EVALUATING THE PERFORMANCE OF IRRIGATION SCHEDULING APPROACHES BASED ON MONITORING AND MODELING SOIL WATER STATUS

By

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Abstract: Improving irrigation management through adopting scientific irrigation scheduling offers a great potential for optimizing irrigation applications and reducing water withdrawals. However, adoption of scientific irrigation scheduling approaches in irrigated agriculture is limited. More research and investigations are needed to demonstrate the performance and effectiveness of different irrigation scheduling approaches under variable soils, crops, and climatic conditions. The objectives of the research were to: (1) evaluate the performance of a multi-sensor capacitance probe in determining soil water content and field capacity, (2) study the effects of soil data accuracy on irrigation scheduling using a soil water balance model for different crops and climatic conditions across western Oklahoma, and (3) investigate the impact of variable soil data and root water uptake distributions on multi-layer soil water status and irrigation parameters simulated by a vadose-zone water transport model. The performance of a commercially available probe and its six calibrations provided by the manufacturer revealed how each calibration performed differently depending on clay and salinity levels. Evaluation of two sensor-based approaches in determining field capacity showed that both approaches were unreliable and highly sensitive to variations in soil texture and layers, irrigation systems, and irrigation management. Investigation of soil data accuracy using a soil water balance model revealed that easily obtainable web soil survey data may have relatively large impacts on irrigation recommendations at field scale, whereas the impacts could be small at regional scale. Evaluation of a vadose-zone model using variable soil data and root water uptake distributions, as model inputs demonstrated the importance of using accurate input data in irrigation scheduling models to achieve improvements in irrigation management.

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CHAPTER I

INTRODUCTION

1.1. Background

The world population is growing rapidly and is expected to reach over 9.7 billion by 2050 (United Nations, 2019). This will increase the food and water demand dramatically, making it critical to improve crop production using limited water resources. Keeping up with the growing demands and maintaining the economic and environmental sustainability of crop production requires advancements in irrigation management technologies. Development and application of better irrigation management technologies in agriculture can play a vital role in conserving water, securing crop production, and reducing the adverse impact on groundwater quality (Chen et al., 2020; Jabro et al., 2018). Thus, finding tools and methods to manage water more efficiently is critical to the future success of irrigated agriculture in the U.S. and globally (Howell, 2001; Pereira, 2017; Taghvaeian et al., 2020).

Several scientific methods have been developed to improve irrigation management decisions (i.e., irrigation scheduling) based on soil water status (SWS), plant characteristics, and/or crop modeling (Andales et al., 2014; Taghvaeian, 2020). Irrigation scheduling based on SWS is a widely accepted approach, which can be divided into two categories: SWS monitoring and soil water balance modeling (Taghvaeian et al., 2020). Monitoring SWS using accurate, reliable, and properly installed and maintained soil water sensors can help with developing effective irrigation scheduling, reducing over- and under-irrigations, decreasing energy requirements, and improving crop yield (Belayneh et al., 2013; Lichtenberg et al., 2013; McCann and Starr, 2007). Despite these potential advantages, the adoption of soil water sensors is still limited in irrigation management (Campbell et al., 2009; Lichtenberg et al., 2013). About 12% of farms across the U.S. are currently using soil water sensors for irrigation scheduling (USDA-NASS, 2019), showing a small increase compared to the 10% in 2013 (USDA-NASS, 2014).

Several factors could be responsible for the limited adoption of these sensors. One factor is the complexity of selecting sensors that could perform reliably under variable field conditions. This is because sensors with different technologies perform differently under variable soil and water conditions. For instance, many studies have shown that the errors in sensor readings are impacted by clay content (e.g., Haberland et al., 2014; Parvin and Degré 2016; RoTimi Ojo et al., 2015; Tedeschi et al., 2014) and salinity (e.g., Baumhardt et al., 2000; Thompson et al., 2007). Most of these studies have calibrated sensors and suggested site or soil-specific calibrations for more accurate estimation of SWS. This could be a challenge for growers because of time commitment, labor requirements, and lack of financial and technical resources. In this case, a practical solution is to conduct sensor performance studies under variable field conditions and using factory calibration to recommend the most suitable sensor for a range of field conditions. However, there has been a lack of studies that test soil water sensors under variable irrigated fields.

Although soil water sensors can provide accurate estimation of SWS, they may not be the desired choice of some growers due to the complexity of choosing appropriate sensor (discussed above), cost of sensors, and time commitment involved in installing, maintaining, and removing them. In these cases, the other SWS-based approach to irrigation scheduling, namely soil water balance modeling, can be used to simulate SWS (Simunek et al., 2005). Soil water balance models can be as simple as a bucket-type water balance model or as advanced as models like HYDRUS that estimate SWS at various soil depths. A challenge in using these models is that they require several input data for reliable estimation of SWS and other water fluxes. A key group of input data is related to soil conditions (texture, bulk density, hydraulic properties). Advanced models, which are more powerful tools (Negm et al., 2017) and can describe most of the physical processes in the soil-plant-atmosphere system (Panigrahi and Panda, 2003), require more input data, such as root water uptake distribution (RWUD).

Improper representation of model inputs could largely impact the outputs of the model. The importance of input data accuracy has been recognized for a long time. Miyamoto (1984), for example, developed a computer model for scheduling pecan irrigation and argued that reliability of model outputs depends on the quality of model inputs and assumptions. In the case of soil characteristics, input data for applications in the U.S. are typically obtained by one of two methods: in-situ soil sampling (ISS) and USDA's Web Soil Survey (WSS) online database. The soil data from WSS are free-of-charge and easy to access manually by the user or automatically by the model but are less accurate than ISS. Krounbi et al. (2011) mentioned that SWS at different layers is highly dependent on soil properties including soil texture. According to Zylman et al. (2005), soil texture showed weak relationships between WSS and ISS. Thus, less accurate soil data could produce larger errors in estimating SWS and that could eventually impact irrigation scheduling decisions. Previously, many studies have simulated SWS and irrigation decisions using soil data from WSS (e.g., Awal and Fares, 2019; Liang et al., 2016; Resop et al., 2011) or ISS (e.g., Chen et al., 2014; Datta et al., 2021; Wang et al., 2016). However, there has been a lack of studies that compared the two sources of data and investigated their effects on model outputs.

In the case of RWUD, Ojha et al. (2009) highlighted that improper representation of this parameter could be one of the challenges for accurate simulation of SWS. RWUD can be assumed constant or linearly distributed in the crop root zone or can be obtained from field measurements that require equipment, labor, and time. Most previous studies have used constant or linear RWUD (e.g., Iqbal et al., 2020; Jiang et al., 2010; Li et al., 2017; Tafteh and Sepaskhah, 2012). Li et al. (1999) compared constant and linear RWUDs with the RWUD based on field measurements and found that the field-based approach provided better estimates of SWS. Besides this study, there have been only a few other studies that compared different RWUDs and their impacts on simulating SWS (e.g., Li et al., 2001a; Li et al., 2001b; Prasad, 1988). To the best of our knowledge, none of them investigated the eventual effects on SWS-based irrigation parameters.

Due to ease of applicability at the field scale level, soil water balance models have been used for irrigation recommendations by web-based tools (Andales et al., 2014; Chauhan et al., 2013; Sassenrath et al., 2013) and mobile applications (e.g., Bartlett et al. 2015; Migliaccio et al., 2016; Peters et al., 2013; Vellidis et al., 2016). Use of inaccurate input data in these models could produce errors in recommended irrigation amounts and frequencies. There is a critical need to investigate the possible impacts on SWS simulations and irrigation recommendations due to variability in major data sources under variable field and climatic conditions.

1.2. Objectives

The main goal of this research was to evaluate the performance of irrigation scheduling approaches based on monitoring and modeling SWS to improve irrigation management decisions. The specific objectives of this research were:

1. To evaluate the performance of a multi-sensor capacitance probe in determining soil water content and field capacity,

2. To study the effects of soil data accuracy on irrigation scheduling using a soil water balance model for different crops and climatic conditions across western Oklahoma, and

3. To investigate the impact of variable soil data and RWUDs on multi-layer SWS and irrigation parameters simulated by a vadose-zone water transport model.

CHAPTER II

PERFORMANCE OF A MULTI-SENSOR CAPACITANCE PROBE IN ESTIMATING SOIL WATER CONTENT AND FIELD CAPACITY

2.1. Introduction

Accurate measurement of soil water content is important for efficient irrigation scheduling (Irmak and Irmak, 2005). Different approaches are available for irrigation scheduling based on soil water content. Among them, monitoring by soil water sensors is a widely known approach that can be used effectively in irrigation scheduling (Chappell et al., 2013; Kukal et al., 2020; Yadav et al., 2020). However, only 12% of farms in the U.S. are currently irrigated based on soil water sensor readings and this number is even smaller in Oklahoma (5%) (USDA-NASS, 2019). The low adoption rate of sensors raises concerns about technology transfer between research and applications (Kukal et al., 2020). Factors such as difficulty in selecting sensors, errors in soil water content estimates, spatial heterogeneity in the fields, and the knowledge required to properly translate sensor readings to irrigation decisions have been mentioned as potential reasons behind the limited adoptions of sensors (Campbell et al., 2009; Dietrich and Steidl, 2021; Kukal et al., 2020; Sharma et al., 2021; Taghvaeian et al., 2020).

Multi-sensor capacitance probes have been among the most popular types of soil water sensors because of their lower cost, relatively easier installation and removal, and ability to represent several points across the soil profile. However, volumetric soil water content (θ_v) from capacitance sensors is sensitive to clay content and salinity (Baumhardt et al., 2000; Thompson et al., 2007; Haberland et al., 2014; Tedeschi et al., 2014; RoTimi Ojo et al., 2015; Parvin and Degré 2016). Several previous studies have suggested the development and use of soil-specific calibrations to improve sensor accuracy. This, however, could be challenging from the growers' perspective due to their lack of financial and technical resources and time to conduct such calibration projects. Accuracy assessment and calibration studies conducted by universities and research institutions are not always helpful either, especially if conducted under laboratory conditions or a few field locations with limited variability in clay content and salinity levels (e.g., Caldwell et al., 2018; Chow et al., 2009; Datta et al., 2018; Ganjegunte et al., 2012; Leib et al., 2003; Singh et al., 2018). Furthermore, new or upgraded sensors are introduced to the market every season, requiring continuous evaluation of sensor performance.

Knowledge of soil water content alone is not sufficient for scheduling irrigation events. Water content readings of sensors and probes must be compared against soil moisture thresholds to determine the need for irrigation and the amount to apply. The most critical threshold used in irrigation scheduling is field capacity (FC), which indicates the upper limit of plant available water retained by the soil (Cassel and Nielsen, 1986). FC is either measured in lab or (more commonly for irrigation scheduling) obtained from tables based on soil texture. Estimating FC based on soil water sensors would be beneficial to end-users as it allows them to use the information collected by the same device to decide about both the timing and the amount of water to apply. Several previous studies have looked at FC estimation based on soil water sensor data. For example, Hunt et al. (2009) ranked the collected data during a few growing seasons and considered the 95th percentile as the FC. Datta et al. (2018) implemented the same approach and found that it significantly overestimated FC when compared to laboratory measurements. They mentioned the limited range of soil water content data and errors in sensor readings as potential reasons for poor performance of this approach. Sui and Vories (2020) and Vories and Sudduth

(2021) assumed soil water content data 1-2 days after major watering events is a good estimate of FC for different soil types. However, 1-2 days may not be sufficient to reach FC depending on soil type and layer depth.

Jabro et al. (2009) estimated FC based on soil water retention curve developed from soil water content and soil matric potential data and found that soil water content reached FC about 2 days for sandy loam and 19 days for clay loam soils. A study by de Jong van Lier and Wendroth (2016) assessed FC based on reaching a fixed bottom flux (1 mm d^{-1}) using numerical simulations of internal drainage experiments at 46 locations and found that FC condition occurred 4 days after watering events when considering only the top 15 cm and 2 weeks for a 75-cm profile depth. Other studies have used automated computer algorithms for determining FC. In the study by Fazackerley and Lawrence (2011), a nonlinear curve fitting model was used, and Bean et al. (2018) evaluated machine learning approaches, obtaining promising results for coarse textured and well drained soils. Evett et al. (2019) highlighted that field-observed FC values differ from laboratory-determined values and mentioned that as accurate sensors become more available, these differences will become more evident. It is necessary to further investigate field estimates of FC based on sensor data in variable climatic conditions, crop types, and soil conditions and explore the effectiveness of these approaches.

The overall goal of this study was to assess the performance of a commercial multi-sensor capacitance probe for irrigation scheduling under a wide range of field and climatic conditions. The specific objectives were to 1) evaluate the accuracy of the probe for different calibrations provided by the manufacturer in irrigated crop fields with variable clay content and salinity levels, 2) investigate the effects of clay content and salinity on sensor performance, and 3) estimate sensor-based field capacity used in irrigation scheduling.

2.2. Materials and Methods

2.2.1. Study Sites

The study was conducted during the 2020 and 2021 crop growing seasons at thirty-six sites across western Oklahoma (Figure 2.1). The sites varied in climatic condition, irrigation system, crop, clay content, and salinity. The climate conditions varied from semi-arid (BSk) in Oklahoma panhandle to humid subtropical (Cfa) in west central according to the Koppen-Geiger climate classification. The irrigation systems included furrow, center pivot, and subsurface drip. Cotton (*Gossypium hirsutum* L.) and maize (*Zea mays* L.) were the dominant crops. Clay content varied from 8 to 45% and electrical conductivity of the soil solution (1:1 soil-water ratio; $EC_{1:1}$) ranged from 0.5 to 28.5 dS m^{-1}.

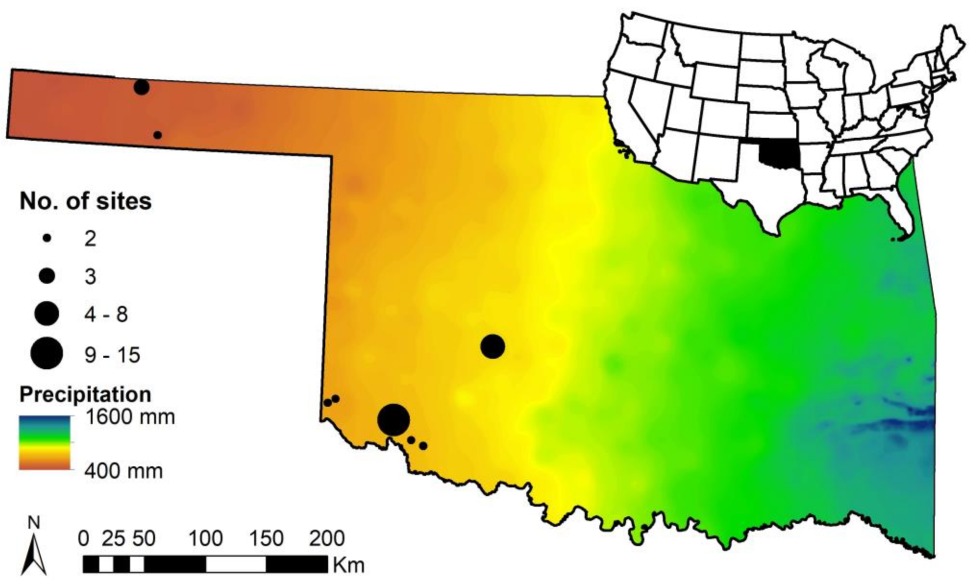


Figure 2.1. Study locations and the number of testing sites at each location. The background map displays long-term average annual precipitation.

2.2.2. Accuracy Assessment

Volumetric water content (θ_v; cm^3 cm^{-3}) was estimated at each site by Sentek Drill & Drop probes (Sentek Sensor Technologies, Stepney, South Australia). The probe had 12 capacitance sensors located at 10-cm intervals along its length of 1.2 m. A representative spot was selected at each location and a hole was drilled between two healthy plants in the crop row. The probe was wetted with water and inserted carefully into the hole, pushing it all the way down until the top of the probe was flush with the soil surface. The probes recorded θ_v at 60-min intervals and automatically uploaded the data to cloud servers. The recorded data were downloaded separately for six calibrations provided by the manufacturer: Default, Combined, Heavy clay, Sand, Silt loam, and Silty clay loam calibrations.

