CONSERVING AGRICULTURAL WATER RESOURCES IN OKLAHOMA USING SMART TECHNOLOGIES

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Title: Conserving Agricultural Water Resources in Oklahoma using Smart Technologies

Authors' Names and Affiliations: Sumon Datta[1], Saleh Taghvaeian[2]

[1]PhD Student; Department of Biosystems & Agricultural Engineering, 111 Ag Hall, Oklahoma State University, Stillwater OK, 74078; Phone: 701-730-4742; email: sdatta@okstate.edu

[2]Assistant Professor; Department of Biosystems & Agricultural Engineering, 111 Ag Hall, Oklahoma State University, Stillwater OK, 74078; Phone: 405-744-8395; email: saleh.taghvaeian@okstate.edu

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Principal Investigators: Saleh Taghvaeian, Assistant Professor, Oklahoma State University; Sumon Datta, PhD Student, Oklahoma State University.

Publications:

1. Masasi, Blessing; Saleh Taghvaeian; Randy Boman; Sumon Datta, 2019, Impacts of Irrigation Termination Date on Cotton Yield and Irrigation Requirement, Agriculture, 9(2), 39.
2. Datta, Sumon; Saleh Taghvaeian; Tyson E. Ochsner; Daniel Moriasi; Prasanna Gowda; Jean L. Steiner, 2018, Performance Assessment of Five Different Soil Moisture Sensors under Irrigated Field Conditions in Oklahoma, Sensors, 18(11), 3786.

Problem and Research Objectives:

Agricultural irrigation is the prime consumer of freshwater in Oklahoma, accounting for 41% of the total water withdrawal in the state in 2007. The demand for irrigation water is expected to increase 20% by 2060 in Oklahoma, whereas, the “Water for 2060” plan outlined by Oklahoma Comprehensive Water Plan has set a goal of maintaining the level of freshwater use in 2060 similar to 2012. A main approach to meeting the increasing demand is through water conservation in irrigated agriculture by improving irrigation management. This is not possible without implementing smart technologies to perform a precise irrigation scheduling (Masasi et al. 2019). Use of soil water sensors is one of these promising smart technologies. Currently, however, only 11% of Oklahoma growers use any type of sensors to schedule irrigations. This number is 23% for Nebraska and 17% for California. Thus, there is an enormous potential for improving irrigation management using soil water sensors.

Implementation of soil water sensors is not straightforward. One reason is that variabilities in agricultural, climatological, and field conditions impact the accuracy and performance of sensors (Schwartz et al. 2016; Rüdiger et al. 2010). The lack of information on what type of sensor performs best under a given set of local conditions is one of the main barriers towards adoption of smart technologies. Therefore, conducting local research on the performance of different sensors can provide critical information for optimizing irrigation management. The primary objective of this study was to conduct a performance assessment test of five commercially available soil water sensors under soils with varying salinity and clay content in Oklahoma and to investigate how sensor-reported values can be used in irrigation management.

Methodology:

Two sites were selected for performance assessment, one with lower salinity and lower clay content (LSLC) located in central Oklahoma and the other in southwest Oklahoma with higher salinity and higher clay content (HSHC) (Figure 1). The EC of the soil solution was 1.2 dS m^{-1} at LSLC compared to 7.0 dS m^{-1} at HSHC. The clay content was 13.4% at LSLC and 38.7% at HSHC. Corn was planted at the LSLC site under center-pivot irrigation system and HSHC site was under furrow-irrigated cotton.

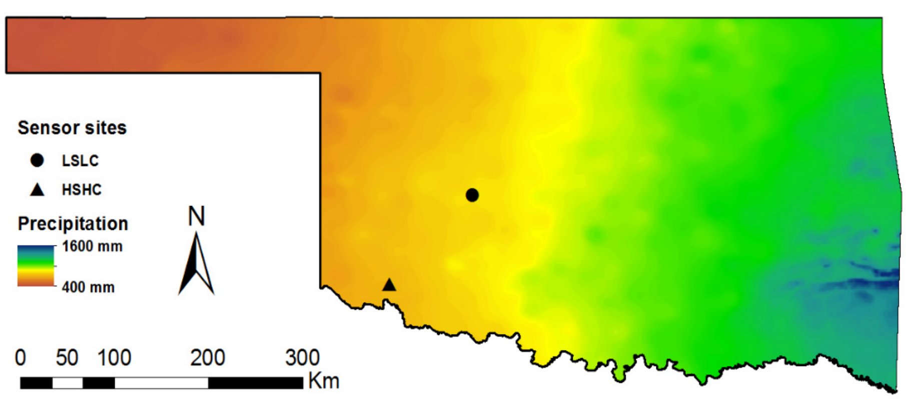

Figure 1. Experimental study site locations.

