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In-field Optimization of Soil Water Parameters for Irrigation Scheduling

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IN-FIELD OPTIMIZATION OF SOIL WATER PARAMETERS FOR IRRIGATION SCHEDULING

by

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Several precision technologies are being developed to assist farmers in informed irrigation decision-making. These technologies aim to enhance irrigation water efficiency, check overirrigation, boost crop water productivity, and promote the sustainable utilization of water resources. We hypothesize that soil moisture parameters used in irrigation decision tools need to be validated to best represent the correct state of soil moisture in the field. This is an important factor that affects the accuracy of the irrigation recommendations forecasted by the decision support tools. In this research, we evaluated different methods of estimating field capacity (FC) and wilting point (WP) to optimize soil moisture parameters for irrigation scheduling. Several studies have emphasized the importance of observational FC but none have been able to quantify and compare various methods relative to observational FC (FC_{obs}). To test our hypothesis, we used one irrigation decision support system (IDSS) and compared it to Web Soil Survey (WSS) and Pedo Transfer Functions (PTF) for FC. For WP, we compared the IDSS, WSS and PTF methods to laboratory method (LAB). IDSS was categorized into two different types of methods- Single Data Point Optimization (SDPO) and Time Series Optimization (TSO), based on how they estimate FC and WP. Furthermore, we quantified the uncertainty of predicting the soil moisture parameters by those methods using RMSPE (Root Mean Square Prediction Error). The study area covered eight locations in three states across the Great Plains of North America

including North and South Dakota, Eastern and Western Nebraska, and Kansas for the 2023 growing season. The results showed that WSS had the highest $RMSPE_{WSS}$ of 18.6% with a potential delay in irrigation of 15 days and 6 fewer irrigation events followed by PTF with $RMSPE_{PTF}$ of 13.6% with a potential delay in irrigation of 11 days and 5 fewer irrigation events. The SDPO had the lowest $RMSPE_{SDPO}$ of 0.7% with a potential delay in irrigation of -1 day and no missed irrigation event. TSO had an $RMSPE_{TSO}$ which reflects the temporal variability in the estimation of FC, and it was around 0.8%. Soil Water Depletion (SWD) was plotted for each of the four methods to compare them with the baseline (FC_{obs} and WP_{LAB}). This study will benefit irrigation scheduling practices by providing a better understanding of the insights available from field and lab data and how to best manage the data from the soil moisture probes.

Dedicated to my husband and daughter,

Ankit and Aina

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1.0 Introduction and Motivation

The question of when and how much to irrigate has been important and challenging for producers, as well as agronomists and irrigation engineers from time immemorial. Several precision technologies are being developed to assist farmers in informed irrigation decision-making (Barker et al., 2019; Bhatti et al., 2020; Haghverdi et al., 2016; Lena et al., 2020; Mendes et al., 2019; O'Shaughnessy et al., 2015; Osroosh et al., 2016; Stone et al., 2020; Sui & Yan, 2017; Taghvaeian et al., 2014; Thorp, 2020; Vories et al., 2021). These technologies aim to enhance irrigation water efficiency, check overwatering, boost crop water productivity, and promote the sustainable utilization of water resources. However, precision irrigation has drawbacks, including associated costs and the absence of effective algorithms and real-time data availability for irrigation scheduling (Evett et al., 2020a, 2020b, 2020c).

Integrated sensing systems, advanced modeling tools, and irrigation scheduling algorithms are identified as beneficial for both site-specific and conventional irrigation methods (Thorp et al., 2022). Precision agriculture data streams necessitate a thorough understanding of soil, plant, and field characteristics in both temporal and spatial dimensions (Zhang et al., 2021). To ensure sustainable irrigation water management, precision irrigation technologies should prioritize plant-water relations within the soil-plant-atmosphere continuum. Furthermore, precision irrigation tools that integrate sensor data, remote sensing inputs, and modeling approaches have shown promise as effective decision-support systems for irrigation management (Bhatti et al., 2023).

The estimation of soil moisture relies on various sensing methods, each with its own set of principles, leading to potential errors and uncertainties. Numerous studies have evaluated the accuracy of these methods across different soil conditions and textures (Evett et al., 2002; Leib et al., 2003; Baumhardt et al., 2000; Varble and Chávez, 2011; Jabro et al., 2018; Zhu et al., 2019; Chow et al., 2009). The primary objective of these studies has been to assess the ability of sensors to accurately represent soil moisture content (measured as volumetric water content or θ_v) and to develop correction strategies for improving θ_v estimation (Evett and Steiner, 1995; Irmak and Haman, 2001; Heng et al., 2002; Quinones et al., 2003; Irmak and Irmak, 2005; Jabro et al., 2005; Brocca et al., 2007; Irmak et al., 2010; Mittelbach et al., 2012; Su et al., 2014; Datta et al., 2018; Irmak, 2019a; Zhu et al., 2019). Research on this topic emphasizes the importance of accurate θ_v estimation to determine the suitability of sensors for specific applications. Soil moisture sensors are expected to inform irrigation decisions rather than solely reporting θ_v values and other metrics like total soil water could be better metrics for irrigation management (Sharma et al., 2021).

Singh et al. (2020) in their study tested the impact of soil structure and texture on the accuracy of θ_v measurements using a capacitance-based electromagnetic sensor and evaluated the uncertainty associated with irrigation scheduling using soil water depletion-based methods and management-based θ_v. Their study reported that it might be more suitable for producers to evaluate the effectiveness of a soil moisture sensor directly in the field rather than conducting soil tests in a laboratory and calibrating the sensor accordingly.

There is a research gap in exploring the utilization of irrigation decision support systems for in-field optimization of soil water parameters and evaluating the extent to which these new precision irrigation technologies could reduce uncertainties in irrigation scheduling, especially when compared to conventional and simplistic methods. I hypothesize that irrigation decision support systems need to validate soil moisture parameters to best represent the correct state of soil moisture in the field. This is an important factor that affects the accuracy of the irrigation recommendations forecasted by the decision support tools. The soil moisture parameters to be calibrated include field capacity (FC), wilting point (WP), and management-allowed depletion (MAD). This capability to adjust the soil water parameters based on field observations of the soil moisture is a feature of Valley Scheduling™ (VS), a product of Valmont Industries, Inc.

To test the hypothesis, the VS irrigation decision support system (IDSS) was used and compared to the Web Soil Survey (WSS) and Pedo Transfer Functions (PTF) for FC. For WP, IDSS, WSS, and PTF methods were compared to the laboratory method (LAB). Studies have shown that the laboratory analysis of FC are not capable of duplicating soil-water dynamics in situ; thus, it is preferable to conduct field tests to determine the FC (Zettl et al. 2011). Hence, the laboratory analysis of only WP was conducted in this study. IDSS was categorized into two different types of methods- Single Data Point Optimization (SDPO) and Time Series Optimization (TSO), based on how they estimate FC and WP.

The study was conducted at eight locations across three states in the Great Plains of North America, including North and South Dakota, Eastern and Western Nebraska, and Kansas. Data and soil samples were collected from corn fields for the 2023 growing season.

This study will help understand the role of parameterization in an irrigation scheduling program and how one can effectively adapt and utilize calibration of the soil moisture readings to enhance the accuracy of decision-making in irrigation water management. It will provide insights into how to streamline the calibration of the capacitance-based soil moisture sensor readings and also help understand how different soils across the Great Plains of North America affect the need to recalibrate the soil moisture data from the probe during the growing season.

In this research, I evaluate different technologies available to growers to assist in irrigation scheduling and compare them with in-field optimization of soil moisture parameters with the specific objective of quantifying the impact of soil parameter method on soil water depletion and irrigation scheduling.

1.1 Soil Water Parameters

Soil water parameters are essential for assessing plant water stress, determining irrigation requirements, and optimizing crop management strategies. The amount of water in a soil can be expressed in various ways but θ_v is often more meaningful than others. This is because θ_v provides a standardized measure that is independent of soil texture and bulk density variations. It allows for easier comparison and interpretation of soil moisture data across different soil types. The different soil water parameters that are essential to define for this study are Field Capacity (FC), Permanent Wilting Point (WP), and Management Allowed Depletion (MAD).

FC and WP define the upper and lower limits of water availability respectively. θ_{FC} is defined as the soil water content at which the rate of drainage, induced by gravity, becomes negligible. FC indicates the maximum amount of water that soil can retain against gravity after excess water has drained away. θ_{WP} is defined as the soil water content at which the crop permanently wilts and cannot recover even with irrigation. At WP, plants can no longer extract water from the soil and experience water stress resulting in significant yield loss. Therefore, irrigation is required before the available water is entirely depleted to avoid significant water stress and yield loss. Hence, the management-allowed depletion (MAD) concept is commonly employed, initiating irrigation when the soil water decreases to a specific θ_{MAD} level (Evett, 2007). MAD serves as a management strategy to maximize soil water extraction and prevent yield reduction from water stress. The θ_{MAD} level varies based on soil type, rooting depth, crop sensitivity to water stress, season timing, irrigation system characteristics, and other factors (Martin et al., 1990). It is typically chosen to ensure the soil never becomes excessively dry to limit plant growth and yield, although it may sometimes allow for some level of plant stress. Irrigation is often triggered at a θ_v higher than θ_{MAD} to compensate for potential errors in θ_v measurement that could lead to unintended crop stress (Singh et al., 2020).

1.2 Observational Field Capacity (FC_{obs})

Values of FC is highly dependent on operational method. The lab method as well as field method can result in different values for the same soil. There are several reasons for this. For instance, the soil water potential associated with FC is related to texture which is difficult to predict (Romano and Santini, 2002). Another major issue is the characteristics of each soil horizon and the interactions between them. This further increases the uncertainty in the estimation of FC.

Martin et al., 1990 and Romano and Santini, 2002 asserted that the soil water potential associated with FC can increase with soil layering. Furthermore, an intact soil profile captures in-situ effects of free drainage that can be problematic in determining FC.

The classic method for measuring FC involves saturating the soil profile, covering the soil surface, and monitoring soil water content and drainage (Romano and Santini, 2002). Lo et al. (2017) suggested that a less demanding method for determining FC would be by measuring "observational field capacity" (FC_{obs}), by estimating FC in the field under non-experimental conditions. The concept of FC_{obs} is consistent with the suggestion by Martin et al. (1990) that "a good indication of the field capacity water content can be determined by sampling field soils one to three days after a thorough irrigation or rain and when crop water use is small." Also, FC_{obs} has been measured in previous site-specific research (Hezarjaribi and Sourell, 2007; Jiang et al., 2007; Haghverdi et al., 2015). Figure 1 shows a diagrammatic representation of estimating FC_{obs}.

2.0 Methodology

The methodology section is divided into different parts. Firstly, each of the different methods used in this study for the estimation of FC and WP is described. The FC was estimated using four different methods – WSS, PTF, IDSS – SDPO and TSO. The WP was estimated by the aforementioned methods and a LAB analysis was conducted using the thermocouple psychrometer.

