MEASUREMENT AND MODELING OF SOIL

MOISTURE FOR IRRIGATION MANAGEMENT

By

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Abstract: Increasing strain on freshwater resources due to population growths, climate change, and excessive depletion of water resources necessitates research in maximizing beneficial water use in agriculture regions. Smart technologies have a vital role to play in achieving this goal. Soil moisture sensors (SMS) have been well-recognized as effective smart technologies due to their proven ability to deliver efficient and practical irrigation management. However, the adoption of SMS by agricultural producers has remained limited over the last 20 years. There is an urgent need to investigate the barriers behind the low adoption of SMS and conduct applied research projects to demonstrate the advantages of SMS utilization. The objectives of this study were to: (1) conduct a Strengths, Weaknesses, Opportunities, Threats (SWOT) analysis on published literature related to SMS applications in irrigation management to identify shortcomings and potentials; (2) assess the performance of commercially available soil moisture sensors in irrigated fields of Oklahoma; and, (3) investigate the performance of computer models in estimating soil moisture dynamics and quantifying irrigation fluxes under field conditions. The SWOT analysis revealed the lack of adequate local field studies in determining SMS accuracy, reliability, and affordability under variable soil and climatic conditions. The accuracy of five commercially available SMS was determined under variable soil texture and salinity in Oklahoma. The evaluation of moisture thresholds obtained from different methods showed the effects of threshold variability on practical irrigation management. Using a combination of measurement and modeling techniques, water fluxes in an agricultural watershed provided valuable information on actual irrigation practices employed by producers. This methodology can be applied to other irrigated areas to evaluate irrigation management strategies.

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CHAPTER I

INTRODUCTION

1.1. Background

Water is one of the vital natural resources, facing significant challenges in many parts of the world (Jacobson et al., 2017). Only 1% of this resource is in form of freshwater, which can be utilized to meet growing global demands in various sectors such as agriculture, industry, and domestic. This makes freshwater a severely limited and extremely valuable resource. In future, the strain on freshwater resources is bound to increase due to population growths, climate change, and excessive depletion of available resources (Kisekka et al., 2017). Thus, proper freshwater utilization will be of paramount importance. In 2015, about 42% of total freshwater withdrawal was for irrigation in the United States (U.S.) (USDA, 2014), making it the biggest consumer of freshwater resources (Schaible & Aillery, 2012).

The withdrawn irrigation water is divided into two uses: beneficial and non-beneficial. Beneficial uses involve transpiration by plants (directly related to the crop yield) and leaching of salts (Jägermeyr et al., 2015). Non-beneficial use is the water lost during conveyance or application of water. To supply food, feed, and fiber for the ever-increasing world population, the beneficial water usage needs to increase significantly (Tilman et al., 2002). The only way to increase beneficial water use without increasing withdrawals is to minimize the non-beneficial uses, leaving a larger portion of extracted water for beneficial uses. Technological advances in irrigation hardware and improved irrigation management can play a crucial role in the U.S. and around the world to minimize non-beneficial uses while sustaining, if not increasing, crop yields (Howell, 2001; Tilman et al., 2002).

Over the past few decades, several technologies have been developed to improve irrigation management based on key variables such as soil moisture, crop evapotranspiration (ET), canopy development, and canopy temperature. These technologies have used in-situ measurements, remotely sensed estimates, or modeling approaches to estimate the key variables mentioned before (Howell, 2001). Soil moisture monitoring is one of the available management technologies that has received a significant attention due to its several advantages. It can reduce irrigation amounts, labor costs, and energy requirements substantially (Belayneh et al., 2013), and can promote yield amount and quality (Lichtenberg et al., 2013). Despite these advantages, the adoption of soil moisture sensors has been limited since its commercialization a few decades ago (Lichtenberg et al., 2015). In the U.S., only 11% of the farmers use soil moisture sensors to schedule irrigation events (USDA, 2014). The barriers to the low adoption of soil moisture sensors must be investigated and removed to allow for improved irrigation management using this technology.

One of the major reasons behind low adoption of soil moisture sensors is the complexity of choosing a sensor that would perform best under specific, yet spatially variable conditions of irrigated fields (Peters et al., 2013). This is because different sensors perform differently under various soil and water conditions. For example, the clay content can have variable impacts on sensor accuracy based on the type of sensor. Some researchers have reported over-estimation of soil moisture in soils with high clay content (Kisekka et al., 2017; Rüdiger et al., 2010), while others have observed under-estimation (Fares et al., 2011; Schwartz et al., 2016). The soil salinity can also add to the errors of some sensors. In most of the previous studies, sensors in saline soils over-estimated soil moisture (Dalton, 1992; Wyseure et al., 1997), but Schwartz et al. (2016) observed under-estimation of soil moisture in saline soil. Due to these variable and inconsistent performances, there is a critical need to assess the accuracy and reliability of commercially available soil moisture sensors under different levels of soil salinity and clay content.

Another barrier to adoption is the ease of interpreting data reported by sensors. Producers need to understand the sensor-reported data in order to implement a precision irrigation management. Commercially available sensors usually report soil moisture in either matric potential or volumetric water content units (Bittelli, 2010; Bittelli, 2011). There is a steep learning curve for most producers and irrigation managers to understand reported numbers and to convert them to decisions on irrigation timing and amount. In addition, information about soil moisture thresholds is usually necessary, which adds to the complexity of the process. Several previous publications have reviewed the measurement principles of different types of soil moisture sensors and their performances (Adeyemi et al., 2017; Bittelli, 2010; Bittelli, 2011; Cardenas-Lailhacar & Dukes, 2010). However, most of these publications did not focus on how sensor-reported soil moisture can be used for practical irrigation management in real-world situations. Therefore, a comprehensive analysis is needed on relevant published papers to explore current barriers and challenges to adoption of soil moisture sensors and explore how to promote practical use of soil moisture sensors for efficient and precise irrigation management.

Although sensors can provide accurate and precise estimates of soil moisture depending on field conditions and user experience, implementing sensors may still not be feasible due to a number of reasons such as relatively large cost and time commitment to purchase, install, and maintain sensors. When using sensors is not an option, computer modeling can be an alternative in simulating soil moisture dynamics with reasonable accuracy (Simunek et al., 2005). Computer models can also simulate important water fluxes such as evapotranspiration (ET), runoff, and deep percolation (DP). Estimating irrigation fluxes has many applications, for example in determining if irrigation is responsible for water quality impairment in downstream groundwater and surface water resources (Malakar et al., 2019) and can also indicate the efficiency of irrigation applications (Kebede et al., 2014). Many previous studies have evaluated the performance of computer models under lab and greenhouse conditions (Kandelous & Šimůnek, 2010; Zhang et al., 2009). However, limited studies have investigated these models under actual field conditions with high levels of heterogeneity across locations and depths.

1.2. Objectives

The overarching goal of this research was to assess the performance and effectiveness of existing measurement and modeling approaches to monitor soil moisture in irrigated fields to improve conservation of freshwater quantity and quality in irrigated agriculture. The specific objectives of this research were:

1. To conduct a Strengths/Weaknesses/Opportunities/Threats (SWOT) analysis on published literature related to soil moisture sensor applications in irrigation management to identify shortcomings and potentials;

2. To assess the performance of commercially available soil moisture sensors in irrigated fields of Oklahoma; and,

3. To investigate the performance of computer models in estimating soil moisture dynamics and quantifying irrigation fluxes under field conditions.

CHAPTER II

A SWOT ANALYSIS OF SOIL MOISTURE SENSOR APPLICATIONS FOR IRRIGATION MANAGEMENT

2.1. Introduction

Smart sensing technologies play a vital role in conserving agricultural water resources and increasing crop yield by improving irrigation management (Steele et al., 1994). Soil moisture sensors (SMS) have been recognized as one of the effective tools among available smart sensing technologies for irrigation management. Despite numerous research studies conducted over the past few decades that show the usefulness of SMS, the adoption of this technology has remained limited and seen only a modest rise over the years in the United States (US) and other parts of the world (Stirzaker, 2006). The low SMS adoption requires conducting a literature review along with an analysis of strengths, weaknesses, opportunities, and threats (SWOT) to investigate potential reasons behind low transfer of SMS technology and to identify solutions to improve its utilization.

A decent number of SMS review articles have been published in the past (Adeyemi et al., 2017; Bittelli, 2010; Bittelli, 2011; Pardossi et al., 2009; S.U. et al., 2014; Shock & Wang, 2011; Thompson & Gallardo, 2005). However, the primary focus of these articles has been on technical aspects such as measuring principles of SMS, ways to improve sensor accuracy, factors affecting accuracy, and spatial variability of soil moisture, to name a few. A study by Leib et al. (2002) addressed the low adoption of scientific scheduling tools in general, but SMS was not their focus.

To the best of our knowledge, no other studies have been published on the reasons behind low SMS adoption and the possible direction forward. Therefore, there is an urgent need to assimilate information from previously published literatures to investigate the gap between research and practical applications of soil moisture sensors. The specific objectives of this study were: 1) to examine the current situation of SMS adoption in the US and possible factors impacting it based on the national surveys conducted over the past 20 years; 2) to conduct a critical literature review of previously published SMS papers; and, 3) to perform a SWOT analysis to identify internal and external helpful and harmful factors that must be considered to improve SMS utilization in irrigation management.

2.2. Materials and Methods

2.2.1. Adoption of Soil Moisture Sensors in the US

The data on adoption of soil moisture sensors (SMS) in irrigation scheduling were obtained from the Farm and Ranch Irrigation surveys conducted every five years by the National Agricultural Statistics Service of the United States (US) Department of Agriculture. The data from the five recent surveys conducted in 1998, 2003, 2008, 2013, and 2018 were used in the present study. Since a fraction of all irrigated farms are contacted in these surveys (e.g. 18% on average in 2018), only the states that had a total irrigated area larger than one million acres (about 400,000 ha) were selected for analysis to ensure the sample size was not too small. This criteria resulted in selecting the following 15 states: Arkansas (AR), California (CA), Colorado (CO), Florida (FL), Idaho (ID), Kansas (KS), Mississippi (MS), Missouri (MO), Montana (MT), Nebraska (NE), Oregon (OR), Texas (TX), Utah (UT), Washington (WA), and Wyoming (WY). These 15 states have been consistently among the top 18 irrigated states since 1998 and represent 84% of the total irrigated area in the US. The exclusion of the remaining 35 states with smaller irrigated areas and sampled farms helps improve the confidence in the results obtained. To investigate the potential factors contributing to observed patterns in the adoption of SMS, Pearson's correlation coefficients (r) were calculated to determine the level of association between SMS adoption (percent of farms using SMS in each of the selected 15 states) and other factors reported in the surveys (Benesty et al., 2009). The guideline from Evans (1996) was followed to describe the correlations based on ranges of r as very weak ($0 \leq r \leq 0.19$); weak ($0.20 \leq r \leq 0.39$); moderate ($0.40 \leq r \leq 0.59$); strong ($0.60 \leq r \leq 0.79$); and very strong ($0.80 \leq r \leq 1.00$). The statistical significance of the estimated r was also evaluated at the significance level of $\alpha = 0.05$.

2.2.2. Literature Review

Several scholarly databases were searched to identify previously published peer-reviewed journal manuscripts on the use of SMS in irrigation management. These databases included, but were not limited to Google Scholar, ProQuest, Scopus, and Web of Science. The search focused on those studies that had improving irrigation scheduling as one objective or their main goal. Hence, the papers that investigated the SMS utilization for other purposes were excluded. This resulted in identifying 84 papers, with publication dates spanning from 1994 to 2020.

2.2.3. SWOT Analysis

The SWOT analysis is conducted on a regular basis to perform strategic planning, identify barriers to achieving goals, and decide about future directions for a wide range of entities, policies, and initiatives. In this study, the entity that was considered for performing the SWOT analysis was all scientists and engineers at public and private research organizations (e.g. universities, government agencies, non-governmental organizations, etc.) who share the same goal of improving agricultural irrigation management using sensing technologies. In this specific SWOT analysis, each of the main four elements were assumed to represent:

- Strengths: The areas (skills and capacities) that allow researchers to advance the SMS technology and its adoption.

- Weaknesses: The areas that need improvement, including critical aspects of transferring SMS technology that have received less attention from researchers.

- Opportunities: The potential helpful factors available to researchers that can assist with increasing the effective and affordable SMS utilization in irrigation management.

- Threats: The potential harmful factors (mostly external) that can act against the efforts of researchers and impede the adoption of SMS technology.

2.3. Results and Discussion

2.3.1. Adoption of Soil Moisture Sensors in the US

In general, the adoption of soil moisture sensors (SMS) has been limited, but slowly increasing over the past two decades (Figure 2.1a). At the national level (considering all fifty states) the percentage of farms that used SMS technology for irrigations scheduling was 9%, 7%, 9%, 10%, and 12% in 1998, 2003, 2008, 2013, and 2018, receptively. The range of SMS adoption was large among the top 15 irrigated states, varying from 2% in UT and WY to 31% in NE in 2018. From 1998 to 2018, there was a combined two-fold increase in SMS adoption in the top 15 states, ranging from a decrease of 45% in UT to a nine-fold increase in TX. Other leading states in terms of increasing SMS adoption were MS and NE with about four- and five-fold increases experienced in the past 20 years, respectively. CA and WA witnessed doubling of SMS utilization during the same period (Figure 2.1b).

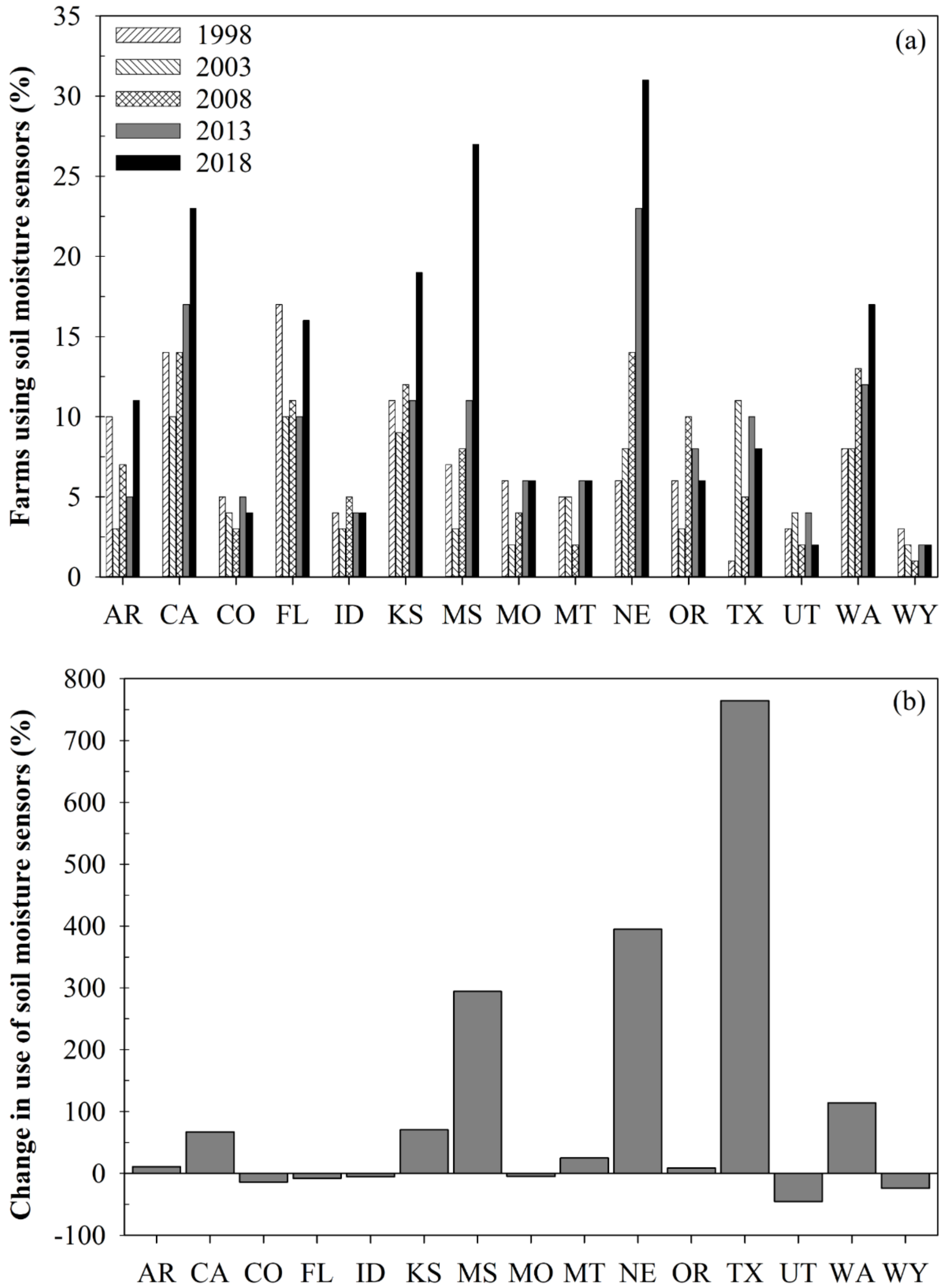

Figure 2.1. Percentage of farms using soil moisture sensors (a) and percentage of change in use of soil moisture sensors from 1998 to 2018 (b).

Among factors that were investigated for potential influence on SMS adoption (percent of farms using SMS in each state), the total irrigated area of each state had a significant moderate correlation ($r = 0.55$) with SMS adoption. But a major player was the level of control over irrigation management. In 2018, there was a strong, statistically significant negative correlation ($r = -0.66$) between the farms that used SMS and those that relied on scheduled delivery of irrigation water by supplier. In addition, scheduled delivery by supplier was the dominant method of irrigation scheduling (reported by 35-48% of irrigated farms in 2018) in the three states of CO, UT, and WY that experienced a decrease in SMS adoption over the last 20 years. This is most probably due to the fact that growers who receive water on a schedule decided by suppliers have limited flexibility in modifying irrigation management and are thus less motivated to invest in utilizing SMS. There was a strong and statistically significant positive correlation ($r = 0.76$) between the farms using SMS and those using daily crop evapotranspiration reports for irrigation decision making. This suggests the states that had a higher rate of SMS adoption relied on additional advanced methods of irrigation scheduling.

Another parameter that was significantly correlated with percent of farms utilizing SMS adoption was the total expenditure on computers, control panels, and computer-controlled hardware for water conservation in irrigation management, with a moderate r value of 0.56. The largest correlation coefficients among all investigated parameters belonged to the sources of information that growers relied on for reducing irrigation costs and conserving water. The percent of irrigated farms that relied on electronic information services had very strong and statistically significant relationships with the percent of farms that utilized SMS in their irrigation scheduling, with a r value of 0.82. The next largest r value (0.80) described the relationship with the percent of irrigated farms that relied on private irrigation specialists or consultants. This is not surprising as the successful implementation of SMS in irrigation decision making requires considerable knowledge and experience that can be gained from online resources and experienced specialists.

