gravimetrically-determined volumetric soil water content in (a) silt loam and (b) loamy sand (Central City) soils. The data points represent spatially distinct, multi-depth (0.30-1.80 m) information collected concurrently from NP and gravimetric sampling in the Irmak Research Laboratory.

accounted for potential spatial variability exists in vertical direction of each experimental site. Fig. 2a and b clearly show that the NP had an excellent accuracy in measuring volumetric soil water content for both sites with minimum error and, indicating its use as a reference method to compare all other soil moisture sensing technologies is justified (Irmak, S., unpublished research notes). Two NP access tubes were installed at each site for reference soil moisture information. These tubes were installed in close vicinity of the sampling area of the sensors evaluated. For example, in silt loam, NP access tubes were installed in the inter-plant spacing in the same row as other sensors, ensuring fair evaluation. The access tubes were covered at all times, except when measuring soil moisture, to avoid any interaction with ambient moisture conditions due to rain and/or irrigation.

Site-specific calibration equations were developed for the NP (Irmak, S., unpublished research data) for both sites by correlating the factory-calibrated NP measurements to the gravimetric sample-determined θ_v. It was hypothesized that these calibration functions, when implemented on independent soil moisture data will result in some degree of improvement in end-user targeted metric estimation, as has been observed when estimating θ_v. Thus, these calibration functions were implemented on the original (raw) independently collected moisture data from 2018. The original sensor estimated TSW, ET_c, and IT and those estimated post-calibration were assessed against NP-measured TSW_{ref}, ET_{cref}, and IT_{ref} in 2018. Also, a measure "improvement in RMSE post-calibration (I_{RMSE})" to represent the percentage change in success (improvement, decline or no change in sensor performance) to estimate TSW, ET_c and IT was computed after the calibrations were implemented relative to original RMSE. Thus, a positive I_{RMSE} implies improvement and a negative I_{RMSE} implies no improvement or even worsening of the estimation.

2.4. Installation specifications

All sensors that can be installed in varying orientations were investigated under two orientations (vertical and horizontal). Although limited research (Zhu et al., 2019; Plauborg et al., 2005; Caldwell et al., 2018; Chen et al., 2020) has been conducted on this topic, it has been seen that sensor installation orientation might have an effect on sensor accuracy. Soil profiles (pits) were dug at both sites for horizontal sensor orientation so that the four boundary walls of the pits were perpendicular to the pit bottom plane. The soil beyond the cuboidal pit was ensured to be undisturbed and soil structure was maintained. In silt loam soil, the pit was dug in the furrow, whereas in loamy sand soil, the pit was dug in a representative grassed area. For horizontal orientation, the sensors were installed parallel to the ground surface against one of the pit walls at 60 cm from soil surface, such that the sensing components of the sensor (prongs, ceramic disks, etc.) resided in undisturbed soil volume and sampled soil moisture in undisturbed soil. This depth was selected to avoid spatial heterogeneous wetting patterns at shallower depths as well as due to its coincidence with effective root volume. Sensor outputs are highly sensitive to the effectiveness of sensor installation, requiring that extreme caution is used in the installation procedure. The volume of influence for EM sensors is $< 500\ cm^3$ (Evett, 2008; Chen et al., 2020), and thus enough inter-sensor distance was allowed with an additional buffer so that these volumes are independent for each sensor, and there is no overlap (to avoid signal interference). Post-installation, the pit was refilled with the same volume of soil, compacted to original conditions as best as possible and the same soil layers were placed back in their original depths to enable the construction of the original soil layers. It has to be noted that the soil was backfilled only over the non-sensing part of the sensors, and thus any changes in bulk density post-backfill should not affect sensor measurements.

For vertical orientation, the sensors were installed perpendicular to the ground surface such that the sensing components completely rest in undisturbed soil volume and are below the non-sensing components. The geometrical mid-points of the vertically installed sensors' sensing components align with each other (lie on a common horizontal imaginary line). This installation fashion ensured that most of the sensing volume (manufacturer-reported) was comparable across all the sensors. This is a commonly known issue in soil moisture sensor evaluation setups and exists because every sensor has a different geometry of sensing components, and it will be impossible to make their sensing volumes totally coincide. Thus, the best strategy is to match the maximum proportion of each sensor's sensing volume to that of NP by aligning their midpoints, and this strategy was used in this research. For silt loam V, the imaginary horizontal line was at 30 cm from the ground surface, while for loamy sand V, it was 50 cm from the ground surface (installation was deeper due to higher infiltration rates than silt loam). For silt loam site H, the sensors were installed directly under the plant row within the root zone; and for silt loam V, they were installed in the inter-plant spacing, ensuring sampling of the root zone. All sensors, including NP access tubes, were installed between the healthy maize or soybean plants in an area with uniform emergence so that representative soil moisture measurements are made. Similarly, in loamy sand side, sensors were installed in an area with healthy grass cover with uniform grass cover.

The JD probe, being a multi-depth probe, had different installation specifications than those discussed above. JD probes can only be vertically installed perpendicular to the soil surface, and hence, we were not concerned with installation orientations in this case. The probe was installed into a cylindrical hole made by a snugly fitting Giddings probe, such that there was not any undue opportunity for preferential flow around the probe. Nevertheless, soil slurry (prepared from the soil taken from the same depth at the site) was used to ensure this. The JD probes were compared to NP soil moisture at five different depths where the capacitors are placed, i.e., 10, 20, 30, 50 and 100 cm. It should be noted that these depths are alterable, but manufacturer default depths were used in this research. All sensors and the NP access tubes remained in the soil throughout the two calendar years to maintain consistency and minimize soil disturbance.

2.5. Soil moisture data measurement and retrieval

All the sensors investigated were equipped with various manufacturer-recommended data loggers that read soil moisture status every minute and output hourly averages throughout the two growing seasons. It was ensured that the sub-hourly sensor readings were the same (do not change in such short time frame) and were accurately represented by the hourly average outputs, and there was no sampling time mismatch between instantaneous NP measurements and hourly average sensor measurements that were used for comparison. The datasets were retrieved manually, except for JD probe, for which telemetry system was used for data retrieval. The NP measurements were conducted at both access tubes at the two sites roughly every week throughout the two growing seasons. At each access tube, eight neutron count measurements were conducted each week, each corresponding to the depths where various sensors were installed, i.e., 10 cm (JD probe), 20 cm (JD probe), 30 cm (JD probe and all sensors under silt loam V), 50 cm (JD probe and all sensors under loamy sand V), 60 cm (for all sensors under silt loam H and loamy sand H), and 100 cm (JD probe). Measurement of weekly soil moisture resulted in a broad range of soil moisture conditions encountered to test the soil moisture sensors against at both sites. Although there were no sensors to be investigated at 90 cm and 120 cm depths, θ_{vref} was measured at these depths as well to aid in a scaling procedure, which is detailed in Section 2.7.