Five commercially available sensors were installed at each study site: Acclima TDR315, Campbell Scientific CS655, MeterGroup GS1, Spectrum Technologies SM100, and CropX. Each sensor had four replications, except CropX (two replications). Dataloggers recommended by manufacturer were used to collect hourly soil water content (SWC) data in form of volumetric water content (θ_v). The sensors were used with factory calibrations because the results obtained in this manner would best represent the conditions that irrigators and farm managers would face in the field. All sensors were installed at a soil depth of 20 cm (~8 inches).

At each replication, a pit was dug between two rows of crops to install the sensors. Soil samples were taken to determine important soil moisture thresholds, soil salinity, and soil textural information. Sensors were inserted horizontally into the sidewall of the pit (undisturbed soil) so that the rods of the sensors were on top of each other (vertical orientation). Tipping bucket rain gages were installed to collect irrigation and precipitation data. During the growing season, multiple gravimetric soil samples (four replications on each visit) were taken using Giddings soil sampling probe to estimate reference θ_v.

To evaluate the performance of the selected sensors, their θ_v readings were compared with reference θ_v values. Four statistical parameters, namely root mean square error (RMSE), RMSE-observations' standard deviation ratio (RSR), mean bias error (MBE), and index of agreement (k) were estimated. Better sensor performance was indicated by lower RMSE/MBE and RSR/k closer to unity. The coefficient of correlation was also determined to identify correlations between readings of different sensors.

Efficient irrigation management requires knowledge of two important soil moisture thresholds that indicate water availability for plant consumption (Datta et al. 2017). These thresholds are field capacity (FC) and wilting point (WP). Any water application over FC would be wasted to deep percolation. It is also desired to maintain SWC of an irrigated field above WP to avoid water stress. The FC and WP were determined using three different approaches: laboratory, sensor-based, and the Rosetta model. Laboratory method is SWC determination at -33 kPa for FC and -1500 kPa for WP. Sensor-based method was based on ranking of the collected data following the procedure proposed in Hunt et al. 2008. Rosetta model estimated FC and WP based on various level of inputs, having soil textural information and bulk density in consideration. Soil moisture deficit (SMD), an indicator or required irrigation depth, was calculated as the difference between FC and measured θ_v.

Principal Findings and Significance:

The fluctuations in θ_v were similar across all sensors at both study sites (Figure 2). All sensors responded to most irrigation and precipitation events. In some cases, there was little or no change in θ_v following a watering event, mainly because the amount of water received was not large enough to reach sensor installation depth. The results of performance evaluation (statistical indicators) are summarized in Table 1. In general, all sensors performed better at the LSLC, compared to HSHC. At LSLC, the RMSE was the lowest for CS655 (0.019 $m^3 m^{-3}$), followed by TDR315 (0.028 $m^3 m^{-3}$) and GS1

(0.048 m^3 m^{-3}). These sensors can be implemented for effective irrigation scheduling under conditions similar to those of LSLC. The MBE and RSR values indicated the same trend in overestimating the θ_v reported by sensors that can be also observed in Figure 3 (most points in the figure are above the 1:1 line).

All sensors had larger RMSE at the HSHC site compared to LSLC. However, the magnitude of the increase in RMSE was not uniform and changed from a slight increase for CropX to over an eight-fold increase for CS655. The CropX sensor had the smallest RMSE, followed by TDR315, GS1, CS655, and SM100. High clay content and elevated levels of salinity seem to be the main reasons behind lower sensor accuracies at the HSHC site. Most of the previous studies have also reported overestimation error for electromagnetic sensors under saline conditions.