Interestingly, the percent of farms that sought information from their neighbors was negatively correlated with percent of farms using SMS (r = -0.80).

It was hypothesized that a few other factors may be correlated with SMS utilization among the top 15 irrigated states, including the methods of irrigation application (i.e. gravity, sprinkler, and/or drip systems) and the total and average quantity of water applied. However, the estimated correlations coefficients with these parameters were not statistically significant.

2.3.2. SWOT Analysis

2.3.2.1. Strengths

The irrigation research community in general has two core competencies that can strengthen the improvements in adoption and utilization of SMS technology. The first competency is the vast network of human resources (graduate students, researchers, technicians, etc.) who have the required knowledge and skillset to perform complicated SMS research studies. Through collaborations between universities and public/private agencies, the research community also has the capacity to recruit new talents and to train them through in-class and hands-on approaches to join the community and continue the efforts towards tackling challenges and identifying solutions to new issues related to SMS-based irrigation scheduling.

The second competence is the existing collaborations with a comprehensive network of extension and outreach personnel that can bridge the gap between research and practical applications. In the US, land-grant universities are homes to cooperative extension services that allow access to local producers through developing extension materials in traditional and modern formats and hosting numerous extension events and field days. The local extension educators can play the same role that local dealers and sales representatives play for businesses, taking the research findings to end users and selling them the innovative, effective, and affordable ideas to improve irrigation management. Although the vast extension network may not be equally appreciated and utilized across irrigated regions, its presence serves as a major strength to the research community.

2.3.2.2. Weaknesses

A major weakness that hinders the implementation of SMS technology in practical irrigation management is the low accuracy of available sensors. Accuracy is one of the most important factors that influences the decision to invest in SMS technology as well as the selection of the most appropriate sensor (Kukal et al., 2020). Guidelines are available on evaluating the accuracy of sensors and determining their suitability for irrigation scheduling based on the estimated root mean square error (RMSE). Fares et al. (2011) suggested the following categories of accuracy: good (RMSE <0.010 cm^3 cm^{-3}), fair (0.010 ≤ RMSE < 0.050 cm^3 cm^{-3}), poor (0.050 ≤ RMSE < 0.100 cm^3 cm^{-3}), and very poor (RMSE ≥ 0.100 cm^3 cm^{-3}). Hignett and Evett (2008) argued that the RMSE should be in the order of 0.010 to 0.020 cm^3 cm^{-3} for effective irrigation management. Previous studies have used a wide range of statistical indicators and about 10% of them did not even report RMSE. Among over 500 sensor RMSEs reported, only 3% fell under the good accuracy category according to Fares et al. (2011). About 55% of tested SMS had fair accuracy, followed by 25% in poor and 17% in very poor accuracy categories (Figure 2.2). In addition, only 15% of the reported RMSE in past literatures was complying with the criteria set by Hignett and Evett (2008).

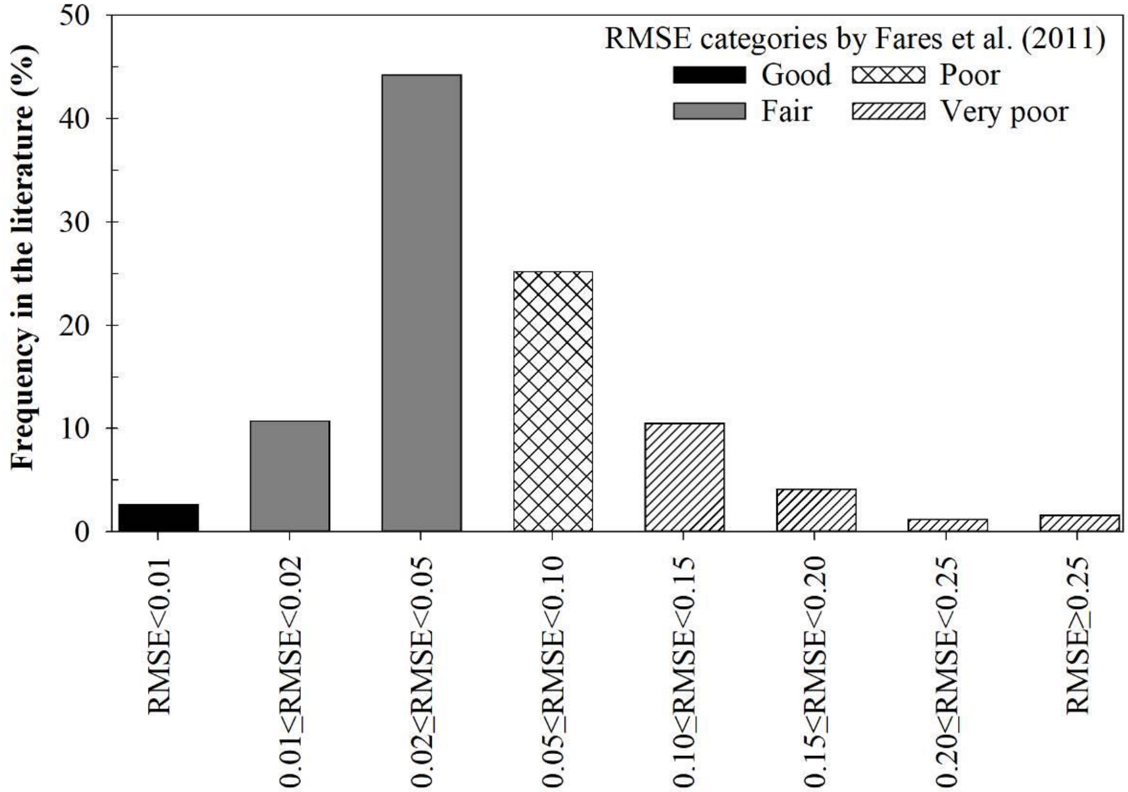

Figure 2.2. The frequency distribution of reported root mean square error (RMSE) of sensors in the literature.

The accuracy categories mentioned above represent RMSEs reported based on factory calibrations, which is the type of calibration that producers are exposed to. Obviously, site-specific calibrations would significantly increase the accuracy of sensors (Komilov et al., 2002; Leib et al., 2003). However, producers usually do not have the financial and technical resources to conduct site-specific calibrations on their own. As a result, they need to rely on local accuracy and calibration studies conducted by researchers under soil, crop, and climatic conditions similar to those of their operation. This requires a significantly large number of research studies conducted at high density across irrigated areas to capture the high level of variability in agricultural fields. After reviewing the available literature, a total of 18 study sites were identified in the conterminous US where field experiments were conducted to evaluate sensor accuracies. This translates to less than one site per every two states within conterminous US on average.

Figure 2.3 shows the geographical distribution of these sites. The studies that were conducted outside conterminous US or those that were conducted under laboratory conditions were excluded from this map. The study sites are differentiated based on the method that was implemented to obtain the reference soil water content estimate, including the three main methods of gravimetric sampling, neutron probe readings, and Time Doman Reflectometry (TDR) readings.

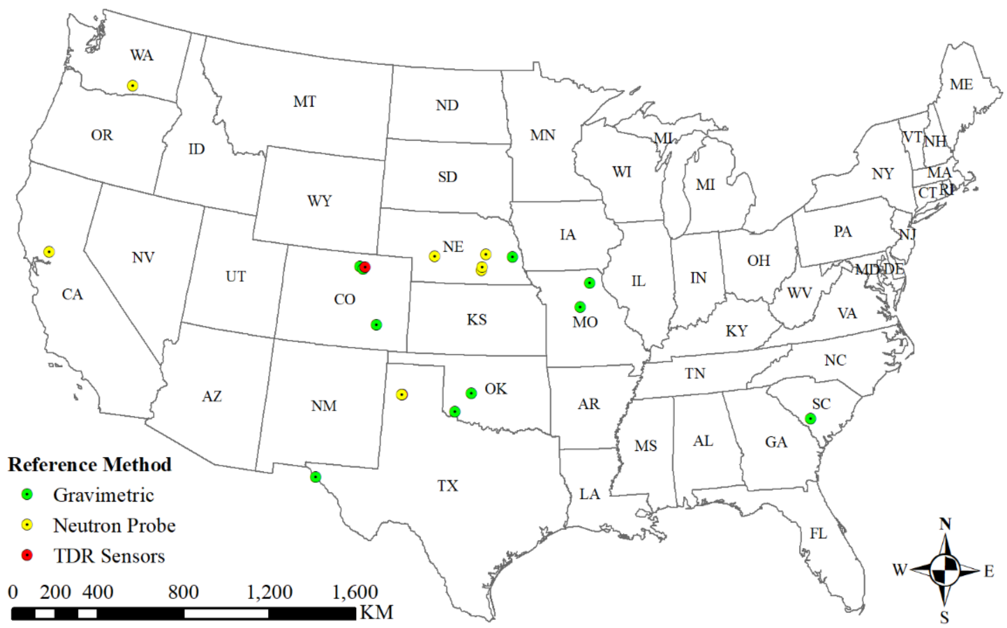

Figure 2.3. The location of study sites where field evaluations of SMS accuracies have been conducted.

Despite the need for dense accuracy studies, especially in the western US, there are states and large areas within some states with no local sensor performance study as evident in Figure 2.3. Among the states that had field assessment of sensor accuracy, NE and CO were the leading states, each with 26% of all sites. It is worth reminding the readers that NE was also the leading state in terms of SMS adoption, with about one-third of the irrigated farms using this technology for irrigation decision making. Another point to consider is that the studies included in Figure 2.3 have only assessed the performance of a limited number of sensors due to limitations in financial and human resources. This map would look different (larger gaps) if specific sensors were considered. The lack of local studies on sensor accuracy and performance is the second major weakness that negatively impacts SMS adoption in irrigation scheduling.

2.3.2.3. Opportunities

As mentioned under weaknesses, the adoption of SMS technology is hindered by lack of local studies on the performance of sensors under variable soil, crop, and climatic conditions. Producers could benefit from the results of these studies in selecting the most accurate sensor under their specific condition and in identifying the right calibration if needed. The challenge posed by lack of local studies is exacerbated by the large number of new sensors that are introduced to the market every season, requiring their own performance assessments. Hence, a key opportunity for the research community is to increase the number of local studies, especially in areas where SMS adoption is low. Considering the following points in designing and conducting future studies could significantly improve their quality, reliability, and usefulness:

a) Two critical factors that have been found to have considerable effects on SMS accuracy are soil texture (specifically clay content) and salinity. The RMSE has been reported to increase with increasing clay content (Datta et al., 2018; Singh et al., 2018; Singh et al., 2019). The mean bias error, however, has had mixed responses. While over 80% of previous studies have reported overestimation of soil moisture with increasing clay content, some studies have observed underestimation error (Abbas et al., 2011; Geesing et al., 2004; Singh et al., 2019). In addition, most studies have reported an increase in errors with soil salinity. Previous studies have reported salinity thresholds for acceptable SMS errors at soil bulk electrical conductivity of 2.0 dS m^{-1} (Wyseure et al., 1997) and 2.8 dS m^{-1} (Schwartz et al., 2016). However, many irrigated soils have salinities well above these limits.

b) Producers could benefit from recommendations and guidelines on two specific aspects of sensor installation: the number and placement of sensors in the root zone at each monitoring location and the installation orientation of every sensor. Besides effects on sensor performance (Blonquist et al., 2006; Chen et al., 2019; Chow et al., 2009), these factors impact the cost of sensors and the time and effort required to install them. Previous studies have offered variable recommendations on the number and depths of sensors. For example, Pardossi et al. (2009) recommended installing one sensor in the top 33% of the rootzone and another in the bottom 66%, while Haise and Hagan (2015) recommended putting two sensors at the top and bottom of the active root zone. On the other hand, Adeyemi et al. (2017) recommended placing one sensor in every quarter of the maximum root depth. Soulis and Elmaloglou (2018) argued a minimum of two sensors must be used to accurately describe average soil moisture and Sui et al. (2019) recommended placing sensor at multiple depths in the predominant soil type inside the field.

   The installation approach has also shown to impact sensor performance. Sensors can be simply buried in disturbed soil or inserted in undisturbed soil horizontally, vertically, or at an angle (Chen et al., 2019; Jaria & A. Madramootoo, 2013). Sui et al. (2019) mentioned that inserting the sensors horizontally minimizes disturbances to the soil and helps sensor rods to achieve a good contact. Chen et al. (2019) compared different orientations of undisturbed installation and found horizontal orientation to achieve the best accuracy, a finding that has been reported by Zhu et al. (2019) as well. In contrary, Kukal et al. (2020) found out the vertical insertion to provide the best estimates of soil moisture.

c) It is highly recommended for research studies to follow accepted best practices when assessing the performance of SMS. In particular, special attention should be paid to the minimum number of replications required to capture soil heterogeneity, the reference method used in estimating the true soil water content, and the differences in the volume of influence of each sensor (Schwartz et al., 2018).

A second major opportunity available to irrigation researchers in conducting experiments and disseminating the results is to quantify and report the benefits of utilizing SMS in irrigation decision making. These benefits include i) saving in water application; ii) saving in energy consumption for extraction, delivery, and application of irrigation; iii) improvements in crop yield; and, iv) financial benefits gained. Agricultural production is a business operation and hence, producers are more likely to adopt technologies that have a proven return on investment (Giannakis et al., 2015). A survey conducted by Lichtenberg et al. (2015) found that US greenhouse and nursery producers who were willing to invest in soil moisture network for irrigation management expected a significant profit in return for their investment. Quantifying and reporting the financial benefits of SMS utilization can help improve the adoption of this technology.

Among the 84 previously published journal manuscripts reviewed in this study, 23% reported water savings realized through SMS adoption and 24% documented changes in crop yield. A smaller percentage (6%) mentioned financial benefits of SMS utilization and only 2% reported energy savings. It is highly recommended for any study on the effects of advanced irrigation scheduling methods to quantify and report more than one of the four benefits listed here (water saving, energy saving, yield increase, financial gains) and possibly all of them. Out of all reviewed SMS studies, 23% reported two benefits, 4% reported three benefits, and only one provided information on all four types of benefits. The reported savings in water ranged from 7 to 69%. The reported yields were either comparable to or higher than traditional irrigation management approaches, with an increase from 3 to 54%. Only Migliaccio et al. (2010) observed a yield decrease of 13% in irrigated tomato in Florida. However, the water saving in their study was the largest (64-69%) among all reviewed studies. The study conducted by Irmak et al. (2012) is one of the most comprehensive studies in documenting the impact of SMS adoption and can serve as an example in designing and developing future researcher projects. One interesting aspect of this study was that comparisons were made against the traditional irrigation scheduling decided by local producers at the scale of commercial fields. In addition, the benefits of implementing SMS technology were reported in terms of water saving, energy saving, and net income. These type of studies and reporting benefits make it easier for producers to evaluate the advantage of adopting SMS technology and estimate the potential return on their investment.

The two opportunities described above are about research methods of the irrigation research community and hence are considered somewhat internal. In a SWOT analysis, however, more emphasis is placed on external helpful factors when identifying opportunities. One external opportunity is future advances in SMS technologies pioneered by the industry. These advances should target four specific areas. The first area is improved performance under a wide range of soil conditions. The need for higher sensor accuracies has been discussed in detailed in previous sections. The second area is regarding sensor reliability. Previous studies have reported gaps (missing data) in SMS readings ranging from 21 to 64% (Datta et al., 2018; Sugita et al., 2016). These gaps could be caused by extreme range of soil clay content and salinity that result in signal attenuation or due to the wireless signals being blocked by tall crop canopies. The third area for technology advancement is related to developing and packaging sensing systems that reduce the need for technical knowledge and experience to install and operate sensors (mistake proofing). Plug and play systems that provide audio and/or visual alerts when the system is not performing satisfactorily is one example. Another example is sensor designs and installation tools that minimize the installation time and errors, such as leaving air gaps around sensing devices. The fourth area of industry innovations is regarding the cost of sensing systems and storing/transmitting the collected data through wireless technologies. As these costs reduce, the potential users would be further incentivized to invest in SMS utilization.

Another opportunity (fourth one) that mainly relies on industry is to provide more support for converting raw SMS readings into actionable irrigation management decisions, or in other words answers to the two main questions of when to irrigate and how much water to apply. Without the availability of easy-to-understand decision support systems, it is extremely difficult and time-consuming for producers to analyze collected data and turn them into decisions. Several SMS manufacturers have started offering simple graphical tools (e.g., MeterGroup Environment, AgSpy Inc., Irrometer Inc., MonitoredTech) that let the users know where their soil water content fall within the range of readily available water for crop consumption. They also allow for setting and adjusting full and refill thresholds. Other manufacturers have moved to provide near-term irrigation demand forecasts, which are one of the major needs of producers based on our observations. Making these user interfaces more widely available and easier to understand would have a significant impact on increasing the adoption of SMS technology in irrigation management.

The fifth opportunity that can be facilitated and supported by local and national governments is to better understand the perception of agricultural producers when it comes to SMS utilization. Such comprehensive sociological studies can help identify the needs and concerns of potential users of this technology and would shed light on future direction of research and extension projects to improve SMS adoption. As suggested by Giannakis et al. (2015), irrigation scheduling decision support systems in general have suffered from the lack of a comprehensive understanding of users' needs, as well as the failure to employ the language and the logic familiar to producers.

2.3.2.4. Threats

Two external harmful factors could potentially threaten the utilization of SMS technology to improve irrigation management. The first external factor relates to laws and policies at local and national levels that would disincentivize investments in water conservation technologies. Examples may include subsidizing water and energy costs, lack of regulation and monitoring on water extraction, and water laws that encourage “use it or lose it” attitudes. Previous studies have found that low water pricing is a major barrier towards adoption of irrigation water conservation in general (Ward et al., 2007) and that increasing water price would have a more significant impact on water conservation than offering financial assistantship to cover the cost of implementing conservation measures in irrigated agriculture (Huffaker & Whittlesey, 2003). Insecurities in right to conserved water and land tenure situation (owned or leased) have been also found to effect motivations to conserve irrigation water (Ward et al., 2007).

The second external factor threatening SMS adoption is related to the economic profitability of agricultural production as impacted by fluctuations in commodity prices. When farm net income and profit decline, even those producers who are interested in SMS adoption would not be able to afford its implementation without the availability of financial assistantship programs that would cover a large portion of associated costs. The results of the irrigation surveys conducted by the US Department of Agriculture show that the top two barriers to reducing energy use and conserving water among the top 15 irrigated states were related to affordability of conservation measures. The most common barrier mentioned by 35% of total irrigated area was that improvements would not reduce costs enough to cover technology installation costs. The second common barrier, cited by 30% of all irrigated area, was that survey responders could not finance improvements. Table 2.1 provides a summary of the SWOT analysis conducted in the present study.

Table 2.1. The SWOT analysis of utilizing soil moisture sensors (SMS) in irrigation management.