2.6. Statistical analysis

All sensors were evaluated for their performance in estimating θ_v, TSW, ET_c and IT using root mean squared error (RMSE, $m^3\,m^{-3}$), computed as in Eq. 1. It was aimed to compare various target variables predicted by sensors in question with those measured using true NP technique.

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(E_i-M_i)^2}{n}} \tag{1}$$

where, M_i is sensor-estimated variable, E_i is corresponding NP-reported reference variable, and n is number of observations. RMSE was used to denote the absolute value of the error that would be associated with these sensor-estimated variables, if the sensor in question is used to report soil moisture status, as calculated from the experimental data. Additionally, linear regression was used among pairwise data of sensor-estimated variables (on the ordinate) and true variables (on the abscissa) to quantify the estimates of slope and intercept, coefficient of determination (R^2).

2.7. Scaling of sensor performance to the root-zone profile

The experimental evaluation of the sensors was only accomplished at one depth. However, the objectives of this research entail that end-user targeted metrics (TSW, ET_c, and IT) be computed, which require incremental θ_v and measurements throughout the root zone profile. For example, computing TSW and ET_c will require implementing a soil water balance model at the root-zone scale, as water extraction occurs from the entire root length. Similarly, determining IT or irrigation scheduling has to account for the water deficit in the entire root zone. Having not measured sensor performance at multiple depths, a scaling approach was used to apply the performance models quantified at the experimental depths at incremental depths in the soil profile. The incremental depths were 30 cm, 60 cm, 90 cm and 120 cm and thus the root zone considered was 0 − 120 cm. The scaling approach assumes that the performance of the sensors with respect to the reference NP measurements does not change with depth, implying that the performance of sensors installed at 60 cm with respect to NP measurements can be scaled up to other depths within the root zone. As mentioned in Section 2.5, θ_{vref} was measured at all four incremental depths. Using these data, site-specific linear functions were developed among θ_{vref} measured at various depths (namely, θ_{vref} at 60 cm vs. θ_{vref} at 30 cm, θ_{vref} at 60 cm vs. θ_{vref} at 90 cm, and θ_{vref} at 60 cm vs. θ_{vref} at 120 cm). These functions (not presented here) model the relative moisture availability in the soil profile at various depths. Although the sensors in question are subject to errors, their inter-depth relative behaviour is systematic and thus, should mimic the inter-depth patterns demonstrated by NP-derived θ_{vref}. Thus, the inter-depth θ_{vref} relationships were applied to all the sensors to estimate sensor-specific θ_v at 30 cm, 90 cm, and 120 cm using θ_v at 60 cm as an independent variable. These operations resulted in sensor specific θ_v datasets at 30, 60, 90 and 120 cm at each site, which thereby were used for calculation of end-user targeted variables. It is critical to note that these estimated θ_v magnitudes at three additional depths were assumed to be subject to the same degree of inaccuracy that was measured at one depth.

2.8. Quantification of end-user targeted variables

Sensor-measured θ_v data as well as NP-measured θ_{vref} data were each used as input to compute sensor-derived and NP-derived TSW, ET_c, and IT, respectively, for both growing seasons using the methodologies outlined below. For all the end-user targeted variables, the exact same computational procedures (listed in 2.8.1 − 2.8.3) were adopted across all the sensors. The computational procedures use other variables, constants and assumptions in a certain manner to deduce the end-user targeted variables. For example, the water balance used to determine ET_c uses several input and output flux terms, that have their own methodologies. In order to not confound the signal of θ_v in the end-user targeted variables, it is critical that the methodologies are held constant across all the sensors, as well as the reference values of the same variables derived from NP. In doing that, the possibility of errors and uncertainties associated with other components of the computational procedure (e.g., the error associated with runoff or deep percolation estimation) was removed, which could have impact the inferences about propagation of θ_v errors into TSW, ET_c and IT metrics. Thus, any differences in TSW, ET_c, and IT deductions among various sensors would only be the function of θ_v, as other assumptions, constants, and variables are held stationary among investigated sensors and NP, and thus the effect of methodology is negated or cancelled out.

2.8.1. Total soil water (TSW)

The total soil water (TSW) in the complete monitored soil profile (0 − 120 cm) reflects the integration of moisture detected at individual incremental depths throughout the profile at daily scale. The depth of water present in each layer (0 − 30, 30 − 60, 60 − 90, 90 − 120 cm) was calculated by multiplying θ_v for each layer to the depth of layer (i.e., 300 mm).

$$\mathrm{TSW}=(\theta_{vlayer1}+\theta_{vlayer2}+\theta_{vlayer3}+\theta_{vlayer4})\times 300 \tag{2}$$

where, TSW is total soil water in the soil profile (mm), $\theta_{vlayerx}$ is θ_v (fraction; $m^3\,m^{-3}$) at xth layer (x ranges from 1 to 4). Layer 1, layer 2, layer 3 and layer 4 represent 0 − 30, 30 − 60, 60 − 90 and 90 − 120 cm depth of soil profile, respectively, and 300 represents the depth of each layer in mm. TSW reprsents the water storage in the soil matrix and does not account for macropore storage. The JD probes sensed θ_v at 10, 20, 30, 50 and 100 cm, and thus, unlike other sensors, represented 0 − 100 cm soil profile. Nevertheless, their assessment was conducted against NP-derived variables for the same profile depth, thus maintaining fairness of comparisons.