Then details on the field sites, sampling techniques, calibration techniques, and laboratory analysis followed by statistical analysis are provided. In general, the soil parameters FC and WP were optimized to give the best performance for practical irrigation management. We call this process parameterization. This is distinct from calibration, for example, calibrating a soil water sensor to give a more accurate reading of volumetric water content (θ_v).

2.1 Different methods of optimizing soil water parameters

i. Web Soil Survey (WSS)

WSS is an online platform developed by the United States Department of Agriculture (USDA) to provide comprehensive soil survey information. This tool offers a vast database of soil data, including soil maps, classifications, and properties, covering various locations across the United States. Users can access this information through an interactive map interface or by inputting specific geographical coordinates or addresses. The WSS enables in-depth exploration and analysis of soil characteristics, aiding users in assessing soil suitability for different land uses, understanding soil-water interactions, and studying soil-health dynamics.

The WSS provides estimates of FC and WP based on soil texture, organic matter content, and other soil properties. These values are typically presented in soil data tables or as part of soil interpretation reports generated for specific locations. The FC is typically expressed as the soil moisture content (in percentage or volumetric water content) at a specific tension (i.e., -33 kPa or -1/3 bar). The WP is commonly defined as the soil moisture content (in percentage or volumetric water content) at a specific tension (i.e., -1500 kPa or -15 bars).

For the purpose of this study, the area of interest(s) (AOIs) were created on the WSS platform by inputting the geographic coordinates for each field. This was the only input to the platform to get the FC and WP values. The WSS is an easy-to-use, free-of-cost method of estimating field capacity and wilting point for decisions regarding irrigation scheduling, crop water requirements, and soil management practices tailored to their specific soil and climate conditions.

ii. Pedo Transfer Functions (PTF)

PTFs are empirical relationships that aim to predict soil hydraulic properties based on easily measurable soil attributes. The PTFs developed by Saxton and Rawls are particularly noteworthy for their robustness and widespread application.

Saxton and Rawls (2006) proposed a set of PTFs that relate soil hydraulic properties, such as hydraulic conductivity (K) and soil water retention characteristics ($\theta(h)$), to basic soil properties including soil texture, organic matter content, bulk density, and soil structure. These functions are typically developed using large databases of soil data collected from various locations, allowing for the development of models that can generalize across different soil types and conditions. The basic premise behind PTFs is to establish empirical relationships between soil properties that are easy to measure in the field or laboratory and those that are more difficult or costly to determine directly. They are often implemented in soil and water management models, hydrological models, and agricultural decision support systems to simulate soil-water dynamics, optimize irrigation scheduling, assess soil erosion risk, and support land use planning.

PTFs estimate FC and WP based on soil texture, organic matter content, bulk density, and other soil properties. These functions utilize empirical relationships derived from extensive soil database analyses to predict FC and WP for different soil types and conditions.

In this study, the composite soil samples were collected for three different depths (0 – 30 cm, 30 – 60 cm and 60 – 90 cm) from each of the eight locations and sent for texture analysis and organic matter content to the Ward Laboratories, Inc. The sand percentage and clay percentage, and organic matter content from the laboratory results were used as input for the SPAW Version 6.02.75 to estimate the soil water characteristics. The FC and WP were estimated for the three different soil depths for the eight locations.

2.2 Irrigation Decision Support System (IDSS)

IDSS tools and platforms optimize water management in agriculture by providing real-time data, analytics, and recommendations to farmers and stakeholders. These tools utilize various algorithms and models to estimate critical soil parameters and forecast irrigation recommendations, which are essential for effective irrigation scheduling and water conservation. These tools empower farmers to make informed decisions regarding irrigation scheduling, water allocation, and crop management, ultimately improving water use efficiency and agricultural productivity.

The IDSS used in this study was Valley Scheduling™ (VS), a product of Valmont Industries, Inc. This is an advanced irrigation water management software developed to improve irrigation scheduling decisions. This tool utilizes real-time data, including soil moisture levels, weather forecasts, and crop water requirements, to generate customized irrigation schedules tailored to specific field conditions and crop growth stages. The tool integrates the real-time data and water balance model to provide decisions on when and how much to irrigate, helping to prevent crop stress, over-irrigation while minimizing negative environmental impacts.

This platform has the ability to calibrate the soil moisture readings in real-time based on time-series data, field observations, etc. This feature allows flexibility in improving the soil water parameter readings by the sensor and thus helps in better irrigation recommendations. For the purpose of this study, I focused on only the calibration feature out of the many different features of this tool. All eight sites in this study used the VS platform for irrigation scheduling. Each site had one soil moisture probe installed at a location decided by the Irrigation Specialist.

The length of the soil moisture probe used was 90 cm with a sensor at every 10 cm. In Valley Scheduling, this can be visualized under the Root Zone

Graph. This divides the root zone into 9 equal layers giving the soil moisture readings at different depths of soil horizons.

iii. Single Data Point Optimization (SDPO)

After installation of the soil moisture probe, the soil moisture parameters i.e., FC and WP were calibrated by the hand feel soil moisture data collected by the Irrigation Specialist while installing the soil moisture probe. The hand-feel or touch-feeling soil moisture estimations were rated using a 20-point scale that ranges from 1 – 10 with an interval of 0.5. These ratings represent different soil moisture levels expressed in terms of percentage of FC. For example, if the farmer or Irrigation Specialist selected 88% that means that they felt that the soil had moisture equivalent to 88% of FC. Here are the ratings used for the hand-feel method: 1 – 100%, 1.5 – 96%, 2 – 92%, 2.5 – 88%, 3 – 83%, 3.5 – 79%, 4 – 75%, 5 – 67%, 5.5 – 63%, 6 – 58%, 6.5 – 54%, 7 – 50%, 7.5 – 43%, 8 – 35%, 8.5 – 27%, 9 – 18%, 9.5 – 9%, 10 – 0%.

Although the hand-feel method is a good approximation of the soil moisture level in the field, it is subjective. It can also vary from one individual to another. However, it gives a starting point for the soil moisture parameters and helps visualize if the data makes sense and if the probe was installed correctly or not.

For the purpose of this study, the SDPO is described as a method that estimates FC and WP by using a combination of the hand-feel method and initial sensor reading to calibrate the soil water parameters. It is possible that the initial soil calibration values might have been very slightly adjusted to reflect the real-time condition of the field, but no major adjustments were made to the FC and WP values.

iv. Time Series Optimization (TSO)

SDPO and TSO both fall under the IDSS, but they are different in terms of how they calibrate the soil moisture values. This is why we are treating them as separate methods for estimating the soil water parameters.

The soil moisture sensors start sending the soil moisture values after they are installed in the field. The sensors update soil moisture values approximately every 30 minutes and approximately send four values in 2 hours. These sensor readings can be visualized under the 'Sensor Graph' option. These graphs are regularly monitored by the Irrigation Specialists. The time series soil moisture curves for the eight sites in this research were regularly monitored.

Rainfall or irrigation appears as a peak or an increase in the sensor line on the Chart. In VS, FC is determined for each soil layer (9 layers). FC can be determined after an irrigation or rainfall event when the water percolates down to the sensor below. This percolation is observed as an increase in soil moisture content in the soil moisture (SM) sensor lines below. It is common to see an increase in soil moisture for the top 8-16 inches (SM1, SM2, SM3). In soils that have good drainage, one may see an increase in the bottom layers too. We select a point after the soil moisture line peaks and the slope of the line begins to flatten. This may be

1-2 days after the rainfall or irrigation event. If a lower sensor does not increase after rainfall or irrigation, it shouldn't be used to determine FC. For example, the time series data was visualized and the points on the curve were identified that coincided with a rainfall or irrigation event. The soil profile can be fully or partially saturated after this event. We wait for maybe a day or two until the readings stabilize and select that point as the field capacity. Another thing to note here is that it is very common to observe that only the top few layers reach field capacity. It varies due to soil texture, porosity, amount of rainfall, crop growth stage, etc. We can better estimate the soil water parameters for all the layers by regular monitoring of the field sites. The calibration of the soil water parameters can be updated based on the time series data readings of the sensors.

Although it is typically assumed that FC and WP are constant in time, we observed that the soil water parameters sometimes change during the growing season. There might be situations where one calibration worked well until a specific date but after that, it needs to be adjusted. In this case, VS allows to create a new calibration and gives the option to update the date when we want to implement the new calibration. This results in multiple calibrations for the soil moisture parameters in the growing season. This is a unique feature, and it helps in making informed decisions for irrigation scheduling. The reason why there is a need for multiple calibrations is unclear and crop growth stage can be thought to be one of the driving factors. Nevertheless, this feature helps in the real-time calibration of soil parameters based on field observations and time series data.

Thus, the TSO method estimates the FC which is the exact definition of observational field capacity. FC_{obs} might be best represented by FC_{TSO} because the process used to determine the FC by TSO determines FC in the field under non-experimental conditions after a major rainfall or irrigation event.

v. Laboratory analysis (LAB)

The LAB analysis was only conducted for WP analysis. The DewPoint PotentiaMeter method was used for measuring the water content associated with the soil samples that were close to the WP (-1.5 MPa). The water potential (Ψ) is the measurement of the energy status of the water in a system, in other words, it indicates how tight water is bound, structurally or chemically, within a substance.

The following procedures were used to get a precise reading. In general, an iterative process was used to adjust the gravimetric water content (w) of soil samples that were close to WP. Firstly, the soil texture analysis from the Ward Laboratories for each soil sample was classified based on sand, silt, and clay percentage. An initial target gravimetric water content was selected based on the soil texture. The following equation was used to calculate the amount of water that needs to be added to a 50g soil sample.

$$M_w = M_{ad}[(1 - w_{ad})w - w_{ad}] \tag{1}$$

where, M_w is the mass of water to add to a given mass of air-dry soil to get the desired water content, M_{ad} is the mass of air-dry soil, w is the desired final water content, and w_{ad} is the air-dry water content of the soil.

Then the soil samples were finely ground and 50g of the soil was measured and put in a container. The calculated amount of water was added to the 50g soil and mixed. It was then covered and sealed using a tape and then it was allowed to sit for at least 24 hours to equilibrate. After 24 hours the Dewpoint PotentiaMeter was first calibrated before taking the readings. Then a small portion of the sample was put in the plastic cup, and it was inserted into the WP4's sample drawer. If the MPa readings fall within the range of -0.8 and -3.0, then the soil sample container is weighed and placed in the drying oven for 48 hours. After 48 hours, the soil containers are weighed again, and this gives the first reading for calculating the WP. To be able to find the WP two samples are required. One that is dryer than -1.5 and one that is wetter than -1.5. The second sample was prepared based on the readings from the first sample. After getting two readings that were within the range of -0.8 and -3.0, the following natural log interpolation equations were used for getting the gravimetric WP values.

$$w_{-1.5} = w_1 + (w_2 - w_1)\frac{ln(\Psi_1/-1.5)}{ln(\Psi_1/\Psi_2)} \tag{2}$$

where, w_1 is the measured water content corresponding to the water potential Ψ_1 of the first sample and Ψ_2 is the measured water content corresponding to the water potential of the second sample. Then the following equation was used to get the volumetric water content (θ) WP values.

$$\theta_{-1.5} = w_{-1.5} \frac{\rho_b}{\rho_w} \qquad (3)$$

where, $\theta_{-1.5}$ is the volumetric WP, ρ_b is the bulk density of the soil and ρ_w is the density of water.