Strengths	**Weaknesses**
1. Access to experienced professionals and ability to train new ones. 2. Presence of a vast network of local professional extension specialists.	1. Low sensor accuracy and high sensitivity to soil heterogeneity. 2. Lack of local studies on sensor performance.
Opportunities	**Threats**
1. Conduct more local studies to investigate sensor performance under variable conditions. 2. Quantify and report reductions in water and energy use and increases in yield and financial benefits. 3. Increase accuracy, reliability, easy-of-use, and affordability of sensors through technological advances. 4. Assist with converting SMS readings to actionable irrigation decisions using easy-to-understand user interfaces. 5. Better understand the perception, needs, and concerns of agricultural producers.	1. Discouraging laws and policies (water pricing, land tenure, right to conserved water, etc.). 2. Decreased farm net income that would negatively impact users' ability to finance technology adoption.

2.4. Conclusions

The present study evaluated the results of surveys conducted by the US Department of Agriculture over the past 20 years to investigate adoption of soil moisture sensors (SMS) in irrigation decision making and potential factors that are correlated with changes in SMS adoption. In addition, a literature review and a strengths, weaknesses, opportunities, and threats (SWOT) analysis were conducted to identify internal and external factors that can help or harm the utilization of SMS in irrigation scheduling. The results of surveys showed that SMS adoption has been generally low, but highly variable among the top 15 irrigated states. The level of adoption was significantly correlated with the level of control over irrigation deliveries, being lowest in states where irrigation deliveries are dictated by water suppliers. The strongest relationships were found between SMS adoption and the source of irrigation management information relied on. SMS adoption increased with increases in reliance on private irrigation specialists and electronic media and with decreases in reliance on neighboring farms to obtain information on water conservation.

The literature review and SWOT analysis revealed that the major strengths of irrigation research community were availability and the continued inflow of experienced personnel with practical experience to design and carry out SMS experiments, as well as access to networks of extension educators that can bridge the gap between researchers and agricultural producers. The most significant weaknesses harming improvements in adoption of SMS technology were low sensor accuracy and a high level of variability in sensor performance caused by soil heterogeneity, as well as lack of local field experiments that would provide useful information on the best available sensors and possibly site-specific calibrations. Several opportunities were also identified, including increasing local studies, quantifying and reporting a wide range of benefits (including financial) gained through implementing SMS technology, improving accuracy, reliability, and affordability of SMS, developing SMS decision support systems, and studying the perception of producers towards SMS adoption to direct future research projects based on their needs and concerns. The external factors that can threaten the higher adoption of SMS include discouraging laws and policies such as subsidizing energy and water costs and preventing producers from benefiting from water conservations, as well as possible reductions in farm revenue that negatively impact producers' ability to invest in SMS technology.

CHAPTER III

PERFORMANCE ASSESSMENT OF FIVE DIFFERENT SOIL MOISTURE SENSORS UNDER IRRIGATED FIELD CONDITIONS IN OKLAHOMA

3.1. Introduction

Irrigated agriculture, a major contributor to the United States (U.S.) economy, plays a vital role in supplying the demand for food, feed, and fiber. Although only 27% of all croplands in the U.S. are irrigated, this sector is responsible for nearly 50% of crop revenues (USDA, 2014). Sustaining high levels of food production through irrigated agriculture requires large amounts of water. In 2010, irrigation was the second largest consumer of freshwater withdrawals in the U.S., accounting for approximately 33% (approximately 159 million m^3 $year^{-1}$) of the total water withdrawals (Maupin et al., 2014). Irrigation water sources, however, are usually limited in amount and are subject to increasing competition. In addition, more variability in precipitation patterns is expected due to climate change, which may threaten the availability of irrigation water supplies (Fischer et al., 2007; Fishman, 2012). These challenges create the need to optimize irrigation management and avoid over- or under-irrigation. Over-irrigation, in addition to wasting water and valuable nutrients, can create favorable conditions for pests and diseases, increase energy costs, and reduce the lifespan of irrigation infrastructure. It can also result in erosion of topsoil and contamination of downstream water resources due to movement of water-soluble chemicals (Datta et al., 2017). In contrast, under-irrigation reduces crop yield and negatively impacts economic viability of agricultural production.

Several advanced technologies are available to assist with achieving and implementing optimized irrigation management, including weather stations, air- and spaceborne remote sensing platforms, computer models, plant feedback sensors, and soil moisture sensors (Broner, 2005; Martin, 2009). Soil moisture sensors, in particular, can be used effectively to improve irrigation management (Martin et al., 1995). As a tool for irrigation scheduling, these sensors have been shown to increase crop yields while conserving water (Fisher et al., 2009; Kebede et al., 2014; Martin et al., 1995; Sui, 2017). For example, Zotarelli et al. (2009) showed that users who manage irrigation with soil moisture sensors applied 15 to 51% less irrigation water compared to fixed-time irrigation plan and observed a crop yield increase of 11 to 26% in Florida, U.S. In addition, sensors can provide continuous estimate of soil moisture conditions in a nondestructive way at a reasonable cost and usually require little maintenance over their lifetime (Cardenas-Lailhacar & Dukes, 2010). Soil moisture sensors include tensiometers, neutron gauges, electromagnetic sensors, electrical resistance sensors, and heat dissipation sensors, to name a few (Yoder et al., 1998). Among these different types, electromagnetic sensors have been widely used by producers for irrigation scheduling.

Despite their numerous advantages, electromagnetic sensors are sensitive to soil salinity and clay content. The impact of soil salinity on sensor readings of soil volumetric water content (θ_v) (m^3 m^{-3}) has been highlighted in several studies (Dalton, 1992; Topp et al., 1980; Wyseure et al., 1997). For example, Wyseure et al. (1997) reported that θ_v error was acceptable at soil bulk electricity conductivity (EC) (dS m^{-1}) levels below 2.0 dS m^{-1}, and Schwartz et al. (2016) found that θ_v estimates were not affected at bulk EC levels below 2.8 dS m^{-1}. These thresholds are exceeded in many irrigated areas in arid/semi-arid regions, where there is a great need for improving irrigation management using sensor technologies. The results from prior studies on the impact of clay content have been somewhat variable. Rüdiger et al. (2010) observed overestimation error in θ_v that increased with clay content. In contrast, Fares et al. (2011)

observed underestimation of θ_v for electromagnetic sensors due to high clay content, which was more prevalent at lower soil moisture content. Mittelbach et al. (2012) reported both under- and overestimation errors at different depths of a clay loam soil in Switzerland. In light of these variable results, and since high salinity and clay content conditions are encountered in many agricultural fields, there is a need to undertake further field studies to investigate the accuracy of electromagnetic soil moisture sensors under varying levels of salinity and clay content.

The goal of this study was to evaluate the performance of soil moisture sensors for irrigation scheduling purposes under low and high salinity/clay content conditions. Specific objectives were to (1) assess the performance of five different commercially available electromagnetic sensors in estimating θ_v in situ under soils with variable salt and clay content, (2) compare the accuracy of several approaches of determining soil moisture thresholds used in irrigation scheduling, and (3) investigate the accuracy of estimated soil moisture depletion based on sensor readings and different threshold approaches.

3.2. Materials and Methods

3.2.1. Sensor Description

Five commercially available electromagnetic sensors were evaluated in this study: TDR315, CS655, GS1, SM100, and CropX.

3.2.1.1. TDR315

The TDR315 (Acclima Inc., Meridian, ID, USA) is a recently commercialized sensor for agricultural applications (Schwartz et al., 2016). This sensor operates on principles of Time Domain Reflectometry (TDR) that estimates the soil apparent permittivity (K_a) (unitless) at relatively higher frequencies (3.5 GHz), which are less sensitive to bulk EC compared to lower frequency electromagnetic techniques (Robinson et al., 2003). Conventional TDR sensors have a problem sustaining high frequency signals because of signal attenuation in the sensor's coaxial cables. The TDR315 addresses this issue by embedding all the electronics required for pulse generation and waveform acquisition in a compact circuit within the probe head. The data are transmitted digitally via SDI-12 (Serial Data Interface at 1200 baud) protocol, which is an asynchronous, ASCII, serial communications protocol and can support a cable length of up to 60 m. The sensor shares the same advantages of the conventional TDRs, but, it is more portable, affordable, and convenient to use (Schwartz et al., 2016). These sensors have a planar three-conductor transmission line, each 15 cm long, and transmit the incident pulse in the center rod and two exterior grounds. The TDR315 reports volumetric water content (θ_v) (%) based on a proprietary dielectric mixed model which estimates K_a using Topp equation (Equation (1)) (Topp et al., 1980). The sensor also reports soil temperature (°C), bulk relative permittivity (unitless), bulk EC (µS cm^{-1}), and soil pore water EC (µS cm^{-1}). DataSnap SDI-12 data-loggers from the same manufacturer were used with TDR315 sensors to collect data on hourly basis.

$$\theta_v = 4.3\times10^{-6}\times(K_a{}^3) - 5.5\times10^{-4}\times(K_a{}^2) + 2.92\times10^{-2}\times(K_a) - 5.3\times10^{-2} \qquad (1)$$

3.2.1.2. CS655

The CS655 sensor (Campbell Scientific, Inc., Logan, UT, USA) is a water content reflectometer. An electronic pulse is sent from the probe head and reflected at the end of the rods (12 cm in length). Upon detecting the returned pulse, another pulse is sent. Then, the probe records the frequency of these pulses and inverses the frequency as period in microseconds (µs). This period is impacted by the velocity of electromagnetic pulse, which is influenced by K_a (Chávez et al., 2011; Topp et al., 1980). The probe estimates θ_v from K_a using the Topp equation (Equation (1)) (Topp et al., 1980). Apart from θ_v, other measured parameters include period average (µs), soil's relative dielectric permittivity (unitless), bulk EC (dS m^{-1}), and soil temperature (°C). Like the TDR315, the CS655 communicates with a data-logger using an SDI-12 interface. To collect hourly data, CR1000 data-loggers (Campbell Scientific, Inc., Logan, UT, USA) were used in this study.

3.2.1.3. GS1

The GS1 sensor (METER Group, Inc., Pullman, WA, USA) estimates θ_v by generating an electromagnetic field to measure the dielectric constant of the surrounding medium. This sensor uses capacitance and frequency domain technology and operates at 70 MHz (Environment, 2015). It provides oscillating waves to the sensor rods that charge in response to the dielectric of the material. The sensor quantifies the charge and provides a raw value (RV) that is strongly correlated with θ_v (Equation (2)). The GS1 has a rugged design and is capable of remaining in the soil for a long time. It has a two-rod design, with each rod measuring 5.5 cm in length. Hourly data were collected throughout the cropping season using EM5B analog data-loggers (METER Group, Inc., Pullman, WA, USA).

$$\theta_v = 3.62 \times 10^{-4}(RV) - 0.554 \tag{2}$$

3.2.1.4. SM100

The WaterScout SM100 sensor (Spectrum Technologies, Aurora, IL, USA) has two electrodes functioning as a capacitor, with surrounding soil acting as the dielectric. The capacitor is driven by an 80 MHz oscillator and converts the soil’s dielectric permittivity to an output signal, which correlates with θ_v. Watchdog 1400 data-loggers from the same manufacturer were used to collect hourly data.

3.2.1.5. CropX

The CropX sensor (CropX Ltd., Tel Aviv, Israel) integrates soil moisture sensing and a cellular communication package. The sensor electrodes are built into a helical wing attached to a central shaft for installation with reduced soil disturbance. The sensor measures soil moisture based on the amplitude domain reflectometry. When the amount of water changes in the soil, the sensor measures the change in amplitude differential due to changes in dielectric permittivity, which directly correlates to changes in water content. CropX is a multiprobe sensor that measures θ_v at 20 and 46 cm depths in the soil.

3.2.2. Study Sites

The study took place during the 2017 crop growing season. Two sites were selected for sensor installation, one with lower salinity and lower clay content (LSLC) located in central Oklahoma and the other in southwest Oklahoma with higher salinity and higher clay content (HSHC). Figure 3.1 shows the location of the study sites overlaid on the map of long-term mean annual precipitation across Oklahoma, obtained from Daly et al. (2008). The LSLC site had a Pond Creek fine sandy loam soil (fine-silty, mixed, superactive, thermic Pachic Argiustolls) while the HSHC site had a Hollister silty clay loam soil (fine, smectitic, thermic Typic Haplusterts). The EC of the soil solution (1:1 soil–water ratio) was 1.2 dS m^{-1} at LSLC compared to 7.0 dS m^{-1} at HSHC. Table 3.1 provides additional information on soil characteristics at each site. In addition to variations in soils, the two sites were different in crop types, irrigation systems, and climatic conditions. Corn (Zea mays L.) was planted at the LSLC site under a center-pivot irrigation system, while the HSHC site was under furrow-irrigated cotton (Gossypium hirsutum L.). Key meteorological parameters for each site are given in Table 3.2.

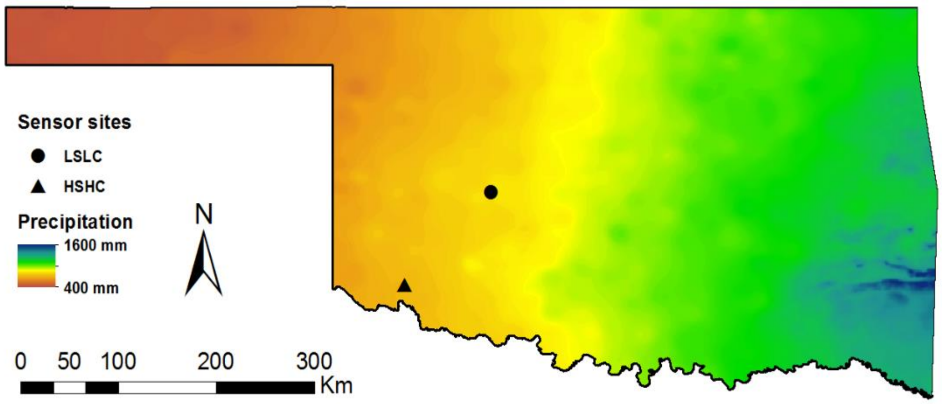

Figure 3.1. Experimental study site locations.

Table 3.1. Soil properties at study sites.

Site	Soil texture	Particle Size Distribution			EC [¥]	θ_v ($m^3\ m^{-3}$)			K_{sat} [†]
		% Sand	% Silt	% Clay	(dS m^{-1})	Sat. [‡]	FC [§]	WP *	(mm day^{-1})
LSLC	Fine sandy loam	72.2	14.4	13.4	1.2	0.34	0.17	0.05	390.0
HSHC	Silty clay loam	23.5	37.8	38.7	7.0	0.39	0.32	0.21	32.4

[¥] Electrical conductivity. [‡] Saturation level; [§] Field capacity at −33 kPa; * Wilting point at −1500 kPa; [†] Saturated hydraulic conductivity.

Table 3.2. Twenty-year (1997–2016) average annual and study period (July to October 2017) meteorological parameters obtained from Oklahoma Mesonet weather network.

Parameter	Annual		Study Period	
	LSLC	HSHC	LSLC	HSHC
Total Prec. [1] (mm)	752	616	451	340
Mean R_s [2] (MJ m^{-2})	17.1	17.7	19.9	21.8
Minimum T_{air} [3] (°C)	9.4	10.0	18.1	18.9
Maximum T_{air} (°C)	22.1	24.1	30.6	31.2
Mean T_{air} (°C)	15.4	16.8	23.9	24.8
Minimum RH [4] (%)	41.9	37.6	45.5	44.7
Mean VPD [5] (kPa)	0.9	1.0	1.0	1.1
Mean U_2 [6] (m s^{-1})	2.5	2.5	3.0	2.5

[1] Precipitation; [2] Daily accumulation of solar radiation; [3] Daily air temperature; [4] Daily relative humidity. [5] Daily vapor pressure deficit; [6] Daily wind speed at 2.0 m above the ground.

3.2.3. Experimental Setup

Four replications of TDR315, CS655, GS1, and SM100 and two replications of CropX were installed on 7/20/2017 and 7/27/2017 at LSLC and HSHC sites, respectively. The sensors were used with manufacturer-provided data-loggers and calibrations because the results obtained in this manner would best represent the conditions that irrigators and farm managers would face in the field (Leib et al., 2003). Therefore, the raw θ_v readings reported by the sensors were used in analysis without any alteration (Cardenas-Lailhacar & Dukes, 2010). It should be noted that developing and utilizing site-specific calibrations can significantly improve accuracies if the required technical and financial resources are available to users. All sensors were installed at a depth of 20 cm from the soil surface. The top 20 cm is important for plant water uptake as root distribution of plants is denser in this layer than deeper in the soil profile (Brutsaert, 2014).

At each replication, a pit was dug between two rows of crops to install the soil moisture sensors. Physical properties of soil in each pit were determined in the Soil Physics Laboratory at Oklahoma State University (OSU) by taking 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) on the day of sensor installation. Soil textural information (particle size distribution) were determined by hydrometer following the protocol proposed by Ashworth et al. (2001). Additionally, four replications of soil samples were taken at each site on the installation day to measure soil salinity. The salinity test was done by Soil, Water and Forage Analytical Laboratory at OSU using the 1:1 soil water extraction method (Zhang et al., 2002).

Sensors were inserted horizontally into the side wall of the pit (undisturbed soil) so that the rods of the sensors were on top of each other (vertical orientation) and the middle point of the sensor rods was directly under the crop row. The θ_v readings are often impacted by the sensor installation procedure (Aguilar et al., 2015), so extra care was taken to maintain minimal disturbance to the surrounding soil while inserting the rods. The spacing between the sensors was determined based on the volume of influence of individual sensors plus an additional distance to eliminate any possible interference. This spacing between the sensors were varied from 10 to 18 cm depending on the volume of influence of sensors' electromagnetic field. Then, wires were run below and away from the sensors for some distance to avoid creating any preferential flow channels. After that, the wires were run through PVC pipes to the data-logger encasement. The CropX sensors were installed using the spiral auger provided by the manufacturer to minimize soil disturbance.

The excavated soil was collected in different buckets for different soil layers and carefully used to backfill the pits, attempting to recreate the original bulk density. Precipitation amounts were recorded by a tipping bucket rain gage (model TE525-L, Campbell Scientific, Inc., Logan, UT, USA) at the LSLC site, whereas, these measurements were collected from an Oklahoma Mesonet weather station located 678 m to the southwest of the sensor installation location at the HSHC site (McPherson et al., 2007). Gravimetric soil samples (diameter = 3 cm, height = 5.1 cm) were collected using a Giddings soil sampling probe (Giddings Machine Company, Windsor, CO, USA) to estimate reference θ_v (θ_{ref}) ($m^3 m^{-3}$) throughout the crop growing season. On each sampling date, four gravimetric samples were taken at each site and the probe was centered at the sensor installation depth (20 cm). If there was an irrigation and/or precipitation event around the sampling dates, extra care was taken not to compact the areas above the sensors. Soil samples were put in plastic bags immediately after sample collection and kept out of sunlight to minimize evaporation. All soil samples of known volumes were oven-dried at 105 °C for 24 h and used to determine bulk density.