2.8.2. Crop evapotranspiration (ET_c)

A general soil water balance was used to compute ET_c as a residual from the closed equation:

$$P+I+U+R_{on}=R_{off}\pm\Delta SW+ET_c+D \tag{3}$$

where, P is rainfall (mm), I is irrigation water applied (mm), U is upward soil moisture capillary flux (mm), R_{on} is surface runon within the field (mm), R_{off} is surface runoff from the field (mm), ΔSW is the change in soil moisture storage in the soil profile (mm), and D is the deep percolation (mm) below the root zone. The deep percolation was estimated by daily soil water balance approach using a computer program that was written in Microsoft Visual Basic. The calculation of D considers a root zone that is modeled between a minimum (10 cm) and maximum value (120 cm) as a function of minimum and maximum values of basal crop coefficient (K_{cb}) derived from Jensen and Allen (2016). The inputs to the program were daily weather data (including air temperature, incoming shortwave irradiance, relative humidity, wind speed, and rainfall), irrigation dates and amounts, initial water content in the soil profile at crop emergence, and crop- and site-specific information such as planting date, maturity date, soil parameters, maximum rooting depth, etc. (Payero et al., 2009; Bryant et al., 1992). The computer program calculated daily ET_c and the water balance in the crop root zone using the two-step approach ($ET_c = K_c \times ET_o$, where ET_o is grass-reference evapotranspiration, and K_c (stage-based crop coefficients adopted from FAO-56 methodology) is the crop coefficient). In the program, ET_o is calculated using the weather data as input to the Penman- Monteith equation (Monteith, 1965; Monteith and Unsworth, 2007), and K_c is used to adjust the ET_o to that of the desired crops at different growth stages and growing environments. The daily soil water balance equation for deep percolation is:

$$D_j = Max(P_j - R_j + I_j - ET_{cj} - CD_{j-1}, 0) \tag{4}$$

where, D_j is deep percolation on day *j*, CD_{j-1} is root zone cumulative depletion depth at the end of day *j-1*, P_j is precipitation, R_j is precipitation and/or irrigation runoff from the soil surface on day j (mm), I_j is irrigation depth on day *j* (mm), and ET_{cj} is crop evapotranspiration on

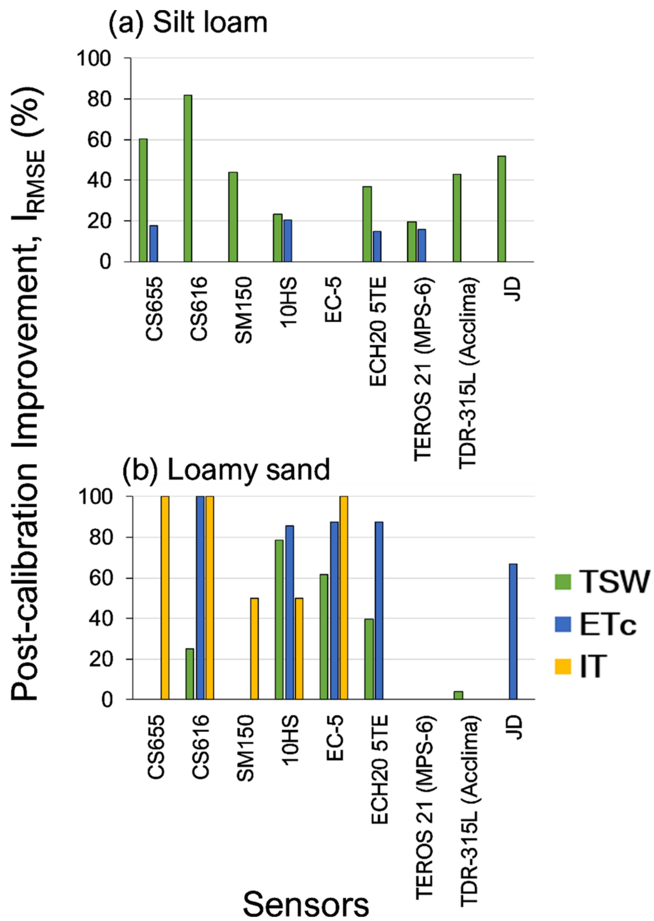

Fig. 3. Post-calibration (site-specific) improvement in estimation of total soil water (TSW), crop evapotranspiration (ET_c), and irrigation triggers (IT) in silt loam and loamy sand soils.

day *j* (mm) estimated by the two-step approach. CD_{j-1} was calculated via two pathways depending on the data availability: for days when total depletion is available from θ_{vref} or θ_v measurements, they were used directly. On the days when these were not measured, it was estimated as previous day's depletion (CD_{j-2}) minus (P_{j-1} + I_{j-1} - R_{j-1} - ET_{cj-1} - D_{j-1}). To initiate the calculations on the first day of soil water balance (i.e., planting date for silt loam soil), the CD_{j-1} was taken as initial depletion, which is 0, to initiate the water balance. The surface runoff from each field was estimated using the USDA Natural Resources Conservation Service (NRCS) curve number method (USDA-NRCS 1985). As outlined in USDA-NRCS (1985), Hydrologic Soil Groups for each soil type were determined, and curve numbers were determined for row crops and pasture surface covers under all antecedent moisture conditions to estimate daily Rj. The same procedure has been used to estimate field-scale and plot scale surface runoff at the experimental site previously (Kukal and Irmak, 2020; Irmak, 2015a). Runon was ignored from the soil water balance as the experimental field was not adjacent to any other field from which runon could be possible. Precipitation in each field was measured on an hourly basis (precipitation was sampled every 1 min, and output as hourly totals) using Bowen Ratio Energy Balance System (BREBS) equipped with rain-gauges in the field site, which were part of the larger Nebraska Water Energy Flux Measurement, Modeling and Research Network (NEBFLUX) (Irmak, 2010).With substantial research and experience with both the field sites in the past, it was established that the upward capillary flux (usually caused by a shallow water table, which is not the case here) and runon are negligible, due to the soil textural and hydraulic properties at the sites, and negligible slopes as well as no source of runon adjacent to the field sites, respectively. Thus, the soil water balance equation is reduced to the following form for calculating crop evapotranspiration ET_c:

$$ET_c = P + I - R - D \pm \Delta SW \tag{5}$$

2.8.3. Irrigation triggers (IT)

For the purpose of this research, an irrigation trigger was defined as the situation in the soil moisture time series when the TSW was equal to or lower than readily available water (RAW). RAW was computed for each experimental site as a difference of soil water at field capacity and maximum allowable depletion (MAD). For the purpose of IT computation, MAD was taken as 35 % for both the sites, which is a typical MAD value used with a safe buffer to avoid plant water stress. This should not be confused with the MAD that was used to actually irrigate the silt loam field (40–45 %), as mentioned in Section 2.1. Finally, the number of times an IT was observed in a soil moisture dataset sourced to each of the sensors were counted and compared to NP-derived IT as:

$$IT = n\,(TSW \leq RAW) \tag{6}$$

where, n indicates number of times the condition in the paranthesis is met. All units are in mm. The number of IT accounts for whether the senosor was able to report the attainment of the irrigation threshold used for management, when the reference NP did so. As mentioned earlier, the methods used to calculate the end-user targeted variables here are the standard, best available, and previously used methods (Irmak, 2015a). Nevertheless,weaknesses in methods, even if any, would not impact the assessments, given that the stationarity of methods across sensors and reference NP allows for only the θ_v signal to be propagated into the final magnitudes, and negation of the any methodological impacts.