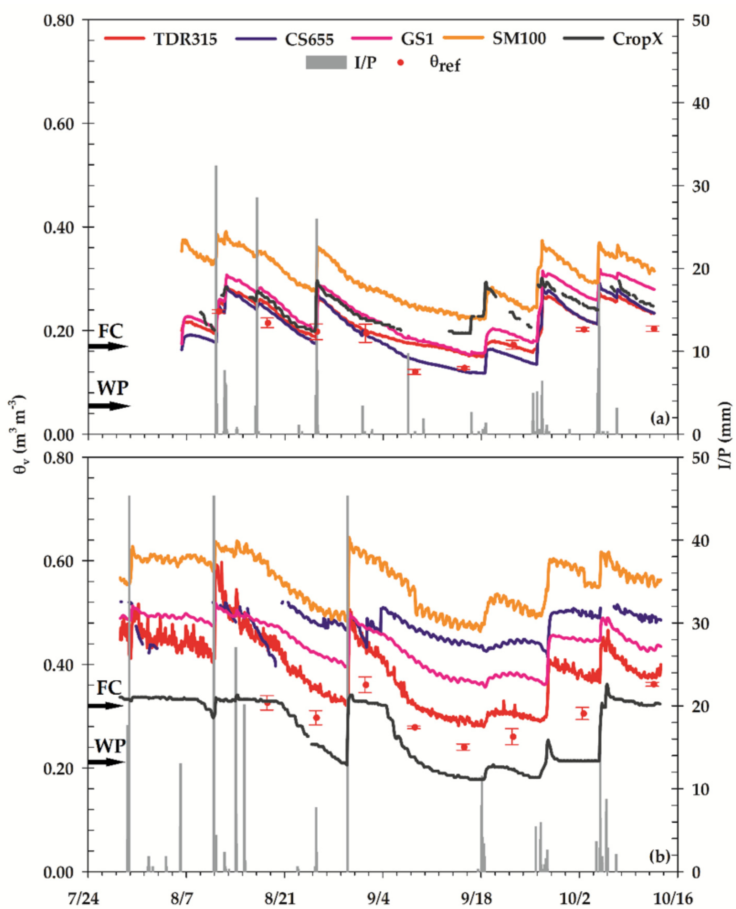

Figure 2. Sensor-estimated and reference θ_v at (a) LSLC and (b) HSHC sites.

Table 1. Performance indicators of soil moisture sensors.

Indicators	TDR315		CS655		GS1		SM100		CropX	
	LSLC	HSHC	LSLC	HSHC	LSLC	HSHC	LSLC	HSHC	LSLC	HSHC
RMSE (m^3 m^{-3})	0.028	0.064	0.019	0.165	0.048	0.122	0.110	0.233	0.051	0.055
RSR	0.76	1.55	0.53	3.99	1.31	2.97	3.00	5.66	2.53	1.34
MBE (m^3 m^{-3})	0.020	0.053	0.008	0.160	0.042	0.121	0.108	0.233	0.045	−0.049
k	0.85	0.69	0.94	0.30	0.69	0.41	0.44	0.26	0.58	0.75

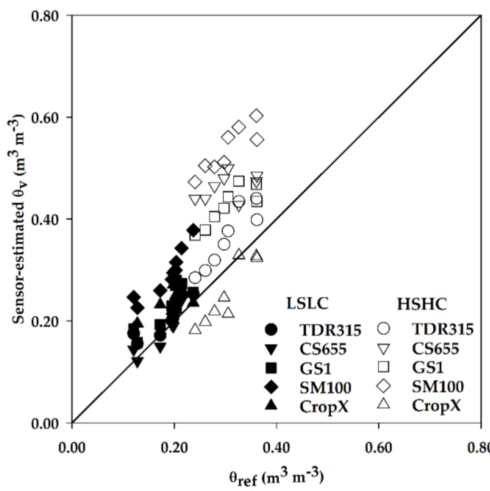

Figure 3. Sensor-estimated vs reference θ_v.

In utilizing soil moisture sensors for irrigation management, obtaining a complete time series is as important as taking accurate readings. In this study, CropX and CS655 had significant data gaps for different reasons. On average, 41% of the CropX data were missing at LSLC compared to less than one percent at HSHC. Correspondences with the manufacturer revealed that the potential reason behind this issue could be the tall corn canopy at LSLC, which can block the transmitted signals. Upon recommendation from the manufacturer, extension antennas were installed on CropX sensors at LSLC. The observed crop height was 2.16 m and the extension antennas were installed in such a way that the tops of the antennae were 1.91 m from the ground. However, this modification did not help with the apparent transmission problem. Reliability of the sensors is as important as the accuracy. The CS655 had 21% missing data at HSHC due to combined effects of elevated salinity and clay content causing attenuation of electromagnetic signal from the sensor.