Undisturbed soil samples (3 replications) were collected at about 5 cm distance from the probe center and 10-cm depth intervals from the surface to 60 cm below the soil surface, matching the top six sensor depths on the probe. A Giddings soil sampling tool (3-cm diameter, Giddings Machine Company, Windsor, CO, USA) was used for sample collection. Soil samples were placed in sealed plastic bags immediately after collection and stored in a box to reduce evaporation. After transfer to the Soil Physics Laboratory at Oklahoma State University (OSU), samples were oven-dried at 105 ºC for 24 h to determine their bulk density and soil water content, which is regarded as observed θ_v. Soil samples were then sent to the Soil, Water, and Forage Analysis Laboratory at OSU for soil textural analysis based on the protocol set by Ashworth et al. (2001) and electrical conductivity measurements using the 1:1 soil to water extract ($EC_{1:1}$) method explained in Zhang et al. (2002).

To identify the accuracy of sensor-based θ_v, the readings based on each of the six manufacturer calibrations were compared with their corresponding observed θ_v. Two commonly used statistical indicators of mean bias error (MBE) and root mean square error (RMSE) were calculated:

$$\mathrm{MBE}= \frac{1}{n}\sum_{i=1}^{n} (\theta_{vs(i)} - \theta_{vo(i)}) \tag{1}$$

$$\mathrm{RMSE}= \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\theta_{vs(i)} - \theta_{vo(i)})^2} \tag{2}$$

where n is the number of observations, $\theta_{vs(i)}$ is the sensor-based θ_v, and $\theta_{vo(i)}$ is the observed θ_v. These error indicators were further analyzed for three ranges of clay (≤15%, 15-30%, and >30%) and three ranges of $EC_{1:1}$ (≤2, 2-9, and >9 dS m^{-1}) to better understand the effects of clay and salinity on sensor accuracy.

2.2.3. Field Capacity Estimation

Observed field capacity estimates were obtained by taking three replications of undisturbed soil cores (diameter = 2.5 cm, length = 5.1 cm) using the Sample Ring Kit (Model C, Eijkelkamp Soil &Water, Inc., Giesbeek, The Netherlands) near 13 Sentek probes and centered on two soil depths of 5 and 15 cm. The samples were placed in a sand-kaolin box to determine field capacity at two matric potential levels of -10 and -33 kPa, following the method described by Romano et al. (2002).

The laboratory FC estimates were then used to evaluate and modify two sensor-based approaches: days to reach laboratory FC after major watering events and the percentile of collected sensor readings that represent laboratory FC. In the first approach, major watering events were considered those that had at least 15 mm d^{-1} of rain or irrigation, similar to Hunt et al. (2009). The time series of sensor-based θ_v after these events were analyzed during the crop growing season and the number of days it took sensor θ_v to reach laboratory FC was identified for each event at each of the 13 sites and the two soil depths of 5 and 15 cm. In the second approach (percentile), sensor-based θ_v data collected during 60 days in the middle of the growing season were ranked and the percentile that matched laboratory FC was determined, resulting in one estimate per each soil depth and site. The sites and depths that had a sensor θ_v error larger than 0.08 cm^3 cm^{-3} when compared to gravimetric sampling were excluded from the analysis. The decision about which laboratory FC (the one measured at matric potential of -10 kPa or the one at -33 kPa) to use in evaluating sensor-based approaches was based on soil texture of each site and depth and following the recommendations of previous studies. The laboratory FC at -10 kPa was used for soils/depths that had sand percentage greater than 70% and laboratory FC at -33 kPa was used for all others (Rivers and Shipp, 1972; Lena et al., 2022).

2.3. Results and Discussion

2.3.1. Accuracy Assessment

Sensor accuracy was influenced by the manufacturer calibration used in estimating θ_v. When all sites and soil depths were combined, the smallest RMSE belonged to the Silty clay loam calibration (0.05 cm^3 cm^{-3}), followed by the Combined and Silt loam calibrations (Table 2.1). Interestingly, the Default calibration resulted in the largest RMSE (0.19 cm^3 cm^{-3}), suggesting that careful selection of the appropriate calibration and not simply relying on the default setting could have a major impact on sensor performance. Based on the sensor accuracy classification of Fares et al. (2011), the RMSE of Silty clay loam and Combined calibrations would fall under the poor category and the other calibrations under very poor.

Table 2.1. Root mean square error (RMSE) and mean bias error (MBE) of six manufacturer provided calibrations when considering all samples.

Statistical indicators	Manufacturer's calibrations					
	Default	Combined	Heavy clay	Sand	Silt loam	Silty clay loam
RMSE (cm^3 cm^{-3})	0.19	0.08	0.14	0.18	0.11	0.05
MBE (cm^3 cm^{-3})	0.16	0.05	0.13	0.15	0.07	0.00

The errors found in this study were comparable to or larger than previous studies. For example, Campora et al. (2020) tested the same capacitance probe (Sentek Drill & Drop) in two types of sand and reported RMSE range of 0.02-0.04 cm^3 cm^{-3} for three manufacturer calibrations, including the Default one. The smaller errors of their study could be attributed to the fact that only sands were tested (low clay content) and that the study was conducted under laboratory conditions. Gabriel et al. (2010) tested another model of Sentek probes (EnviroSCAN) that uses the same technology as Drill & Drop and found RMSE range of 0.04-0.09 cm^3 cm^{-3} for manufacturer's Default calibration during calibration and validation under lab and field conditions. A more recent study of Sentek EnviroSCAN reported larger RMSE of 0.06, 0.14, and 0.18 cm^3 cm^{-3} based on Default calibration in sand, clay, and loam soils, respectively (Kibirige and Dobos, 2021). However, texture-specific calibrations from the manufacturer's libraries improved sensor performance and reduced RMSE to 0.02-0.04 cm^3 cm^{-3}. Other sensors that use similar capacitance technology (e.g., Sentek Diviner 2000, AquaCheck, Decagon Devices ECH_2O EC-5, WaterScout SM100) have shown to have RMSE estimates ranging from 0.04 to 0.23 cm^3 cm^{-3} when used with their manufacturer calibrations (Al-Ain et al., 2009; Francesca et al., 2010; Tedeschi et al., 2014; Sing et al., 2018; Hajdu et al., 2019), with the larger RMSE estimates obtained under higher clay content and salinity (RoTimi Ojo et al., 2015; Provenzano et al., 2016; Datta et al., 2018).

The other statistical indicator, MBE, resulted in a ranking of calibrations that was similar to the ranking based on RMSE. The Silty clay loam calibration had the smallest MBE, followed by Combined and Silt loam calibrations (Table 2.1). The Default calibration had the largest MBE, indicating the importance of changing the calibration by users according to the conditions of their intended application site. The MBE estimates showed general overestimation of θ_v for all calibrations except Silty clay loam (Figure 2.2). Many previous studies have found overestimation of θ_v when manufacturer calibrations were used with capacitance probes and sensors (Leib et al., 2003; Gabriel et al., 2010; Ganjegunte et al., 2012; Al-Ghobari and El Marazky, 2013). Other studies have observed underestimation errors for lower water contents and overestimation errors for higher water contents when capacitance sensors were used with factory calibration (Geesing et al., 2004; Polyakov et al., 2005; Kibirige and Dobos, 2021). Hajdu et al. (2019) showed underestimation of θ_v by AquaCheck probe for various calibrations.

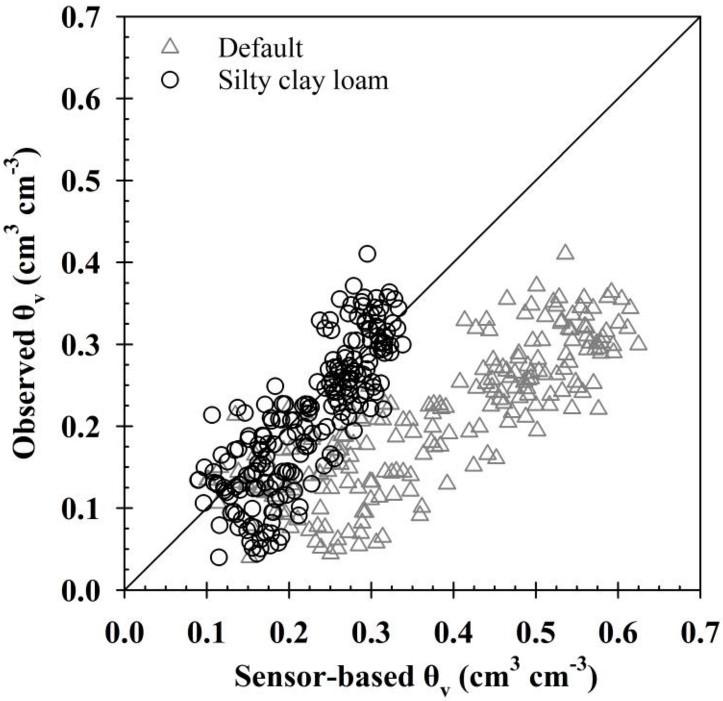


Figure 2.2. Comparison between volumetric soil water content (θ_v) obtained based on the Default (largest RMSE) and Silty clay loam (smallest RMSE) calibrations and observed θ_v.

Sensor accuracy is an important factor in sensor-based irrigation scheduling. In addition to accuracy, however, probes and sensors must be able to capture the full range of soil water content fluctuations. Investigating different calibrations revealed that besides their different accuracies, they result in different ranges of soil water content, a factor that should be considered in choosing the most appropriate calibration. Figure 2.3 shows the frequency distribution of the ratio of sensor-based θ_v to saturation θ_v for the three most accurate calibrations at five sites with the highest clay and five sites with the highest sand and three soil depths of 5, 15, and 25 cm at each site. The three shallowest soil depths were selected because they are subject to more fluctuations in water inputs and outputs compared to deeper layers. The Silty clay loam calibration that had

RMSE of 0.05 $cm^3 cm^{-3}$ had smaller range of ratios (0.26-0.71 for high clay sites and 0.16-0.56 for high sand) compared to the other two calibrations and never approached saturation, even after major watering events at the 5 cm depth. The ranges of these ratios for the Combined calibration with RMSE of 0.08 $cm^3 cm^{-3}$ was 0.21-0.91 for high clay and 0.11-0.66 for high sand. Considering the larger and more realistic ratios of the Combined calibration, it would be recommended over the Silty clay loam calibration for practical irrigation scheduling, despite its slightly larger RMSE.

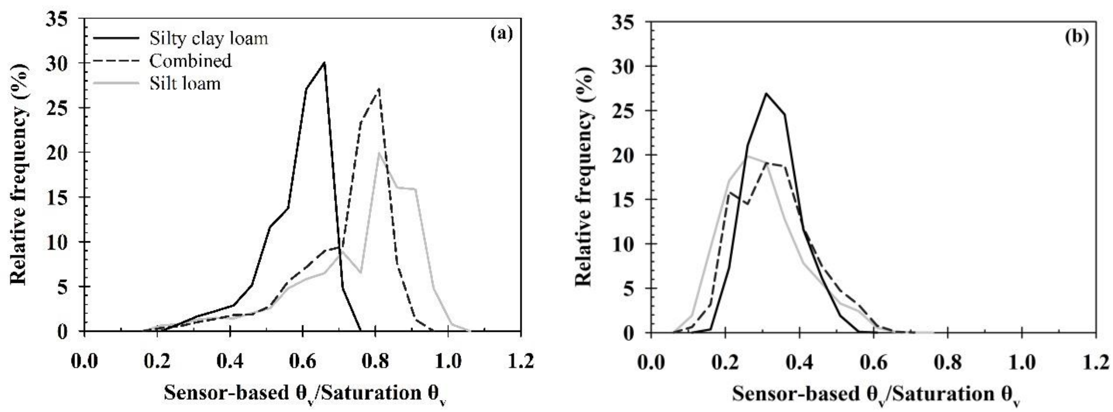


Figure 2.3. The ratio of sensor-based θ_v to saturation θ_v for (a) high clay content sites and (b) high sand content sites for 5, 15, and 25 cm soil depths.

Two key factors that affect sensor accuracy are soil texture and soil salinity. The wide range of soil textures and salinities in this study allowed us to further investigate the effects of these factors on sensor performance. As expected, higher clay and salinity negatively impacted accuracies. Figure 2.4 shows bubble graphs of RMSE for various ranges of clay and electrical conductivity of the 1:1 soil to water extract ($EC_{1:1}$) for each of the six manufacturer calibrations. Larger bubbles indicate larger RMSE and vice-versa. Default (Figure 2.4a) and sand (Figure 2.4d) calibrations were more sensitive to increases in clay and salinity compared to other calibrations. For example, RMSE of Default calibration was 0.11 $cm^3 cm^{-3}$ at the smallest clay and salinity range and increased to 0.26 $cm^3 cm^{-3}$ at the largest clay and salinity range. This was the largest increase in RMSE. The other error indicator, MBE, had similar trends, revealing larger overestimation of θ_v at higher clay and salinity. Heavy clay was the only calibration that had an opposite trend and showed smaller errors at larger clay ranges regardless of salinity.

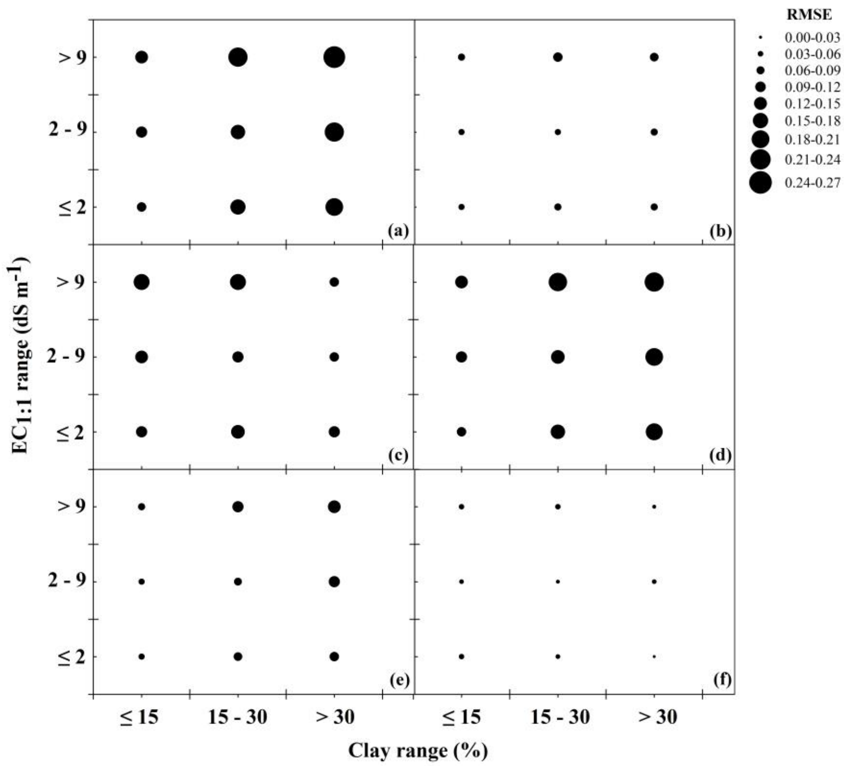


Figure 2.4. Bubble graphs of RMSE for variable ranges of clay content and soil electrical conductivity of 1:1 soil to water extract for a) Default, b) Combined, c) Heavy clay, d) Sand, e) Silt loam, and f) Silty clay loam calibrations.

Previous studies have reported comparable results on the effects of clay and salinity on sensor accuracy. For example, Thompson et al. (2007) showed that overestimation error of a capacitance sensor increased with EC of applied water to a level and then remained stable. Al-Ain et al. (2009) found that Sentek Diviner 2000 capacitance probe was sensitive to soil EC and estimated RMSE as high as 0.07 $cm^3\ cm^{-3}$. Using the same type of probe and Default calibration, Provenzano et al. (2016) estimated larger errors at sites with higher clay content (RMSE increased from 0.05-0.08 to 0.10-0.17 cm^3 cm^{-3}). In a greenhouse experiment in Texas, Baumhardt et al. (2000) found that θ_v readings of Sentek EnviroSCAN probe under saline water application were 0.25 cm^3 cm^{-3} larger than soil porosity. In Oklahoma and using five soil water sensors, Datta et al. (2018) found considerably larger errors at a site with high salinity and clay compared to a site with low salinity and clay, with RMSE reaching 0.23 cm^3 cm^{-3}.