3.2.4. Soil Moisture Thresholds

Efficient irrigation management requires knowledge of two important soil moisture thresholds that indicate water availability for plant consumption (Datta et al., 2017). These thresholds are field capacity (FC) and wilting point (WP). The FC is often estimated as the water retained at a soil matric potential of −33 kPa, although research has shown that this can result in underestimation of FC and −10 kPa may provide a more suitable approximation (van Lier, 2017). The WP is often estimated as the water retained at −1500 kPa (Tolk, 2003). These values can be different depending on soil texture, crop type, and other factors.

In this study, FC and WP were determined using three different approaches: laboratory, sensor-based, and the Rosetta model (Schaap et al., 2001). Undisturbed soil cores extracted from each site were used in laboratory tests where FC was determined at −33 kPa using the Tempe cell method and WP at −1500 kPa using the pressure plate method (Dane & Hopmans, 2002). The sensor-based approach was based on ranking of the collected data following the procedure proposed in Hunt et al. (2009). This method uses sensor readings to estimate FC and WP as the 95th and the 5th percentiles of all θ_v values collected during the study period. This method assumes that the hydrologic conditions during the measurement period result in θ_v values, which span from values lower than WP to values higher than FC. The Rosetta model uses hierarchical pedotransfer functions to estimate van Genuchten water retention parameters (Schaap et al., 2001). In this study, three different FC-WP outputs were generated from the Rosetta model by providing different types and combination of input data. The three types of input data included (i) only the textural class of soils at study sites, (ii) textural information (percentages of sand, silt, and clay), and, (iii) textural information and bulk density. Estimated FC and WP from all methods described above were compared with those reported in the U.S. Department of Agriculture's Web Soil Survey at each study site (NRCS, 2009). In addition to FC and WP, the available water content (AWC), which is the difference between FC and WP, was calculated and compared with values obtained from different methods described above (Cassel & Nielsen, 1986).

To optimize irrigation management based on soil moisture sensing, sensor readings must be converted to soil moisture depletion (SMD) (m^3 m^{-3}). In this study, SMD was calculated as the difference between FC and θ_v:

$$SMD_{(i)} = \theta_{FC} - \theta_{v(i)} \tag{3}$$

where, $SMD_{(i)}$ is the soil moisture depletion at the i^{th} time-step, θ_{FC} is the θ_v at FC (constant) (m^3 m^{-3}), and $\theta_{v(i)}$ is the θ_v at the i^{th} time-step. In estimating SMD, $\theta_{v(i)}$ values were obtained from sensor readings and θ_{FC} values were based on two different approaches, resulting in two SMD estimates for each sensor at each site. The two θ_{FC} approaches were the laboratory and the ranking methods explained above. The results were compared against SMD estimates based on θ_{ref} (gravimetric measurements) and laboratory θ_{FC}. After SMD is estimated, it can be multiplied by the root zone depth to obtain an estimate of irrigation requirement in units of water depth.

3.2.5. Statistical Analysis

To evaluate the performance of the selected sensors, θ_v readings of sensors were compared with θ_{ref} values. Four statistical parameters, namely root mean square error (RMSE), RMSE-observations standard deviation ratio (RSR), mean bias error (MBE), and index of agreement (k) were estimated according to the following equations.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{4}$$

$$RSR = \frac{RMSE}{STDEV_{O_{(i)}}} = \frac{\sqrt{\sum_{i=1}^{n}(O_i - P_i)^2}}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2}} \tag{5}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i) \tag{6}$$

$$k = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}\left(\left|P_i - \overline{O}\right| + \left|O_i - \overline{O}\right|\right)^2} \right] \tag{7}$$

where, n is the sample size, i is the index of sample pairs, P is the sensor reading (predicted), O is the θ_{ref} (observed), and $\overline{O}$ is the mean of all θ_{ref} values.

The accuracy categories outlined in Fares et al. (2011) were adopted in this study for interpreting RMSE values. These categories include good (RMSE ≤ 0.01 $m^3\ m^{-3}$), fair (0.01 ≤ RMSE ≤ 0.05 $m^3\ m^{-3}$), poor (0.05 ≤ RMSE ≤ 0.10 $m^3\ m^{-3}$), and very poor (RMSE ≥ 0.10 $m^3\ m^{-3}$). The RSR provides benefits of incorporating error index statistics and it includes a normalization factor applicable to various constituents (Moriasi et al., 2007). The RSR varies from a value of zero indicating zero RMSE and a perfect model simulation to a large positive value. The performance of a model is determined by different categories of RSR: very good model fit (0.00 ≤ RSR ≤ 0.50), good model fit (0.50 ≤ RSR ≤ 0.60), satisfactory model fit (0.60 ≤ RSR ≤ 0.70), and unsatisfactory model fit (RSR > 0.70). However, these categories are based on simulations running on a monthly time-step. Moriasi et al. (2007) noted that the acceptable range of RSR would increase in magnitude when using smaller time-steps, which was the case in this study. The MBE measures the average difference between sensor-estimated θ_v and θ_{ref}. A MBE of zero indicates the predicted and observed values are unbiased. A positive value of MBE means sensor is overestimating θ_v, and negative MBE indicates underestimation (Addiscott & Whitmore, 1987). The index of agreement (k) was used to determine how well the sensor-estimated θ_v agreed with θ_{ref} (Willmott, 1981). The value of k can range from zero to one, with one representing the highest level of agreement and zero representing complete disagreement (Mishra et al., 2017).

In addition to the above statistical parameters, Pearson correlation coefficients (r) were calculated for pairwise sensor comparisons to evaluate the similarity in their temporal variations throughout the study period. Closely correlated temporal patterns have a r value near one, while this parameter is near zero in case of uncorrelated patterns (Cosh et al., 2004). Finally, linear regression models were fitted to sensor-estimated θ_v and θ_{ref} using the Minitab statistical software (version 17.3) (Minitab, Inc., State College, Pennsylvania, USA) (Montgomery et al., 2012). These linear models and the reported intercepts and slopes for each sensor can be used as field calibration equations in future applications at the study sites.

3.3. Results and Discussion

3.3.1. Sensor Performance

The fluctuations in θ_v were similar across all sensors at both study sites (Figure 3.2). All sensors responded to most irrigation and precipitation events. In some cases, there was little or no change in θ_v following a watering event, mainly because the amount of water received was not large enough to reach sensor installation depth. The results of performance evaluation (statistical indicators) are summarized in Table 3.3. In general, all sensors performed better at the LSLC. At this site, the RMSE was the lowest for CS655 (0.019 $m^3\ m^{-3}$), followed by TDR315 (0.028 $m^3\ m^{-3}$) and GS1 (0.048 $m^3\ m^{-3}$). These values belong to the fair accuracy category defined in Fares et al. (2011), suggesting that CS655, TDR315, and GS1 can be implemented for effective irrigation scheduling under conditions similar to those of LSLC. The RMSE values obtained in this study were smaller than the RMSE values of 0.105 and 0.049 $m^3\ m^{-3}$ reported by Singh et al.

(2018) for the CS655 and TDR315 in a loam soil, respectively. Adeyemi et al. (2016) found a similar RMSE of 0.020 $m^3\ m^{-3}$ for TDR315 and 0.050 $m^3\ m^{-3}$ for GS1 in a sandy loam soil under laboratory conditions. The RMSE of CropX was 0.051 $m^3\ m^{-3}$, which is in the poor category. The SM100's RMSE was very poor (0.110 $m^3\ m^{-3}$).

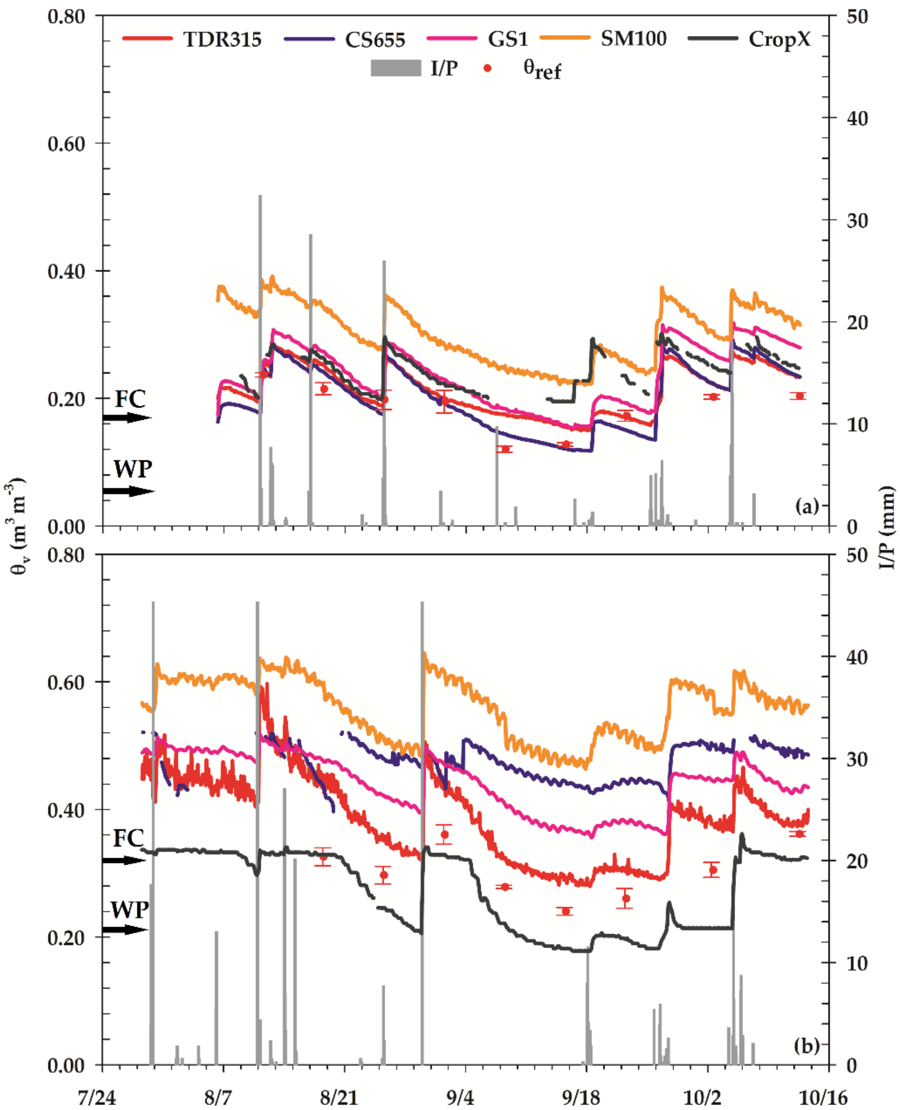

Figure 3.2. Time series of sensor-estimated θ_v along with point measurements of θ_{ref} at (a) lower salinity and lower clay content (LSLC) and (b) higher salinity and higher clay content (HSHC)

sites. Error bars for θ_{ref} represent standard error of mean. The FC and WP limits were determined in the laboratory.

Table 3.3. Performance indicators of soil moisture sensors.

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

The MBE and RSR revealed similar patterns in sensor performance at the LSLC, with the CS655 performing the best, followed by TDR315, GS1, CropX, and SM100. The MBE indicated that all sensors overestimated θ_v at LSLC. This overestimation can also be observed in Figure 3.3 as most of the points were above the 1:1 line. Overestimation of θ_v by CS655 was observed by Kisekka et al. (2014) and Michel et al. (2015) too. Adeyemi et al. (2016) found that TDR315 and GS1 underestimated θ_v in sandy loam soil, but, with increasing clay content, the underestimation became overestimation. The RSR ranged from 0.53 for CS655 to 3.00 for SM100 at LSLC site. According to categories defined by Moriasi et al. (2007), the CS655 had a good model fit whereas all other sensors were classified as having unsatisfactory model fit. But as mentioned previously, running a model on temporal resolution higher than monthly would warrant less strict performance rating. Therefore, higher RSR values are expected in this study because of hourly time-step analysis. This trend was also observed in a study by Wyatt et al. (2017), which produced high RSR values at daily time-step.

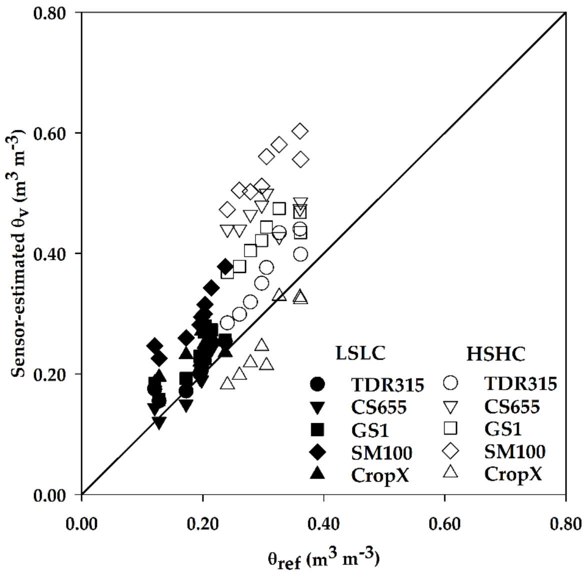

Figure 3.3. Sensor-estimated θ_v vs θ_{ref} at LSLC and HSHC sites.

All sensors had larger RMSE at the HSHC site compared to LSLC (Table 3.3). However, the magnitude of the increase in RMSE was not uniform and changed from a slight increase for CropX to over an eight-fold increase for CS655. The CropX sensor had the smallest RMSE, followed by TDR315, GS1, CS655, and SM100. The values of RMSE belonged to the poor accuracy category in case of CropX and TDR315 and very poor category for other sensors according to classifications in Fares et al. (2011), suggesting that none of the sensors can be implemented for effective irrigation scheduling under conditions similar to those of HSHC. In addition, the variability of readings among the replications of the same sensors increased at HSHC; the average standard deviation (SD) ranged from 0.021 m^3 m^{-3} for TDR315 to 0.050 m^3 m^{-3} for CS655. At LSLC, the average SD varied from 0.011 m^3 m^{-3} for TDR315 to 0.023 m^3 m^{-3} for GS1. The average SD of θ_{ref} was 0.015 m^3 m^{-3} at LSLC and 0.010 m^3 m^{-3} at HSHC.

High clay content and elevated levels of salinity seem to be the main reasons behind lower sensor accuracies at the HSHC site. Adeyemi et al. (2016) concluded that the errors in TDR315 and GS1 would increase with an increase in soil salinity level. In addition, Wyseure et al. (1997) reported that the error in TDR sensors would remain within reasonable limits if the bulk EC is kept less than 2 dS m^{-1}. The bulk EC at HSHC, however, was well over this threshold. The MBE estimates were larger at HSHC than LSLC and showed that all sensors except CropX overestimated θ_v. This is also evident in Figure 3.3. Most of previous studies have reported overestimation error for TDR sensors under saline conditions. This is mainly due to the fact that in saline soils, the dielectric permittivity measured by TDR increases and therefore θ_v is overestimated as mentioned in Dalton (1992). However, Schwartz et al. (2016) found that TDR315 underestimated θ_v in a saline Pullman clay loam soil. The RSR values followed a pattern similar to other error indicators at HSHC, having the smallest value of 1.34 for CropX and the largest value of 5.66 for SM100.

Some noise in θ_v readings of the TDR315 at HSHC can be seen in Figure 2.2b. Schwartz et al. (2016) reported that TDR315 sensors were insensitive to bulk EC up to 2.8 dS m^{-1} and corresponding pore water EC up to 7.3 dS m^{-1}. The bulk EC and pore water EC exceeded these thresholds at HSHC on many days at the beginning of the study period. This might have caused signal attenuation that induced noise in θ_v readings. This noise was quantified using standard deviation (SD) in θ_v among the replications. At the beginning of the growing season, the SD had a range of zero to 0.099 m^3 m^{-3} and an average of 0.021 m^3 m^{-3} at HSHC for TDR315, which is much larger when compared to the range of 0.002 to 0.043 m^3 m^{-3} and average of 0.012 m^3 m^{-3} at LSLC during the same period. The observed noise was reduced later in the growing season, probably due to decrease in soil EC because of leaching of salts by irrigation water.

The hourly bulk EC estimates from TDR315 and CS655 were in agreement with soil EC determined in the laboratory and showed the significant difference between the two study sites (Figure 3.4). Both sensors reported small bulk EC at LSLC with similar ranges of 0.1 to 0.4 dS m^{-1}. At HSHC, however, the bulk EC was significantly larger with ranges of 1.1 to 3.4 and 0.9 to 3.0 dS m^{-1} based on TDR315 and CS655 sensors, respectively.

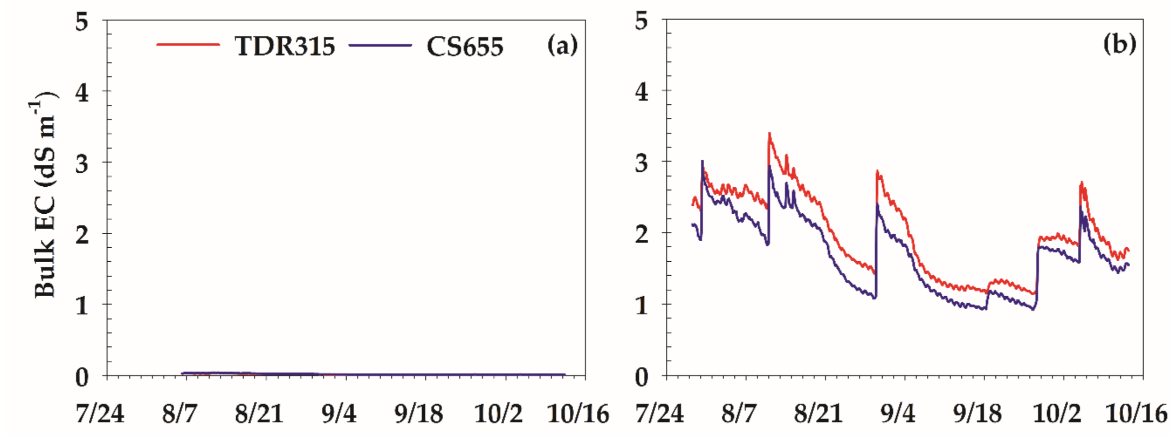

Figure 3.4. Time series of sensor-estimated Bulk electricity conductivity (EC) at (a) LSLC and (b) HSHC sites.