2.3 Description of the Field Sites

The field sites selected for this study are spread across six counties and four states across the Great Plains of North America. These fields are commercial fields of farmers and not experimental sites. Hence, the geolocation and names of these fields are anonymized in this study. These sites are referred to as the County names they are located in. This study was conducted during the 2023 growing season. All the field sites selected for this study cultivated corn (*Zea mays*) during this cropping season. Below is the list of these fields: -

i. York County, Eastern Nebraska (York)
ii. Dawson County, Western Nebraska (Dawson)
iii. Custer County, Western Nebraska (Custer)
iv. Beadle County- Site 1, South Dakota (Beadle Site-1)
v. Beadle County- Site 2, South Dakota (Beadle Site-2)
vi. Oliver County- Site 1, North Dakota (Oliver Site-1)
vii. Oliver County- Site 2, North Dakota (Oliver Site-2)
viii. Shawnee County, Kansas (Shawnee)

2.4 Installation specifications

The soil moisture sensors installed were Sentek Drill and Drop soil moisture probes. These probes feature capacitance-based technology in which soil profile measurements can be taken on a near-continuous basis. These soil moisture probes allow user-defined or site-specific calibration equations to be applied to each sensor. The probe is fully encapsulated and is completely buried in the soil to reduce the risk of machinery damage. The probes installed were of length 90 cm with sensors at every 10 cm.

The location where the soil moisture probe was installed was selected based on several considerations. The appropriate soil moisture probe location was determined with the help of available satellite imagery including previous normalized difference vegetation index (NDVI) maps, publicly-available soil mapping, and also by asking the growers for their preferences and knowledge of the field soils. The location is assessed by the irrigation specialist to check if the plants around the site are healthy and look uniform. The probe is carefully installed in the crop row between two plants and special attention is paid to not damage any plants close to the probe.

These soil moisture probes were installed at a location that best represents the condition of the field. These locations were selected by the Irrigation Specialists based on their experience from past years and the considerations mentioned above. In the case of a center pivot irrigation system, the installation site is selected after radially crossing at least two wheel tracks of the center pivot. The installations were done from the emergence to the 8-leaf stage of corn. The irrigation specialist assessed the location by checking the uniformity of the plants growing around that area. Then the probe was installed by drilling a hole to the soil with the help of a special auger in the row between two healthy plants. It ensured that the plants growing near the sensor were not damaged during the installation. This is a very important step to ensure that the soil moisture sensor senses the soil moisture sensed by the roots of the crop. The soil moisture sensor is then connected to the telemetry device that sends soil moisture data approximately at every 30-minute interval.

Only one probe is installed per field because the objective is to get an approximation of the soil moisture in the soil profile so that we can predict and prescribe irrigation schedules to farmers. Another reason is to minimize the cost of irrigation scheduling because installing multiple sensors in a single field is too costly. Moreover, the field sites selected in this study are fairly uniform in their soil type.

2.5 Soil sampling

The soil samples were collected from each of the field sites. The sampling was conducted at the time of removal of the soil moisture probes. I used the Dakota probes for soil sampling at three different depths. The first sample was collected at a depth of 0 to 30 cm (R_1), the second sample at a depth of 30 to 60 cm (R_2), and the third sample at 60 to 90 cm (R_3). The soil samples were taken within an approximate radius of 30 centimeters around the soil moisture probe by digging five different holes. The samples collected from different holes were mixed to make a composite sample. This was done to account for spatial variability. I did not collect soil samples from different locations of the field because the objective of the study was to evaluate the calibration of the soil moisture probe readings by placing the probe at the selected location chosen by the irrigation specialists. The soil samples from each field site were collected just before removing the probes from the field at the black layer formation stage of corn.

2.6 Uncertainty analysis and statistics

Statistical Method:

Randomized Controlled Block Design (RCBD) model was used for conducting statistical analysis. Locations were considered as a blocking factor in the design. Linear model was for analysis of the response variables (FC and WP) individually where both follow a normal distribution.

$$y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + \alpha\gamma_{ik} + e_{ijk} \tag{4}$$

where, $y_{ijk} = FC\ or\ WP\ for\ i^{th} method\ at\ k^{th} root\ depth\ in\ j^{th} block$, $\mu = overall\ mean$, $\alpha_i = fixed\ effect\ due\ to\ i^{th} method$, $\beta_j = random\ effect\ due\ to\ block$, $\gamma_k = fixed\ effect\ due\ to\ k^{th} soil\ depth$, $\alpha\gamma_{ik} = interaction\ effect\ due\ to\ i^{th} method\ at\ k^{th} soil\ depth$ and $e_{ijk}\ is\ the\ error\ term.$

The PROC MIXED procedure in SAS 9.4 was used to analyze the response variables: FC and WP. When differences occurred, they were reported at the α = 0.05 significance level with Tukey-Kramer adjustment applied to obtain appropriate p-values, and significant effects or significant differences were reported by determining the p-value. The p-value is dependent upon either the t-values or F-values and is indicated as Pr >F or Pr >|t|. If the p-value is less than 0.05, we claim that there is a significant effect of that factor.

Interactions occur when the effect of one variable depends on the value of another variable. In other words, the mean value of the response at a given level of a variable depends on the level of another variable. Interaction effects could be present between a categorical and a continuous variable. Interaction effects could also be present between two categorical variables. In the case of three categorical variables, there may be two-way interactions between pairs of variables and three-way interactions between the three variables. In this study, there are four treatment factors for field capacity and five treatment factors for wilting point. Therefore, all possible interactions were compared and assessed. Tukey-Kramer adjustments were used to account for multiple comparisons, where appropriate to control the family-wise error rate of α and to prevent inflation of Type I error.

Uncertainty analysis:

Uncertainty analysis was performed using Root Mean Square Prediction Errors (RMSPE). This provided valuable insights into the reliability and precision of predictions generated by different methods. By quantifying the average magnitude of prediction errors, RMSPE offers a measure of uncertainty inherent in the predictive capability of a method. A higher RMSPE indicates greater variability and uncertainty in predictions, suggesting less confidence in the model's accuracy. Conversely, a lower RMSPE signifies more precise predictions and reduced uncertainty. Incorporating RMSPE into uncertainty analysis helps in the quantification of the potential impact of prediction errors on decision-making processes. The following equation was used for calculating the RMSPE for the four methods used in this study for the estimation of FC and WP:

$$RMSPE_{Method}^{FC\ or\ WP} = \sqrt{\frac{\sum_{i=1}^{n}(\theta_m - \theta_b)^2 R_d}{n}} \quad (5)$$

where, RMSE = Root Mean Square Prediction Error for FC or WP, Method refers to the different optimization methods: WSS or PTF or SDPO or TSO, θ_m = Predicted or estimated Field capacity or Wilting by a method, θ_b = Baseline estimation which is the average of all the time series optimizations for FC and average of all laboratory estimations for WP, R_d = Root depth and n = Total number of field sites.

3.0 Results and Discussion

3.1 Evapotranspiration, rainfall and irrigation

Real-time weather data were imported from the VS platform. VS uses weather station data for the weather statistics. Each site had a weather station at their location except the sites in South Dakota. For the South Dakota sites, ClearAg® data was used. The actual crop evapotranspiration (ET_c), rainfall, and irrigation were imported from the VS platform for all the sites. ET_c is estimated by using the following equation in VS:

$$ET_c = ET_0 * K_C * K_S * K_L \tag{6}$$

where ET_0 is the short-grass reference evapotranspiration based on the Penman-Monteith equation, K_C is the crop coefficient that adjusts the ET_0 based on crop growth stage, K_S is the stress coefficient based on the soil moisture content, K_L is the localization coefficient that accounts for reduced evaporation when irrigation does not cover the whole area (Allen et al., 1998). VS uses three different models to estimate K_L for different crops. For the eight sites in this study, Keller & Bliesner (1990) model was used to estimate K_L. The highest recorded cumulative ET_c between June 15 to September 15, 2023 was for the Western Nebraska sites with an ET_c of 400 mm (16 inches) and the lowest was for the North Dakota sites with an ET_c of 290 mm (12 inches). The intra-seasonal crop water requirement (CWR) for maize across the eight sites are in the following order: Dawson (404 mm) = Custer (404 mm) > Shawnee (386 mm) > Beadle Site-2 (353 mm) > Beadle Site-1 (343 mm) > York (323 mm) > Oliver Site-1 (300 mm) > Oliver Site-2 (295 mm).

Each of the eight locations had a tipping bucket rain gauge installed on top of the telemetry device. The rain bucket captures all the water that is applied to the crops, i.e., rainfall and irrigation. Out of the eight sites only the sites in York, Oliver Site-2, and both the sites in Beadle had an irrigation sensor (pressure and GPS location) installed to their pivots. During the season, there are instances when there are technical issues associated with the data import to the platform. There is also a possibility of the rain bucket being shaded by the maize leaves. These are some of the potential factors that might lead to errors associated with the measurement of these parameters. The cumulative rainfall of the eight sites is in the following order: Oliver Site-2 (405 mm) > Dawson (367 mm) > Oliver Site-1 (349 mm) > Shawnee (290 mm) > Custer (276 mm) > Beadle Site-1 (209 mm) > Beadle Site-2 (201 mm) > York (164 mm).

The irrigation amounts of the sites are in the following order: York (260 mm) > Custer (213 mm) > Dawson (153 mm) > Oliver Site-1 (133 mm) > Beadle Site-2 (122 mm) > Beadle Site-1 (119 mm) > Oliver Site-2 (98 mm) > Shawnee (73 mm). Table 1 shows the average temperature, actual crop evapotranspiration, rainfall, and irrigation data for all eight sites.

3.2 Soil properties

Soil properties of the eight sites are presented in Table 2. Composite soil samples were collected from each location at three different soil depths (R_1, R_2 and R_3). The air-dried samples were sent to the Ward laboratories for texture analysis (Sand%, Silt%, and Clay%) and organic matter content (OM). The bulk density of the soil was estimated by using the soil texture and organic matter content as inputs for the Saxton and Rawls (2006) pedotransfer function.

The soil properties table shows the variability in the soil across the sites and different soil horizons. The soil texture, organic matter, and bulk density directly affect the soil water parameters and soil water holding properties. The table shows that the site in York had silty clay loam and silty clay soil type with the highest organic matter content (OM-LOI) of 3.2% at depths 30 to 60 cm compared to other sites. The highest bulk density recorded was for the sites in Oliver at a depth of 60 to 90 cm, 1.59 $kgcm^{-3}$.

3.3 Outputs from irrigation decision support system or VS platform

The IDSS or emerging irrigation scheduling platforms are devised for farmers and irrigation managers to equip them with the necessary information required to reduce the uncertainty around irrigation decision-making. They make use of real-time localized weather data, weather forecasts, crop phenology, irrigation machinery, and soil properties to model crop water requirements and provide irrigation scheduling reports. These irrigation scheduling reports include information on when and how much to irrigate. Figures 4, 5, 6 and 7 show graphs that are visible to the farmers or users of the Scheduling platform in real-time.