2.3.2. Field Capacity Estimation

The laboratory FC varied considerably among the two sampling depths (5 and 15 cm) and 13 sites. The FC at -10 kPa had a range of 0.18-0.33 cm^3 cm^{-3} and an average of 0.27 cm^3 cm^{-3}, whereas FC at -33 kPa had a range of 0.12-0.31 cm^3 cm^{-3} and an average of 0.23 cm^3 cm^{-3}. The difference between FC at -10 and -33 kPa was larger (44% on average) at sites with clay<15% (coarser soils) compared to the difference (16%) at sites with clay=15-30% (finer soils). Romano and Santini (2002) highlighted that in general, a matric potential value of about -10 kPa correlates well with the field-measured FC of sandy soils and values of about -35 kPa and -50 kPa with medium-textured and clayey soils, respectively.

In the first sensor-based approach, 1 to 9 days were required to reach laboratory FC. Figure 2.5 shows days to reach laboratory FC for each soil depth (5 and 15 cm) and two clay ranges (<=15% and 15-30%). For the coarser soil (clay<=15%), average days to reach FC were 1 and 3 days at 5 and 15 cm depths, respectively. For the finer soils (clay=15-30%), average days were 2 and 3 days at the same depths, respectively. These estimates were comparable to those suggested or used by many previous studies with a range of 1-3 days (Veihmeyer and Hendrickson, 1931; Obreza, 1997; Evett et al., 2019; Sui and Vories, 2020; Vories and Sudduth, 2021). However, Zettl et al. (2011) reported 18 hours to reach FC after watering events for very coarse (88-99% sand), which was smaller than the time for sandy sites of the current study. Ratliff et al. (1983) mentioned that in general 2-12 days is required for soils to reach FC and it may take longer (up to

20 days) for some fine-textured soils and soils with restrictive layers. The largest number of days to reach FC in this study was 9 at the 15 cm depth of a loam soil.

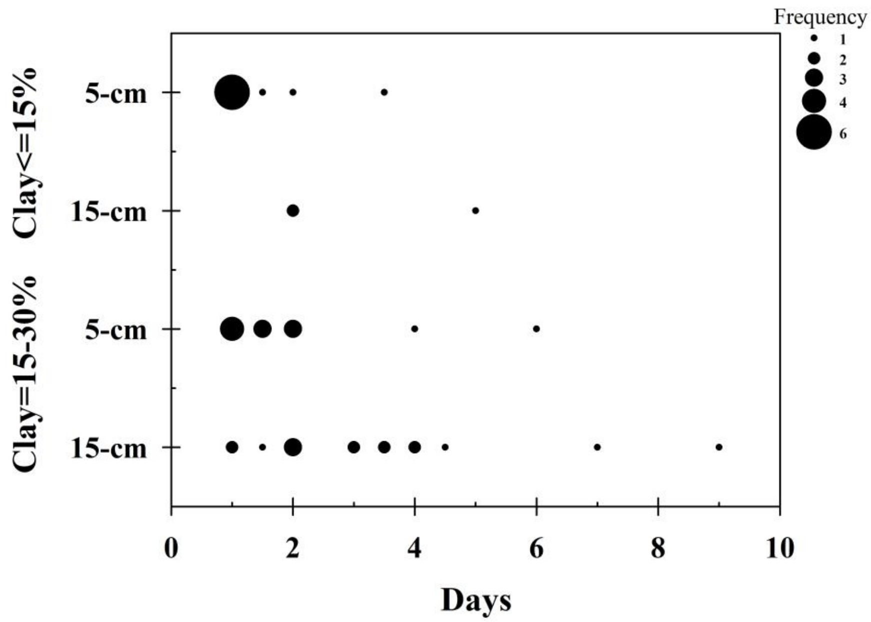


Figure 2.5. Days to reach laboratory field capacity after major water events at two soil depths (5 and 15 cm) and two clay ranges.

In the second sensor-based approach, the percentiles representing laboratory FC were inconsistent and highly variable, ranging from 3 to 97% with an average of 56% (Figure 2.6). Theoretically, larger percentiles are expected since the soil water content would not be at and above FC for long periods of times. Under an efficient irrigation management, soil water content would be mostly below FC and would increase to the level of this threshold in each irrigation event. Most of the larger percentiles (77-97%) in this study were observed at the 5 cm depth for both clay ranges. A potential reason could be that the 5 cm depth is more prone to direct evaporation and thus a higher percentile is estimated compared to the 15 cm depth.

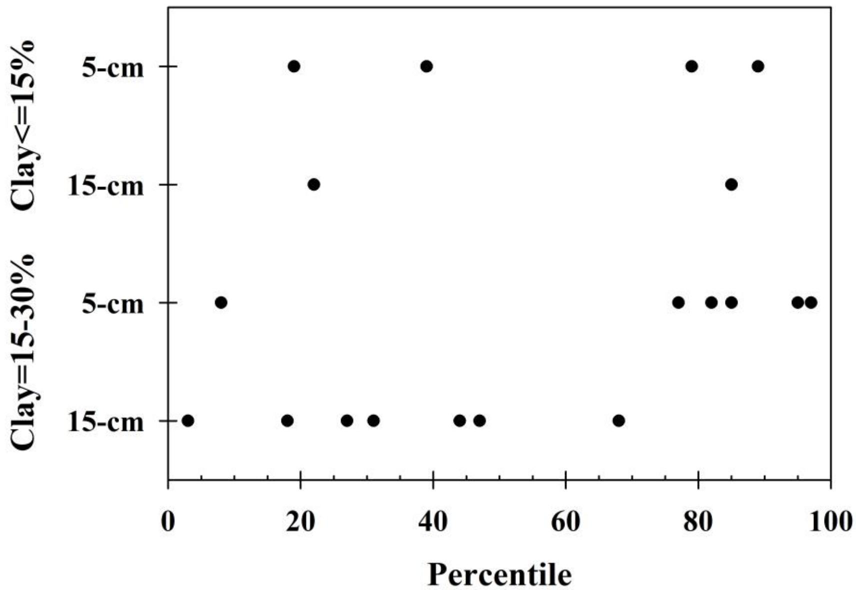


Figure 2.6. Percentile values to reach FC for combinations of two soil depths (5 and 15 cm) and two clay ranges (<=15% and 15-30%).

The smallest percentile at 5 cm depth and clay<=15% was 19%, indicating that sensor-based θ_v was larger than laboratory FC 81% of the time. This site received very frequent irrigations (2-day interval), which helped keep soil water content high. The smallest values at 15 cm for both clay ranges may be due to larger overestimation error in sensor-based θ_v, which results in sensor readings being larger than laboratory FC most of the time. In other cases of obtaining smaller percentiles, the clay content of layers below 15 cm was considerably larger (finer layers impeding downward water movement).

Some previous studies have discussed the challenges of the percentile approach. For example, Hunt et al. (2009) used the 95th percentile approach to estimate FC and concluded that it would be difficult to estimate FC if a very short period of data is available. They also mentioned that in semi-arid regions it could take a few years to reach FC at deeper soil depths. Datta et al. (2018) highlighted that the poor performance of the 95th percentile approach could be due to lack of full range of soil water conditions in the irrigated areas and overestimation of sensor-based θ_v.

Further, the author added that it is difficult to have the full range of soil water conditions in many irrigated areas because producers attempt to refill soil water well before reaching wilting point to avoid water stress and yield loss. Overall, the current study showed the inconsistency of the sensor-based approaches in determining FC.

2.4. Conclusions

The accuracy of a multi-sensor capacitance probe (Sentek Drill & Drop) was determined by comparing the readings based on each of six manufacturer calibrations with observed soil water content from gravimetric sampling. Among the calibrations, Default and Silty clay loam produced the largest and smallest errors with RMSE of 0.19 and 0.05 $cm^3\ cm^{-3}$, respectively. The errors of all calibrations except the Heavy clay had a direct relationship with clay and salinity. Besides the accuracy of sensor readings, the relative values and the range of soil water content captured is important for practical irrigation scheduling. Hence, the ranges of sensor readings based on each calibration were also investigated. The Combined calibration, which had the second smallest RMSE, produced larger and more realistic ranges compared to the Silty clay loam calibration and would be recommended for irrigation management.

Two sensor-based approaches to determine FC were assessed to identify the appropriateness and feasibility of relying on sensor readings for FC estimation and thus reduce the need of soil water sensor users to additional measurements. The number of days to reach laboratory FC after major watering events varied from 1 to 9 days with average values of 1-3 days. The percentile of sensor readings that corresponded to laboratory FC had a range of 3-97% with an average of 56%. Both approaches were found to result in spatio-temporally variable and inconsistent FC estimates and thus are not recommended for irrigation scheduling. Future studies could investigate sensitivity of temperature on the performance of the probe with different calibrations provided by the manufacturer.

CHAPTER III

EFFECTS OF SOIL DATA ACCURACY ON OUTPUTS OF IRRIGATION SCHEDULING TOOLS

3.1. Introduction

Scientific irrigation scheduling methods are important for deciding appropriate timing and amount of irrigation in agriculture, the largest consumer of freshwater in the world (Wallace, 2000; Ward and Pulido-Velazquez, 2008). As water scarcity increases in many regions along with population growth and economic development, implementing scientific irrigation scheduling is considered a solution to conserving limited and declining freshwater resources (Liu et al., 2007; Taghvaeian et al., 2020). In addition, robust scientific scheduling can save energy, minimize possible negative effects on the environment (e.g., nutrient leaching below the root zone), increase crop yield, and improve the financial viability of agricultural production (Kukal et al., 2020; Taghvaeian et al., 2020). Further, efficient use of freshwater resources is essential for balancing food production and long-term sustainability of irrigated agricultural systems (Gibson et al., 2019), which can be achieved by implementing and advancing science-based irrigation scheduling.

Out of all scientific irrigation scheduling methods, those based on soil water status in the crop root zone are among the most widely researched and applied (Taghvaeian et al., 2020). Soil water status can be monitored using soil water sensors or it can be estimated using soil water balance models. Models require several inputs but offer many advantages over sensors including reduced cost, convenience, and the ability to analyze a range of scenarios and forecast short-term irrigation demand. A critical input to soil water balance models is soil data such as texture and water thresholds. Soil data can be obtained in two main ways: (1) in-situ soil sampling (ISS), which is the most accurate but tedious, laborious, and expensive, and (2) online databases where users can retrieve data at minimal cost (or no cost) with the ability to embed automatic data collection within irrigation scheduling tools and applications. Compared to ISS, a potential caveat of publicly available soil data is lower accuracy, necessitating onsite investigations for conservation planning and engineering applications. The most used soil database in the United States is the Soil Survey Geographic Database (SSURGO), which allows access to data through the Web Soil Survey (WSS) online user interface (Soil Science Division Staff, 2017).

Several previous studies have discussed the accuracy of WSS when compared to ISS. Brevik et al., (2003), for instance, explored WSS accuracy in a uniform field in central Iowa and argued that survey estimates were adequate for highly uniform fields, but not appropriate for precision agriculture applications in nonuniform fields. Later, Zylman et al. (2005) investigated the accuracy of WSS-based texture data for 22 different mapping units in north-central Texas and found weak relationships with ISS-based texture. They also warned about misuse of WSS data beyond the intended use and capacity of the database. Whisler et al. (2016) reported errors in WSS textural data in two counties in Indiana and Illinois. In a field experiment in New York, Mikhailova et al. (2019) observed that texture classes based on ISS and WSS were different for many soil map units and argued that this would have profound impact on assessing ecosystem services. Other studies have suggested that WSS does not have enough precision for many site-specific applications including irrigation recommendations (Sui and Vories, 2020; Vories and Sudduth, 2021).

Although the studies mentioned above have shown that WSS data are less accurate compared to ISS and their precision is not enough for site-specific irrigation recommendations, many soil water balance models in irrigation scheduling tools rely on WSS due to its easy, free, and fast access. One example is the web based NDAWN Irrigation Scheduler (Scherer and Morlock, 2008), where soil data are automatically collected from SSURGO after the field of interest is delineated by user. Other examples include the Irris Scheduler computer program (Joern and Hess, 2017), Irrigation Scheduler mobile application (Peters et al., 2019), and the cloud-based Water Irrigation Scheduler for Efficient (WISE) application (Andales et al., 2020). WSS data have also been used for making irrigation decisions at sub-field scales. For instance, the University of Georgia's web-based model (Smart Sensor Array) generates irrigation scheduling recommendations at sub-field scales based on soil textural information obtained from WSS (Liang et al., 2016). ARSPivot, a computer program, also uses WSS for delineating management zones across the field and generating site-specific irrigation prescription maps for variable rate irrigation systems in Texas (Andrade et al., 2020).

As SSURGO/WSS data are gaining more popularity in irrigation management tools at variable scales, there is a gap in knowledge on how the textural inaccuracies in WSS data may affect the output of irrigation decision making tools that are based on soil water balance modeling. The main goal of this study was to investigate the effects of soil data accuracy on irrigation scheduling using the Soil water balance model, a commonly used water balance model. Specific objectives were to 1) examine the differences in soil textural data and soil water thresholds obtained from ISS and WSS and 2) investigate the effects of soil data sources (ISS and WSS) on estimated irrigation demands, evaporation, transpiration, runoff, and deep percolation under variable soil, crop, and climatic conditions. The study contributes to science-based irrigation scheduling by illuminating the implications of the localized inaccuracies in WSS for quantifying irrigation demand.

3.2. Materials and Methods

3.2.1. Study Area

The study included six sampling sites at each of three regions (18 sites total) across western Oklahoma: Panhandle, southwest, and westcentral. These three regions are notably different in climate, crops, soils, and irrigation water resources and encompass the range of conditions experienced in Oklahoma irrigated lands. According to the Koppen-Geiger climate classification, Panhandle is classified as semi-arid (BSk), whereas southwest and westcentral exhibit a humid subtropical climate (Cfa) characterized by hot and humid summers. Soil types vary from loamy sand to clay loam. The two most dominant crops in each region based on Oklahoma Agricultural Statistics are grain corn and grain sorghum in Panhandle, cotton and grain sorghum in southwest, and cotton and soybean in westcentral. The same crops were selected for each region in this study. Figure 3.1 shows the location of the study sites in each region along with a map of normal precipitation.

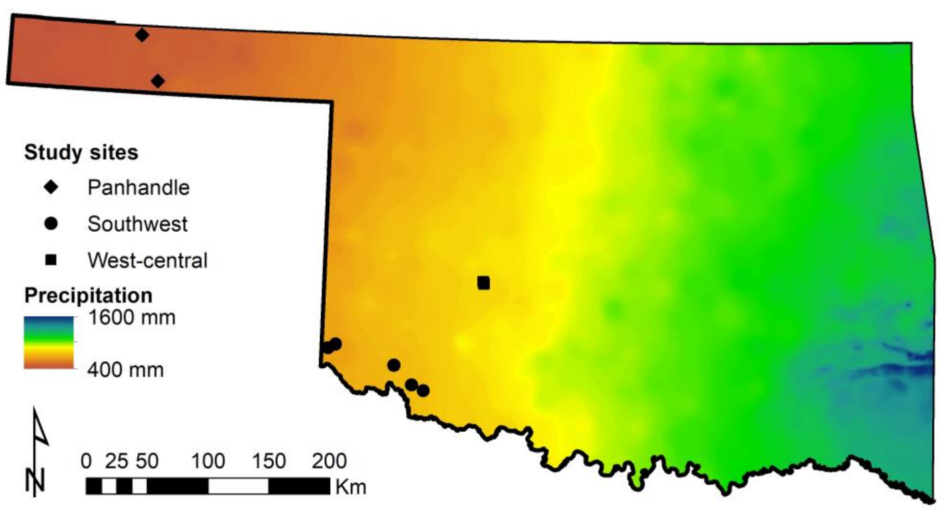


Figure 3.1. The location of the study sites in western Oklahoma.