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

The CS655 had 21% missing data at HSHC. Sugita et al. (2016) conducted a reliability test on CS655 and found that the sensor was missing 64% of the measurements when exposed to high salinity levels (bulk EC = 1.2–2.1 dS m^{-1}). The bulk EC at HSHC was larger than the values reported in Sugita et al. (2016). In addition to high salinity, the HSHC site had relatively high clay content (38.7%). The clay particles have highly charged surface areas which increase dielectric losses and cause the apparent permittivity (K_a) values to go outside the acceptable range of Topp equation (Topp et al., 1980). The combined effect of higher soil salinity and clay content results in the attenuation of the electromagnetic signal from the sensor (Schwartz et al., 2016). Therefore, the sensor fails to report θ_v in case of $K_a \geq 42$ and $\theta_v \geq 0.52$ m^3 m^{-3} as the internal logical test rejects these data.

Linear regression equations were developed to estimate θ_{ref} based on sensor-estimated θ_v (Table 3.4). These equations can be used to get more accurate θ_v readings in areas matching this study's local conditions. At LSLC, the regression models were all statistically significant at $\alpha = 0.05$, with r^2 values ranging from 0.57 for CropX to 0.85 for CS655. Although SM100 had low accuracy, the high r^2 value (0.84) indicates that this sensor had high degree of correlation with the reference values. At the HSHC site, the linear regression model for CS655 was not statistically significant. Models of other sensors were significant and had r^2 values varying from 0.73 to 0.85.

Table 3.4. Parameters and the p-values of the linear regression equation: θ_{ref} = Slope × (sensor θ_v) + Intercept.

Site	Sensor	Intercept	Slope	r^2	p-value
LSLC	TDR315	−0.017	0.975	0.80	0.001
	CS655	0.036	0.771	0.85	<0.001
	GS1	0.017	0.737	0.70	0.005
	SM100	−0.033	0.747	0.84	0.001
	CropX	−0.052	1.030	0.57	0.018
HSHC	TDR315	0.056	0.683	0.85	0.001
	CS655	−0.056	0.774	0.20	0.267 Ŧ
	GS1	−0.108	0.971	0.73	0.007
	SM100	−0.165	0.873	0.79	0.003
	CropX	0.137	0.656	0.85	0.001

Ŧ The linear regression model was not statistically significant.

3.3.2. Correlations Between Sensors

In general, the Pearson's correlation coefficients (r) of θ_v readings were larger at LSLC than HSHC (Table 3.5). At this site, the strongest correlation (r = 0.99) was between TDR315 and CS655 and the weakest was between CropX and SM100 (r = 0.79). The correlation coefficients for CropX were smallest among all sensors at the LSLC site, ranging from 0.79 to 0.81. Despite being the least accurate sensor, SM100 had strong correlation with the top two accurate sensors, i.e., TDR315 and CS655. This indicates that SM100 closely followed the temporal changes in θ_v of more accurate sensors. At HSHC, the correlation between TDR315 and GS1 was the strongest ($r = 0.97$). The SM100 also had strong correlations with TDR315, GS1, and CropX. On the other hand, CS655 had weak correlations with other sensors.

Table 3.5. Pearson correlation coefficients among installed sensors at study sites.

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

Note all correlation coefficients were significant at $p = 0.05$.

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

3.3.3. Soil Moisture Thresholds

At LSLC, the FC and WP estimated in the laboratory were similar to the output of the Rosetta model based on textural class, textural information, and textural information plus bulk density (Table 3.6). Thresholds obtained from USDA's Web Soil Survey (USDA-WSS) were slightly larger than the results of the laboratory and Rosetta methods. However, the estimates based on the ranking of sensor readings were significantly larger than those of the other methods. The FC and WP values were larger at HSHC compared to LSLC irrespective of the method used because of larger clay content in the soils. The FC values from the Rosetta model and the USDA-WSS were either similar or slightly smaller than those obtained with the laboratory approach. All ranking estimates of FC were significantly larger than those with laboratory approach except for CropX, which was slightly larger. In the case of WP, estimates from the Rosetta model were significantly smaller than those with the laboratory approach, while USDA-WSS reported a similar value. Ranking method estimates were significantly larger except for CropX. The differences between AWC estimates of the ranking and laboratory methods were smaller than the differences in the FC and WP estimates of the same methods at both sites, mainly because overestimations in FC and WP estimates of the ranking method were of similar magnitudes and thus cancelled out to a large extent.

Table 3.6. Estimates of field capacity (FC), wilting point (WP), and available water content (AWC) (all in $m^3\ m^{-3}$) obtained from various methods.

Method	LSLC			HSHC		
	FC	WP	AWC	FC	WP	AWC
Laboratory [1]	0.17	0.06	0.11	0.32	0.21	0.09
Rank-TDR315 [2]	0.27	0.16	0.11	0.49	0.29	0.20
Rank-CS655 [2]	0.27	0.12	0.15	0.51	0.43	0.08
Rank-GS1 [2]	0.31	0.16	0.15	0.50	0.37	0.13
Rank-SM100 [2]	0.37	0.23	0.14	0.62	0.48	0.14
Rank-CropX [2]	0.28	0.17	0.11	0.34	0.18	0.16
Rosetta-TC [3]	0.17	0.06	0.11	0.31	0.12	0.19
Rosetta-TI [4]	0.17	0.07	0.10	0.29	0.14	0.15

Rosetta-TBD [5]	0.15	0.07	0.08	0.26	0.14	0.12
USDA-WSS [6]	0.21	0.12	0.09	0.29	0.21	0.08

[1] Laboratory measurement; [2] Ranking method performed for each sensor; [3] Rosetta model using soil textural class only; [4] Rosetta model using soil textural information (% sand, silt, and clay); [5] Rosetta model using textural information and bulk density; [6] USDA's Web Soil Survey.

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

Variations in hourly SMD are presented in Figure 3.5. In this figure, dots represent observed SMD based on θ_{ref} and laboratory-determined FC, while lines represent sensor SMD based on sensor θ_v and FC from two methods: laboratory and ranking. The Rosetta model was not considered here because the FC values obtained from the model were similar to those of the laboratory. At LSLC, observed SMD values were zero except on two sampling dates in early September. This is because this site was under full to slightly over-irrigation at most times during the study period. The only exception for the same period was in September when crop water demand outpaced irrigation application. Possible underestimation of θ_{FC} in the laboratory method may have contributed to zero SMD on most measurement dates too. In this study, a soil matric potential of −33 kPa was used to measure θ_{FC}. But as mentioned before, this value can be as high as −10 kPa in sandy loam soil, resulting in a larger θ_{FC} and consequently a larger SMD estimate. Sensor SMDs based on laboratory-FC had similar patterns, indicating no depletion during the study period except in the month of September (Figure 3.5a). On the other hand, sensor SMDs based on ranking-FC showed significant depletions at most times, reaching values as large as 0.15 $m^3\ m^{-3}$ (Figure 3.5b). This increase in SMD is mainly due to overestimation of FC in the ranking method, since the same sensors readings were used in both SMD approaches.

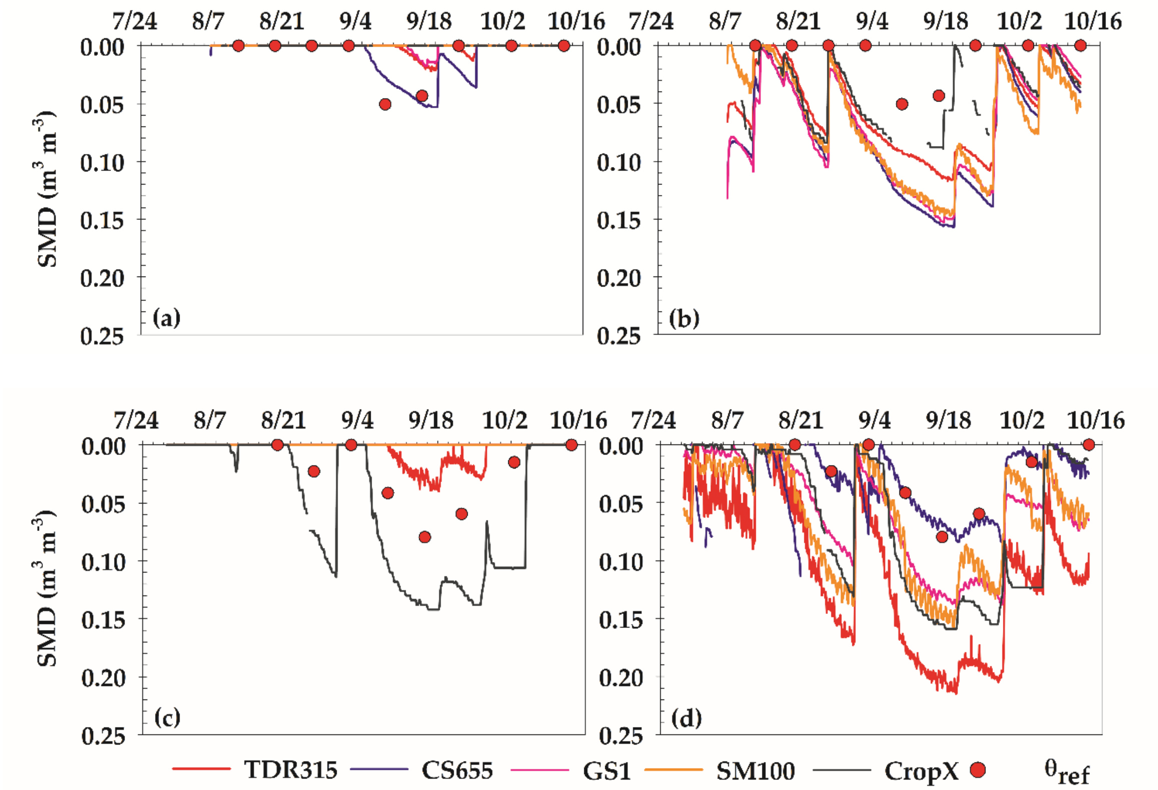

Figure 3.5. Time series of hourly soil moisture depletion (SMD) estimated based on sensor readings of θ_v and FC estimates from laboratory (a) and ranking (b) methods at LSLC site and laboratory (c) and ranking (d) methods at HSHC site. Dots represent SMD estimated based on θ_{ref} and FC estimates from laboratory method.

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

3.4. Conclusions

The performance of five types of commercially available soil moisture sensors was evaluated at two fields with significantly different salinity levels and clay contents. The sensors included TDR315, CS655, GS1, SM100, and CropX. The accuracy of each sensor was determined by comparing its readings with gravimetric measurements of soil water content obtained at several times during the study period. In general, all sensors responded to wetting and drying events. The TDR315, CS655, and GS1 sensors had acceptable accuracies for managing irrigations at the site with low salinity and low clay content (LSLC) based on root mean square error (RMSE). However, none of the sensors performed satisfactorily at the site with high salinity and high clay content (HSHC), with RMSE estimates that were up to eight times larger compared to the values at LSLC. In addition, high levels of noise were observed in TDR315 due to high salinity and out-of-range responses and consequently missing readings in case of CS655 sensor. A potential solution for using soil moisture sensors in irrigation scheduling under such conditions is the use of site-specific calibrations.

For practical irrigation scheduling, sensor readings must be used in conjunction with soil moisture thresholds of field capacity (FC) and wilting point (WP) in order to estimate soil moisture depletion (SMD) and consequently irrigation requirement. In this study, FC and WP values determined in the laboratory using undisturbed soil cores were compared against those obtained from three independent approaches: the Rosetta model, the ranking of sensor readings, and the values reported in the U.S. Department of Agriculture's Web Soil Survey (USDA-WSS). The Rosetta model was capable of providing estimates similar to those of the laboratory approach, regardless of the type and number of input data used in the model. The USDA-WSS approach resulted in acceptable estimates of FC and WP. The ranking method, however, significantly overestimated FC and WP at both sites, even for accurate sensors. The ranking method did not perform well in estimating SMD either, except for one sensor at the HSHC site where the overestimation error in FC was similar to overestimation error in soil water content and canceled each other out. The results of this study show that two major conditions are required before the ranking method can be used effectively in estimating soil moisture thresholds: sensor readings that are the basis of calculations must be accurate; and, the full range of moisture conditions from below WP to above FC must be experienced during the data collection period.

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

CHAPTER IV

QUANTIFYING WATER FLUXES OF IRRIGATED FIELDS IN AN AGRICULTURAL WATERSHED IN CENTRAL OKLAHOMA

4.1. Introduction

Inefficient use of irrigation water can increase non-beneficial fluxes such as direct evaporation before reaching the root zone, runoff, and deep percolation (Hoekstra, 2019). The increase in these fluxes would negatively impact water and energy costs of irrigation applications and ultimately the financial viability of agricultural production (Chebil et al., 2019)). In addition, these non-beneficial fluxes may carry sediments, chemicals (from fertilizer applications) (Burow et al., 2010), and other harmful constituents to downstream land and water resources (Malakar et al., 2019), causing soil and water pollution (Gillispie et al., 2015). Furthermore, over-irrigation may lead to increased greenhouse gas emission as more energy is used to extract, deliver and pressurize water. To minimize the adverse impacts of irrigation inefficiencies on the sustainability of farming practices and global food security, it is of great importance to accurately quantify different water fluxes in irrigated agriculture.

Water fluxes can be quantified through in-situ measurements, computer simulations, or a combination of these two approaches. In-situ measurements provide the most accurate estimation. However, this approach is labor-intensive, time-consuming, costly, and susceptible to variability in the skills of the operator using the instruments (Allen et al., 2011). Computer models can help eliminate the shortcomings of sensors and provide additional capabilities while estimating water fluxes with reasonable accuracy. However, several challenges exist with models. The first challenge is that models require detailed inputs to estimate water fluxes and more often, a large number of these inputs are assumed. Many critical input parameters related to irrigation practices have been assumed in previous studies, including but not limited to irrigation efficiency (Masasi et al., 2020; Yalcin, 2019), irrigation application depth and timing (Acero Triana et al., 2020; Masasi et al., 2020), and root growth and water uptake (Metselaar et al., 2019). Needless to say, any major difference between assumed parameters and their actual values can result in significant errors in model outputs.

Many of the computer models that rely on assumed input data on irrigation management are used to evaluate the environmental impacts of irrigated agriculture and the potential effects of implementing a wide range of conservation practices within impaired agricultural watersheds. One example of such watersheds is the Fort Cobb Reservoir Experimental Watershed (FCREW) in central Oklahoma, U.S., which has been suffering from soil erosion and water quality issues in its major tributaries over the last few decades. The entire watershed and drainage area for Fort Cobb lake and its tributaries were listed as nutrient limited by Oklahoma Water Quality Standards (OCC, 2009). Irrigation accounts for approximately 77% of the total water withdrawal in FCREW that predominantly has coarse-textured soils (Fairchild et al., 2011). High irrigation water use coupled with a coarse-textured soil with high percolation potential may leach chemicals from the crop root zone and introduce contaminants to groundwater systems. Becker et al. (2011) reported high levels of suspended solids in major streams in the FCREW during the crop growing season and suggested that agricultural activities could increase suspended solids, although no emphasis was given to the role of irrigation management. Storm et al. (2006) implemented soil and water assessment tool (SWAT) in the FCREW and found out that some irrigated crops were contributing the largest amount of sediments and nutrients to the reservoir. However, no comprehensive research has been undertaken before to determine the current irrigation management practices in this watershed and their potential impact on water quality.

The goal of this study was to investigate current irrigation management practices and efficiencies in the FCREW using a combination of in-situ measurements and computer models to estimate water fluxes under irrigated conditions. The specific objectives were to: 1) evaluate current irrigation management practices in the area; 2) use two widely accepted modeling approaches to estimate water fluxes; 3) identify irrigation efficiencies; and, 4) evaluate the accuracy and appropriateness of irrigation management assumptions made in other studies.

4.2. Materials and Methods

4.2.1. Study Area

This study was conducted in the Fort Cobb Reservoir Experimental Watershed (FCREW) in Western Oklahoma, U.S. during three crop-growing seasons from 2017 to 2019. A total of 12 irrigated fields stretched across FCREW were selected for estimating water fluxes (Figure 4.1). These sites had Pond Creek fine sandy loam and silt loam soils (Fine-silty, mixed, superactive, thermic, Pachic Argiustolls), except for one site that had Grant loam soil (Fine-silty, mixed, superactive, thermic Udic Argiustolls) and another under Hollister silt loam soil (Fine, smectitic, thermic Typic Haplusterts). The electrical conductivity (EC) of the soil solution (1:1 soil-water ratio) samples extracted from the top 0.7 m of the soil profile ranged from 0.4 to 7.2 dS m^{-1} with an average of 1.3 dS m^{-1}. All sites were irrigated by center-pivot sprinkler systems drawing water from the Rush Springs aquifer (Neel et al., 2018). Table 4.1 provides additional information on crop type and growing season of each experimental sites in each study year.

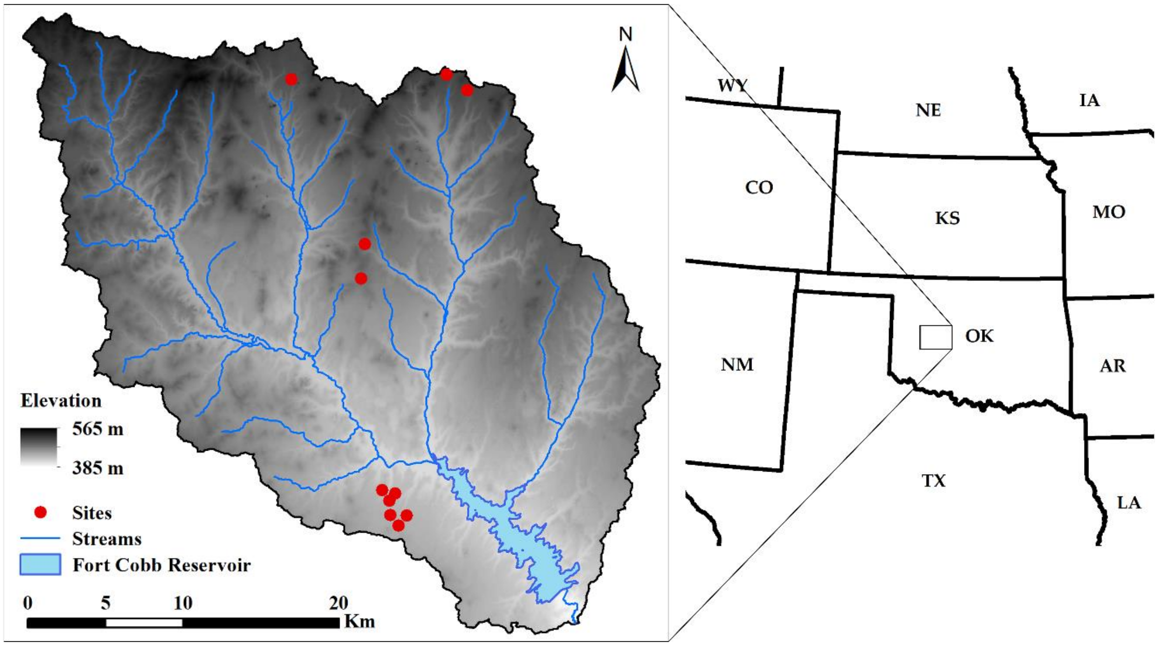

Figure 4.1. Location of the experimental sites within the study area.