2.9. Performance assessment of sensor-reported end-user targeted variables

The θ_v- and θ_{vref}-derived end-user targeted variables from 2017 were used to assess the sensors for their performance. Each sensor under factory calibration (F.C.) was characterized for its performance to reflect true TSW, ET_c and IT using RMSE. Additionally, soil-specific calibration functions to correct sensor-reported θ_v using regression analyses among θ_v and θ_{vref} were developed using datasets from 2017. Consequently, these functions were applied to F.C. sensor-reported 2018 θ_v datasets, and the resulting improved θ_v information was used to predict TSW, ET_c and IT under site-specific calibration (S.S.C.), and assessed against NP-derived variables. Thus, these calibration functions were implemented on the original (raw) independently collected moisture data from 2018. The original sensor TSW estimates and those after θ_v calibration were assessed against NP-measured TSW (TSW_{ref}) in 2018 and the respective RMSE's were calculated. Also, a measure metric "improvement in RMSE post-calibration (I_{RMSE})" was computed to represent the percentage change in success (improvement, decline or no change in sensor perfornamce) to estimate TSW after the calibrations were implemented relative to original RMSE. Thus, a positive I_{RMSE} implies improvement (Fig. 3) and a negative I_{RMSE} implies no improvement or even worsening of the estimation.

3. Results and discussion

3.1. Sensor performance in θ_v estimation

The pairwise θ_v and θ_{vref} data from the 2017 growing season were used in an ordinary least squares (OLS) regression analysis, and calibration parameters, i.e., slopes and intercepts of θ_v versus θ_{vref} regressions were determined. These parameters were used as observations to conduct a 3-way ANOVA test to statistically infer if sensor performance varied by soil types, installation orientation, and the choice of sensor. It was observed that the slope and intercepts were statistically different among the two soil types (at 99 % and 90 % confidence intervals). The slopes were statistically different among sensors (at 90 % CI), while the intercepts were not. Both the slopes and intercepts were not statistically different among the two orientations. Thus, while the choice of sensor and soil type significantly affected sensor performance, the installation orientation was not found to be a significant driver of sensor performance. The differences seen in the θ_v among V and H orientations can be a consequence of the differences in spheres of influence when the sensors in question are installed horizontally or vertically. For example, the volume of influence for a sensor such as CS655 will be a cylindrical one with a major and minor axis. The sensor will encounter more vertical volume in V orientation, and more horizontal volume in H orientation. The patterns of moisture dynamics can vary in these differently aligned volumes (with V orientation subject to greater θ_v along the sensing components), while NP sampling volume is static, which can cause differences in performance statistics.

Based on the abovementioned findings, the focus of this research inferences and discussion of sensor error propagation into end-user targeted variables will only be limited to the H sensor orientation. Since orientation did not affect estimation of θ_v, it follows as a corollary that it is also not a significant driver of end-user targeted variables as well. The H orientation was chosen due to the fact that the sensors' sampling volumes' major axes will be aligned in the horizontal soil cross-section, which encounters relatively lower spatial variability than its V orientation counterparts. Also, by selecting H orientation, it was ensured that research findings are consistent with the literature as most of the studies have evaluated sensors when installed in H orientation.

Sensor installation orientation can be an important on-farm water irrigation/management decision to make from an operational standpoint, although it did not affect sensor accuracy. This issue is relevant only for probe-based sensors, as it alters the actual volume of soil sampled by the sensor. Installation orientation is a critical decision to make at the field-level due to its role in conveying the geometry of sampled volume for soil water status, and both orientations (H and V) can be of varying interest to the user, depending on the intention and objectives. While installation orientation is also a strong function of sensor type used, a vast majority of soil moisture sensors are designed to be installed vertically. There are also labor-based differences resulting from specific orientations, as the ease and avoidance of labor can be vastly different during both installation and removal for one orientation over the other. The installation orientation remains an open question to the users, as majority of commercial sensors are often recommended (from manufacturer) to be installed in either orientation, without much or quantitative discussion of how these orientations will impact soil moisture reporting. This question can be answered by the users by evaluating if their intended applications require horizontally or vertically aligned spatial averaging. Moreover, it has to be evaluated by the users if the uncertainties involved with the use of a particular orientation are considerable enough when compared to their management resolution, and if they will potentially affect their decisions.