3.2.2. Soil Water Balance Model

A simple and widely used soil water balance model was implemented to estimate irrigation and other water fluxes based on two different sources of soil data (discussed in section 3.2.2.4) according to the method described in Allen et al. (1998, 2020). The model was run for each site of each region and the two common crops of that region over a 15-year (2006-2020) period. This resulted in 36 combinations per study year (6 sites × 3 regions × 2 crops). The model accounts for incoming and outgoing water fluxes of the crop root zone based on the following equation:

$$P_i + I_i + CR_i = E_i + T_i + DP_i + RO_i + D_{i-1} - D_i \qquad (1)$$

where P_i is precipitation on day i; I_i is irrigation; CR_i is capillary rise from shallow groundwater; E_i is evaporation; T_i is transpiration; DP_i is deep percolation; RO_i is surface runoff; D_{i-1} is soil water depletion in the root zone at the end of the previous day; and D_i is soil water depletion at the end of day i. In this study, CR_i was assumed zero since groundwater levels were considerably lower than the root zone at all sites. RO_i was estimated based on the curve number method (USDA-NRCS, 2004) and antecedent water conditions were computed from the daily surface soil water balance for adjusting the curve number, following the procedures explained by Jensen and Allen (2016). DP_i was estimated as the amount of water passing below the root zone when soil water content in the root zone was at or above field capacity. D_i was assumed zero on the first day of the growing season and was estimated on subsequent days by subtracting the amount of water applied from the sum of previous day depletion and ET_i. The remaining components of equation 1 and any supporting data were obtained based on methods explained below.

3.2.2.1. Weather Data

Daily precipitation, short-crop reference evapotranspiration (ET_o), air temperature, dew point temperature, and wind speed data were obtained from the Oklahoma Mesonet weather stations in each region: Goodwill station in Panhandle, Altus station in southwest, and Fort Cobb station in westcentral (McPherson et al. 2007). Data quality assurance and quality control procedures were employed before using the data (Shafer et al., 2000). Less than 3% of air temperature, dew point temperature, and wind speed data and less than 1% of precipitation data were missing during April to November, which encompasses the growing season of all crops considered in the present study. Gap filling of missing values was accomplished using data from nearby weather stations and according to procedures described in Allen et al. (1998) for air temperature, dew point temperature, and wind speed. In case of missing precipitation, Parameter-elevation Relationships on Independent Slopes Model (PRISM; Daly et al., 2008) data were used to fill the gaps.

3.2.2.2. Evaporation and Transpiration

These components were estimated using the dual crop coefficient method following Allen et al. (1998, 2020) and Jensen and Allen (2016):

$$E = K_e \times ET_o \tag{2}$$

$$T = K_s \times K_{cb} \times ET_o \tag{3}$$

where K_e is the soil evaporation coefficient; K_s is the water-stress coefficient; and K_{cb} is the basal crop coefficient (details in a sub-section below). In this study, irrigation demand was estimated for well-watered conditions, meaning that an irrigation event was triggered whenever K_s fell below unity to avoid water stress. The irrigation depth was the amount of water needed to bring soil water depletion to zero. A maximum limit of 51 mm (2 inches) was applied to irrigation depths based on the actual capacity limit of sprinkler irrigation systems, which are the most common methods in Oklahoma.

3.2.2.2.1. Basal Crop Coefficient

Kcb curves for different crops were developed following the approach described in Huntington et al. (2015) and Allen et al. (2020) and fine-tuned to represent local conditions in Oklahoma. This approach is based on normalized cumulative growing degree days (NCGDD), calculated by dividing the cumulative growing degree days (CGDD) since planting by the total CGDD from planting to effective full cover:

$$NCGDD = \frac{CGDD_i}{CGDD_{plant\text{-}to\text{-}EFC}} \tag{4}$$

where $CGDD_i$ is the CGDD for day i after planting and $CGDD_{plant\text{-}to\text{-}EFC}$ is the total CGDD from planting to full cover. NCGDD is zero at planting, one at full cover, and larger than one after reaching effective full cover until harvest or killing frost. A slightly different approach based on percentage time from planting to full cover and then days after full cover to termination was used for sorghum as suggested by and explained in Allen et al. (2020).

3.2.2.2.2. Planting Date

The planting dates, required in estimating K_{cb}, were estimated for each region-crop and study year based on a 30-day moving average of mean daily air temperature (T_{30}) as described in Allen et al. (2020). In this approach, planting day is the day when T_{30} reaches a predefined threshold for the first time in each year. The thresholds for grain corn, grain sorghum, cotton, and soybean were taken from Allen et al. (2020) and adjusted, if needed, based on documented actual planting dates in the study area (Table 3.1).

Table 3.1. T_{30} thresholds for each region and crop.

Region	Crop	T_{30} Threshold (°C)	
		Allen et al. (2020)	This study
Panhandle	Grain corn	10-15	12.5
	Grain sorghum	20	18
Southwest	Grain sorghum	20	16
	Cotton	20	19
Westcentral	Cotton	20	19
	Soybean	21	21

3.2.2.3. Root Growth and Crop Height

The dynamic sigmoidal root growth model described by Borg and Grimes (1986) and Allen and Robison (2007) was implemented. This growth model is a function of time between the minimum (initial) root depth at planting until the time of maximum rooting depth. The minimum and maximum root depths were taken from Allen et al. (2020) except for the maximum root depths for cotton and soybean that were based on reported values by Mehata et al. (2022) for the study area (Table 3.2). Maximum crop height was determined based on field observations and consultation with local extension educators (Table 3.2).

Table 3.2. Rooting depths and crop height used in this study.

Crop	Minimum root depth (m)	Maximum root depth (m)	Maximum crop height (m)
Grain corn	0.12	1.5	2.0
Grain sorghum	0.25	1.2	1.5
Cotton	0.25	1.0	1.2
Soybean	0.25	1.0	1.0

3.2.2.4. Soil Data

Soil data were obtained from two sources: measured from in-situ soil samples (ISS), which was considered as the most accurate; and obtained from web soil survey (WSS). In case of ISS, undisturbed soil samples (3 replications) were collected at 10-cm intervals at each site using a soil coring tool (Giddings Machine Co, Windsor, CO, USA). Collected samples were sent to the Soil, Water, and Forage Analysis Laboratory at Oklahoma State University for soil textural analysis based on the protocol proposed by Ashworth et al. (2001). For WSS, soil data were retrieved from the online interface (ver. 3.4.0, Soil Science Division Staff, 2017) as the weighted average for the same 10-cm increments. For both ISS and WSS, soil water thresholds of field capacity and wilting point were estimated using the textural information and the Rosetta model (Schaap et al.

2001). Total available water was determined as the difference between field capacity and wilting point and the maximum allowed deficit for different crops was based on Allen et al. (2020).

3.3. Results and Discussion

3.3.1. Soil Data Sources

The ISS data showed that of the three regions, Panhandle had the finest and westcentral had the coarsest soil textures, with average sand percentage of 41% and 60%, respectively. The variations in soil texture among the six sampling sites of each region were smallest in Panhandle and largest in southwest. Among the three soil particles, the largest variation was observed in sand, with ranges of 25-60% in Panhandle, 31-90% in westcentral, and 25-85% in southwest. Variations in clay were the smallest, with Panhandle having the smallest range (20-40%) and southwest the largest (8-40%). These observations depict the considerable spatial heterogeneity in soil texture data even among sites located in close vicinity in the same region, and point to the need for accurate representation of soil data in soil water balance models.

There were major differences in soil textural and total available water data between ISS and WSS (Figure 3.2). Overall, WSS textures were finer than ISS across all sampling locations and depths. WSS sand estimates were smaller than ISS in 89% of the cases, whereas its clay estimates were larger in 78% of the cases. Among the three regions, the differences were smallest in the Panhandle and largest in westcentral. Among the soil particles, the differences in sand and clay were largest and smallest, respectively, in all three regions. The median differences in sand estimates (WSS percentage minus ISS percentage) were -8% in Panhandle, -11% in southwest, and -23% westcentral. Previous studies have reported similar results. Drohan et al. (2003) evaluated textural classes in forested plots in Pennsylvania and found similarities between ISS and WSS in most cases. However, in some cases, WSS underestimated sand and overestimated clay. Whisler et al. (2016) reported overestimation of silt and clay based on WSS in grasslands and crop fields in Indiana and Illinois. Cole et al. (2017) also found underestimation of sand and overestimation of silt by WSS in an agricultural farm in New York. Finer textural classes by WSS have been documented for crop fields in California (Perez–Quezada et al., 2003) and a ranch in Texas (Zylman et al., 2005) too.

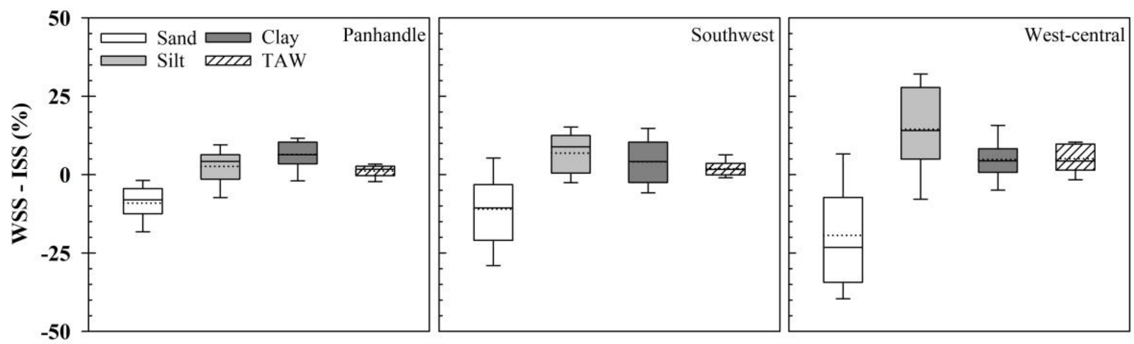


Figure 3.2. Differences in soil textural data and total available water (TAW) between WSS and ISS in each region. The dotted lines indicate the mean. The whiskers represent 10^{th} and 90^{th} percentiles.

Total available water, an important parameter in irrigation scheduling, was affected by differences in soil textures. The differences were largest in westcentral and smallest in Panhandle, with averages of 54 mm and 8 mm for the top one meter of the soil profile, respectively. WSS-based estimates were larger (due to finer textures) than those from ISS in over three-quarters (77%) of all samples. Fuka et al. (2016) found larger total available water contents based on WSS in grasslands and croplands in Texas. However, Datta et al. (2018) had an opposite observation in two irrigated fields in Oklahoma.

3.3.2. Water Fluxes Based on ISS

Irrigation demand estimated by the soil water balance model based on ISS (I_{ISS}) varied widely among the six combinations of regions and crops, with average values ranging from 377 mm for soybean in westcentral to 545 mm for corn in Panhandle. When comparing the three regions, average I_{ISS} was smallest in westcentral (398 mm) and largest in Panhandle (542 mm). The spatial variations were partly due to differences in climate (Panhandle being more arid) and partly due to differences in soil texture. Table 3.3 summarizes average I_{ISS} and other fluxes based on ISS data, including transpiration (T_{ISS}), evaporation (E_{ISS}), deep percolation (DP_{ISS}), and runoff (RO_{ISS}).

Table 3.3. The average seasonal water fluxes, precipitation, and reference ET (ET_o) for different crops and regions.

Region	Crop	I_{ISS} (mm)	T_{ISS} (mm)	E_{ISS} (mm)	DP_{ISS} (mm)	RO_{ISS} (mm)	Precipitation (mm)	ET_o (mm)
Panhandle	Corn	545	709	286	8	14	273	1010
	Sorghum	538	613	287	4	15	266	987
Southwest	Sorghum	535	653	289	32	18	356	992
	Cotton	511	645	244	32	17	353	1035
Westcentral	Cotton	419	667	159	52	39	426	887
	Soybean	377	583	139	43	29	351	769

Within each region, considerable I_{ISS} variability was found among the six sampling sites and study years. Figure 3.3 demonstrates the box plots of water fluxes for each region-crop, created using the 90 data points, which resulted from the six sites at each region and the 15 years of study. The maximum I_{ISS} occurred during 2011 for all region-crops, with estimates that were 49-119% larger than the average I_{ISS} of the 15 years of study. This was expected as a historic drought event occurred in 2011, when all study sites were under exceptional drought from late July to early November. On the other hand, the minimum I_{ISS} was obtained in wet years, which were different for different region-crops. For example, corn and sorghum in Panhandle had their minimum I_{ISS} during 2018 and 2015, respectively, whereas 2007 and 2016 were the years with the smallest I_{ISS} for sorghum and cotton in southwest, respectively. The southwest region had the largest range of I_{ISS}, most likely due to the fact that this region had the largest range of variability in soil texture.

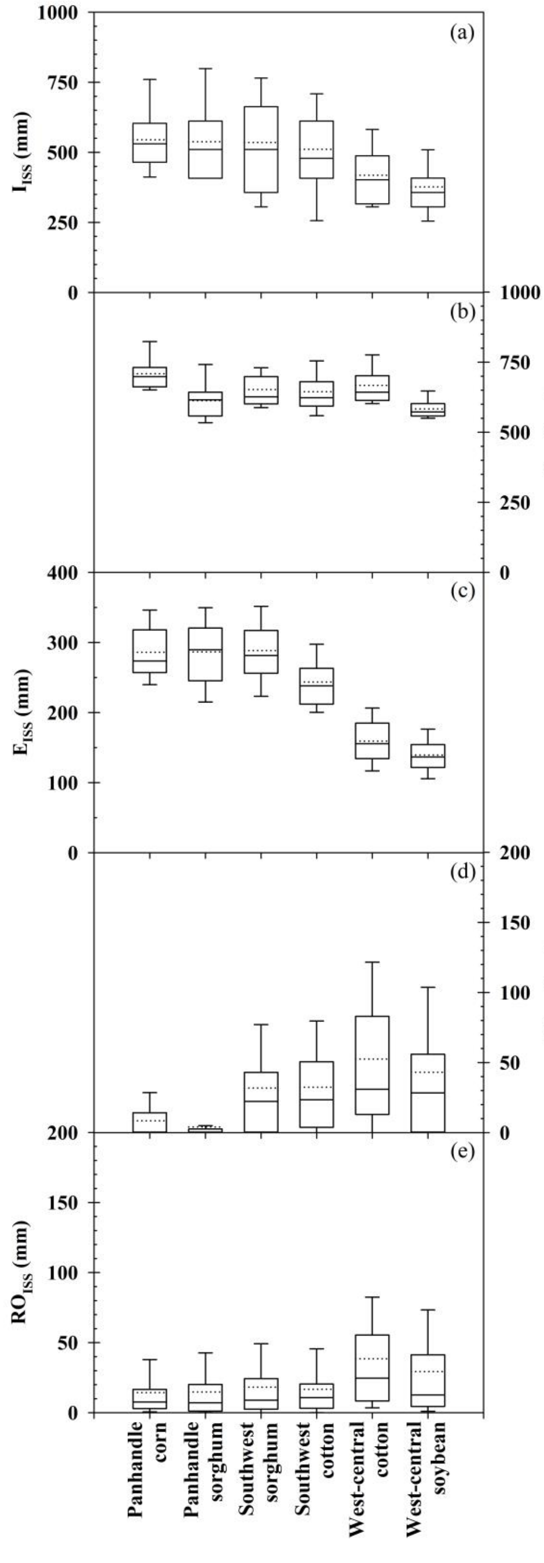


Figure 3.3. Water fluxes based on ISS soil data for each region and crop. The dotted lines indicate the mean. The whiskers represent 10th and 90th percentiles.

The I_{ISS} estimates of this study are comparable with estimated or measured I_{ISS} in previous studies. Tolk and Howell (2001) reported irrigation amounts for grain sorghum in Texas Panhandle (similar climate to Oklahoma Panhandle) that varied from 510 to 604 mm during 1997-1999 and had an average of 543 mm. In this study, sorghum irrigation depths in Panhandle were 357-818 mm and had an average of 538 mm. Hao et al. (2015) conducted another study in Texas Panhandle and reported seasonal irrigation amounts of 754, 612, and 608 mm for grain corn in 2011, 2012, and 2013, respectively. Our irrigation estimates for corn in Oklahoma Panhandle for the same years were similar at 810, 748, and 572 mm, respectively. DeLaune et al. (2012) estimated and applied 200-380 mm of irrigation during 2008-2010 at their cotton plots near Chillicothe, Texas, which is a few miles from southwest sites in the present study. Our I_{ISS} estimates for southwest cotton during the same years were larger at 408-506 mm, mostly influenced by longer growing seasons estimated in our study. In a study in southwest Oklahoma, Masasi et al. (2020) mentioned that seasonal irrigation amounts applied to cotton varied from 304 to 532 mm during 2015-2017, close to our estimated range of 204-567 mm for the same years.