The SDPO method explained in the methodology section includes a combination of hand-feel and the initial data from the soil moisture sensor to calibrate the soil water parameters. The feel and appearance method is widely used but requires a great deal of judgment and experience for good estimates of soil water. Experienced users probably achieve an accuracy of a fraction of available water remaining (f_r) plus or minus 0.10 (Eisenhauer et al., 2021). The results show that for some locations the FC estimate of SDPO was as good as TSO. These locations were York and both the sites at Beadle.

The sites at Shawnee, Custer, Dawson, and both the sites at Oliver had multiple TSOs during the season. This means that for these fields the FC estimates were adjusted during the season based on the time series data received from the soil moisture sensor. These decisions were made by observing the soil moisture trends, especially after heavy rainfall. The multiple TSOs during the season also reflect the intra-season variability that occurs in a non-experimental site during the growing season.

3.4 Statistical analysis

Firstly, the normality of response variables was assessed for both FC and WP. The graphs of the studentized residual panel for FC and WP are provided in the Appendix. The bottom-left graph of the studentized residual panel shows the QQ plot. The tails of the response data were observed to be fairly on the straight line suggesting that the data was normally distributed. The top-right shows the histogram of the data and the overlaid curve was observed to be symmetric, again indicating normal distribution. Thus, normal distribution was used to model both the response variables (FC and WP).

The covariance parameter estimates provide the estimated variance in ‘Locations’ as well as ‘Residual Variance’. ‘Locations’ refers to the eight field sites which were considered as ‘Blocks’. The estimated variance among the eight sites or blocks for FC was estimated to be 17.7 and for WP, it was estimated to be 6.2. The residual variance for FC was estimated to be 24 while for WP it was estimated to be 12.9.

The ‘Type III test of fixed effects’ table gives the results of testing the effect of ‘Methods’, and ‘Root depth’ and their interaction on ‘FC’. Here, the ‘Methods’ refers to the different methods that were used in the estimation of FC and WP. The ‘Root depth’ refers to the three different root depths that were sampled to test their effect on the estimation of FC and WP. The results showed that there is a significant difference between the estimates of FC for at least one pair of methods as suggested by a p-value of less than 0.0001. However, the main effect of ‘Root depth’ was found to be marginally significant since the p-value associated with it was 0.0378, not very small compared to 0.05. The interaction effect of ‘Methods by Root depth’ was not found to be significant.

The tables in the appendix show the least square means estimates for various levels of each ‘Methods’ and ‘Root depth’. The columns provide the estimates and their standard error for ‘FC’ and ‘WP’ for each level of factor variables.

As the main effect of Methods and Root depth were found to be significant, further investigation was done to understand which possible pair/s were significantly different from each other. Therefore, all possible pair-wise combinations between levels of each variable were compared. Tukey-Kramer adjustment was used to control the family-wise error rate of α. In other words, with many comparisons done, the Tukey-Kramer adjustment helps prevent inflation of Type I error (rejecting null when it is true). The significant differences are marked with '*' in Tables 5 and 6.

There was a significant difference in the estimated mean 'FC' between PTF and SDPO as suggested by a p-value of less than 0.0001. The other pairs that had significant differences in the estimated mean were PTF and TSO, SDPO and WSS, and TSO and WSS. PTF and WSS had moderately significant differences with a p-value of 0.03. However, TSO and SDPO did not have a significant difference in their estimation. In addition, with 95% confidence, the true mean 'FC' for TSO was 9.1 to 16.5 units (percent volumetric water content) higher compared to PTF. The mean for TSO was 14.2 to 21.6 units higher compared to WSS. For PTF, the mean was 1.3 to 8.8 units higher as compared to WSS. The Figure 2 shows the correlation between the means of the methods with respect to TSO along with the confidence intervals for the methods, $R^{2,}$ and equation.

There was a significant difference in the estimated mean WP between LAB and SDPO, LAB and PTF, and LAB and TSO as suggested by a p-value of less than 0.0001. There was a moderately significant difference between LAB and WSS with a p-value of 0.02. The other pairs that were significantly different were WSS and PTF, WSS and SDPO, WSS and TSO. In addition, with 95% confidence, the true mean WP for LAB was 7.3 to 13.1 units lower compared to TSO and 7.4 to 13.2 units lower compared to SDPO. The mean for LAB was 4.9

to 10.7 units lower compared to PTF. For PTF, the true mean was 1.3 to 8.8 units higher as compared to LAB and 1.7 to 7.5 units higher compared to WSS.

The results showed that there are differences between the estimated field capacity and wilting point among different methods. For FC, these differences are, however, not significant between the pairs SDPO and TSO. There are differences in the estimated field capacity between different root depths. In addition, there is a moderately significant difference between the root depths pair R_2 (30 – 60 cm) and R_3 (60 – 90 cm). For WP, the differences were significant for all the pairs with LAB and WSS. The pair WSS and LAB was moderately significant. The Figure 3 shows the correlation between the means of the methods with respect to LAB along with the confidence intervals for the methods, $R^{2,}$ and equation.

3.5 Uncertainty analysis

The uncertainty analysis was performed by calculating the 'Root Mean Square Prediction Error' (RMSPE) for FC and WP. The RMSPE for FC was calculated using Equation 5 and θ_b in this case is the average of all the time series optimizations (TSO). The F-statistic was calculated to test the significant difference in the RMSPE estimations after accounting for the correlation between the four methods. The Table 7 shows the RMSPE values for the four methods for the estimation of FC with their statistical difference. The RMSPE of WSS and PTF were significantly different from SDPO but not significantly different from each other. The RMSPE for FC of the four methods is in the following order: WSS (169.9 mm) > PTF (124.1 mm) > TSO (7.5 mm) ≈ SDPO (6.0 mm).

It is important to note that the RMSPE for WSS, PTF, and SDPO gives the value of prediction error across all the field sites. Hence, the RMSPE can capture the prediction error within blocks for a given season across the different sites. However, the RMSPE for TSO gives the prediction error which might capture the intra-season error in the estimation of FC (since some field sites had multiple FCs through the season from the TSO method). Therefore, it is worthwhile to say that calculating the RMSPE for different methods captures the spatial variability across sites (i.e., blocks) in the estimation of FC and the RMSPE for TSO can capture the temporal variability in the estimation of FC.

The RMSPE for WP was calculated using equation 5 and θ_b in this case is the average of LAB estimations for WP. Similar to the FC, the F-statistic was calculated to test the significant difference in the RMSPE estimations after accounting for the correlation between the four methods. The table 8 shows the RMSPE values for the four methods for the estimation of FC with their statistical difference. The results showed that none of the RMSPEs were significantly different from each other. The RMSPE for WP of the four methods is in the following order: WSS (41.6 mm) < PTF (82.2 mm) < TSO (94.8 mm) ≈ SDPO (96.0 mm).

4.0 Research implications

4.1 Value of using Soil Water Depletion (SWD) instead of Volumetric Water Content (θ_v)

Soil water depletion (SWD) or soil water deficit (SWD) is defined as the amount of available water that has been removed from the root zone. It is the difference between θ_{FC} and θ_v, the actual soil water content. The difference between θ_v and θ_{WP} is the amount of available water remaining.

SWD was plotted for each of the four methods. Figure 8 shows a panel of graphs comparing the SWD of each method with the baseline. SWD was calculated by the following equation:

$$SWD = \frac{(\theta_{FC_{base}} - \theta_v)}{100} * Root\ depth \tag{7}$$

θ_v is the volumetric soil water content average across the root zones. The baseline for FC is the average of all the TSOs and the baseline for WP is the average of the LAB estimates across the eight sites. FC, MAD, and WP were calculated in terms of SWD. FC_{base} was set as 0 because the baseline FC corresponds to 0 water depletion. WP_{base} was calculated by calculating the Total Available Water (TAW) in the root zone.

$$TAW = (\theta_{FC_{base}} - \theta_{WP_{base}}) * Root\ depth \tag{8}$$

WP_{base} corresponds to 100% depletion of the total available water in the root zone. MAD_{base} was calculated by assuming it to be 70% of the FC_{base} which corresponds to 30% of the TAW. The FC, WP, and MAD for different methods were calculated by the following equations:

$$FC_{Method} = (FC_{base} - FC_{method}) * Root\ depth \tag{9}$$

$$WP_{Method} = (FC_{Method} - WP_{Method}) * Root\ depth \quad (10)$$

$$MAD_{Method} = (0.3 * TAW_{method}) \quad (11)$$

The Figure 8 shows the SWD panel graph for Shawnee, KS for the 2023 growing season. The four different panels show how the soil water parameters (FC, WP, and MAD) shift for the different methods compared to FC_{obs} and WP_{LAB}. The figure clearly shows the value of using SWD over θ_v lies in its direct relevance to plant water stress and irrigation management. SWD quantifies the actual reduction in available water in the root zone, which directly affects plant water uptake and growth. This metric provides a clearer indication of the water stress experienced by plants and helps in determining the timing and amount of irrigation needed to maintain optimal soil moisture levels for crop growth. While θ_v measures the proportion of water present in the soil relative to its total volume, providing a general indication of soil moisture status and is valuable for monitoring soil moisture levels it may not directly translate to plant water stress or irrigation scheduling decisions.

By calculating SWD, we mitigate bias in the soil moisture sensor readings sensor might have in the measurement of θ_v.

4.2 Implications of the uncertainty in the estimation of Observational Field Capacity (FC_{obs})

To illustrate the magnitude of the RMSPE in terms of impact on irrigation scheduling and water use, the potential delay in irrigation was calculated using the following equation:

$$Delay\ in\ irrigation = \frac{RMSPE_{Method}}{ET_{avg}} * w_{FC\ or\ WP} \tag{12}$$

where ET_{avg} is calculated by first finding the maximum ET_c for all the individual fields and then taking the average of the ET_c across the field sites from between June to September which was found to be 7.7 mm per day. $w_{FC\ or\ WP}$ is the weighing factor of FC or WP on MAD. For FC, the w is 0.7 and 0.3 for WP.

The delay in the number of irrigation events or the irrigation events that could potentially be missed due to the error in the estimation of FC was calculated using the following equation:

$$No. of\ irrigation\ events\ missed = \frac{Delay\ in\ irrigation}{T_C} \tag{13}$$

where, T_C is the cycle time or the amount of time taken by the center pivot to complete one revolution and it was assumed to be 2.5 days per event.

The WSS had the highest $RMSPE_{WSS}$ (169.9 mm) of 18.6% with a potential delay in the start of irrigation by 15 days and 6 missed irrigation events followed by PTF with $RMSPE_{PTF}$ (124.1 mm) of 13.6% with a potential delay in the start of irrigation by 11 days and 5 missed irrigation events. The SDPO had the lowest $RMSPE_{SDPO}$ (6.0 mm) of 0.7% with an early start of irrigation by 1 day and no missed irrigation event. TSO had a $RMSPE_{TSO}$ (7.5 mm) which reflects the temporal variability in the estimation of FC and it is around 0.8%. Since the real value of FC_{obs} can be determined towards the end of the growing season, considering an intermediate value of FC_{TSO} can result in an early start of irrigation by 1 day and no missed irrigation event.