3.2. Sensor error propagation in end-user targeted metrics

3.2.1. Sensor error propagation in TSW estimation

A wide range of differences were observed when TSW was computed using soil moisture sensor-derived θ_v with respect to that computed using NP derived θ_{vref}. These differences were found to be soil type-specific, for a given sensor. To represent the errors resulting in TSW with the use of each sensor, RMSE of θ_v derived TSW values against θ_{vref} derived TSW was calculated (Table 2). In silt loam, all the sensors resulted in fairly large RMSE values for TSW estimation. The most and least accurate sensors in silt loam were Teros 21 (MPS-6) and CS616 (RMSE's of 111 mm and 551 mm, respectively). In loamy sand, the most and least accurate sensors, respectively, were CS655 (RMSE of 25 mm) and 10 HS (RMSE of 155 mm). Overall, it was found that, in general, the use of sensors to represent soil water dynamics (TSW) is a more challenging task in silt loam soil than loamy sand. It was found that post-calibrated TSW estimation for all sensors was improved in silt loam soil, and this improvement (I_{RMSE}) ranged from 19 % to 82 %. In loamy sand, however, not all sensors show improvement in TSW estimation. CS616, 10HS, EC-5, 5TE and TDR-315 L show I_{RMSE} that ranged from 4 % to 79 %. On an average, post calibration improvements were 45 % and 42 % in silt loam and loamy sand, respectively (Fig. 3). It is interesting to note that even after S.S.C., the reduced RMSE magnitudes in silt loam soils were three to five times the RMSE in loamy sand soils. However, the inherent differences in the plant available water (field capacity minus permananent wilting point) among the two soil profiles have to be taken into account. The plant available water is 201 mm and 171 mm in in silt loam soil and loamy sand soil, respectively. Nevertheless, the error encountered in TSW estimation was largely greater in loamy sand than silty loam soil, even after S.S.C. In both silt loam and loamy sand soils, JD probe demonstrated the best performance to estimate TSW, with or without S.S.C. The observation of no improvement in some sensors in loamy sand soil may be primarily due to: (a) already satisfactorily high performance under factory calibrations, (ii) low systematic component of the sensor performance than that in silt loam soils, and (iii) as a consequence, application of calibration functions resulting in overfitting, and hence, no improvement in performance. Thus, it might be more useful for these sensors to be used under factory calibrations in loamy sand, which implies that using site-specific calibrations does not always result in improved performance while estimating θv, or TSW. Efficient and objective sensor selection entails that appropriate resources that take into account measured performance statistics be made available for possible conduitions of use by the clientele. Thus, the performance statistics of all the investigated sensors were translated into simple relative rankings based on errors observed in their TSW estimation when compared to TSW_{ref}, under factory and site-specific calibration (Table 3). Across both F.C. and S.S.C., as well as both soil types, JD probe was ranked the best. It is recommended that these ranks be considered as a criteria for sensor selection, when accurate representation of end-user targeted variables is desirable, e.g., TSW, which is a common target for researchers studying crop root zone water dynamics. Moreover, Table 2 should be consulted for any sensor that is selected for use, so as to be aware of the errors they are subject to when under use in particular conditions, and keep these uncertainties under consideration to decide reliability of the sensor for decision-making and allowing a safe buffer for error.

3.2.2. Sensor error propagation into ET_c estimation

In addition to TSW, an important variable that is of interest to research community, water resources planning and management agencies, irrigators, and other agricultural professionals as an indicator of ET_c. To assess each sensor for their performance to reasonably estimate ET_c, θ_v measured by each sensor in a soil-water balance was used to compute ET_c as a residual from soil-water balance. Identical soil water balance approach was implemented for each sensor and both soil types to ensure that the resulting differences in ET_c are not confounded by the methdology deployed in this research. The components of the soil water balance differed across the two sites, including precipitation/irrigation (due to different location and management), runoff (due to different values of constants/inputs to NRCS curve number methodology), and deep percolation (due to different crop coefficients and soil inputs to the FAO-56 deep percolation methodology). However, these components were constant for all sensors within each of the given sites/soil type, to ensure fair comparisons and evaluation. The sensors were installed in the root zone profile of the row crops as well as grass, and thus measured the representative soil water conditions available for each crop for transpiration and evaporation processes. Since the two vegetative surfaces were drastically different (crop configuration, crop physiology, leaf area, ground cover fraction, root zone structure and volume), it is not recommended to compare ET_c values across the two sites for various sensors. As with TSW, the resulting sensor-estimated

Table 2
Performance statistics of soil moisture sensors to estimate total soil water (TSW) in the plant root zone profile (0-1.20 m) under factory calibration (F.C.) and site-specific calibration (S.S.C.) in silt loam and loamy sand soils. TSW_{ref} refers to the reference (true) TSW measured using neutron probe. *N/A* implies that the sensors were damaged/malfunctioned during the experiments.

Soil type	Year	Calibration	CS655	CS616	SM150	10HS	EC-5	5TE	TEROS 21	TDR-315 L	JD
			RMSE in TSW (vs. TSW_{ref}) in 0 − 1.20 m soil profile (mm)								
Silt loam	2017	F.C.	246	550	131	147	240	127	111	139	90
	2018		281	684	189	176	*N/A*	144	138	185	115
		S.S.C.	111	125	107	135	*N/A*	91	111	105	53
Loamy sand	2017	F.C.	25	30	27	155	86	38	251	26	20
	2018		28	30	29	158	71	35	*N/A*	34	18
		S.S.C.	31	23	36	34	27	21	*N/A*	33	18

ET_c quantities were compared with true ET_c (ET_{cref}) estimated from θ_{vref}. The percent deviation of sensor-estimated ET_c from ET_{cref} can be compared among different sensors at a given site (Table 4). It should be noted that in silt loam soil, ET_c represents maize water use in 2017, and soybean water use in 2018, while in loamy sand soil, ET_c represents pasture grass water use in both 2017 and 2018.

It was found in 2017 that all sensors underestimated ET_c in silt loam soil. The deviation of sensor-measured ET_c from true ET_c ranged from −14 % to −31 % (negative sign signifies underestimation), which implies that the choice of sensor under a given soil type impacts the quantification of consumptive use of the soil-vegetation system being monitored. Based on their absolute deviation from NP-determined ET_c, the sensors were ranked if they are used under F.C. (Table 3). In silt loam, JD probe, SM150 and CS655 ranked the best to estimate ET_c, while in loamy sand, SM150, TDR-315 L and CS615 ranked the best. Post-S.S.C., these rankings changed slightly (Table 3), which is a consequence of varying degrees of improvement achieved in different sensors using S.S.C, affecting the performance ranks achieved. While a sensor might rank among the best in a given soil, it still might be subject to high errors that can be detrimental to crop water use assessments and decision-making. For example, TEROS 21, when used under F.C. in silt loam soil, is ranked the third best sensor while demonstrating a deviation of 17 % from ET_{cref}, which might be unacceptable for research assessments of crop water uptake. Due to these reasons, the rankings have to be considered alongwith the statistics presented in Table 4.