In general, the Pearson's correlation coefficients (r) of θ_v readings were larger at LSLC than HSHC (Table 2). At this site, the strongest correlation (r = 0.99) was between TDR315 and CS655 and the weakest was between CropX and SM100 (r = 0.79). The correlation coefficients for CropX were smallest among all sensors at the LSLC site, ranging from 0.79 to 0.81. Despite being the least accurate sensor, SM100 had strong correlation with the top two accurate sensors, i.e., TDR315 and CS655. This indicates that SM100 closely followed the temporal changes in θ_v of more accurate sensors. At HSHC, the correlation between TDR315 and GS1 was the strongest (r = 0.97). The SM100 also had strong correlations with TDR315, GS1, and CropX. On the other hand, CS655 had weak correlations with other sensors.

The strong correlation between sensors with different accuracies suggests that the response of less accurate sensors to soil moisture fluctuations was similar to those of more accurate sensors. The differences in θ_v readings were relatively constant over the study period (offset error). This provides an opportunity for potential utilization of less accurate sensors in some limited applications where the user is only interested in determining the movement of the water front in the soil profile. One example of this application is leaching salts below the root zone. In this case, the user needs to ensure water front has moved below the bottom of the root zone. Another example is preventing deep percolation to ensure applied water remains within the root zone and that soluble chemicals are not transported to shallow groundwater resources.

Table 2. Pearson correlation coefficients among installed sensors at study sites.

	TDR315	**CS655**	**GS1**	**SM100**	**CropX**
LSLC					
TDR315	1.00				
CS655	0.99	1.00			
GS1	0.97	0.99	1.00		
SM100	0.95	0.95	0.92	1.00	
CropX	0.79	0.81	0.81	0.79	1.00
HSHC	**TDR315**	**CS655**	**GS1**	**SM100**	**CropX**
TDR315	1.00				
CS655	0.50	1.00			
GS1	0.97	0.57	1.00		
SM100	0.90	0.48	0.90	1.00	
CropX	0.86	0.42	0.85	0.78	1.00

Note all correlation coefficients were significant at p = 0.05.

Results of this study reveal that the Rosetta model is capable of accurately estimating soil moisture thresholds (FC and WP) even with minimal input data (textural classes). The USDA’s Web Soil Survey also performed satisfactorily, despite the fact that it is based on coarse soil surveys. However, the ranking method resulted in significant overestimation of FC when compared to laboratory estimates, ranging from 59 to 117% at the LSLC and from 6 to 94% at HSHC site. The difference between WP estimates of the ranking and laboratory methods varied from 100 to 283% at LSLC and from −14 to 129% at HSHC. A potential reason behind this poor performance could be that the full range of soil moisture conditions was not experienced at both sites during the period of study. However, this situation could be the case in many irrigated areas, since producers attempt to replenish soil moisture well before it reaches WP to avoid water stress and yield loss. Another reason behind the poor performance of the ranking method is the error in sensor readings, especially at HSHC, where most sensors overestimated soil moisture due to high clay content and elevated salinity levels.

Variations in hourly SMD are presented in Figure 4. In this figure, dots represent observed SMD based on reference θ_v and laboratory-determined FC, while lines represent sensor SMD based on sensor θ_v and FC from two methods: laboratory and ranking. At LSLC, observed SMD values were zero except on two sampling dates in early September. This is because this site was under full to slightly over-irrigation at most times during the study period. The only exception for the same period was in September when crop water demand outpaced irrigation application. Possible underestimation of θ_v at FC in the laboratory method may have contributed to zero SMD on most measurement dates too. In this study, a soil matric potential of −33 kPa was used to measure SWC at FC. But as mentioned before, this value can be as high as −10 kPa in sandy loam soil, resulting in a larger SWC at FC and consequently a larger SMD estimate. Sensor SMDs based on laboratory-FC had similar patterns, indicating no depletion during the study period except in the month of September (Figure 4a). On the other hand, sensor SMDs based on ranking-FC showed significant depletions at most times, reaching values as large as 0.15 $m^3 m^{-3}$ (Figure 4b). This increase in SMD is mainly due to overestimation of FC in the ranking method, since the same sensors readings were used in both SMD approaches.