For WP, the WSS had the lowest $RMSPE_{WSS}$ (41.6 mm) of 4.6% with an early start of irrigation by 2 days and 1 extra irrigation event followed by PTF with $RMSPE_{PTF}$ (82.2 mm) of 9% with an early start of irrigation by 3 days and 1 extra irrigation event. The SDPO had the highest $RMSPE_{SDPO}$ (96.0 mm) of 10.5% with a an early start of irrigation by 4 days and 1 extra irrigation event. TSO had a $RMSPE_{TSO}$ (94.9 mm) with an early start of irrigation by 4 days and 1 extra irrigation event.

5.0 Limitations and Future Work

In this research, different methods of estimating FC and WP to optimize soil moisture parameters for irrigation scheduling were evaluated. However, several limitations should be considered when interpreting the results of this study. The calculation of Root Mean Square Prediction Error (RMSPE) provided insights into the uncertainty associated with each method. However, uncertainties in measurement, calibration, and data processing may still exist, influencing the accuracy and reliability of the results. The study was conducted in eight specific regions across three states in the Great Plains of North America. The findings may not be directly applicable to other geographic regions or different cropping systems, limiting the generalizability of the results. Soil moisture conditions exhibit temporal and spatial variability, which may not be fully captured by the methods evaluated in this study. Variations in data collection protocols, sensor calibration, laboratory data, and data processing techniques could introduce discrepancies or biases in the analysis.

Future studies could focus on evaluating the impact of different soil moisture estimation methods on crop yield and economic outcomes. They could analyze the cost-effectiveness of reducing uncertainty in soil moisture estimation through the adoption of new precision technologies. By comparing the costs associated with implementing and maintaining different soil moisture estimation methods, including sensor installation, calibration, and data processing, researchers can assess the economic feasibility of investing in these technologies to improve irrigation decision-making and optimize crop management practices. Furthermore, integrating agronomic data, such as crop yield and water use efficiency, with economic indicators, such as input costs and crop market prices, would provide a comprehensive understanding of the trade-offs between accuracy, cost, and potential yield gains associated with different soil moisture estimation methods.

6.0 Conclusions

In conclusion, this research provides insights into the estimation of soil moisture parameters for irrigation scheduling using various methods by evaluating the uncertainty of these methods across different soil conditions. Our findings highlight the importance of considering FC_{obs} for the estimation of FC in irrigation decision-making. IDSS demonstrated promising results in minimizing RMSPE and optimizing irrigation timing. While WSS and PTF exhibited higher uncertainties and potential delays in irrigation events.

Overall, this research contributes to advancing our understanding of soil moisture estimation methods and their implications for improving irrigation decision-making and enhancing agricultural productivity and sustainability. This study will benefit irrigation scheduling practices by developing a better understanding of the insights available from the estimation of FC_{obs} for different soils and how to best manage the data from the soil moisture probes. It will benefit the use of soil moisture probes and help direct irrigation specialists and their customers on the use of irrigation scheduling software. This is also relevant to other parts of the world where the use and calibration of soil moisture probe data is limited by the expertise or lack of expertise of the available irrigation specialists and farmers. By focusing on SWD, farmers, and irrigation managers can better understand the dynamics of water availability in the root zone and make more informed decisions regarding irrigation timing and efficiency

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List of Tables

Table 1: Average temperature, actual crop evapotranspiration, rainfall, and irrigation data for all eight sites during the 2023 growing season (from emergence to maturity)

Site	Average Temperature (°C)	Rainfall (mm)	Crop Evapotranspiration "ET_c" (mm)	Irrigation (mm)
Oliver County North Dakota Site 2	19.3	404.9	294.6	98.0
Dawson County Western Nebraska	21.4	367.3	403.9	153.4
Oliver County North Dakota Site 1	19.3	349.0	299.7	133.4
Shawnee County Kansas	25.5	289.6	386.1	73.4
Custer County Western Nebraska	21.4	275.8	403.9	213.4
Beadle County South Dakota Site 1	22.4	208.8	342.9	119.4
Beadle County South Dakota Site 2	22.4	200.9	353.1	121.9
York County Eastern Nebraska	23.1	163.8	322.6	259.6

Table 2: Measured physical properties of soil at the eight sites.

Sites	**Soil depth**	**Sand %**	**Silt %**	**Clay %**	**Organic Matter, %**	**Bulk density, g/cm^3**
York County Eastern Nebraska	0 – 30 cm	12	50	38	3.2	1.26
	30 – 60 cm	6	40	54	2.5	1.21
	60 – 90 cm	6	40	54	1.8	1.22
Dawson County Western Nebraska	0 – 30 cm	14	48	38	2.6	1.30
	30 – 60 cm	18	47	35	1.6	1.38
	60 – 90 cm	25	46	29	1.2	1.45
Custer County Western Nebraska	0 – 30 cm	18	44	38	2.2	1.34
	30 – 60 cm	47	24	29	1.3	1.52
	60 – 90 cm	23	54	23	1.2	1.47
Beadle County South Dakota Site 1	0 – 30 cm	49	28	23	2.7	1.45
	30 – 60 cm	51	24	25	1.6	1.52
	60 – 90 cm	57	18	25	1.1	1.56
Beadle County South Dakota Site 2	0 – 30 cm	47	26	27	2.1	1.48
	30 – 60 cm	57	20	23	1.3	1.55
	60 – 90 cm	38	24	38	1.1	1.47
Oliver County North Dakota Site 1	0 – 30 cm	5	37	58	3.1	1.18
	30 – 60 cm	11	40	49	2.3	1.26
	60 – 90 cm	10	40	50	1.8	1.26
Oliver County North Dakota Site 1	0 – 30 cm	18	40	42	2.7	1.31
	30 – 60 cm	23	42	35	1.9	1.38
	60 – 90 cm	59	26	15	0.6	1.59
Shawnee County Kansas	0 – 30 cm	24	45	31	2.2	1.38
	30 – 60 cm	18	40	42	2.7	1.31
	60 – 90 cm	21	48	31	2.2	1.37

Table 3: Comparison of Field Capacity (in volumetric %) estimated by different methods across all sites.

Sites	Web Soil Survey (WSS)	Pedotransfer Function (PTF)	Irrigation Decision Support System (IDDS)	
			Single Data Point Optimization (SDPO)	Time Series Optimization (TSO)
York County Eastern Nebraska	33	42	55	55
Dawson County Western Nebraska	29	36	52	51
Custer County Western Nebraska	32	33	50	51
Beadle County South Dakota Site 1	29	27	40	40
Beadle County South Dakota Site 2	29	30	50	50
Oliver County North Dakota Site 1	29	43	53	51
Oliver County North Dakota Site 2	28	32	36	37
Shawnee County Kansas	30	37	48	48

Table 4: Comparison of Wilting Point (in volumetric %) estimated by different methods across all sites.

Sites	**Web Soil Survey (WSS)**	**Pedotransfer Function (PTF)**	**Irrigation Decision Support System (IDDS)**		**Laboratory Analysis**
			Single Data Point Optimization (SDPO)	**Time Series Optimization (TSO)**	
York County Eastern Nebraska	20	29	28	28	17
Dawson County Western Nebraska	14	21	27	26	15
Custer County Western Nebraska	19	19	25	26	16
Beadle County South Dakota Site 1	15	16	20	20	12
Beadle County South Dakota Site 2	15	18	26	26	13
Oliver County North Dakota Site 1	20	31	26	25	14
Oliver County North Dakota Site 2	19	19	18	18	9
Shawnee County Kansas	15	21	24	24	14

Table 5: Pair-wise combinations between levels of each 'Method' of estimating Field Capacity with Tukey-Kramer adjustment to control the family-wise error rate of α and to prevent inflation of Type I error.

Differences of Least Squares Means of Field Capacity (%)										
Effect	**Methods**	**Methods**	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**	**Adj P**	**Adj Lower**	**Adj Upper**
Methods	**PTF**	**SDPO**	-13.0607	1.4145	77	-9.23	<.0001	<.0001***	-16.7752	-9.3462
Methods	**PTF**	**TSO**	-12.8214	1.4145	77	-9.06	<.0001	<.0001***	-16.5359	-9.1069
Methods	**PTF**	**WSS**	5.0958	1.4145	77	3.60	0.0006	0.0031**	1.3813	8.8104
Methods	**SDPO**	**TSO**	0.2393	1.4145	77	0.17	0.8661	0.9983	-3.4752	3.9538
Methods	**SDPO**	**WSS**	18.1565	1.4145	77	12.84	<.0001	<.0001***	14.4420	21.8710
Methods	**TSO**	**WSS**	17.9172	1.4145	77	12.67	<.0001	<.0001***	14.2027	21.6318

Table 6: Pair-wise combinations between levels of each 'Method' of estimating Wilting Point with Tukey-Kramer adjustment to control the family-wise error rate of α and to prevent inflation of Type I error.

Differences of Least Squares Means of Wilting Point (%)										
Effect	**Methods**	**Methods**	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**	**Adj P**	**Adj Lower**	**Adj Upper**
Methods	LAB	PTF	-7.8158	1.0387	98	-7.52	<.0001	<.0001***	-10.7027	-4.9290
Methods	LAB	SDPO	-10.3642	1.0387	98	-9.98	<.0001	<.0001***	-13.2510	-7.4773
Methods	LAB	TSO	-10.2646	1.0387	98	-9.88	<.0001	<.0001***	-13.1514	-7.3777
Methods	LAB	WSS	-3.2242	1.0387	98	-3.10	0.0025	0.0206*	-6.1110	-0.3373
Methods	PTF	SDPO	-2.5483	1.0387	98	-2.45	0.0159	0.1101	-5.4352	0.3385
Methods	PTF	TSO	-2.4488	1.0387	98	-2.36	0.0204	0.1360	-5.3356	0.4381
Methods	PTF	WSS	4.5917	1.0387	98	4.42	<.0001	0.0002**	1.7048	7.4785
Methods	SDPO	TSO	0.09958	1.0387	98	0.10	0.9238	1.0000	-2.7873	2.9864
Methods	SDPO	WSS	7.1400	1.0387	98	6.87	<.0001	<.0001***	4.2531	10.0269
Methods	TSO	WSS	7.0404	1.0387	98	6.78	<.0001	<.0001***	4.1536	9.9273

Table 7: Root Mean Square Prediction Error for the estimation of Field Capacity and the potential delay in irrigation and missed number of irrigation events caused by the error in estimation.

Methods	RMSPE (mm)	ET_{avg} (mm/day)	Potential delay in irrigation (day)	# of missed irrigation events
WSS	169.9[a]	7.7	15	6
PTF	124.1[a]	7.7	11	5
SDPO	6.0[b]	7.7	-1	0
TSO	7.5[b]	7.7	-1	0

Table 8: Root Mean Square Prediction Error for the estimation of Wilting Point and the potential delay in irrigation and missed number of irrigation events caused by the error in estimation.