Like I_{ISS}, the average T_{ISS} was smallest in westcentral (625 mm) and largest in Panhandle (661 mm). The maximum T_{ISS} for each region-crop was also during 2011 and 12-48% larger than the 15-year average for the corresponding region-crops. The minimum estimates occurred during various years, typically the year with the smallest seasonal ET_o. In case of E_{ISS}, the smallest average seasonal amount was in westcentral (149 mm) and the largest in Panhandle (286 mm). Two main reasons for variations in E_{ISS} were changes in seasonal ET_o and soil texture of the topsoil layer, which contribute to temporal and spatial E_{ISS} variability, respectively. Recorded seasonal ET_o had a direct relationship with E_{ISS}. Regarding soil texture, fine-textured topsoil layers with larger total evaporable water allowed for more E_{ISS} compared to soils with coarser textures, as expected.

The other two fluxes, deep percolation and runoff, were notably smaller in magnitude. This was because the soil water balance model was set up in such a way to replenish soil water deficit and not more. Hence, return flows were only generated after large precipitation events or if precipitation occurred shortly after an irrigation event. The smallest average seasonal DP_{ISS} was in Panhandle (6 mm), which has the driest climate and the finest soil textures. The largest DP_{ISS} was in westcentral (48 mm), characterized by the wettest climate and the coarsest soil textures. Among the study years, the minimum DP_{ISS} (near zero in most cases) was in the drought year of 2011 for all region-crops. The maximum DP_{ISS} occurred in different years, with the largest values of about 200 mm in 2007 in westcentral. The smallest average seasonal RO_{ISS} was in Panhandle (15 mm) and the largest in westcentral (34 mm), mainly because the former received more precipitation. Among the years, the minimum RO_{ISS} was in 2011 (zero or near zero) and the maximum was in different years for different region-crops.

3.3.3. Effects of Soil Data on Fluxes

The effects of soil data sources on estimated irrigation demand were variable among regions and crops. When WSS data were used in the soil water balance models instead of measured values (ISS), the average difference varied from 34 mm less irrigation amount for soybean in westcentral to 19 mm more amount for corn in Panhandle. Table 3.4 presents the average differences in irrigation and other fluxes for each region-crop. Transpiration differences were always zero and thus not included in this table since the implemented water balance model did not allow for any water stress. Hence, transpiration fluxes were the same based on both WSS and ISS. When considering all sampling sites, crops, and study years, WSS data resulted in irrigation flux underestimation in 40% and overestimation in 30% of the cases. For the remaining 30%, WSS and ISS estimates were equal. The underestimation error reached and exceeded 100 mm. However, 49% of the differences were within ±25 mm (±1.0 inch).

Table 3.4. Average differences in irrigation (I), evaporation (E), deep percolation (DP), and runoff (RO) fluxes estimated by subtracting ISS fluxes from WSS fluxes and reported in units of mm. The numbers in parentheses represent the average differences as percentage of the corresponding ISS-based flux.

Region	Crop	I	E	DP	RO
Panhandle	Corn	19 (3%)	14 (5%)	-3 (-32%)	17 (118%)
Panhandle	Sorghum	18 (3%)	21 (7%)	-2 (-58%)	13 (89%)
Southwest	Sorghum	-15 (-3%)	-3 (-1%)	-5 (-14%)	7 (39%)
Southwest	Cotton	-18 (-4%)	-5 (-2%)	-6 (-18%)	7 (39%)
Westcentral	Cotton	-31 (-7%)	11 (7%)	-12 (-22%)	-9 (-22%)
Westcentral	Soybean	-34 (-9%)	9 (6%)	-12 (-28%)	-2 (-8%)

Although the differences in irrigation estimates were relatively small at the region-crop level with values ranging from -9% to 3% of the ISS-based estimates (Table 3.4), larger differences were observed at the sampling site level. The largest underestimation of irrigation was -20% at a southwest-sorghum site and the largest overestimation was 11% at a Panhandle-corn site. As expected, these two sites had the largest errors in their WSS soil texture data. It should be noted that percent differences reported here are averaged over the 15 years of study and some years experienced larger differences. What can be inferred from these findings is that while errors in soil data may not have a major impact at regional scales (although it can be argued that even a few percent difference is too big in water scarce areas), the effects on individual irrigated farms may be much more severe depending on the magnitude of error in soil data. The 11% (55 mm) overestimation error at the Panhandle-corn sampling site, for example, will have a notable impact on irrigation sustainability and profitability as deep groundwater resources in Oklahoma Panhandle are non-renewable and expensive to pump (Handa et al., 2019).

The change in irrigation estimates when WSS data were used instead of ISS was mostly due to soil texture differences across the entire root zone (impacting water holding capacity) and the topsoil (impacting evaporation). As mentioned before, WSS had generally finer soil textures, especially in southwest and westcentral regions. This resulted in larger water holding capacity in the root zone, consequently more efficient use of precipitation and less frequent irrigation events. On the other hand, finer soil textures at the top 10 cm layer resulted in larger E as the smaller pores support higher evaporation rates and thus a more rapid depletion of soil moisture, leading to more frequent irrigations. The opposite effects of soil texture differences on water holding capacity and evaporation resulted in positive and negative differences in irrigation demand between the two soil data sources. However, the effect of larger water holding capacity was more pronounced and irrigation underestimation by finer-texture WSS data were more common.

The impact of root zone water holding capacity on irrigation estimates was further investigated using linear regression analysis (Figure 3.4), where percent irrigation differences for each of the 36 combinations of the six sampling sites and six region-crops were averaged over the 15 years of study and plotted against their corresponding differences in readily available water based on WSS and ISS. The statistically significant (p value <0.01) regression equation had a large coefficient of determination (0.70) and demonstrated an inverse relationship, where the difference in irrigation estimates decreased by 4% on average for every 10% increase in the difference in readily available water.

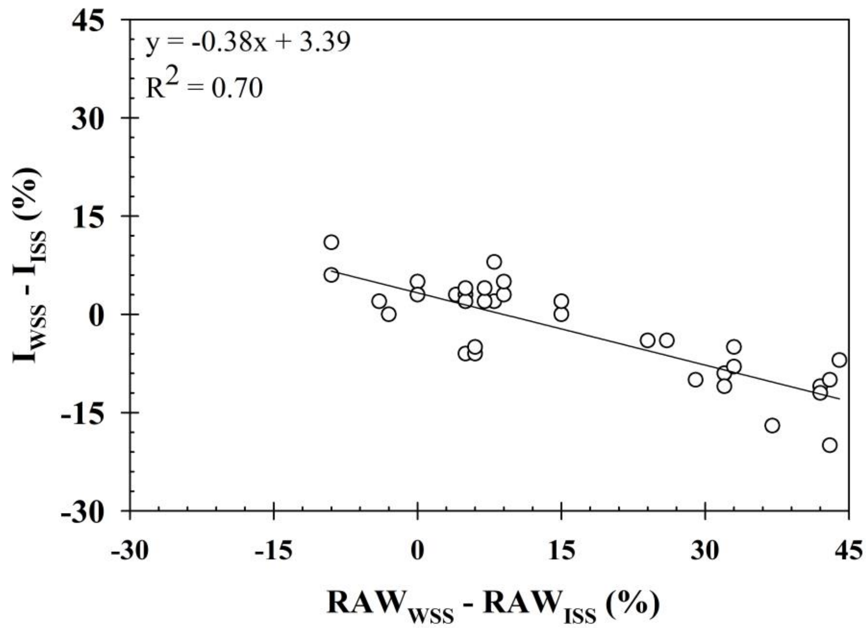


Figure 3.4. Differences in irrigation (I) estimates versus differences in readily available water (RAW) based on WSS and ISS soil data.

Other fluxes (E, DP, and RO) were also impacted by errors in soil data, albeit to a smaller degree compared to irrigation. Figure 3.5 demonstrates box plots of differences in all fluxes, except for T that had no difference since the water balance model did not allow for any water stress and predicted similar transpiration fluxes for both soil data sources. For E fluxes, WSS resulted in larger estimates compared to ISS in 70% of the cases (positive values in Figure 3.5) because WSS soil textures were generally finer. As explained before, fine-textured soils have larger total evaporable water and support more evaporation from the top layer of the soil compared to coarser textures. In 72% of the cases, the differences in E estimates based on WSS and ISS were within ±25 mm (±1.0 inch). At the regional level, the largest average differences were in the Panhandle region that had the finest textures of the three regions. All regional differences were within 7% of the ISS-based evaporation estimates (Table 3.4).

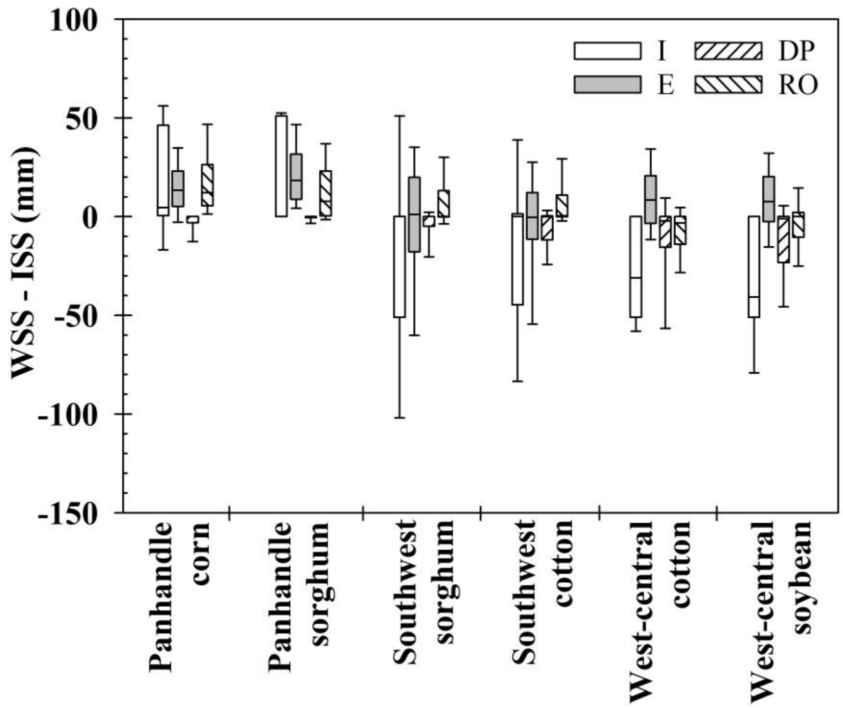


Figure 3.5. Differences in water fluxes based on WSS and ISS soil data. The whiskers represent 10th and 90th percentiles.

With respect to DP, the estimates based on WSS were smaller than or equal to those based on ISS in 85% of the cases, an expected behavior considering WSS textures were finer. This is represented in mostly negative values in Figure 3.5. At the regional level, the average differences in DP estimates ranged from -2 and -3 mm for Panhandle with the finest texture to -12 mm in westcentral with the coarsest texture (Table 3.4). This spatial pattern can be partially explained by the fact that the westcentral region received more precipitation than the other two regions and thus was exposed to more frequent rain events that followed an irrigation application. Converting units of differences from mm to percentages resulted in large values because ISS-based deep percolation estimates (denominator) were small. The finer textures of WSS had an opposite effect on RO fluxes, where estimates based on WSS were larger than those based on ISS in 58% of the cases. The average difference was largest in Panhandle with the finest texture and smallest in westcentral with the coarsest texture (Table 3.4). Like DP, large percentages were obtained since ISS-based fluxes were small and close in magnitude to estimated differences.

3.4. Conclusions

The errors in publicly available soil data (WSS) and their effects on water flux predictions of a soil water balance model commonly used in irrigation scheduling were investigated at three regions in western Oklahoma over a 15-year (2006-2020) period. The free and frequently used WSS database underestimated sand particles in 89% of all samples taken at different regions and soil layers, resulting in finer textures across the root zone than those based on field measurements (ISS). These errors translated into differences in estimated water fluxes, which were variable across seasons and regions. In the case of irrigation, WSS resulted in generally smaller demands than ISS data in southwest and westcentral regions and larger demands in the Panhandle. While large differences were observed at some sites and some years (for example during drought years with elevated irrigation demand), most differences in irrigation estimates were within ±25 mm, with average differences staying within ±9% of ISS-based fluxes. The response of other fluxes was consistent with differences in soil data too. Underestimation of sand by WSS resulted in larger evaporation, smaller deep percolation, and larger runoff fluxes compared to estimates based on ISS in majority of the cases. Temporal variations in reference evapotranspiration, precipitation amount, and precipitation timing influenced inter-seasonal variability in all fluxes.

The results of this study show that relying on publicly available WSS soil data in soil water balance-based irrigation scheduling may have limited impacts on irrigation recommendations at regional scale, but more pronounced effects at field scale depending on the magnitude of errors in WSS data. In addition, the impacts are variable among seasons depending on atmospheric demand and timing and amount of precipitation events. Producers, irrigation planners, and policy makers can use these findings in evaluating the tradeoffs of more accurate but more expensive field measurements versus less accurate but readily and freely available soil survey data. As application of WSS data in irrigation scheduling gains more popularity for site-specific irrigation recommendations, it is important for future studies to expand the present study and consider other soils and crops, especially in areas with more arid climates.

CHAPTER IV

SIMULATING SOIL WATER STATUS OF IRRIGATED FIELDS: THE EFFECTS OF SOIL DATA AND ROOT WATER UPTAKE DISTRIBUTION

4.1. Introduction

Making irrigation decisions based on soil water status in the crop root zone is perhaps the most widely researched and commercially available approach to implementing scientific irrigation scheduling (Taghvaeian et al., 2020). Accurate and timely data on root zone soil water status can help optimize irrigation applications, achieve desired crop yield, improve the financial viability of agricultural production, and minimize potential adverse impacts on downstream ecosystems (Kukal et al., 2020). Soil water status across the root zone is most commonly reported in form of volumetric water content (θ_v). Estimates of θ_v can be obtained by one of three main methods: taking gravimetric samples, installing soil water sensors, or simulating θ_v using models (Howell, 1996; Taghvaeian et al., 2020). The first method can achieve the highest accuracy if conducted properly (Broner, 2005), but is rarely used in practical irrigation scheduling because it is destructive, labor-intensive, and time-consuming (Cardenas-Lailhacar and Dukes, 2010; Rudnick et al., 2015; Walker et al., 2004).

The second method, monitoring θ_v using sensors, is less labor-intensive and less time-consuming, provides continuous readings (Broner, 2005; Cardenas-Lailhacar and Dukes, 2010), and is becoming more widely implemented for irrigation management in the U.S. (Rudnick et al., 2015).

However, only 12% of the farms in the U.S. used this approach to schedule irrigation events in 2018 (USDA-NASS, 2019). The relatively low adoption rate of soil water sensing devices could be due to practical difficulties associated with sensor accuracy, reliability, data interpretability, required maintenance, time commitment, and cost (Kukal et al., 2020; Pardossi and Incrocci, 2011; Taghvaeian et al., 2020).

The third method, simulating θ_v using computer models, offers several advantages such as reduced time and labor requirements, ability to forecast irrigation needs (Broner, 2005), easy application, and sufficient robustness under a wide range of conditions (Pardossi and Incrocci, 2011). In addition, θ_v can be estimated at variable depths and temporal intervals (Bierkens et al., 2015). However, models may obtain lower accuracy than other methods because they rely on the accuracy of several input data (Miyamoto, 1984). For example, reference evapotranspiration and precipitation estimates may not be accurate because of the lack of well-maintained agricultural weather stations that would represent the field of interest (Taghvaeian et al., 2020).

Another major input to models is soil textural data, which may also have errors depending on the source of data and the method of collection. The most accurate soil data are obtained through in-situ soil sampling (ISS). Despite higher accuracy, ISS is tedious, laborious, and expensive. Alternatively, online databases can provide easily accessible soil data at a fraction of a cost or no cost at all. The most used database in the US is SSURGO, which allows access to soil data through its online user interface known as the USDA Web Soil Survey (WSS) (USDA-NRCS, 2017). Although previous studies have shown that WSS data are not as accurate as ISS (Brevik et al., 2003) and not precise enough for site-specific irrigation recommendations (Sui and Vories, 2020; Vories and Sudduth, 2021), many irrigation scheduling models and tools rely on WSS due to its easy, free, and fast access. For example, the Water Irrigation Scheduler for Efficient (WISE) Application, a cloud-based model that is used by producers in Montana, Wyoming, Nebraska, and Colorado, schedules irrigation based on soil data extracted from SSURGO database (Andales et al., 2020). Other irrigation scheduling tools such as Irrigation Scheduler Mobile app (Peters et al., 2019) and the web-based NDAWN Irrigation Scheduler (Scherer and Morlock, 2008) also rely on SSURGO/WSS for obtaining soil data. WSS data have also been used for irrigation scheduling at sub-field scales. For instance, ARSPivot extracts soil maps from WSS to delineate different management zones and create site-specific prescription maps for variable rate irrigation in Texas (Andrade et al., 2020). The University of Georgia's web-based model (Smart Sensor Array) also uses WSS soil textural information at sub-field scales to generate irrigation scheduling recommendations (Liang et al., 2016). As the use of SSURGO/WSS data in irrigation management at sub-field and field scales gains more popularity, it is still unclear how the errors in WSS soil data might impact the outputs of irrigation scheduling models.