Table 4.1. Details of the experimental sites.

Site No.	Crop	Year	Site ID	Growing Season
1	Peanut	2017	PN-17	5/13-9/30
2	Peanut	2018	PN-18	5/24-10/11
3	Peanut	2019	PN1-19	5/16-10/3
4	Peanut	2019	PN2-19	5/14-10/1
5	Cotton	2017	CT-17	5/15-11/11
6	Cotton	2018	CT1-18	5/24-11/20
7	Cotton	2018	CT2-18	5/23-11/19
8	Soybean	2017	SB-17	6/17-10/30
9	Soybean	2018	SB1-18	5/12-9/24
10	Soybean	2018	SB2-18	6/14-10/27
11	Chile pepper	2019	PP1-19	4/22-10/19
12	Chile pepper	2019	PP2-19	5/2-10/29

4.2.2. Experimental Setup and Sample Analysis

At each site, a representative spot was identified based on the condition of emerged plants, dominant soil texture (obtained from USDA web soil survey) of the field and center-pivot's largest wetted radius (excluding the last span). Then, sensors were installed at the spot soon after crop emergence to estimate water application amounts and soil moisture on an hourly basis. Precipitation and irrigation amounts were measured by tipping bucket rain gages (model 900RG, Irrometer Inc., Riverside, CA, USA) installed at each site. The top of the rain gages was well below the nozzles of the center-pivot systems to properly catch irrigation water. The recorded applications were separated into irrigation (I) and precipitation (P) based on the time, durations, and depth of application events after comparing the readings with precipitation measurements at two nearby Oklahoma Mesonet stations. The data provided by collaborating growers on the date and amount of irrigation applications were also used in I/P separation. The hourly data were summed to obtain daily and event totals and further analyzed to estimate the average irrigation depth and the irrigation interval.

Soil moisture sensors (models TDR310S and TDR315, Acclima Inc., Meridian, ID, USA) were installed at four depths of 10, 30, 51, and 71 cm at each site. The accuracy of this type of sensor has been assessed at the study site in a previous experiment and found to be acceptable and better than four other commercially available sensors, with the root mean square error and mean bias error being 0.028 and 0.020 $cm^3 cm^{-3}$, respectively (Datta et al., 2018). The volumetric water content readings of sensors were recorded and stored by dataloggers from the same manufacturer. The installation procedure followed the approach detailed in (Datta et al., 2018) to ensure sensors were installed into the sidewall of excavated pits (undisturbed soil) and that the pits were backfilled in layers to reduce disturbance to soil layers and bulk density. Undisturbed soil samples were also collected at each site at 10-cm increments across the top 70 cm of the soil (maximum sensor installation depth) and analyzed for percentages of sand, silt, and clay according to the protocol set by Ashworth et al. (2001). The sites were visited weekly throughout the growing season to check the sensors, measure crop height, and collect canopy cover data using the Canopeo mobile application (Patrignani & Ochsner, 2015).

4.2.3. Soil Water Balance Model

A simple bucket-type soil water balance (SWB) model was developed for each site following the approach explained in (Allen et al., 1998). This type of model has been previously developed through spreadsheet and used in similar studies (McCann et al., 2008; Thorp et al., 2017; Üzen et al., 2018) and is based on the following water balance equation, assuming a negligible runoff:

$$P_i + I_i = ET_i + DP_i + D_{i-1} - D_i \tag{1}$$

Where the subscript i represents the day; P_i is the precipitation; I_i is the net irrigation that infiltrates the soil; ET_i is the crop evapotranspiration; DP_i is the deep percolation; D_{i-1} is soil moisture depletion in the root zone (previous day); and, D_i is the soil moisture depletion on the day i. Two different versions of the SWB model was developed for each site to evaluate potential under- and/or over-irrigations and their impact on water fluxes. The first version simulated the "actual scenario," where the actual irrigation depth and frequency data as recorded by the rain gages were used in the model. The second version simulated the "well-watered scenario," where irrigation depths and times were determined by the model in a fashion to prevent crops from experiencing any stress.

Under the actual scenario, the actual crop ET (ET_a) was estimated following the dual crop coefficient approach outlined in the FAO-56 publication (Allen et al., 1998; Allen et al., 2005):

$$ET_a = (K_e + K_s K_{cb})\ ET_o \tag{2}$$

where, K_e is the soil evaporation coefficient; K_s is the water-stress coefficient; K_{cb} is the basal crop coefficient, and ET_o is the short-crop reference evapotranspiration. If the irrigation applications fall behind the crop water demand, the root zone depletion eventually exceeds the readily available water, causing the K_s to drop below unity and the ET_a to fall below the well-watered rate. By design, the goal of well-watered scenario was to keep the K_s at unity. Whenever the root zone depletion exceeded readily available water and as a result, the K_s fell below 1, irrigation was applied under well-watered scenario the next day to bring root zone depletion to zero and K_s to 1 (Er-Raki et al., 2010). Thus, crop ET was equal to the well-watered ET (ET_{ww}) of each crop under the given atmospheric conditions. The irrigation amounts under the well-watered scenario could be unrealistically large, especially during the middle of the growing season. A limit of 51 mm (2 inches) was applied on the maximum depth of irrigation that could be assigned by the model during each automatic event. This value was chosen based on the maximum capacity of the local irrigation systems in the study area.

Several additional input data were required for running the SWB model. The meteorological variables were obtained from the two nearest Oklahoma Mesonet weather stations of Hinton and Fort Cobb (McPherson et al., 2007; Sutherland et al., 2005). For each study site, the weather station that was closest to that site was used for data retrieval. The planting dates of crops were obtained from the growers. The length of different growth stages and corresponding K_{cb} were based on tabulated values presented in (Allen et al., 1998) and further adjusted according to the methodology in the same reference to reflect the local weather conditions. The soil hydraulic properties and the two moisture thresholds of field capacity and wilting point were calculated using the Rosetta computer model based on the sampled percentage of sand, silt, and clay (Schaap et al., 2001). The initial soil moisture depletion at planting was assumed zero (soil moisture at field capacity). The value for MAD for different crops was obtained from Allen et al. (1998). For PP, the MAD was taken as 50%, matching the value available for bell pepper. The maximum root depth was assumed equal to the maximum depth at which water extraction took place based on the soil moisture data recorded by a soil moisture probe (AquaSpy Inc., San Diego, CA, USA) at 10-cm increments over the top 1.2 m of the soil. A linear root growth model was implemented following Allen et al. (1998).

4.2.4. HYDRUS Model

In addition to the SWB model, the one-dimensional HYDRUS model (ver. 4.17, PC-Progress S.R.O., Prague, CR) was also used to simulate water fluxes at the same study sites. Compared to the SWB model, HYDRUS provides greater capabilities and functionalities such as estimating runoff and simulating soil moisture at multiple depths in the rootzone in addition to determining water fluxes when the soil-related parameters are measured directly (Ventrella et al., 2019). HYDRUS simulates unsaturated water flow based on the Richard's equation (Simunek et al., 2005):

$$\frac{\partial \theta_v}{\partial t} = \frac{\partial}{\partial x}\left[K\left(\frac{\partial h}{\partial x} + \cos\alpha\right)\right] - S \tag{3}$$

where, θ_v is volumetric water content ($cm^3\ cm^{-3}$), t is time, K is unsaturated hydraulic conductivity function ($cm\ day^{-1}$), h is soil matric potential (cm), x is spatial coordinate, α is angle between flow direction and the vertical axis, and S is the sink term ($cm^3\ cm^{-3}\ day^{-1}$). The sink term is representative of root water uptake.

In setting up the simulation domain, the depth of the soil profile was selected at 1.2 m. The upper boundary condition (BC) was set as atmospheric BC with surface runoff and lower BC was set as free drainage as the water table was below the simulation domain. The input parameters were defined similar to the SWB model. The information on soil material was obtained from samples taken at each site. Soil hydraulic properties were also estimated by the Rosetta model based on soil textural information. The Feddes et al. (1978) root water uptake model was selected with fully compensated root water uptake. The Feddes parameters (h_1, h_2, h_{3high}, h_{3low}, and h_4) were modified to simulate the same root water uptake response to water stress as the SWB model (stress function in Allen et al. (1998)). Under anaerobic conditions, the Feddes parameter, h_1 was set at zero, with h_2 having the same value. This matched the K_s value of 1 in stress function. The modification for h_3 ($h_{3high} = h_{3low}$) was based on moisture thresholds obtained from the soil samples and MAD that reduces root water uptake from the point of MAD to WP, which is taken as h_4. The root growth timeseries utilized in the SWB model was provided as input in HYDRUS. The initial soil moisture was set at FC (similar to zero depletion below FC in the SWB model). Like the SWB model, HYDRUS was run under the actual and well-watered scenarios. The applied water in HYDRUS was the sum of actual irrigation and recorded precipitation for the actual scenario. For the well-watered scenario, the sum of applied water determined by the SWB model under well-watered scenario and recorded precipitation was used as applied water. Finally, the unadjusted evaporation (K_e ET_o) and transpiration (K_{cb} ET_o) estimates of the SWB model under each scenario were used as inputs to each corresponding scenarios of the HYDRUS model.

Unlike the SWB model, HYDRUS does not assume a zero runoff and an estimate is provided for this component of the irrigation water balance. Another difference between the two models was that HYDRUS provides soil water content estimates at variable soil layers, while the SWB model treats the entire root zone as a single uniform unit. To take advantage of this capability in HYDRUS, four observation nodes were defined at 10, 30, 51, and 71 cm below the same surface, which are the same as the installation depths of soil moisture sensors. This allowed comparison between simulated and measured soil moisture at each depth and site, which would provide valuable information on model performance. In presenting the results of both models, the average parameters were reported in the “mean ± standard deviation” format as recommended by Barde and Barde (2012).

4.2.5. Comparison of Fluxes

Two statistical indicators were calculated to compare water fluxes generated by SWB and HYDRUS models, as well as soil moisture simulated by HYDRUS and estimated by in-situ sensors. These indicators were root mean square difference (RMSD) and normalized RMSD (nRMSD):

$$\mathrm{RMSD} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - H_i)^2} \tag{4}$$

$$\mathrm{nRMSD} = \frac{\mathrm{RMSD}}{\bar{S}} \times 100 \tag{5}$$

where, i is the time-step; n is the sample size; S_i is the flux estimate of SWB, H_i is the flux estimate of HYDRUS; and $\bar{S}$ is the mean of S_i dataset. An RMSD of zero represents perfect agreement between the compared datasets (Fares et al., 2011; Reindl et al., 1990). The nRMSD can range from zero to large positive values, with smaller values indicating closer estimates (Leib et al., 2003).

4.2.6. Seasonal Irrigation Efficiency

The seasonal irrigation efficiency (SIE) was calculated as the ratio of the depth of water beneficially used for crop growth to the depth of water delivered to the crops (Howell, 2003; Irmak et al., 2011):

$$\mathrm{SIE} = \frac{ET_a}{(I + P)} \times 100 \tag{6}$$

where, SIE is the irrigation efficiency (%), ET_a (ET under actual scenario) is the depth of water beneficially used by the crop, and (I+P) is the depth of total water delivered to the crops. Any water required for leaching for salinity management may be added to the ET_a term. As salinity is not an issue in the study area and growers do not apply any leaching fraction, there was no need for adding leaching fraction to ET_a. The (I+P) was the total water application, obtained from the rain gages. The seasonal irrigation efficiency has been also called irrigation efficiency, depleted fraction, water application efficiency, consumptive use coefficient, and water efficiency in previous studies (Jensen, 2007; Taghvaeian et al., 2018).

4.3. Results and Discussion

4.3.1. Water Fluxes

4.3.1.1. Irrigation

In general, irrigation season started in late May to early June and ended in mid to late September in the study area (Figure 4.2). Only pepper fields received irrigations in October. In most cases, the irrigation amounts were smaller and applied less frequently during the early season and became larger and more frequent during mid-season. The frequency reduced towards the end of the irrigation season. The depth of irrigation events ranged from 3 to 35 mm during the three study years and averaged 11 ± 5 mm (mean ± standard deviation). The average irrigation interval was 5 ± 5 days. Acero Triana et al. (2020) assumed an average irrigation depth of 25 mm in the FCREW, which is two times larger than the average measured depth in this study. Obviously, the difference between assumed and measured depths could have impacted the results of simulation study by Acero Triana et al. (2020). To further investigate the current irrigation practices, the frequency distribution of the ratio of irrigation depths (I) to readily available water (RAW) was plotted in Figure 4.3. About 90% of the irrigation events had a ratio of 0 to less than 0.30 for I/RAW. Only 2% of the events matched or exceeded the RAW and all of them occurred during the initial stages of the growing season when RAW was smaller due to smaller rootzone. This suggests that producers do not take advantage of the full storage capacity of the root zone and apply irrigation events that are too shallow and frequent.

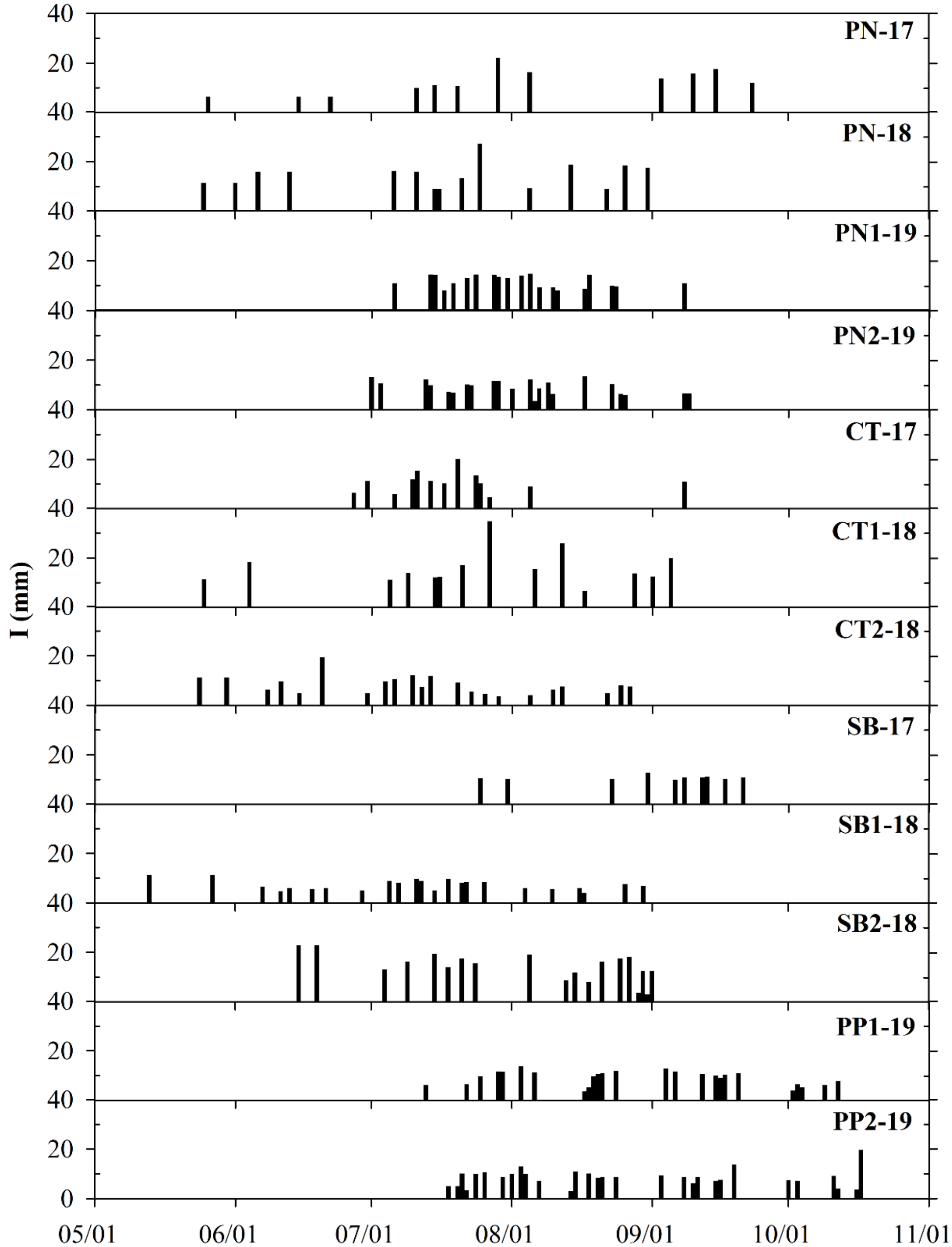

Figure 4.2. Depths and dates of applied irrigation events throughout the growing season.

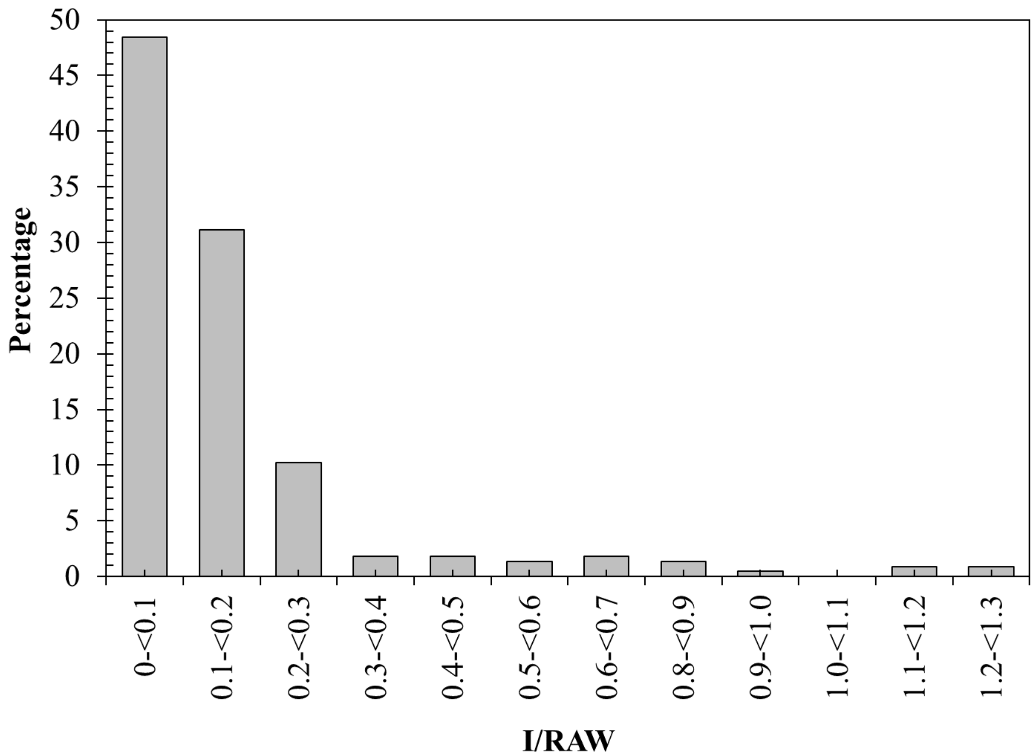

Figure 4.3. The distribution of the ratio of irrigation depth (I) to readily available water (RAW) estimated for each irrigation event under the actual scenario.