Methods	RMSPE (mm)	ET_{avg} (mm/day)	Potential delay in irrigation (day)	# of missed irrigation events
WSS	41.6[a]	7.7	-2	-1
PTF	82.2[a]	7.7	-3	-1
SDPO	96.0[a]	7.7	-4	-1
TSO	94.8[a]	7.7	-4	-1

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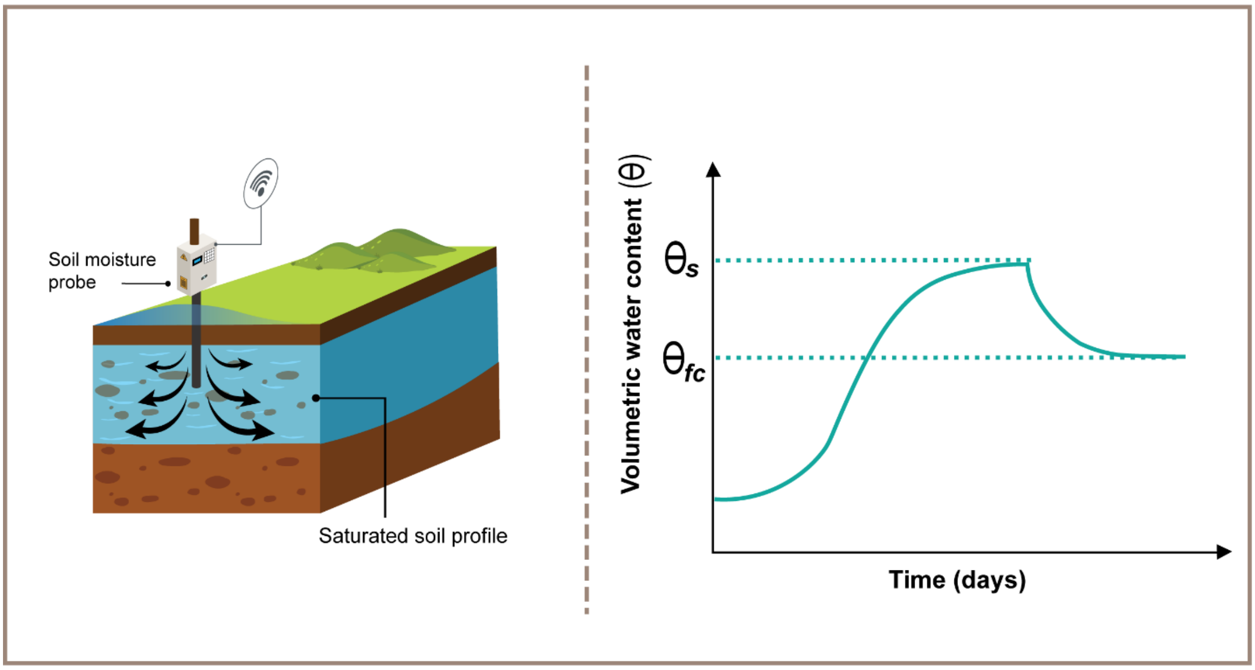


Figure 1: Schematic diagram of in-field estimation of Observational Field Capacity (FC_{obs}) on a non-experimental site. The graph shows the distinction between the volumetric water content at saturation (θ_s) and field capacity (θ_{fc}).

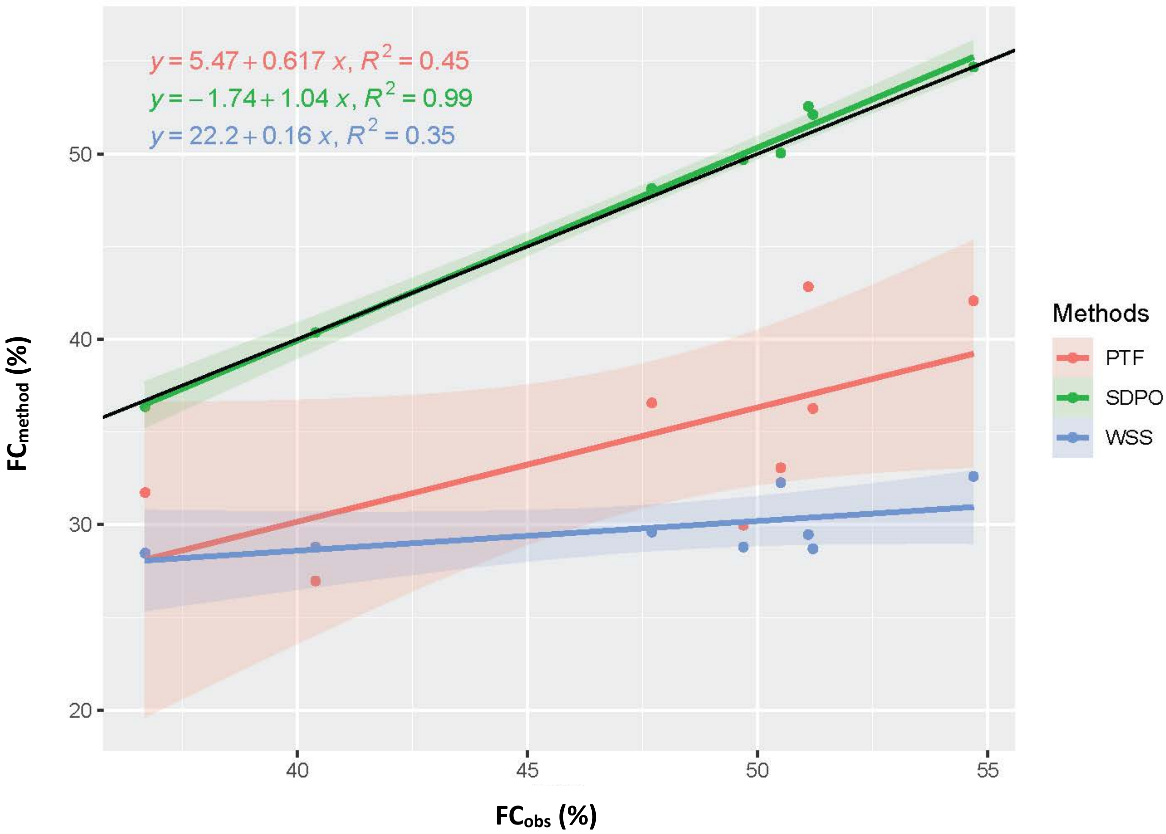


Figure 2: FC regression curve for the different methods (WSS, PTF, SDPO) vs. FC_{obs} (TSO) with their confidence intervals. The shaded area shows the confidence intervals for the methods. The PTF has the highest confidence intervals represented by red color followed by WSS (blue color) and SDPO (green color). The solid black line shows the slope and SDPO is the closest to the slope.

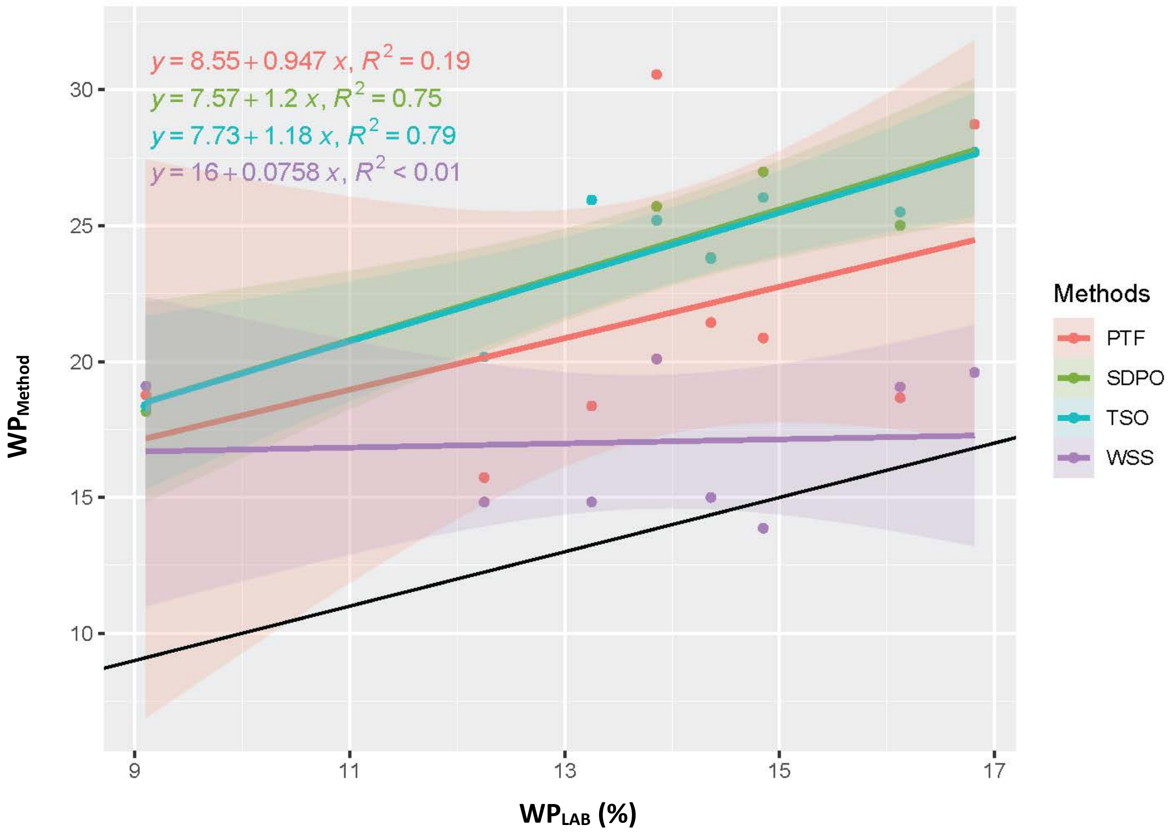


Figure 3: WP regression curve for the different methods (WSS, PTF, SDPO, TSO) vs. WP_{LAB} (LAB) with their confidence intervals. The shaded area shows the confidence intervals for the methods. The PTF has the highest confidence intervals represented by red color followed by WSS (purple color), SDPO (green color) and TSO (blue color). The solid black line shows the slope and WSS is the closest to the slope.