More advanced models such as vadose zone water transport models may require additional input parameters like root water uptake distribution (RWUD). RWUD can be assumed as constant or linearly distributed across the crop root zone or it can be estimated based on field measurements. Most previous studies have used constant or linear patterns due to the challenges of obtaining more accurate RWUDs. Only a limited number of studies have investigated the effects of various RWUDs on simulated θ_v. In one of the earliest studies, Prasad (1988) compared constant and linear RWUD and found that constant resulted in larger errors, whereas linear obtained satisfactory results when compared to measured data. Further, the author highlighted that introduction of a non-linear RWUD would possibly improve model performance. Li et al. (1999) compared measured θ_v with simulated θ_v from constant, linear, and exponential RWUD and showed that the exponential distribution performed better than constant and linear. In a later study, Li et al. (2001a) modified this exponential distribution and showed that the modified version achieved even better results than the earlier version. Another study by Li et al. (2001b) compared linear and different exponential RWUD and found that the model with exponential RWUD performed better than the linear approach. These few studies indicate that implementation of non-linear RWUD could improve the model outputs. However, they have not explored how possible effects on simulated θ_v would translate to irrigation decisions.

The main goal of this study was to assess the performance of a vadose zone water flow and solute transport model, for practical irrigation scheduling when different combinations of soil data and RWUDs are used as input to the model. The specific objectives were (1) to quantify the effects of using two sources of soil data and three RWUDs (from simple to more complex) on simulated θ_v, and 2) to study how the effects on θ_v would translate to end-user variables for irrigation management. Simulated θ_v were compared against the readings of soil water sensors installed at commercial irrigated farms to improve the understanding of the practical implications of errors associated with variable soil data and RWUDs for irrigation scheduling.

4.2. Materials and Methods

4.2.1. Study Area

The study was conducted during the 2017 and 2018 crop growing seasons at six commercial fields within the Fort Cobb Reservoir Experimental Watershed in west central Oklahoma (Figure 4.1). The crops planted at these sites included soybean (*Glycine max* (L.)), cotton (*Gossypium hirsutum* L.), and peanut (*Arachis hypogaea* L.), which are among the dominant irrigated crops in the region. All sites were irrigated with center pivot systems, pumping water from the Rush Springs aquifer (Neel et al., 2018). The soils at the study sites are classified as Pond Creek fine sandy loam (fine-silty, mixed, superactive, thermic Pachic Argiustolls), except for one site that has Grant loam soil (fine-silty, mixed, superactive, thermic Udic Argiustolls). The electrical conductivity of the soil solution (1:1 soil-water ratio) ranged from 0.6 to 0.9 dS m^{-1} with an average of 0.8 dS m^{-1} in the top 70 cm of the soil. Study sites were visited on a weekly basis during the growing season to measure crop height using a tape measure and take canopy cover readings using the Canopeo mobile application (Patrignani and Ochsner, 2015). The Canopeo app analyzes the images taken directly above the canopy and provides the percentage of the image covered by green canopy. Table 4.1 provides additional information on the study sites.

Table 4.1. Crops, growing seasons (planting to harvest), and the total applied water (irrigation and precipitation) during the growing season.

Crop	Year	Growing season	Applied water (mm)
Soybean	2017	Jun. 17 – Oct. 07	458
	2018	Jun. 14 – Oct. 09	714
Cotton	2017	May 15 – Oct. 27	616
	2018	May 24 – Oct. 22	692
Peanut	2017	May 13 – Oct. 19	632
	2018	May 24 – Oct. 01	566

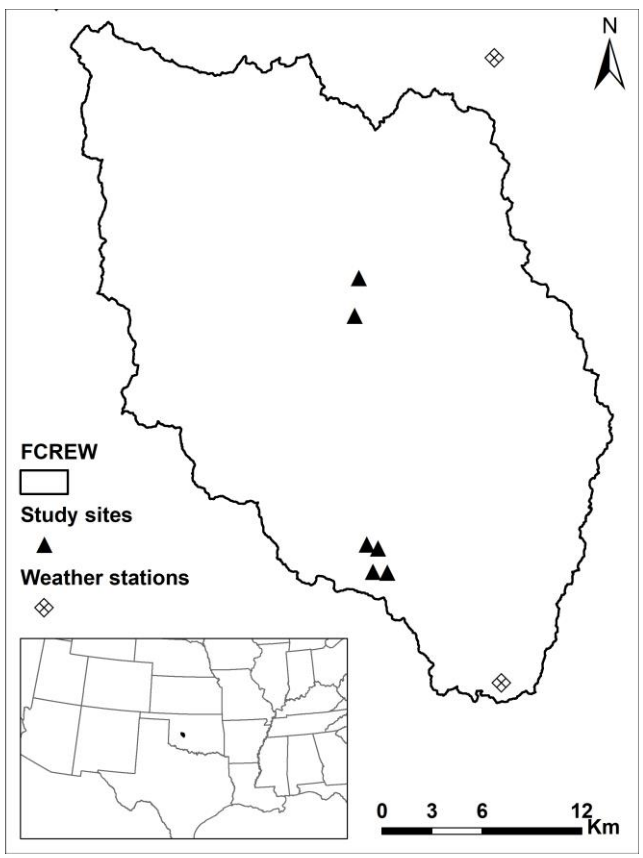


Figure 4.1. Location of the study sites within the Fort Cobb Reservoir Experimental Watershed (FCREW) and the closest weather stations.

4.2.2. Soil Water Status

Soil water status in the form of daily volumetric water content (θ_v) was obtained by implementing two approaches at each site: soil water sensors and a vadose zone water transport model. Readings from sensors were treated as the observed θ_v, while model outputs provided the simulated θ_v.

4.2.2.1. Observed θ_v

Observed θ_v was obtained by installing time domain reflectometry (TDR) sensors (models 315 and 310S, Acclima Inc., Meridian, ID, USA) at soil depths of 10, 30, 51, and 71 cm. The sensors were installed soon after crop emergence in a representative location in the field, following installation protocols described in detail in a recent study conducted at the same sites by Datta et al. (2021). The accuracy of the installed TDR sensors was found to be reasonable at the same study sites, with root mean square error (RMSE) of 0.03 $cm^3\ cm^{-3}$ (Datta et al., 2018). Sensor readings were recorded on hourly basis and then averaged to estimate daily observed θ_v.

4.2.2.2. Simulated θ_v

At each site, daily θ_v was simulated by the mechanistic one-dimensional HYDRUS model (ver. 4.16, PC-Progress S.R.O., Prague, CR) at the same four soil depths as the observed θ_v. This model uses the Richard's equation to simulate unsaturated water flow (Simunek et al., 2005):

$$\frac{\partial \theta_v}{\partial t} = \frac{\partial}{\partial x}\left[K\left(\frac{\partial h}{\partial x} + \cos\alpha\right)\right] - S \tag{1}$$

where t is time (d); K is the unsaturated hydraulic conductivity function (cm d^{-1}); h is the soil matric potential (cm); x is the spatial coordinate (cm); α is the angle between flow direction and the vertical axis (°); and S is the sink term ($cm^3\ cm^{-3}\ d^{-1}$), which represents root water uptake. The HYDRUS model was run as is with the provided input data (explained below) without site-specific calibration to represent actual use for irrigation management where this and similar models would be implemented without fine-tuning the model parameters.

In the simulation domain, the depth of the soil profile was set at 1.2 m. Atmospheric condition with surface runoff was used as the upper boundary condition and free drainage as the lower boundary condition. The initial θ_v for each site and year was separately obtained from TDR sensors. The Feddes non-compensated root water uptake reduction model was selected to simulate the effects of water stress (Feddes et al., 1978). The Feddes parameters for soybean, cotton, and peanut were based on the values reported in studies by Li et al. (1999), Forkusta et al. (2009), and Monfort et al. (2017), respectively. The same parameters were implemented in the study by Datta et al. (2021). Other inputs required for running the HYDRUS model included the amounts of irrigation and precipitation (I/P), evaporation (E), and transpiration (T) during the study period, as well as soil data and RWUDs. The methods used to obtain each of these inputs are explained in the following sections.

4.2.2.2.1. Irrigation and Precipitation

Irrigation and precipitation were measured by tipping bucket rain gauges (model 900RG, Irrometer, Inc., Riverside, CA, USA) installed near TDR sensors at each site. Hourly I/P recorded by the rain gauges were summed to achieve daily amounts and then used in HYDRUS simulations.

4.2.2.2.2. Evaporation and Transpiration

Soil evaporation (E) and crop transpiration (T) were estimated using the dual crop coefficient approach described in Jensen and Allen (2016):

$$E = K_e \times ET_o \tag{2}$$

$$T = K_s \times K_{cb} \times ET_o \tag{3}$$

where K_e is the soil evaporation coefficient; K_s is the stress coefficient; K_{cb} is the basal crop coefficient; and ET_o is the short-crop reference evapotranspiration. E, T, and ET_o have units of length, while K_e, K_s, and K_{cb} are dimensionless. Daily standardized Penman-Monteith ET_o data were estimated and reported by two nearby Oklahoma Mesonet weather stations of Hinton and Fort Cobb (McPherson et al., 2007; Sutherland et al., 2005). Values of K_{cb} were obtained from Jensen and Allen (2016) and were adjusted for mid- and late-season growth stages based on local climatic conditions. The lengths of the four crop growth stages in the piecewise K_{cb} curve were estimated based on observed growth stages and measured canopy cover. K_s was assumed equal to unity (no stress) because the HYDRUS model adjusts T for the effects of water stress using the Feddes function.

4.2.2.2.3. Soil Data

Soil textural data (percentages of sand, silt, and clay) for each study site were obtained from two sources to evaluate their effects on model outputs: in-situ soil samples (ISS) and web soil survey (WSS). For ISS, undisturbed soil samples were collected at 10-cm intervals for the top 70 cm of the soil profile using a Giddings soil sampling probe (Giddings Machine Company, Windsor, CO, USA) and analyzed based on the protocol set by Ashworth et al. (2001). In case of WSS, soil textural data were retrieved from the online user interface (ver. 3.4.0, USDA-NRCS, 2017) at the same location and soil depth increments as ISS. Soil hydraulic parameters (residual water content, saturated water content, saturated hydraulic conductivity, inverse of the air-entry value, pore size distribution index, and pore connectivity) were calculated using the Rosetta model (Schaap et al., 2001) based on the textural data from each source and used as input in HYDRUS.

4.2.2.2.4. Root Water Uptake Distribution

Two commonly used RWUD approaches are constant and linear. Under the constant approach, water uptake is assumed to be uniform across the crop root zone. Under the linear approach, water uptake decreases linearly with soil depth from a maximum value near the soil surface to zero at maximum rooting depth (Feddes et al., 1978; Prasad, 1988). However, these widely used simplified distributions seldom represent the reality of water extraction by roots. Improper representation of root water uptake has been documented as one of the challenges for accurate estimation of θ_v in the studies by Li et al. (1999) and Ojha et al. (2009). On the other hand, the collection of in-situ root samples is costly, labor-intensive, and time-consuming. To overcome these challenges, the sensor-based approach was proposed and implemented in this study.

The sensor-based RWUD was estimated based on the readings of a 1.2 m long soil water probe (AquaSpy Inc., San Diego, CA, USA) installed at each site. Unlike the TDR sensors that were installed at four depths (10, 30, 51, and 71 cm) and provided estimates of θ_v, the AquaSpy probe had 12 sensors at 10-cm intervals along its length and provided estimates of scaled frequency (SF). SF is a dimensionless number ranging from zero to 100, with zero representing air dry and 100 representing saturated conditions. Sensor-based RWUD for each sensor depth (10 cm intervals) was estimated based on changes in SF readings during the 4-day periods after reaching field capacity (FC) if no I/P was recorded in that period. It was assumed that FC is reached within two days after major I/P events given the coarse to medium texture of the soil profiles. Several 4-day periods during the middle of the growing season were identified for each site. The reason for selecting the 4-day periods from the mid-season growth stage is that maximum rooting depth has been reached and root system can be assumed static (Bufon et al., 2012). For each identified period, daily rate of decline in SF at each sensor depth along the 1.2 m of the AquaSpy probe was estimated as:

$$\mathrm{DDSF} = \frac{\mathrm{SF_i} - \mathrm{SF_f}}{\mathrm{n}} \tag{4}$$

where DDSF is the daily decline in SF; SF_i is the initial SF (two days after a major I/P event); SF_f is the final SF (4 days after SF_i); and n is the number of days between SF_i and SF_f. The ratio of

DDSF at each depth to the sum of DDSF values for the entire probe length was then estimated for each period and assumed to represent the relative root water uptake for that period and depth. These relative root water uptakes were averaged for all periods and interpolated between the AquaSpy sensor depths to develop the RWUD curve for each site. The three different RWUDs were provided separately as inputs in the soil profile summary window of HYDRUS to describe the spatial variation of water extraction over the root zone.

4.2.3. Irrigation End-user Variables

End-user variables are crucial indicators for developing and implementing scientific irrigation scheduling (Sharma et al., 2020). Two key end-user variables are irrigation trigger (IT) and soil water depletion (SWD). Together, these variables can determine the timing and the amount of irrigation events. The value of SWD when irrigation is triggered determines the amount of irrigation to be applied. For each site, IT and SWD were calculated based on simulated θ_v obtained from running the HYDRUS model with each of the six combinations of two sources of soil data (ISS and WSS) and three RWUDs (constant, linear, and sensor-based).

4.2.3.1. Irrigation Trigger

IT was calculated by estimating total soil water (TSW) and comparing it to readily available water (RAW) at each site (Sharma et al., 2020). The TSW on each day of the study period was estimated by integrating the simulated θ_v over the rooting depth and converting the units to depth of water. The RAW was estimated for the rooting depth as the level at which half of the available water content (AWC), defined as the difference between FC and wilting point (WP), was depleted. In other words, the maximum allowable depletion was assumed to be 50%, which is a typical estimate for most agricultural crops. Soil water thresholds of FC and WP were computed based on the van Genuchten function (van Genuchten, 1980) using the same soil data that were used as input in HYDRUS. An IT value of one was considered for any day during the study period when TSW was smaller than or equal to RAW, meaning that irrigation should have been triggered. Otherwise, the IT was zero (Equation 5). The sum of IT during the study period was compared among the six combinations of soil data and RWUDs at each site:

$$IT = \begin{cases} 0 & \text{if TSW} > \text{RAW} \\ 1 & \text{if TSW} \leq \text{RAW} \end{cases} \tag{5}$$

4.2.3.2. Soil Water Depletion

SWD is the amount of water required to bring the TSW to FC level (Equation 6). The average SWD during the study period was compared among the six combinations of soil data and RWUDs at each site:

$$SWD = FC - TSW \tag{6}$$

4.2.3. Statistical Indicators

Simulated θ_v obtained from HYDRUS model for each combination of soil data and RWUDs were compared with observed θ_v from TDR sensors to evaluate the effects of input data variability on model performance. Two statistical indicators were used: RMSE and mean bias error (MBE). The RMSE equals zero when the compared datasets show perfect agreement. The MBE indicates under- and/or over-estimation of simulated θ_v compared to observed θ_v:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\theta_{v\_s(i)} - \theta_{v\_o(i)})^2} \tag{7}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n} (\theta_{v\_s(i)} - \theta_{v\_o(i)}) \tag{8}$$

where n is number of days (sample size), θ_{v_s} is simulated θ_v, θ_{v_o} is observed θ_v, and i is the observation index of each time-step. In addition, Pearson’s correlation coefficient (r) was calculated to understand how closely the temporal patterns of simulated and observed θ_v were related to each other. Closely correlated patterns have r values near one, and uncorrelated patterns have a value near zero.