Under the well-watered scenario, the irrigation events were significantly larger than the actual scenario (Figure 4.4), with a range of 14 to 51 mm and an average of 39 ± 15 mm. The average irrigation interval was also significantly larger at 10 ± 7 days. This suggest that the sites investigated in this study applied too small and too frequent events and were under deficit irrigation for most of the growing season. The water holding capacity of the soils in the study area supports larger, less-frequent event, which help with minimizing evaporation and wind drift losses and thus storing more of the applied water in the root zone. To achieve the well-watered condition and avoid water stress, the study sites needed to apply from 42% (SB2-18) to 282% (PN-17) more irrigation water during the entire growing season. Detailed site-specific irrigation data are provided in Table 4.2.

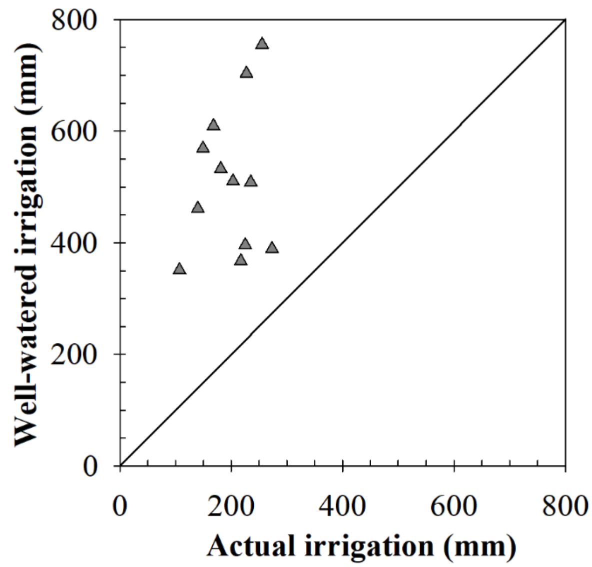

Figure 4.4. Comparison of the actual irrigation water applied at study sites and the well-watered amount that should have been applied.

Table 4.2. Irrigation data of each study site under actual and well-watered scenario.

Site	Actual					Well-watered					P (mm)
	Irrigation depth (mm)			Irrigation interval (days)		Irrigation depth (mm)			Irrigation interval (days)		
	Total	Mean	SD	Mean	SD	Total	Mean	SD	Mean	SD	
PN-17	149	12	5	11	8	569	32	14	7	7	370
PN-18	217	14	5	7	5	367	28	17	8	7	439
PN1-19	235	12	2	3	3	508	39	15	8	6	504
PN2-19	203	9	3	3	3	510	42	12	10	6	552
CT-17	140	11	4	6	9	461	46	10	17	10	480
CT1-18	225	16	7	8	7	396	40	14	10	7	490
CT2-18	181	8	4	5	3	535	35	15	9	8	438
SB-17	107	11	1	6	6	351	35	16	11	10	395
SB1-18	168	7	2	5	3	609	41	15	8	3	345
SB2-18	273	14	5	4	4	389	39	15	9	6	499
PP1-19	227	9	3	4	3	703	47	10	11	7	530
PP2-19	255	8	3	3	3	755	47	10	10	5	482

4.3.1.2. Evapotranspiration

The evapotranspiration (ET) was determined using reference ET and different crop coefficients such as – K_{cb} and K_s. The K_{cb} was plotted against the measured plant height (h) and canopy cover (CC) in Figure 4.5 for all study sites. In general, K_{cb} increased with increase in h until the maximum K_{cb} was reached. At the end of the growing season, K_{cb} decreased while plant height stayed the same. However, large variations were observed in K_{cb} with respect to h. Larger variations were also observed in case of K_{cb} with respect to CC. One possible reason is the differences in canopy height and cover among different crops. For example, peanut reaches near-full canopy cover and maximum K_{cb} at a relatively short height compared to other crops in the present study. On the other hand, soybean and cotton have taller canopies but possibly smaller CC depending on the planting density. Pepper reaches K_{cb} of near one at a smaller CC compared to other crops.

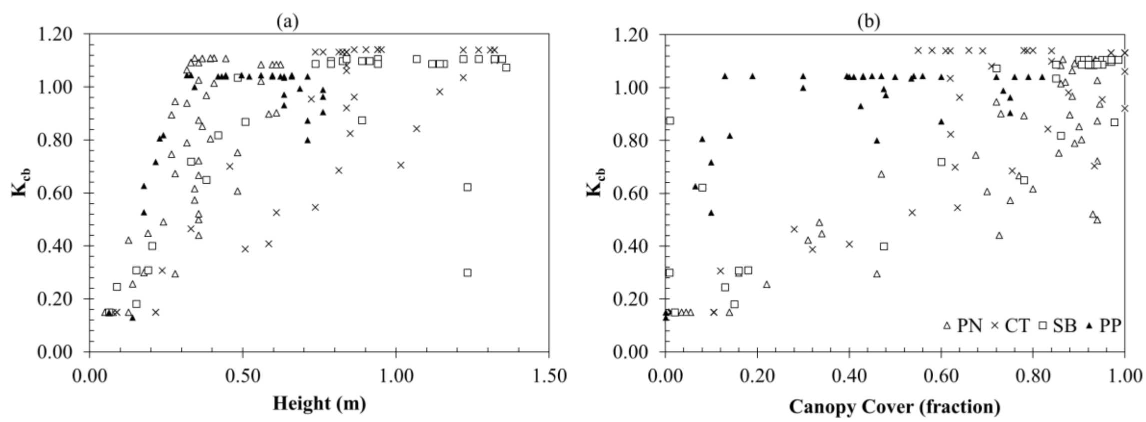

Figure 4.5. Comparison of K_{cb} with respect to the observed plant height (a) and canopy cover (b) at the study sites.

Under actual scenario, the stress coefficient (K_s) used in estimating crop water use fell below unity for many days at all study sites except SB2-18, indicating the crops experienced reduced evapotranspiration due to water scarcity (Figure 4.6). The timing of water stress incidents was not consistent, and stress occurred during different periods of growing season at different sites. When averaged across all sites, K_s was below unity on 64 ± 39 days. The average length of crop growing season at the study sites was 155 ± 21 days. The normalized K_s calculated as the cumulative seasonal K_s divided by the maximum possible cumulative K_s under absence of any stress ranged from 71% at the two pepper sites to 100% at SB2-18, with an average of 86 ± 10% (Figure 4.7). A normalized K_s below 100% indicates water stress at some point during the growing season.

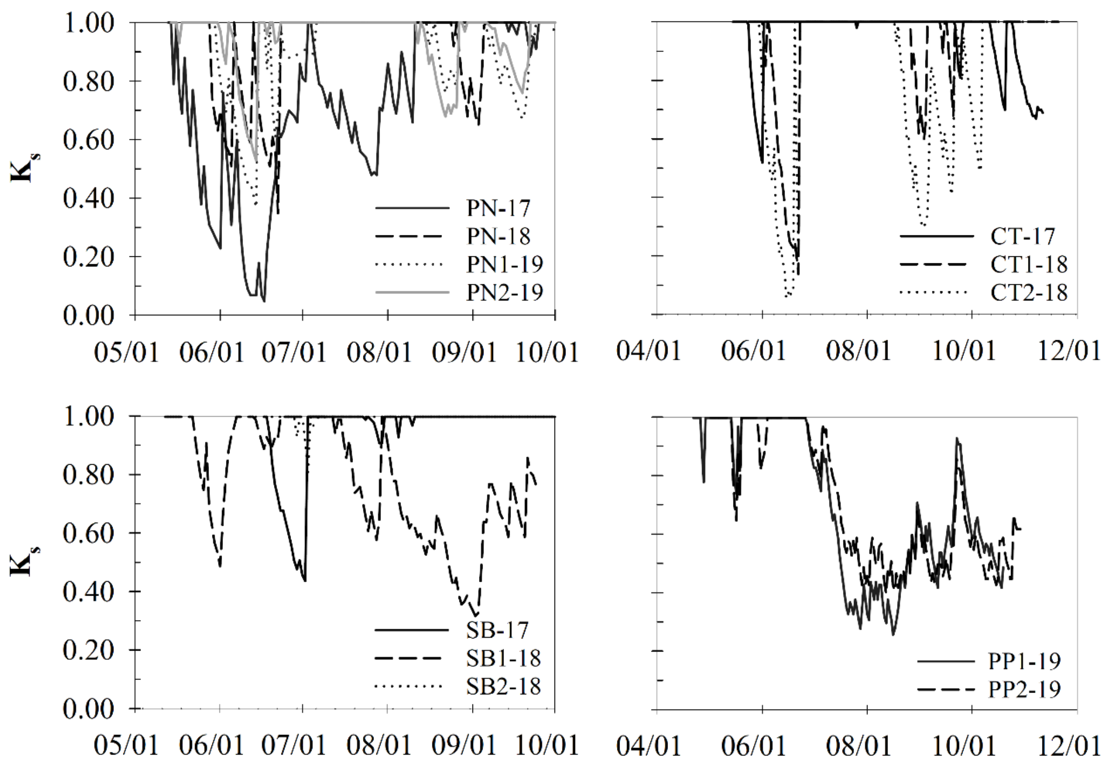

Figure 4.6. Variations of daily stress coefficient (K_s) throughout the growing season. Any day with a K_s value less than unity indicates the presence of water stress.

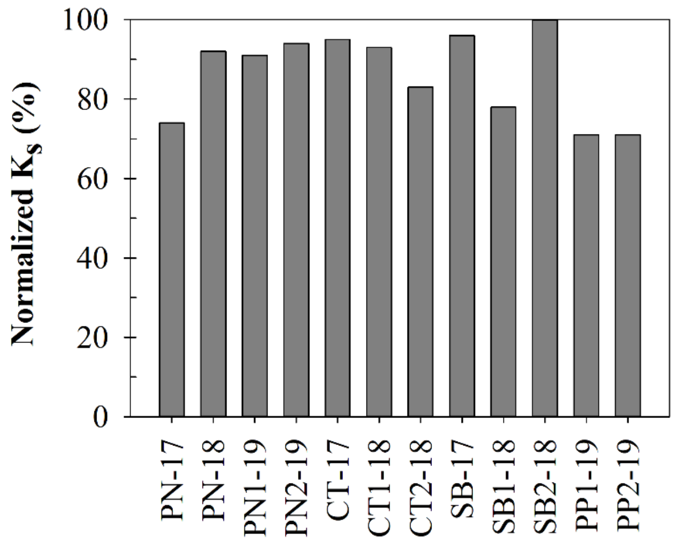

Figure 4.7. Normalized stress coefficient (K_s) at study sites. A value less than 100% indicates water stress was experienced at some point during the growing season.

Table 4.3 presents data on site-specific seasonal crop water use under actual (ET_a) and well-watered (ET_{ww}) scenarios. The average seasonal ET_a was 694 ± 76 mm based on the SWB and 671 ± 86 mm based on HYDRUS models. Seasonal ET_a was larger than seasonal irrigation, with irrigation amount accounting for only 30 ± 4% of the seasonal ET_a based on both models. Seasonal ET_a was also larger than the total applied water (irrigation and precipitation combined) at majority of sites (9 sites according to SWB and 7 sites according to HYDRUS out of 12 sites). The difference between the seasonal water use and applied water was supplied from the root zone water storage and most sites had a significant soil moisture depletion at the end of the season. The partitioning of ET_a to evaporation (E_a) and transpiration (T_a) was similar between the two models. T_a dominated the total water use, accounting for 71 ± 5% and 72 ± 5% of seasonal ET_a according to SWB and HYDRUS models, respectively. These ET flux estimates between SWB and HYDRUS models were different probably because of the differences in evaporation and transpiration estimation mechanisms. In HYDRUS, if a certain layer of rootzone is facing stress, water could still be extracted from other layers through the compensated root water uptake whereas in SWB, the whole rootzone must face stress before the water uptake is reduced. Another contributing factor could be the assumption of zero runoff by SWB model which allowed the model to distribute more of the incoming fluxes (irrigation, precipitation, and pre-season water storage) to outgoing components of SWB. The RMSD of seasonal ET_a, E_a, and T_a between the two models was 38, 16, and 26 mm, respectively. The nRMSD of the same fluxes was 5, 8, and 5%, respectively. These indicators suggest similar results between the models, which can also be observed in Figure 4.8a.

Table 4.3. Seasonal ET in the study sites under actual and well-watered scenarios.

Site	Actual			Well-watered		
	ET_a (mm)		$I_a + P$ (mm)	ET_p (mm)		$I_p + P$ (mm)
	SWB	HYDRUS		SWB	HYDRUS	
PN-17	572	529	518	832	791	939
PN-18	597	580	656	637	604	806
PN1-19	736	719	739	822	808	1012
PN2-19	772	734	755	844	824	1062
CT-17	803	743	620	826	810	941
CT1-18	732	692	715	779	761	886
CT2-18	720	669	619	879	859	970
SB-17	575	537	502	653	637	746
SB1-18	636	603	513	826	809	954
SB2-18	694	681	772	665	648	888
PP1-19	734	776	757	1100	1102	1233
PP2-19	756	789	737	1119	1118	1237

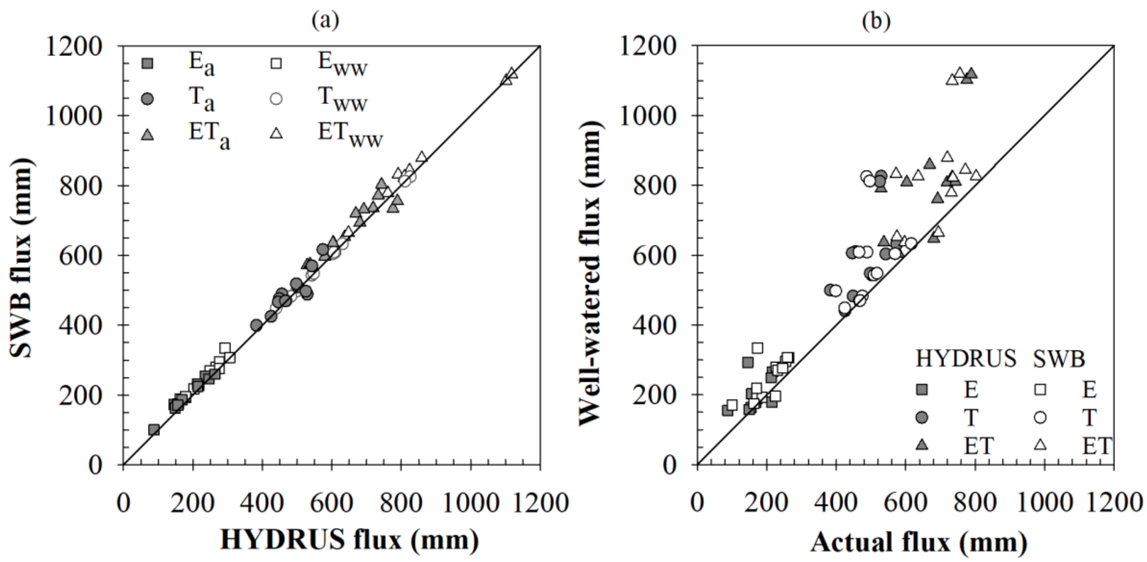

Figure 4.8. Comparison of seasonal ET, E, and T: (a) between the SWB and HYDRUS models; and, (b) between the actual and well-watered scenarios.

The average seasonal well-watered ET (ET_{ww}) was 832 ± 146 mm based on SWB and 814 ± 154 mm based on HYDRUS models. This was 19% and 21% larger than corresponding ET_a estimates by SWB and HYDRUS models, respectively (Table 4.3 and Figure 4.8b). Applied irrigation (determined automatically by model) accounted for 62% of ET_{ww}, which was more than two times larger than under the actual scenario. The E_{ww} and T_{ww} partitioning were similar between the two models, with T_{ww} accounting for 71 ± 5 % and 72 ± 5% of the seasonal ET_{ww} as estimated by SWB and HYDRUS models, respectively. The RMSD was 21, 20, and 3 mm for seasonal ET_p, E_a, and T_a between two models, respectively. These fluxes had nRSMD of 3, 8, and 0%, respectively. As expected, the normalized K_s was at 100% for all sites under the well-watered scenario. Several previous studies have evaluated the performance of the FAO-56 approach used in estimating ET_a in the present study and have found it to be satisfactory under full and deficit irrigation regimes (Cid et al., 2018). Thorp et al. (2017) observed over-estimation of ET_a by this approach when compared to ET_a estimated based on soil moisture measurements of neutron probes in Arizona and reported a nRMSE of 3-7%. Implementing a similar methodology by Gassmann et al. (2011) resulted in an average over-estimation of 5% in ET_a.

4.3.1.3. Runoff and Deep Percolation

The SWB model assumed zero runoff, so the runoff was only estimated by the HYDRUS model. The HYDRUS model predicted a negligible amount of runoff under actual scenario (RO_a), with an average of 1 ± 3 mm. Runoff under well-wateredl scenario (RO_{ww}) was still small at 2 ± 9 mm, despite the fact that the average irrigation amount was more than two times larger than under the actual scenario (Table 4.4). The negligible RO prediction is most likely due to two main reasons: i) the irrigation evens were mostly shallow and frequent; and, 2) the topsoil layer at the study area was coarse textured with an average of 71% ± 11% sand particles in the top 20 cm layer. Two lessons can also be learned from the estimation of negligible RO by HYDRUS. The first lesson is that assuming a zero RO in running the SWB model is a valid assumption and does not introduce a significant error in estimating of other water fluxes. The second lesson is that the elevated loads of suspended sediments observed in FCREW lakes and streams do not appear to be generated at investigated sites because of over-irrigation.

Table 4.4. Seasonal DP and RO in the study sites under actual and well-watered scenarios.