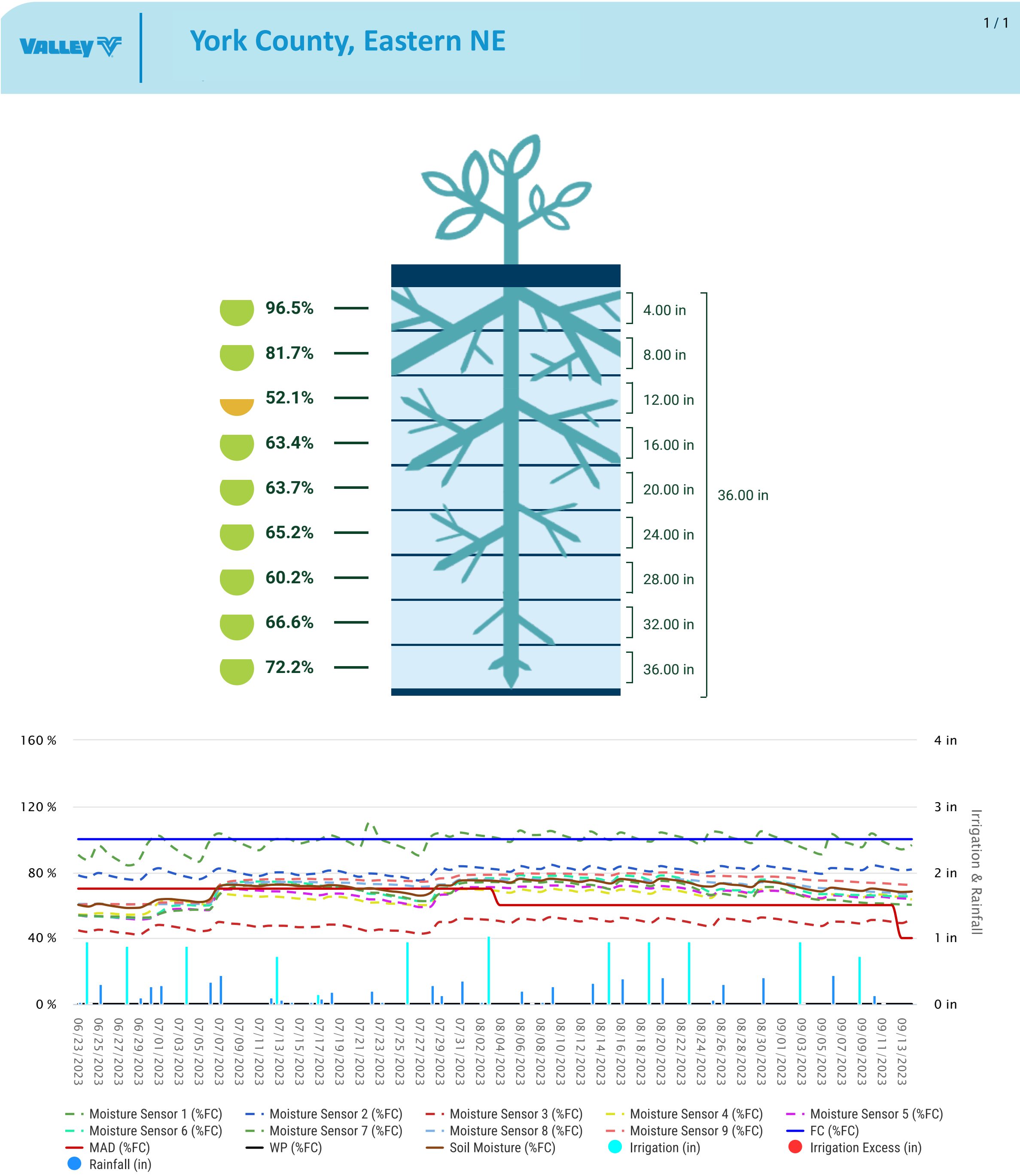


Figure 4: Root Zone soil moisture content for each layer. The lower panel shows the volumetric water content (in % of FC) for all the layers, FC, WP, MAD, rainfall (in inches) and irrigation (in inches) for the site at York County, NE.

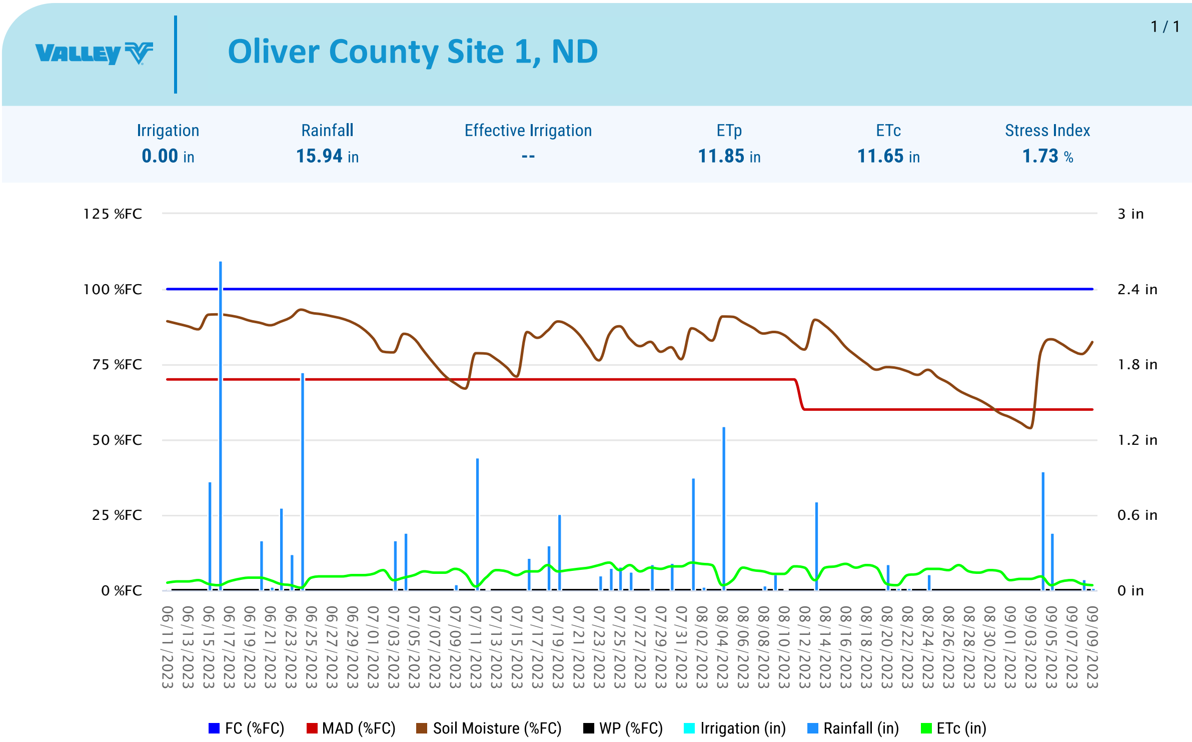


Figure 5: Average soil moisture content, FC, WP, MAD, FC and WP for all layers, and rainfall and ET_c for the 2023 growing season at Oliver County, ND.

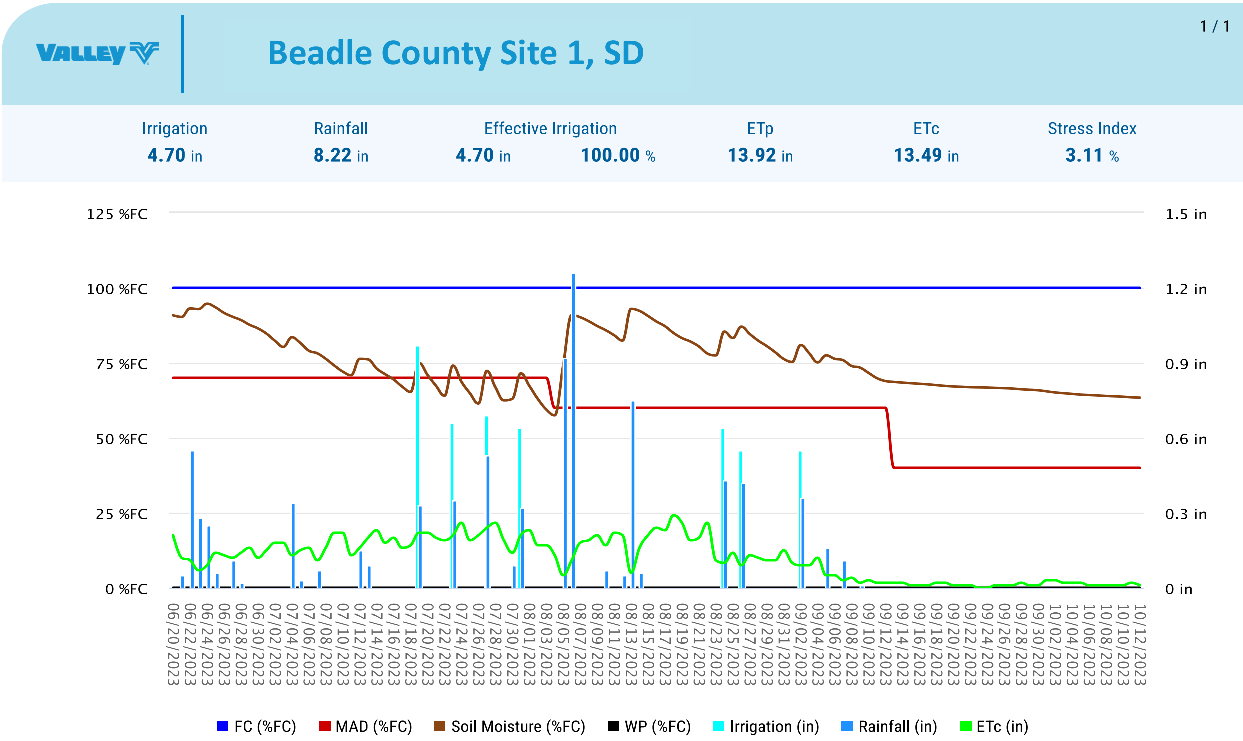


Figure 6: Soil Moisture Graph showing the average soil moisture content for the 2023 growing season. It shows the average volumetric water content for all the layers, FC, WP, MAD, rainfall and ET_c for the site at Beadle County, SD.