At the HSHC site, the observed SMD indicated a larger depletion, especially during early September to early October. This pattern was expected since this site was under a low-frequency (7–10 days) flood irrigation regime that was not able to meet cotton water demand during the hot and dry month of September. At this site, sensor SMDs based on laboratory-FC showed no depletion except for CropX and TDR315. The SMD estimates of CropX were larger and the SMD estimates of TDR315 were smaller than observed SMD. This is because CropX underestimated θ_v, while TDR315 overestimated this parameter. The overestimation errors of the other sensors were so large that their θ_v readings were above laboratory-FC at all times, resulting in no depletion. The sensor SMDs based on ranking-FC were significantly larger than those based on laboratory-FC, except for CS655. This was because of the overestimation of FC by the ranking method. Hence, depletion was calculated at most times. The SMDs of CS655 were similar to the observed SMD, since the overestimation errors in θ_v readings and ranking-FC were similar in magnitude.

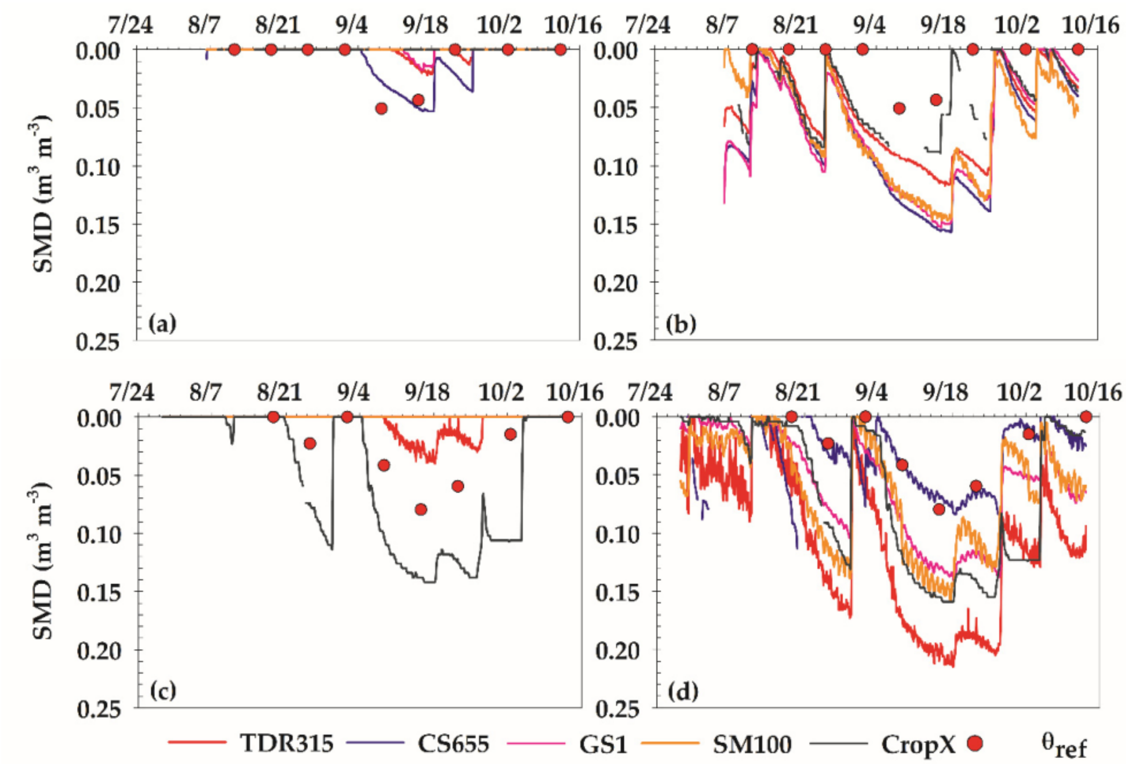

Figure 4. Time series of hourly soil moisture depletion (SMD) estimated based on sensor readings of θ_v and FC estimates from laboratory (a) and ranking (b) methods at LSLC site and laboratory (c) and ranking (d) methods at HSHC site. Dots represent SMD estimated based on reference SWC and FC estimates from laboratory method.

This study contributes to the existing knowledge on sensor-based irrigation scheduling through quantifying the accuracies of five widely-used soil moisture sensors as impacted by soil texture and salinity. In addition, the effectiveness of different soil moisture threshold estimation approaches for agricultural irrigation applications was investigated. The results highlighted the wide range of accuracies that exist among soil moisture sensors and methods for determining soil moisture thresholds. Such a wide range creates major challenges in utilizing soil moisture sensors for irrigation scheduling applications. As new sensors are being developed frequently, studies like this need to be conducted under variable field conditions to evaluate the performance of the new sensors and to provide guidelines on how they can be used for irrigation scheduling purposes.

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