4.3. Results and Discussion

4.3.1. Soil Data Sources

The two sources of soil data (ISS and WSS) had major differences in their estimates of soil textural data (Figure 4.2). The percentage of sand particles had the largest difference, while the percentage of clay had the smallest variation between the two sources. In 95% of the cases, WSS underestimated sand percentage, with a difference that ranged from 5 to 47%. The underestimation error increased with depth, especially below 30 cm. In other words, WSS indicated finer textures at deeper layers. The average percentage of sand among all sites and depths was 66% based on ISS, larger than the average value based on WSS (41%). The underestimation in sand percentage by WSS was accompanied by overestimation of silt percentage. The average silt content was 18% based on ISS, about half of the average silt content from WSS (38%).

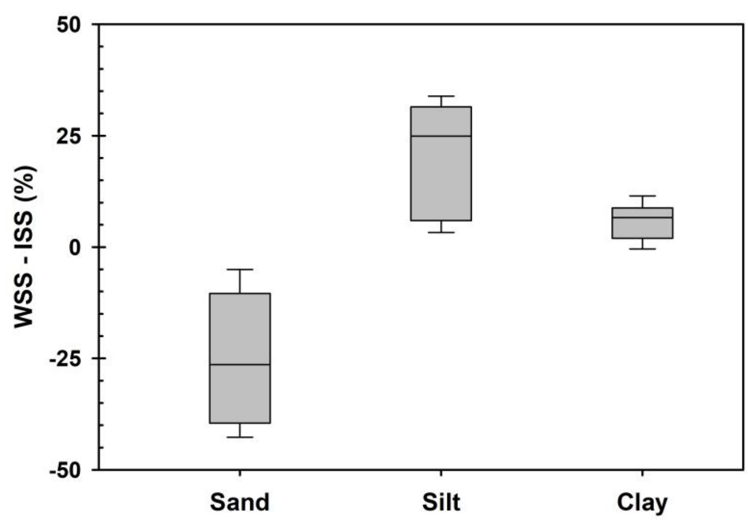


Figure 4.2. Box plots of differences in particle size between WSS and ISS. Whiskers indicate 10th and 90th percentiles.

The differences in soil texture have considerable impact on simulating water movement in the root zone. For example, the average saturated hydraulic conductivity was 51.9 cm d^{-1} for ISS and 19.6 cm d^{-1} for WSS. Key soil water thresholds and parameters used in irrigation scheduling, namely FC, WP, and AWC, were also impacted by errors in soil textural data (Figure 4.3). The average FC estimated based on the ISS and WSS input data were 25% and 33%, respectively. The average WP estimates were closer at 8% and 10% based on the ISS and WSS, respectively. The average AWC estimates were 17% based on ISS and 23% based on WSS. The difference in average AWC estimates is equal to 68 mm of water for 1.0 m of the soil profile. The largest difference observed was about 117 mm for 1.0 m of soil profile.

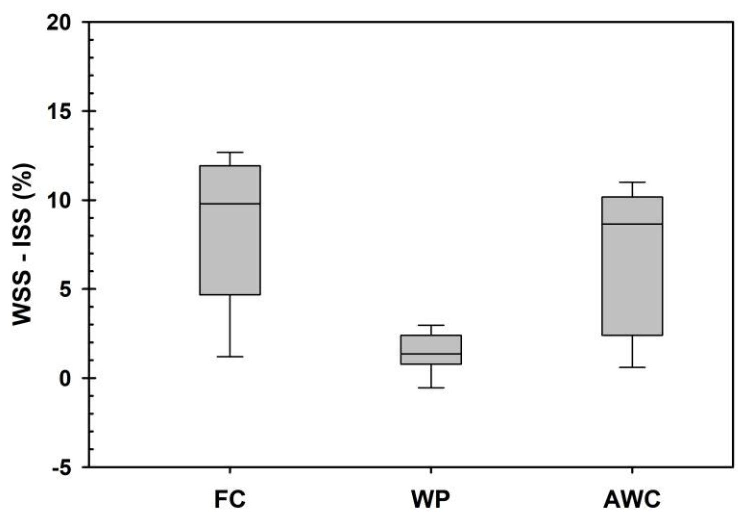


Figure 4.3. Box plots of differences in field capacity (FC), wilting point (WP), and available water content (AWC) between ISS and WSS. Whiskers indicate 10th and 90th percentiles.

4.3.2. Root Water Uptake Distributions

In general, the sensor-based RWUD resulted in larger water extractions than constant and linear distributions at shallow depths and smaller extractions at deeper layers (Figure 4.4). Based on the sensor data, 60% to 81% of the total water extraction occurred within the top 30 cm of the soil profile. This is probably due to considerably large concentration of roots at shallower soil layers. After measuring and monitoring irrigation applications in the same study area, Datta et al. (2021) found that irrigation events were too frequent and small, a situation that would result in shallow root systems.

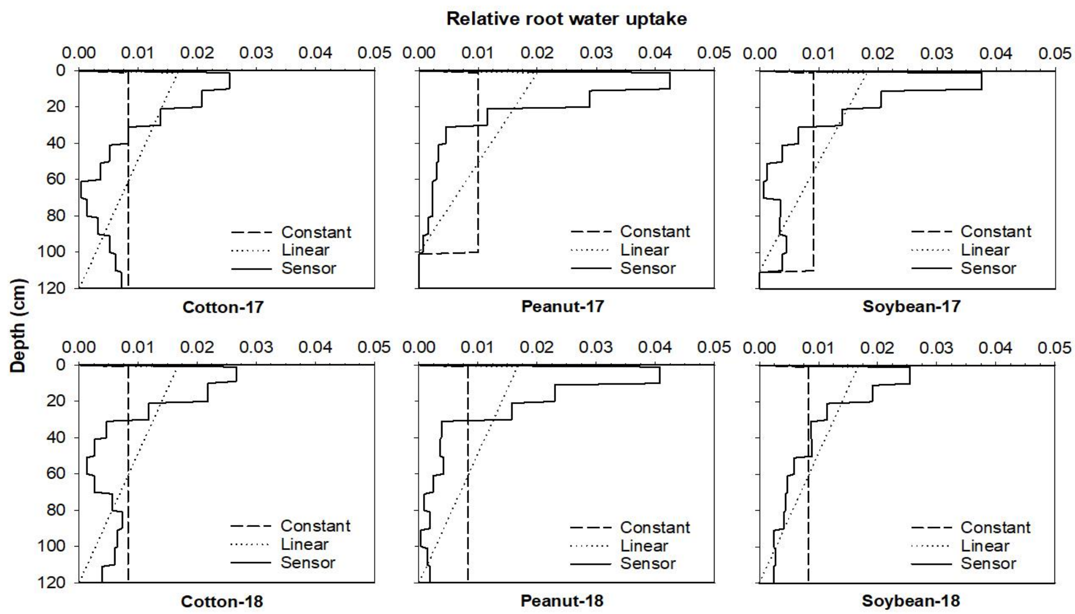


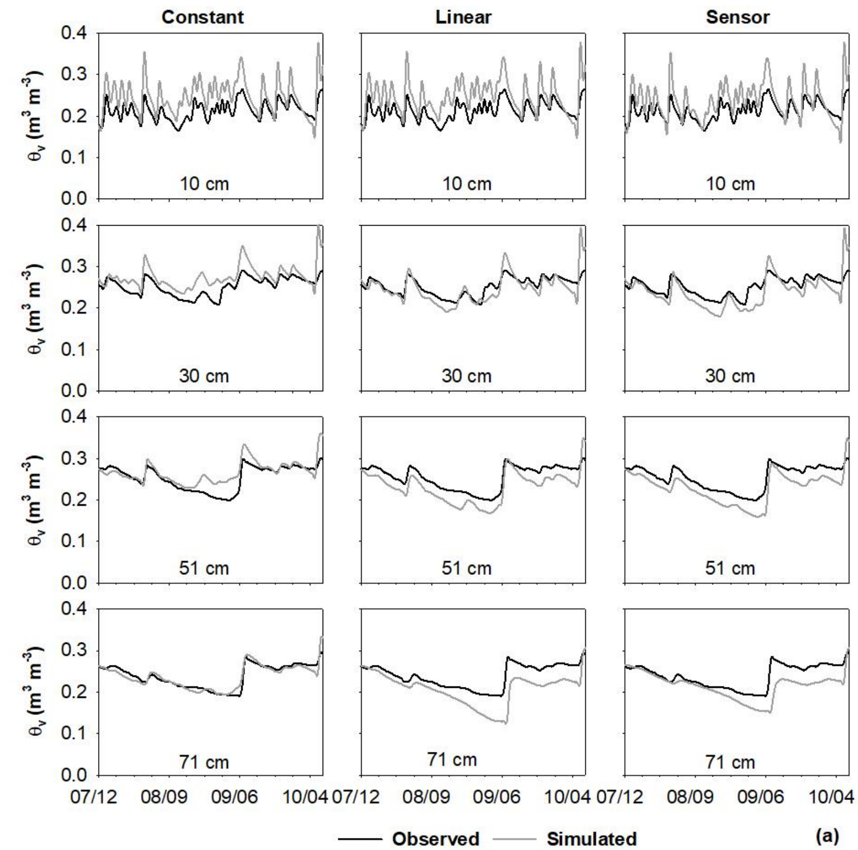
Figure 4.4. Root water uptake distributions at each study site in 2017 and 2018 based on constant, linear, and sensor-based approaches.

Other studies have reported similar results. For example, Payero et al. (2017) estimated root water uptake based on readings of a capacitance probe (same technology as the probe used in this study) and found that 75% and 95% of the total seasonal water extraction by cotton occurred from the top 50 and 110 cm of soil, respectively. In the present study, the portions of the total cotton water uptake for the same two depths were 70% and 95%, respectively. Using θ_v obtained gravimetrically, Patel et al. (2008) found that the portions of total water uptake by peanut roots from the top 30 and 60 cm soil layers were 50% and 87%, respectively. In this study, the estimated portions for the same two depths and the same crop were 80% and 92%, respectively, indicating a larger extraction from shallower layers. For soybean, Curto et al. (2019) estimated that 50% to 65% of total root water uptake occurred in the top 27.5 cm layer based on readings from a capacitance probe. The values for the two soybean fields of the present study were 56% and 72% for the top 30 cm layer.

At half of the sites (cotton-17, cotton-18, and soybean-17), root water uptake decreased to about 60-70 cm and then increased. This behavior may be due to two reasons: 1) presence of a compacted layer around 60-70 cm, which was anecdotally observed during probe installation at these sites, and 2) some level of water stress occurred at the shallower layers during 4-day periods against the assumption made. Roots would extract more water from deeper layers if θ_v at shallow layers is decreased (Thangthong et al., 2016). Regardless of the reason behind observed patterns, the sensor-based approach represents the actual RWUD for the top 120 cm of the soil, providing a useful reference in assessing the effects of variable RWUDs on the output of models such as HYDRUS.

4.3.3. Model Performance

Simulated θ_v by HYDRUS for the six combinations of two soil data sources (ISS and WSS) and three RWUDs (constant, linear, and sensor-based) had generally similar patterns to observed θ_v recorded by TDR sensors at 4 soil depths during the study period. As expected, simulated and observed θ_v at all sites had more pronounced response to water applications at the shallower depths of 10 and 30 cm than deeper layers of 51 and 71 cm. However, model performance varied among sites. Figure 4.5 illustrates simulated and observed θ_v for the two sites that had the best and worst performances. When considering all soil-RWUD combinations, soybean-18 had the smallest errors, and peanut-18 had the largest errors.



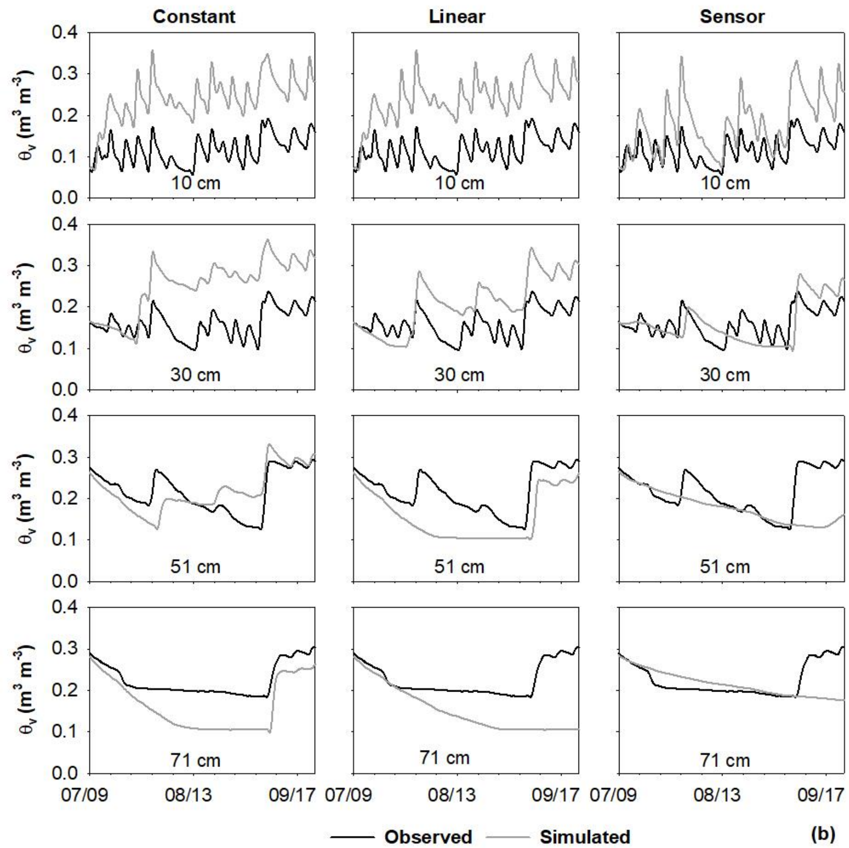


Figure 4.5. Observed and simulated volumetric water content (θ_v) at four soil depths (10, 30, 51, and 71 cm) at the sites with the (a) smallest errors (WSS soybean-18) and (b) largest errors (WSS peanut-18).

Average error indicators for six combinations of soil data and RWUDs are provided in table 4.2, and the ranges are shown in figure 4.6. Among the two soil data sources, WSS resulted in larger average and maximum RMSEs (0.05 and 0.15 cm^3 cm^{-3}, respectively) compared to ISS (0.04 and 0.12 cm^3 cm^{-3}, respectively). Among the RWUDs, constant led to the largest average and maximum RMSEs (0.05 and 0.15 cm^3 cm^{-3}, respectively) and sensor-based resulted in the smallest RMSEs (0.04 and 0.08 cm^3 cm^{-3}, respectively). When averaged over all sites and depths, the largest RMSE was 0.06 cm^3 cm^{-3} for WSS-constant combination and the smallest RMSE was 0.04 cm^3 cm^{-3} for ISS-sensor. As mentioned before, the observed θ_v used in estimating these

RMSEs were obtained from the readings of TDR sensors. A previous study in the same area found the RMSE of the same TDR sensors to be 0.03 cm^3 cm^{-3} when compared against gravimetric measurements (Datta et al., 2018). This indicates that the average accuracy of simulated θ_v based on ISS-sensor was close to the accuracy range of the TDR sensors. Most of the differences in RMSEs were from the shallowest depth of 10 cm and the values for the other three depths were closer.

Table 4.2. Average root mean square error (RMSE) and mean bias error (MBE) for each combination of soil data and RWUD.[a]

RWUD	RMSE (cm^3 cm^{-3})		MBE (cm^3 cm^{-3})	
	ISS [b]	WSS [c]	ISS	WSS
Constant	0.05	0.06	0.03	0.03
Linear	0.04	0.05	0.00	0.01
Sensor	0.04	0.04	0.01	0.01

[a] RWUD = root water uptake distribution, ISS = in-situ soil samples data, and WSS = USDA Web Soil Survey data.