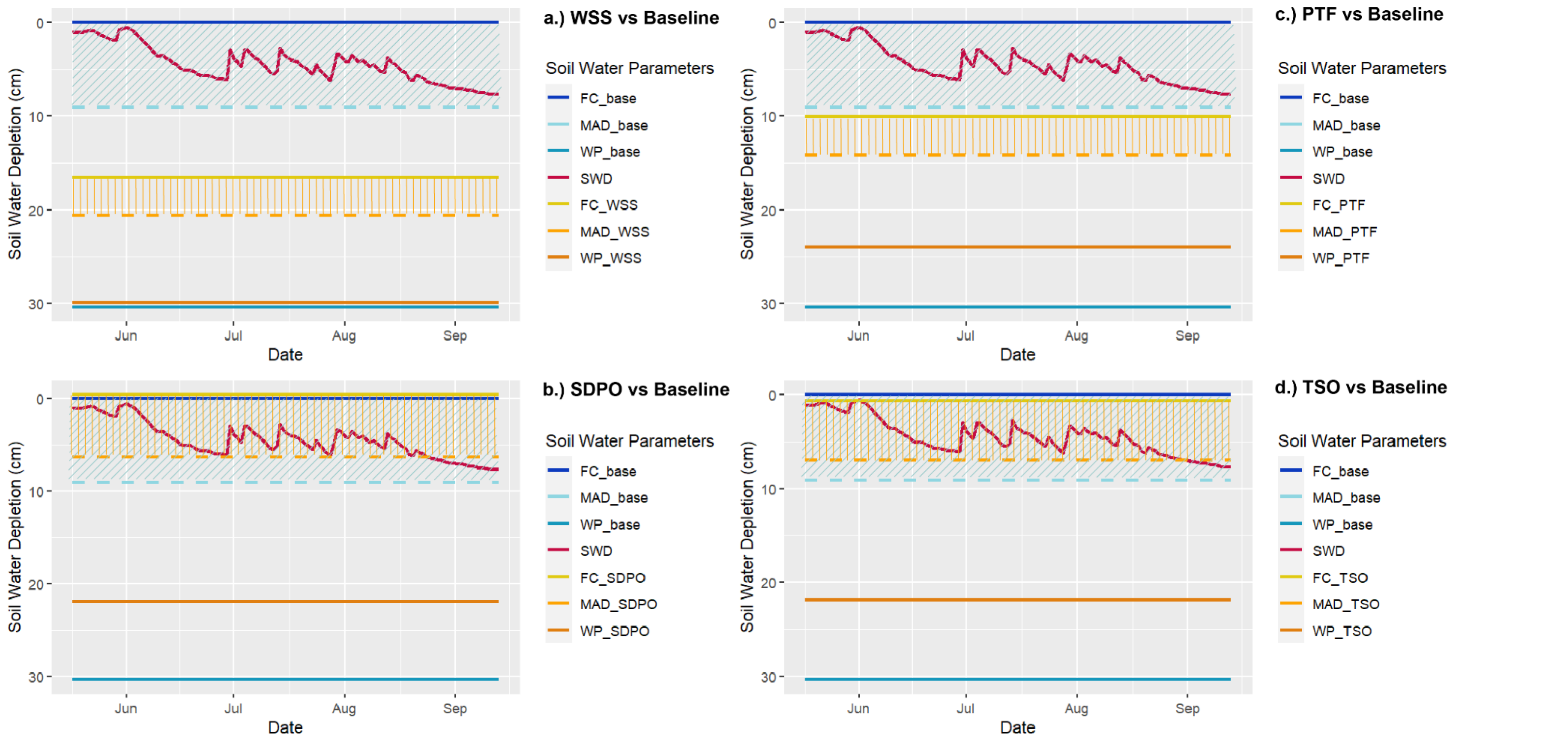
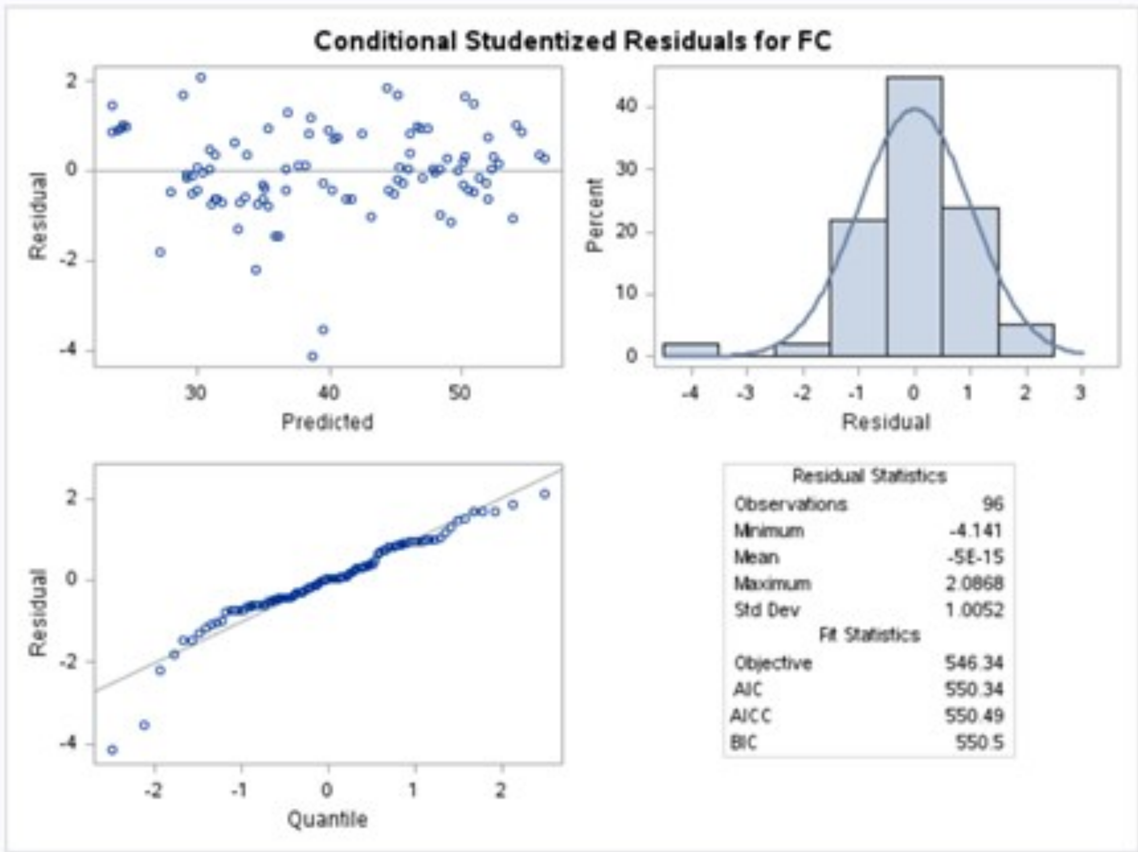
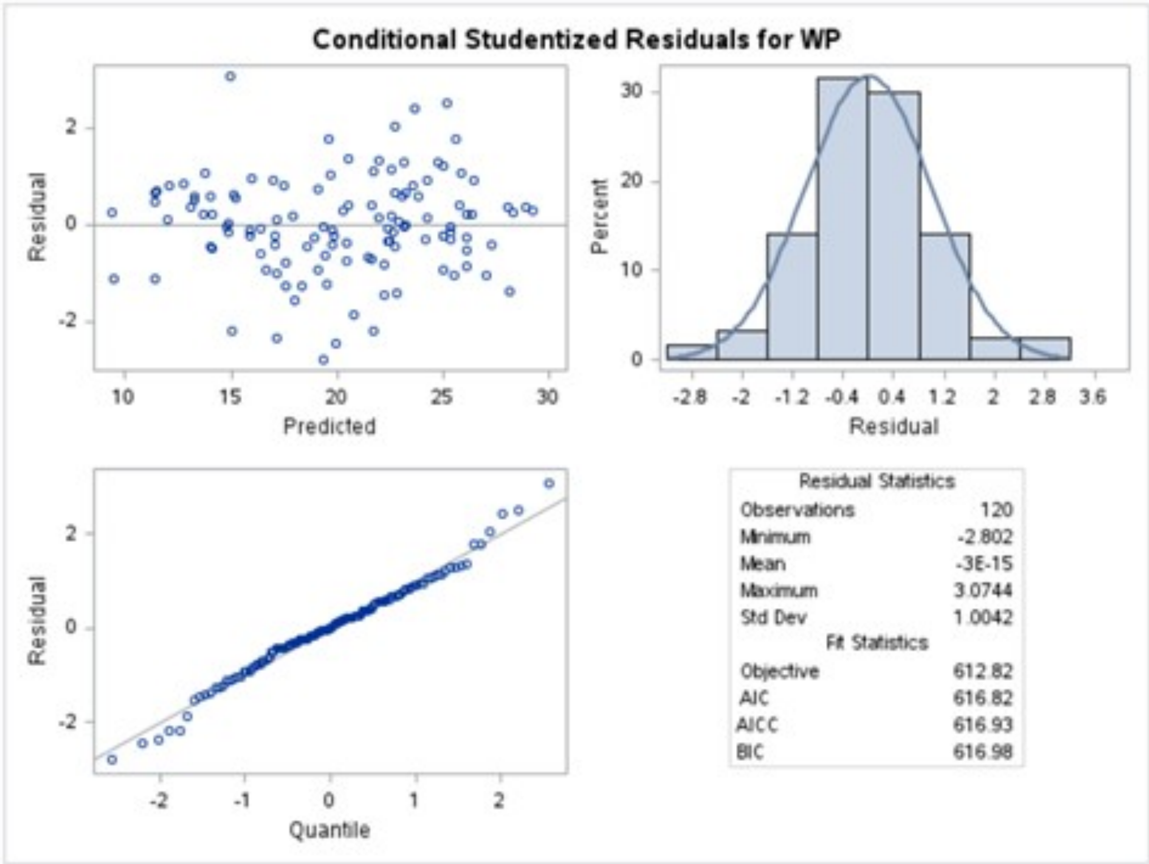


Figure 7: Water Depletion (SWD), FC, WP and MAD for the four methods (WSS, PTF, SDPO and TSO) (yellow lines) as compared to the baseline (FC_{obs} and WP_{LAB}) (blue lines). SWD from the soil moisture sensor is shown in red. The blue shaded area represents the MAD for baseline and yellow shaded area represents the MAD for the different methods. The graph shown here is for Shawnee County, KS but the trends look similar irrespective of the fields.

Appendix



A.1: The graphs of the studentized residual panel for FC showing that the means are normally distributed.



A.2: The graphs of the studentized residual panel for WP showing that the means are normally distributed.

A.3 : Type III Tests of Fixed Effects table shows the results of testing the effect of ‘Methods’, ‘Root depth’ and their interaction on ‘Field Capacity’.

Type 3 Tests of Fixed Effects (Field Capacity)				
Effect	**Num DF**	**Den DF**	**F Value**	**Pr > F**
Methods	3	77	84.27	<0.0001***
Root depth	2	77	3.42	0.0378*
Methods*Root depth	6	77	0.94	0.4712

A.4 : Least squares means estimates of Field Capacity for various levels of each ‘Method’.

Least Squares Means (Field Capacity)							
Methods	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Alpha**	**Lower**	**Upper**
PTF	34.9333	1.7928	19.49	<.0001	0.05	31.3634	38.5033
SDPO	47.9940	1.7928	26.77	<.0001	0.05	44.4241	51.5640
TSO	47.7547	1.7928	26.64	<.0001	0.05	44.1848	51.3247
WSS	29.8375	1.7928	16.64	<.0001	0.05	26.2676	33.4074

A.5 : Type III Tests of Fixed Effects table shows the results of testing the effect of 'Methods', 'Root depth' and their interaction on 'Wilting Point'.

Type 3 Tests of Fixed Effects (Wilting Point)				
Effect	**Num DF**	**Den DF**	**F Value**	**Pr > F**
Methods	4	98	38.78	<.0001***
Root depth	2	98	2.42	0.0939
Methods*Root depth	8	98	0.72	0.6760

A.6 : Least squares means estimates of Wilting Point for various levels of each 'Method'.

Least Squares Means (Wilting Point)							
Methods	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Alpha**	**Lower**	**Upper**
LAB	13.8258	1.1486	12.04	<.0001	0.05	11.5464	16.1053
PTF	21.6417	1.1486	18.84	<.0001	0.05	19.3622	23.9211
SDPO	24.1900	1.1486	21.06	<.0001	0.05	21.9106	26.4694
TSO	24.0904	1.1486	20.97	<.0001	0.05	21.8110	26.3699
WSS	17.0500	1.1486	14.84	<.0001	0.05	14.7706	19.3294