Unlike what was observed in silt loam soil, sensors showed both overstimation and underestimation of ET_c in loamy sand soil. The deviations of sensor-estimated ET_c from ET_{cref} ranged from 14 % to −61 % in loamy sand. Interestingly, the best ranked sensors (SM150 and TDR-315 L) performed almost perfectly (0–1 % deviation) to estimate ET_c within 1 mm of ET_{cref}. The 2018 growing season was used to evaluate if S.S.C. led to any improvement in estimating ET_c using sensors. Fig. 3 shows the percent improvements resulting in ET_c estimation post-calibration (blue bars) under each soil type. On an average, across all sensors that showed any improvement at all, sensors in loamy sand showed an I_{RMSE} of 86 %, while those in silt loam showed an I_{RMSE} of 17 %. Among all the sensors in loamy sand soil, CS616 showed highest I_{RMSE} of 100 %, among others in the range of 67–88 %. However, these F.C. sensors did not have scope for improvement as their deviation was < 10 %. For example, CS616 improved from an underestimation of 0.9 % under F.C. to 0.4 % with S.S.C, which translates into 100 % improvement, but physically does not amount to much. In silt loam soil, 10HS had the highest I_{RMSE} at 21 % (improved from 29 % underestimation to 23 % underestimation), closely followed by CS655 (18 %), TEROS-21 (16 %), and 5TE (15 %). These observations suggest that almost all sensors can be used with S.S.C. in lomay sand soils with high accuracy to estimate ET_c. In silt loam soils, it is possible to estimate ET_c with selected sensors (JD probe, SM150) combined with S.S.C. with < 10 % RMSE.

The statistics provided in Table 4 act as empirical evidence-based criteria to consider while selecting a sensor to accurately quantify ET_c using a soil water balance approach. It is critical to understand that the uncertainties presented here are only attributable to the choice of soil moisture sensors, and not arising from assumptions in other soil water balance components. As mentioned earlier, any other confounding variables/methodologies that could influence the inter-sensor comparisons were strictly held constant. These uncertainty measures convey the impact of sensor selection process on reporting ET_c, which is useful for visualizing impacts, and superior to only considering impacts on θ_v. These details help the user select the best-performing sensor under a given soil type, determine if S.S.C. is beneficial, and become aware of the error/uncertainty associated with its use in hydrological research.

3.2.3. *Sensor error propagation into determining irrigation triggers*

The discussion of the impacts of sensor-estimated θ_v error propagation into derivation of TSW and ET_c was inclined primarily towards research use. However, the most sought-after application of soil moisture sensors, when employed for commercial production

Table 3
Ranking of soil moisture sensors when employed with factory calibration (F.C.) and site-specific calibration (S.S.C.) when measuring total soil water (TSW), crop evapotranspiration (ET_c), and irrigation triggers (IT) in silt loam and loamy sand soils. The color gradient (green to red) represents a transition from best performing sensor to the worst performing sensor. *N/A* implies that the sensors were damaged/malfunctioned during the experiments. The sensors performed equally poorly when used under S.S.C. to estimate IT in silt loam soil, and thus it was not possible to assign ranks.

Soil type	Calibration type	Metric	CS655	CS616	SM150	10HS	EC-5	5TE	TEROS 21	TDR-315L	JD
Silt loam	F.C.	TSW	7	8	6	4	*N/A*	3	2	5	1
		ET_c	3	6	2	8	*N/A*	7	5	4	1
		IT	2	2	2	2	*N/A*	2	1	2	2
Loamy sand		TSW	2	4	3	8	7	6	*N/A*	5	1
		ET_c	4	3	1	6	8	7	*N/A*	2	5
		IT	2	2	3	3	2	3	*N/A*	1	1
Silt loam	S.S.C.	TSW	6	7	4	8	*N/A*	2	5	3	1
		ET_c	3	8	1	6	*N/A*	7	4	5	2
		IT	No ranks; Equally poor performance								
Loamy sand		TSW	5	3	8	7	4	2	*N/A*	6	1
		ET_c	7	3	2	8	6	5	*N/A*	1	4
		IT	1	1	2	2	1	3	*N/A*	2	1

Table 4
Performance statistics of soil moisture sensors to estimate crop evapotranspiration (ET_c) under factory calibration (F.C.) and site-specific calibration (S.S.C.) in silt loam and loamy sand soils. ET_{cref} refers to the reference (true) ET_c measured using neutron probe. *N/A* implies that the sensors were damaged/malfunctioned during the experiments. JD probe-estimated ET_c was compared with ET_{cref} in column 5, while all other sensors were compared with ET_{cref} in column 4.

Soil type	Year	Calibration	Total ET_{cref}	Total ET_{cref} (for JD comparison)	CS655	CS616	SM150	10HS	EC-5	5TE	TEROS 21	TDR-315L	JD
					Total ET_c (mm); Percent Deviation from ET_{cref} (in parenthesis)								
Silt loam	2017	F.C.	492	671	396 (-20)	422 (-14)	349 (-29)	378 (-23)	357 (-27)	384 (-22)	340 (-31)	384 (-22)	472 (-30)
	2018		553	599	458 (-17)	440 (-20)	582 (5)	393 (-29)	*N/A*	403 (-27)	660 (19)	458 (-17)	623 (4)
		S.S.C.			473 (-14)	398 (-28)	502 (-9)	426 (-23)	*N/A*	424 (-23)	462 (-16)	438 (-21)	655 (9)
Loamy sand	2017	F.C.	316	301	329 (4)	334 (5)	317 (0)	179 (-43)	285 (-10)	325 (3)	122 (-61)	329 (4)	344 (14)
	2018		317	308	313 (-1)	314 (-1)	317 (0)	296 (-7)	292 (-8)	292 (-8)	*N/A*	317 (0)	300 (-2)
		S.S.C.			313 (-1)	318 (0)	316 (0)	321 (1)	314 (-1)	314 (-1)	*N/A*	317 (0)	310 (1)

management (by growers), is to aid in irrigation scheduling. Thus, an ideal sensor should be capable of accurately reporting the exact timing corresponding to when the soil-water status is depleted down to MAD, so as to effectively implement irrigation management practices. Irrigation depth is usually a pre-set amount (usually anywhere between 25.4 mm–38.1 mm) and is a function of well and irrigation system capacity. Thus, the sensor is expected to accurately report the timing when the pre-set amount needs to be applied. To evaluate each sensor, the number of times each sensor reported an irrigation trigger (IT) in comparison to what was reported by NP measurements (IT_{ref}) was counted and presented these comparisons in Table 5.