The other error indicator (MBE) provided similar information to RMSE. When comparing soil data sources, WSS had larger average and maximum MBEs (0.02 and 0.14 cm^3 cm^{-3}, respectively) compared to ISS (0.01 and 0.11 cm^3 cm^{-3}, respectively). Among the RWUDs (ISS and WSS combined), constant resulted in the largest average and maximum MBEs (0.03 and 0.14 cm^3 cm^{-3}, respectively). Average and maximum MBEs were 0.00 and 0.12 cm^3 cm^{-3}, respectively, for the linear and 0.01 and 0.07 cm^3 cm^{-3}, respectively, for sensor-based RWUDs. Similar to RMSE, the differences in MBEs based on the six combinations of input data were larger for the 10 cm depth compared to 30, 51, and 71 cm depths. The correlation coefficients showed that in general, simulated and observed θ_v behaved similarly, with average r estimates that ranged from 0.68 based on WSS-sensor combination to 0.75 for ISS-sensor.

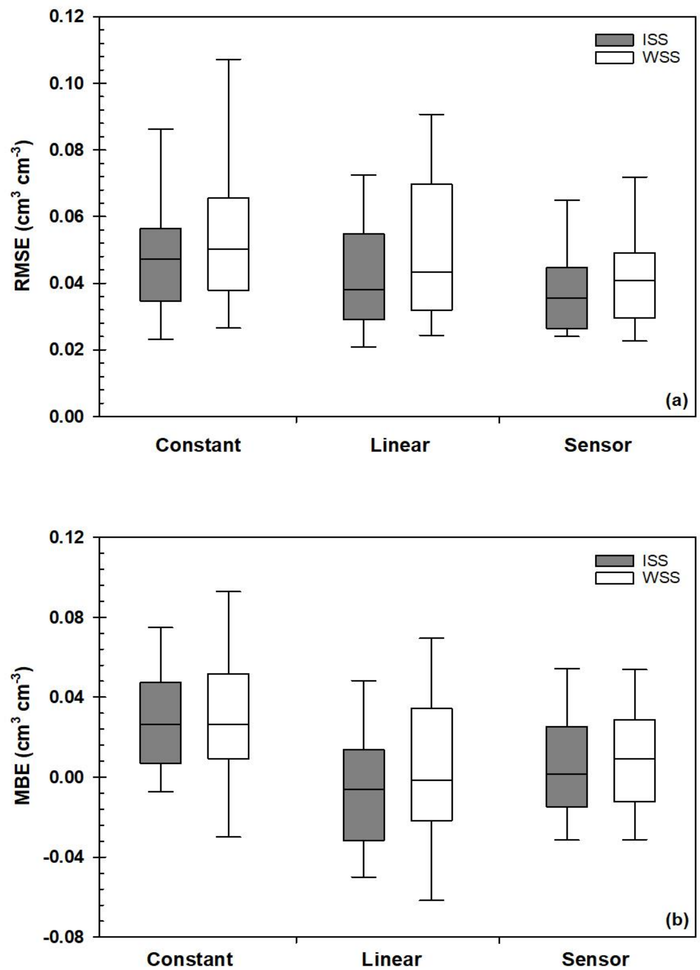


Figure 4.6. Box plots of (a) root mean square error (RMSE) and (b) mean bias error (MBE) (b) of simulated θ_v for the six combinations of soil data and RWUDs. Whiskers indicate 10^{th} and 90^{th} percentiles.

The RMSEs of the present study were comparable to and in some cases larger than those reported in previous studies. For example, Er-Raki et al. (2021) compared θ_v from field-calibrated TDR sensors with the HYDRUS model and found that the average RMSE was 0.02 cm^3 cm^{-3}. Silva Ursulino et al. (2019) reported good agreement between θ_v from lab-calibrated TDR sensors and HYDRUS model, with an RMSE range of 0.01 to 0.02 cm^3 cm^{-3}. Gonzalez et al. (2015) compared θ_v from frequency domain reflectometry sensors and HYDRUS and found RMSE varying from

0.01 to 0.03 cm^3 cm^{-3}. Li et al. (2015) compared neutron probe and HYDRUS-simulated θ_v and reported an RMSE of 0.05 cm^3 cm^{-3}. Several factors can contribute to disagreements between simulated and observed θ_v including, but not limited to, preferential flow caused by macropores and cracks (Garg et al., 2009; Patil et al., 2011), spatial heterogeneity of soil, sensors' errors, errors in field observations (Deb et al., 2013; Vazifedoust et al., 2008), and errors in RWUDs (Simunek et al., 2005).

4.3.4. Irrigation End-user Variables

Large variations in IT and SWD were observed for different combinations of soil data and RWUDs. Figure 4.7 shows the average IT as percentage of the study period and the average SWD for each input data combination. Use of WSS data resulted in an IT being activated during 66% of the study period on average, compared to 18% based on ISS data. Similarly, the average SWD was 157 mm based on WSS, more than twice the average SWD based on ISS (68 mm). These differences were mainly due to large soil textural errors in WSS, which resulted in overestimation of soil water thresholds (FC, WP, and RAW). They also indicate that irrigation management decisions could be highly affected if the errors in WSS are as large as those obtained in this study. The effects could be considerable for web-based irrigation scheduling tools and smart-phone applications that rely on WSS to recommend irrigation timing and amount. Some of these tools allow users to modify WSS data automatically extracted by the tool if they have more accurate information.

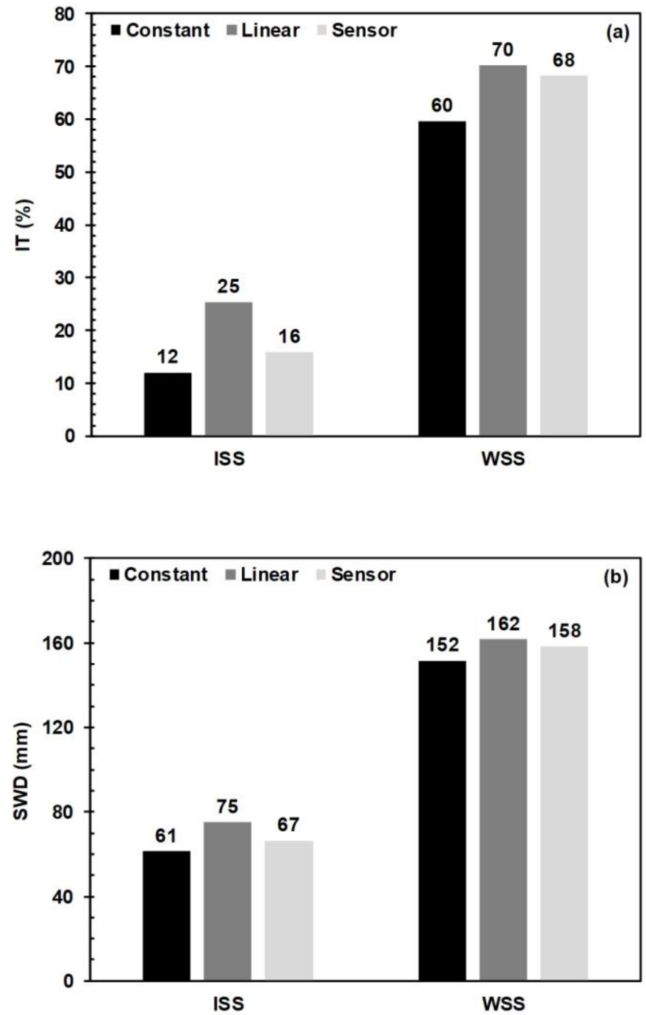


Figure 4.7. (a) Average irrigation trigger (IT) as a percentage of the study period when IT was equal to unity and (b) average soil water depletion (SWD) for each combination of soil data and RWUDs.

The effects of variable RWUDs on IT and SWD were smaller than the effects of soil data variability. The average percent of the study period when IT was equal to unity ranged from 36% for constant to 48% for linear. The minimum and maximum average SWD were 106 and 118 mm for the same two RWUDs, respectively. These small differences suggest that errors in RWUD have limited impact on irrigation end-user variables and thus installing a soil water sensor probe just for obtaining accurate RWUD may not be justified. This is probably due to the fact that irrigation decisions were based on the total water content of the root zone. As a result, changes in relative water extraction across the soil profile, despite having an impact on depth-specific θ_v, had minimal effect on end-user variables. However, this study was conducted during the part of the growing season when roots had reached their maximum length. Sensor data can be useful in estimating root development during early stages of growth and can play an important role in adjusting irrigation management as roots grow.

4.4. Conclusions

Simulated θ_v based on each of the six combinations of soil data and RWUDs were compared against observed θ_v at four soil depths at each of six fields under center pivot irrigation systems. In most cases, errors were larger when WSS data were used as input rather than ISS data. The best model performance was achieved when the ISS-sensor combination was used as input, resulting in an average RMSE of 0.04 $cm^3\ cm^{-3}$ among all sites and depths. The largest average RMSE (0.06 $cm^3\ cm^{-3}$) occurred when the WSS-constant combination was used. Two other indicators of MBE and r showed the same pattern, with simulated θ_v based on ISS-sensor having the smallest errors and being more highly correlated with observed θ_v, especially at shallower depths. Finally, simulated θ_v values were converted to end-user variables (IT and SWD). Based on IT estimates, irrigation was needed 66% of the time on average when WSS was used, while using ISS as input soil data resulted in an IT during only 18% of the time. The average SWD, which represents the amount of irrigation required, was also larger based on WSS at 157 mm compared to 68 mm when ISS was used as input data. Differences in RWUD had a smaller impact on the end-user variables because these variables are estimated for the entire root zone and the distribution of water extraction within the root zone has a smaller impact on them.

The results of this study demonstrate the importance of using accurate input data, especially soil textural data, in irrigation tools and models in order to deliver the desired improvements in irrigation management. As irrigation scheduling tools advance to allow for more capabilities, additional types of input data with different levels of complexity may be required. Future studies should further examine the effects of errors in input data on irrigation model outputs for a range of soil, crop, and climatic conditions. Identifying the magnitude of errors in simulated end-user variables caused by errors in input data can help decision makers prioritize different types of input data and spend their limited resources to increase the accuracy of those that have the largest effects on model outputs.

CHAPTER V

CONCLUSIONS

Development and implementation of scientific irrigation management technologies in agriculture can play a vital role in supplying the growing demands and securing the economic and environmental sustainability of crop production. This research project evaluated the performance and effectiveness of different scientific irrigation scheduling methods under variable soils, crops, and climatic conditions of western Oklahoma. The main goal of each of the three chapters was to: (1) evaluate the performance of a multi-sensor capacitance probe in determining soil water content and field capacity, (2) study the effects of soil data accuracy on irrigation scheduling using a soil water balance model for different crops and climatic conditions across western Oklahoma, and (3) investigate the impact of variable soil data and root water uptake distributions on multi-layer soil water status and irrigation parameters simulated by a vadose-zone water transport model.

In the first study (Chapter 2) the performance of a commercially available multi-sensor capacitance probe with six different calibrations provided by the manufacturer was evaluated at 36 irrigated sites with variable levels of clay content and salinity. The Default calibration resulted in the largest error, indicating the need for changing the factory setting and selecting a more appropriate calibration. The smallest errors considering all sites was obtained by the Silty clay loam calibration. Higher clay content and salinity had major impacts on sensor performance.

Default and Sand calibrations were more sensitive to increases in clay and salinity compared to other calibrations. Heavy clay was the only calibration that had an opposite trend and showed smaller errors at larger clay ranges regardless of salinity. Although silty clay loam obtained the smallest errors, the calibration produced a smaller range of soil water contents. The Combined calibration that had somewhat similar accuracy produced a larger range of readings, which is important for practical irrigation scheduling. Field capacity (FC) for 13 sites and two depths at each site was determined in the laboratory and used to evaluate the performance of two sensor-based approaches in determining FC: days after major watering events to reach laboratory FC and the percentile of sensor readings that represents laboratory FC. Laboratory FC was reached from 1 to 9 days depending on clay and soil depth. The percentile approach had a large range of estimates too, from 3 to 97%. Neither of the two approaches were reliable in providing FC estimates. The main factors impacting sensor-based FC estimates appeared to be soil texture, soil depth, soil layers below the depth of interest, irrigation system, and irrigation management.

In the second study (Chapter 3), the errors in freely available and commonly used web soil survey (WSS) soil textural data were evaluated for three regions of western Oklahoma through comparison with in-situ sampling (ISS) data. The effects of errors on estimated water fluxes of a soil water balance model were also investigated for dominant crops of each region over a 15-year (2006-2020) period. WSS soil textures were finer than ISS at most sites and soil layers, resulting in generally larger root zone total available water estimates. Differences in irrigation demand estimates when WSS data were used instead of ISS reached 20% at one site but were generally within ±9%. Half of the estimated irrigation differences for all sites, years, and crops were within ±25 mm. Soil evaporation, deep percolation, and runoff fluxes were also impacted by soil data accuracy, albeit to a smaller degree than irrigation, at levels and directions (over or underestimation) that were dependent on the sign and magnitude of WSS errors, as well as precipitation amounts and timing.

In the third study (chapter 4), the combined effects of soil textural data accuracy and root water uptake distributions (RWUDs) on simulated soil water content at different layers of six irrigated fields were investigated using the HYDRUS model. In addition, the study assessed how the effect would translate to end-user variables for irrigation management. The percentage of sand particles based on WSS was about half of the measured values on average, resulting in a considerable difference in estimated hydraulic properties and soil water thresholds. Sensor data revealed that RWUDs were highly nonuniform, with more than 60% of water extraction occurring from the top 30 cm of the root zone. Among the six combinations of two sources of soil data and three RWUDs, ISS-sensor resulted in the smallest errors in simulated soil water content and WSS-constant yielded the largest errors. Relying on WSS resulted in irrigation trigger being called about four times more than when measured soil data were used. The average soil water depletion based on WSS was also about two times larger than the average soil water depletion based on ISS.

Overall, this study assisted in knowing how a multi-sensor probe with different calibrations was performed in irrigated fields with a wide range of clay and salinity levels and how errors in the sensor impacted in estimating field capacity and irrigation management decisions. Further, the study provided information that publicly and easily available web soil survey data may have relatively small impacts on irrigation recommendations at regional scale, but the impacts could be large at field scale. Finally, this study helped in understanding the importance of using accurate input data in irrigation scheduling tools and models to improve the estimates of soil water content and irrigation management decisions.

CHAPTER VI

RESEARCH CONTRIBUTIONS

CHAPTER II: PERFORMANCE OF A MULTI-SENSOR CAPACITANCE PROBE IN ESTIMATING SOIL WATER CONTENT AND FIELD CAPACITY

Many new and/or upgraded soil water sensors are introduced in the market every season. There is a need to continuously evaluate the performance of these sensors, as they become available. In addition, several studies have looked at the performance evaluation of various types of commercially available soil water sensors. However, there has been lack of field studies that capture a wide range of field variability in terms of clay and salinity levels. This study assists in understanding how a multi-sensor capacitance probe with different calibrations provided by the manufacturer performed under highly variable field conditions. In addition, the study provides information on the accuracy and reliability of sensor-based approaches to identify field capacity, an area of research that has not received much attention by previous researchers.

CHAPTER III: EFFECT OF SOIL DATA ACCURACY ON OUTPUTS OF IRRIGATION SCHEDULING TOOLS

In recent years, web-based irrigation scheduling tools and smartphone apps that rely on simple soil water balance models have been gaining popularity among growers. Most of these tools obtain their required soil data from USDA's Web Soil Survey (WSS) online database, which is freely available and required less time than taking in-situ soil (ISS) samples and processing them in the laboratory. Several previous studies have reported that WSS data are less accurate, and may not be appropriate for precision agriculture applications including irrigation recommendations. However, no comprehensive studies have been conducted to look at the effects of soil data accuracy on irrigation recommendations. This study provides information on how freely and easily obtainable WSS data impact irrigation recommendations using a soil water balance model in variable soils, crops, and climatic conditions. Such information is lacking in the literature and can be used by producers, irrigation planners, and policy makers to evaluate the tradeoffs between accurate and less accurate soil data.

CHAPTER IV: SIMULATING SOIL WATER CONTENT OF IRRIGATED FIELDS: THE EFFECTS OF VARIABLE SOIL DATA AND ROOT WATER UPTAKE DISTRIBUTIONS

With recent advances in web-based irrigation scheduling tools and mobile applications and the possibility of using more complex modeling approaches, it is important to evaluate the effects of variable input data on the output of these tools and models. This study simulates soil water content at different soil depths using six different combinations of two soil data sources and three root water uptake distributions as input to a vadose-zone water transport model and demonstrates the importance of using accurate input data for irrigation management. The findings can help researchers identify the sensitivity of advanced irrigation tools and models to different input parameters and their accuracies and to prioritize investing limited resources to improve model performance.

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