Site	Actual			Well-watered		
	DP_a (mm)		RO_a (mm)	DP_p (mm)		RO_p (mm)
	SWB	HYDRUS	HYDRUS	SWB	HYDRUS	HYDRUS
PN-17	0	10	0	115	72	0
PN-18	65	18	1	174	87	0
PN1-19	124	82	0	229	172	23
PN2-19	113	69	0	252	164	1
CT-17	1	7	0	162	94	0
CT1-18	16	24	8	150	116	0
CT2-18	14	9	0	136	107	0
SB-17	10	9	1	129	85	0
SB1-18	11	8	0	138	86	0
SB2-18	85	24	0	229	163	0

PP1-19	184	115	0	217	154	1
PP2-19	132	73	0	160	95	1

The average deep percolation under actual scenario (DP_a) was 63 ± 61 mm and 37 ± 36 mm based on SWB and HYDRUS models, respectively (Table 4.4). These amounts were about 9% ± 8% and 5% ± 5% of the total applied water based on the same two models, respectively. The RMSD and nRMSD of DP_a between two models were 39 mm and 62%. These estimates are comparable to Wyatt et al. (2017), who reported a mean annual drainage of 66 mm below a 3-m soil profile for the overlying area of the Rush Springs aquifer, which contains FCREW, under non-irrigated conditions. The DP values estimated under the actual scenario in this study suggest that the risk of groundwater contamination through chemicals carried with DP flux may not be large during the studied growing season. However, this risk should be studied over longer periods (decades). In addition, outside the growing season intense precipitation events and saturated soil profiles along with coarse textured soils may lead to significantly larger DP fluxes that could carry nutrients to groundwater resources. The average DP under well-watered scenario (DP_{ww}) was larger by both SWB and HYDRUS models at 174 ± 44 mm and 116 ± 35 mm, respectively. Approximately 18% ± 4% and 12% ± 3% of applied water became DP_{ww}. The DP_{ww} between two models had RMSD and nRMSD of 61 mm and 35%. The fact that the DP_{ww} was larger than the DP_a suggests that the risk of groundwater contamination due to current irrigation management practices would have been considerably larger under well-watered compared to the actual scenario.

4.3.2. Simulated and Sensor-based Soil Moisture

In general, the volumetric soil moisture (θ_v) based on sensor readings and HYDRUS simulations had similar patterns at different depths throughout the growing season. As expected, soil moisture at shallower depths (10 and 30 cm) had more pronounced responses to water applications compared to deeper depths (51 and 71 cm). Figure 4.9 demonstrates seasonal θ_v fluctuations at all four sensor depths for the sites that had the smallest (PN-18) and largest (PN1-19) errors.

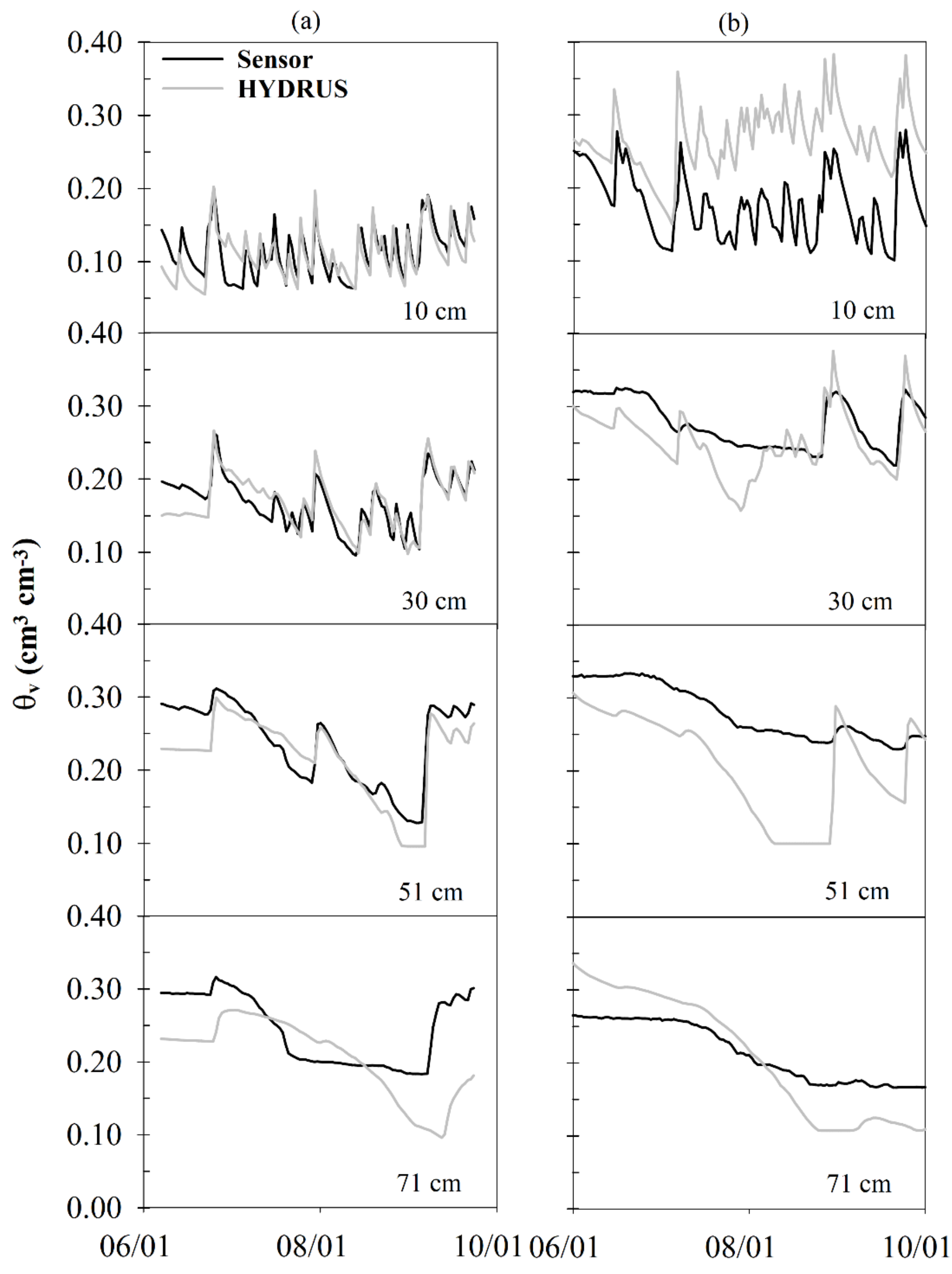

Figure 4.9. Time series of volumetric soil moisture (θ_v) based on sensors readings and HYDRUS simulations for the sites with (a): the smallest errors (PN-18) and (b): largest errors (PN1-19).

The RMSD of θ_v between sensor readings and HYDRUS simulations at the study sites had ranges of 0.02-0.10 cm^3 cm^{-3} at 10 cm, 0.02-0.07 cm^3 cm^{-3} at 30 cm, 0.03-0.08 cm^3 cm^{-3} at 51 cm, and 0.03-0.10 cm^3 cm^{-3} at 71 cm soil depths (Figure 4.10). When combining data from all depths, RMSD varied from 0.03 cm^3 cm^{-3} at the PN-18 to 0.07 cm^3 cm^{-3} at PN1-19, with an overall average of 0.06 cm^3 cm^{-3}. A previous experiment in the same study area found that the sensors used in the present study had a RMSE of 0.03 cm^3 cm^{-3} when compared against gravimetric soil moisture measurements (Datta et al., 2018). This explains half of the difference between HYDRUS estimates and sensor readings. Hence, it appears that the HYDRUS model had an acceptable performance in simulating θ_v.

The nRMSD of θ_v between sensor readings and HYDRUS simulations had ranges of 18-63% at 10 cm, 10-39% at 30 cm, 13-39% at 51 cm, and 14-50% at 71 cm soil depths at the study sites. The nRMSD (combined data from all depths) spanned from 19% at PN-18 to 30% at PN1-19, with the average of 27% at all sites. There was a larger range of nRMSD at the surface indicating the variations in the soil moisture were also larger at the surface.

The RMSD estimates of the present study were smaller than those in Ventrella et al. (2019) who compared HYDRUS results with sensor readings at four similar soil depths and reported RMSE ranging from 0.04 to 0.10 cm^3 cm^{-3}. In contrast, the errors in this study were larger than some other studies. For example, Zhang et al. (2019) reported an average RMSE of 0.03 cm^3 cm^{-3} comparing HYDRUS simulated θ_v with values from soil moisture sensors installed in sandy soils in China. Silva Ursulino et al. (2019) reported an RMSE of 0.01 to 0.02 cm^3 cm^{-3}. However, the sensors in their study were calibrated in the laboratory and were installed at shallow soil depths (0-30 cm). Chen et al. (2014) mentioned that HYDRUS is more accurate when simulating soil moisture at shallower soil depths. At the shallower depths, the RMSD of the present study was comparable with those observed by Silva Ursulino et al. (2019). The literature suggest several factors could contribute to the difference between HYDRUS simulations and sensor readings, including the presence of preferential flow channels, spatial heterogeneity of soil, lateral flux of soil moisture, root water uptake distributions, and errors in soil moisture sensors (Deb et al., 2013; Garg et al., 2009; Patil et al., 2011; Simunek et al., 2005; Vazifedoust et al., 2008; Zhang et al., 2017; Zhang et al., 2018; Zhang et al., 2019).

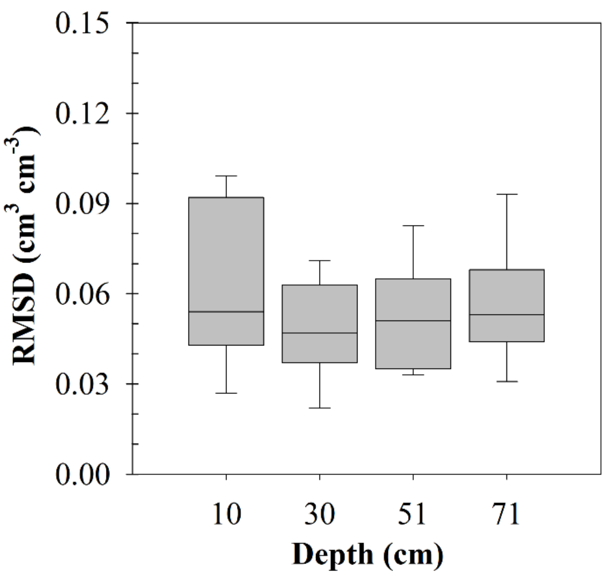

Figure 4.10. The root mean square difference (RMSD) of HYDRUS-simulated and sensor-estimated soil moisture at four soil depths.

4.3.3. Seasonal Irrigation Efficiency

The average seasonal irrigation efficiency (SIE) among the study sites was 107% ± 12% and 103% ± 9% based on the SWB and HYDRUS models, respectively. Out of all 12 sites, eight and seven sites had SIE over 100% according to SWB and HYDRUS, respectively (Figure 4.11). This is expected as most sites were under deficit irrigation management. Taghvaeian et al. (2018) reported a significantly smaller annual SIE of 55% under gravity irrigation in a district in southern California. In another irrigation district under pressurized irrigation, Bastiaanssen et al. (2001) found an annual SIE of 61%. Conrad et al. (2013) reported a much lower SIE of 46% in the observed part of the irrigation system in irrigated areas in Uzbekistan during the vegetation period.

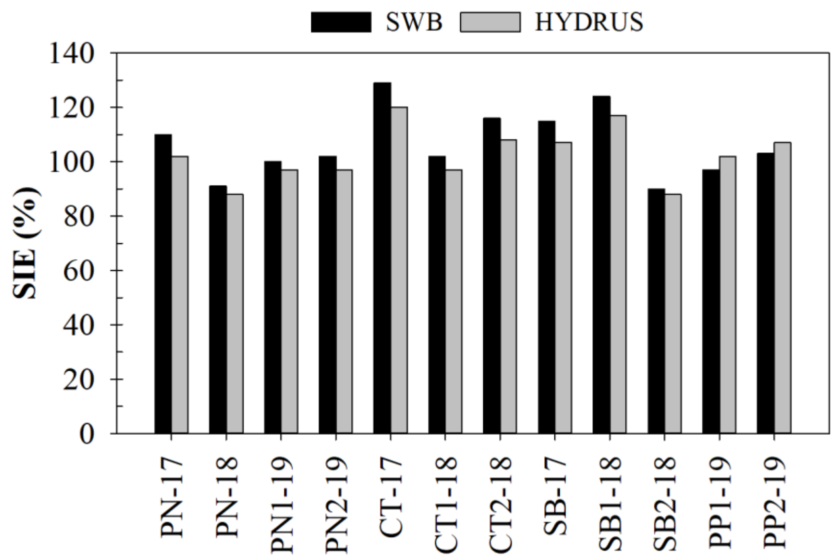

Figure 4.11. Seasonal irrigation efficiency (SIE) of study sites.

4.4. Conclusions

The water fluxes under irrigated condition were either measured or estimated using two modeling approaches at several sites across the Fort Cobb Reservoir Experimental Watershed (FCREW), an agricultural watershed in western Oklahoma. The models included a simple soil water balance (SWB) model and the more complex HYDRUS model, each implemented under two scenarios of actual irrigation management and well-watered irrigation management determined by the SWB model to avoid water stress. Almost all sites during the three years of study were under deficit irrigation. The well-watered irrigation amounts estimated by the model to prevent any stress was about 170% larger than the actual irrigation depths applied at study sites. The measured actual irrigation amounts and intervals suggest that irrigations events were too shallow and frequent. Due to deficit irrigation practices, well-watered crop evapotranspiration (ET) rates were 19-21% larger than the actual ET on average. The partitioning of ET into evaporation (E) and transpiration (T) was similar among models and scenarios, with T accounting for more than 70% of ET. The deep percolation flux was smaller than ET fluxes, accounting for less than 10 and 20% of the total applied water on average under actual and well-watered scenarios, respectively. Negligible runoff was estimated by HYDRUS under both scenarios, which was expected based on high infiltration rates of coarse-textured soils at the study area. These findings suggest that existing deficit irrigation practices may not contribute significantly to elevated nutrient and suspended solids levels in streams and lakes during the studied years within the FCREW. The negative environmental effects would have been larger if irrigations were managed to achieve well-watered conditions.

The volumetric soil moisture simulated by HYDRUS at four depths was similar to the readings of in-situ sensors installed at the same depths, with root mean square differences that were comparable to or smaller than values reported in the literature. The sensor-based and simulated soil moisture agreed with the findings on irrigation fluxes and deficit irrigation management as the water content in the deeper layers was declining throughout the growing season, not responding to water applications. The seasonal irrigation efficiency estimates were similar between the two models, showing close to or above 100% at most sites. These efficiencies were larger than those reported in other irrigated areas and expected under deficit irrigation management, when nonbeneficial fluxes are reduced or eliminated. This study contributes to the existing knowledge of estimating water fluxes in areas through employing a mixture of in-situ measurement and computer modeling and provides an insight to the accuracy of many irrigation-related parameters assumed in a large number of models for predicting the effects of variable agricultural and environmental practices.

CHAPTER V

CONCLUSIONS

Soil moisture sensors (SMS) are among the most effective tools to improve irrigation management for sustainable agricultural production around the world. Despite their usefulness in irrigation management, their adoption has remained limited. This research investigated the barriers behind low adoption of soil moisture sensors in irrigation scheduling and carried out applied research using a combination of measurement and modeling techniques to monitor soil moisture and water fluxes to conserve freshwater resources in irrigated agriculture. The specific objectives were to: (1) conduct a Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis on published literature related to SMS applications in irrigation management to identify shortcomings and potentials, (2) assess the performance of commercially available soil moisture sensors in irrigated fields of Oklahoma, and (3) investigate the performance of computer models in estimating soil moisture dynamics and quantifying irrigation fluxes under field conditions.

In the first study (chapter 2), the results of irrigation surveys conducted by the United States Department of Agriculture over the last 20 years were analyzed to investigate the adoption rate of SMS, along with the potential factors impacting the adoption. According to the surveys, the adoption rate of SMS has been low and highly variable among the top 15 irrigated states. SMS adoption had significant correlations with the level of control over water delivery and sources of information the producers relied on for irrigation management. The SWOT analysis revealed the strengths were the research and extension personnel dedicated to SMS experiments, reducing the gap in technology transfer between researchers and producers. Low sensor accuracy in variable soil and climatic conditions and lack of local field experiments were two of the dominant weaknesses. Identified opportunities were to increase the number of local studies, driven by producer's needs and concerns, to report a wide range of benefits realized through using SMS; to improve performance and affordability of sensors; to develop producer-focused decision support systems; and to conduct studies on the perception of producers towards the adoption of SMS. Major threats included laws and policies discouraging producers to focus on water conservation and reducing farm revenues that may impact the SMS adoption. This study contributes to our existing knowledge on the role of SMS in practical irrigation scheduling by investigating the barriers behind decades-old scientifically proven irrigation scheduling technology through analyzing national irrigation surveys and conducting a comprehensive SWOT analysis.

In the second study (chapter 3), the performance of five commercially available soil moisture sensors was assessed at two fields having different levels of salinity and clay content by comparing sensor-estimated soil moisture with gravimetric measurements. Three of the sensors performed satisfactorily at the site with low salinity and low clay content. However, at the site with high salinity and high content, none of the sensors performed satisfactorily. High level of noise and missing values were observed in the case of some sensors. This shows a need for site-specific calibration. Soil moisture thresholds (SMT) of field capacity and wilting point were obtained from laboratory and compared against values from the Rosetta model, ranking method based on sensors, and USDA web soil survey. The Rosetta model and USDA web soil survey estimated thresholds closer to the laboratory method. The soil moisture deficit (SMD) was estimated using the laboratory and ranking method. The results showed that the ranking method can perform well in estimating SMD with accurate information of SMT experiencing a wide range of soil moisture during the growing season and accurate estimates of soil moisture from sensors. This study provides information on the accuracies of five widely used SMS in variable clay content and salinity conditions in the soil, but its originality is in converting SMS estimates to actual irrigation scheduling information and then investigating the effects of different parameters on estimated irrigation depths.

In the third study (chapter 4), the water fluxes were either measured or estimated using two widely used modeling approaches, the soil water balance (SWB) and the HYDRUS models, at several sites located in the Fort Cobb Reservoir Experimental Watershed (FCREW) in Western Oklahoma. Each of these models was implemented under two scenarios: actual irrigation management and well-watered irrigation determined by the SWB model to avoid water stress. The sites were under deficit irrigation management, with the well-watered irrigation amounts requiring 170% more irrigation than actual irrigation depths. Crop evapotranspiration (ET) estimates were 19-21% larger in case of well-watered scenario compared to the actual scenario on average. The partitioning of evaporation (E) and transpiration (T) was similar among the models and scenarios. The deep percolation (DP) accounted for less than 10 and 20% of the total applied water under actual and well-watered scenarios, respectively. Negligible runoff was estimated by HYDRUS. The soil moisture simulated by HYDRUS agreed well with sensor-estimated values at four soil depths at each study site. The seasonal irrigation efficiency was close to or above 100% at most sites. These values were larger than those reported in other irrigated areas because of the sites being under deficit irrigation management. This study contributes to existing knowledge of quantifying water fluxes in an agricultural watershed through a blend of measurement and modeling techniques and shows the need for use of measured values in models where many irrigation-related parameters are assumed.

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