It was observed that in loamy sand, IT_{ref} were higher than that found in silt loam (10 in silt loam vs. 13 in loamy sand), which is justified due to differences in: (a) soil texture; and (b) irrigated crop production atsilt loam site vs. rainfed production in loamy sand site. During 2017 in silt loam, all the sensors (with the exception of TEROS21) severely underestimated observed IT, to the extent that they did not report even a single IT (Table 5). Thus, in silt loam soil, the use of TEROS21 resulted in perfectly optimal decision-making. In loamy sand soil during 2017, all sensors underestimated IT when compared to IT_{ref} except JD probe, which reported exact IT events. The deviation of IT from ITref varied from 15 % (in TDR-315 L) to 100 %, i.e., 0 IT reported (in SM150, 5TE, TEROS 21). Similar results were found by Fares and Alva (2000), where they found promising results by using capacitance probes (JD probe is a capacitance-based probe) for optimal irrigation in sandy soil. TDR-315 L only missed 2 IT and hence was the second-best performing sensor in loamy sand soils (Table 5). It was observed throughout the research findings that performance indicators of TSW, ET_c and IT estimation were relatively worse in silt loam soil than loamy sand soil. The primary reason for this behaviour is high clay contents in silt loam soil, for which bound water (water molecules bound to soil surfce by adhesive, cohesive and osmotic forces) effects can confound sensor performance. As with free water molecules, application of electrical field does not polarize bound water, which results in low dielectric permittivity, and misrepresentation of soil moisture (Hilhorst et al., 2001; Or and Wraith, 1999; Sun and Young, 2001). Higher the clay content, higher the bound water effects, and misrepresentation that is primarily seen in TDR sensors. Moreover, montmorillonite (a 2:1 clay mineral) is the dominant clay mineral in Hastings silt loam soil. Higher salinity in silt loam soil than loamy sand soil, as measured by electrical conductivity (169 % higher; Table 1) is another critcial factor that hinders accurate soil moisture measurement using both TDR and capacitance sensors. 2:1 clays have large surface areas, affecting bound water and bulk permittivity, confounding soil moisture estimation.

Interestingly, S.S.C. did not result in any improvement in estimating IT in silt loam soils. In fact, using S.S.C. with TEROS 21 resulted in inferior perforemance, as there existed no scope for improvement given that it performed perfectly under F.C. in silt loam. Findings of this research suggest that for these two growing seasons, none of the sensors could estimate IT with robustness, and in fact, none of them reported even one IT, under both F.C. and S.S.C. In loamy sand, however, S.S.C. resulted in improvement in IT estimation in five of the sensors. The I_{RMSE} averaged across all the sensors that showed improvement in loam sand soil was 80 %. Three of these sensors (CS655, CS616, and EC-5) showed a perfect estimation post-calibration (Fig. 3). JD probe maintained its perfect IT estimation both prior to and post-calibration. Table 3 can be consulted for the ranking of the sensors based on their IT-reporting performance, under F.C. and S.S.C., respectively. In silt loam soils, due to all sensors being equally inefficient at estimating IT, the they were limitedly ranked (or no ranks under S.S.C.). The ranks were limited to 1st-3rd for loamy sand soil as well for the same reasons.

When the findigs are viewed at from a sensing principle standpoint rather than a sensor-specific standpoint, there was no consistent observation of superior performance of one technological principal over another. When the performance criteria was averaged by sensor

Table 5
Performance statistics of soil moisture sensors to estimate irrigation triggers (IT) under factory calibration (F.C.) and site-specific calibration (S.S.C.) in silt loam and loamy sand soils. IT_{ref} refers to the reference (true) IT measured using neutron probe. *N/A* implies that the sensors were damaged/malfunctioned during the experiments. JD probe-estimated IT was compared with IT_{ref} in column 5, while all other sensors were compared with IT_{ref} in column 4.

Soil type	Year	Calibration	IT_{ref}	IT_{ref} (for JD comparison)	CS655	CS616	SM150	10HS	EC-5	5TE	TEROS 21	TDR-315L	JD
					IT; Percent Deviation from IT_{ref} (in parenthesis)								
Silt loam	2017	F.C.	10	7	0 (-100)	0 (-100)	0 (-100)	0 (-100)	0 (-100)	0 (-100)	10 (0)	0 (-100)	1 (-86)
	2018		5	4	0 (-100)	0 (-100)	0 (-100)	0 (-100)	*N/A*	0 (-100)	3 (-40)	0 (-100)	0 (-100)
		S.S.C.			0 (-100)	0 (-100)	0 (-100)	0 (-100)	*N/A*	0 (-100)	0 (-100)	0 (-100)	0 (-100)
Loamy sand	2017	F.C.	13	17	7 (-46)	8 (-38)	0 (-100)	2 (-85)	5 (-62)	0 (-100)	0 (-100)	11 (-15)	17 (0)
	2018		4	8	1 (-75)	1 (-75)	0 (-100)	0 (-100)	1 (-75)	0 (-100)	*N/A*	4 (0)	8 (0)
		S.S.C.			4 (0)	4 (0)	6 (50)	6 (50)	4 (0)	0 (-100)	*N/A*	6 (50)	8 (0)

technological principals, it was found that in loamy sand soil, TDR sensors performed the best, followed by capacitance –based, and electrial resistance-based sensors, and these trends were uniform across the three metrics. However, no clear trend was noticed in silt loam soils. This could be due to different mechanisms by which each sensor technology can be affected due from certain medium characteristics. In fact, none of these sensor technologies is capable of holistically accounting for various medium aspects that can be exploited for moisture measurement (Susha Lekshmi et al., 2014). For example, TDR sensors are based on Topp's equation (Topp et al., 1980), which is insensitive to porosity, pore fluid properties, saturation, and mineral constituency (Bhat and Singh, 2007; Susha Lekshmi et al., 2014) In fact, soil specific parameters such as clay content, ion concentration, mineralogy, salinity, porosity, ambient temperature, presence of the organic matter, matrix structure etc. are not being accounted by any of the available techniques. The mechanisms and magnitude of the intensity to which these factors affect the success of various sensing technologies are complex to decipher, especially in two contrasting soils as studied here. Some of these contrasting characteristics are: tilled annual cropped soils vs. long-term grass cover; irrigated vs. rainfed, silt loam vs. loamy sand texture, soil structure affected as a result of grazing vs. agricultural machinery; and salinity arising from agricultural fertilizers vs. no chemical inputs (see properties listed in Table 1).

The findings from this research suggest that assessments of soil moisture sensors can differ when different target metrics are investigated. A given sensor, even if relatively successful in predicting TSW and/or ET_c accurately, might not be equally successful in estimating IT. For example, in silt loam, SM150 performed reasonably well (rank 2) when predicting ET_c, but was ranked 6th when predicting TSW, and did not report IT well either. Although, all the end-user targeted variables rely fundamentally on θ_v for their derivation, the arithmetic nature of θ_v is what dictates them actually. For example, θ_v is used as an input to estimate ETc, but the absolute value of θ_v is not of much relevance in these calculations. Instead, the incremental change in θ_v (or TSW) in the root zone is what drives the soil water balance and thus, estimation of ET_c. As explained in the methodology, a period of roughly a week was considered for implementing the soil water budget. The net change in θ_v (or TSW) dictates the change in soil moisture storage term (ΔSW) of the balance, which consequently affects water available for transpiration or evaporation in the soil-crop system. If a sensor that performed poorly in reporting an accurate θ_v in the soil profile, but reported the same ΔSW (change) over time that the profile underwent, it would result in true representation of ET_c during that period. This characteristic of soil moisture sensors is commonly utilized in irrigation management extension programs to use relative calibrations (as opposed to absolute calibrations) in order to use low-cost sensors for efficient irrigation managemnent. Relative calibrations rely on recording change occuring in sensor output with visual response of wet and dry conditions and suffices proper sensor use because the sensor is just comapred to itself and not an independent standard. IT-oriented performance considers whether a soil moisture sensor is capable of reporting an event, when the sensor-reported θ_v attains a preset threshold required for irrigation scheduling. In this case, the sensitivity of the sensor to respond to drying at a rate that matches the rate truly demonstrated by the soil (as represented by true NP measurements) is more important that the absolute value of θ_v. This concept has also been proposed in assessment of satelite soil moisture products in agricultural landscapes (Champagne et al., 2016). They suggested that SMOS product was better at capturing the relative trends of soil moisture than Aquarius product, although it did not estimate absolute value to the same accuracy. Thus, the real applications of soil moisture sensors expected by diverse audiences require relative (change and rate based data) information rather than absolute θ_v information. In the same way as θ_v cannot be a governing single criterion for sensor selection for several end-user applications, similarly one end-user application cannot alone act as a criterion to dictate sensor selection. Moreover, irrespective of what the targeted metric is and what sensor is used, any application of technology in agricultural water management has to be informed by the margin of uncertainty associated with the application, and the resources presented here will be useful in this direction. Although we have ranked the sensors based on their accuracy statistics under each soil type, we recommend that the accuracy levels be relied upon to quantitatively evaluate how the use of a certain type of technology can affect assessments of critical agrohydrological variables such as total soil water, and evapotranspiration. It also cautioned that the objective of the research, was to translate θ_v based sensor assessments into commonly used agricultural water management terms, and not to communicate any relative suitability/unsuitability of commercial sensors. It is also realized that greater statistical power could have been gained by increasing the number of replicates in these experiments. As a consequence of limited dataset size and possibility of spatial heterogeneity, which is universal in any research relying on spot measurements, the findings may be subject to variability. Outside of sensor accuracy, there exist other operational feasibility factors that can influence the desirability of one sensor over another. Kukal et al., 2020 have discussed such factors including cost, ease of use and telemetry options in addition to sensor performance accuracy to develop a holistic guide for sensor selection.

4. Conclusions

This research evaluated nine soil moisture sensors for their suitability to estimate critical quantitative metrics that are expected by research users and growers. The need for this analyses arises from the facts that (1) accurate estimation of absolute θ_v by a sensor cannot determine its suitability alone, and that several relative aspects of sensor data can be practically useful even when absolute θ_v estimation is unacceptable; and (2) it is preferable to assess errors associated with sensor use in practical metrics used in real applications in addition to θ_v than θ_v alone. To address this, it was proposed that each sensor be evaluated based on its success in accurately reporting three major end-user targeted metrics: (a) TSW; (b) ET_c; and (c) IT. While TSW and ET_c are of greater interest to researchers, water planners and managers, irrigation districts, policy/decision-makers, IT is the primary intended use of the sensors when employed by growers and other commercial production personnel.

Under two different soil types, the sensor performance varied considerably across selected commercial sensors when evaluated for estimating TSW, ET_c and IT. Sensor installation orientation was also investigated as a driver, but was found to be statistically insignificant, and thus the research questions were limited to horizontally installed sensors (commonly employed in research and production settings). Three major sets of findings of how different sensors perform under each soil type for TSW, ET_c and IT estimations were presented: (a) suitability rank of each sensor; (b) the errors associated with each sensor when estimating these quantities; and (c) if S.S.C.s improve the performance of these sensors when compared to F.C. These resources provide objective direction on which sensor to employ and the uncertainty of assessments relying on these estimations

Employing soil moisture sensors was shown to be subject to substantial errors in estimation of TSW, ET_c and IT: as high as 684 mm (RMSE) in TSW in $0 - 1.20$ m soil profile (CS616 in silt loam); as high as 61 % deviation in ET_c (TEROS 21 in loamy sand); and as high as 100 % deviation in IT (no triggers reported at all). At the same time, certain sensors were able to estimate these quantities accurately under F.C. TSW was estimated to the accuracy of 18 mm (RMSE) using JD probe in loamy sand; ET_c was perfectly estimated (0–1 % deviation) using TDR-315 L and SM150 in loamy sand; and IT was estimated perfectly as well (exact number of IT_{ref} reported) using TEROS 21 in silt loam and TDR-315 L and JD probe in loamy sand soil. S.S.C. resulted in improvement in performance with 45 and 17 % improvement observed in TSW and ET_c in silt loam soil, respectively, and 42, 80 and 86 % improvement was observed in TSW, IT, and ET_c in loamy sand soil, respectively. The only exception where S.S.C. did not result in any improvement was IT estimation in silt loam soil.

To the best of authors' knowledge, this research is the first to translate traditional θ_v accuracy assessments into practical and application-oriented criteria and use them to evaluate sensors for these specific applications. The findings of this research are fairly transferrable given that the experiments were conducted in actual field settings that represented major agricultural land use types (row crops and pasture) and major soil types (silt loam and loamy sand) in the region. It is recommended that the resources presented herein can be used as effective and more intuitive assessment criteria along with more operationally relevant factors that can influence sensor suitability and desirability.

Declaration of Competing Interest

The authors declare no conflict of interest.

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